ReSAKSS
Regional Strategic Analysis and Knowledge Support System
by AKADEMIYA2063

Annual Trends and Outlook Report 2021

BUILDING RESILIENT AFRICAN FOOD SYSTEMS
After COVID-19

Edited by
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Established in 2006 under the Comprehensive Africa Agriculture Development Programme (CAADP), the Regional Strategic Analysis and Knowledge Support System (ReSAKSS) supports efforts to promote evidence- and outcome-based policy planning and implementation. In particular, ReSAKSS provides data and related analytical and knowledge products to facilitate CAADP benchmarking, review, and mutual learning processes. AKADEMIYA2063 leads the work of ReSAKSS in partnership with the African Union Commission, the African Union Development Agency-NEPAD (AUDA-NEPAD), and leading regional economic communities (RECs). AKADEMIYA2063's mission is to provide data, policy analysis, and capacity strengthening support to enable African Union (AU) Member States to achieve economic transformation and shared prosperity in support of AU's Agenda 2063.

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Abbreviations

AAgWa	Africa Agriculture Watch
AATM	Africa Agriculture Trade Monitor
AATS	Africa Agriculture Transformation Scorecard
AfCFTA	African Continental Free Trade Area
AfCP	Africa Crop Production
AfDB	African Development Bank
AGRODEP	African Growth and Development Policy Modeling Consortium
AI	artificial intelligence
ATOR	Annual Trends and Outlook Report
AU	African Union
AUC	African Union Commission
AUDA-NEPAD	African Union Development Agency-New Partnership for Africa's Development
BR	Biennial Review
CAADP	Comprehensive Africa Agriculture Development Programme
CEN-SAD	Community of Sahel-Saharan States
CGE	computable general equilibrium
CH	Cadre Harmonisé
CILSS	Permanent Interstate Committee for Drought Control in the Sahel
DHS	Demographic and Health Surveys
EAC	East African Community
EC	European Commission
ECCAS	Economic Community of Central African States
ECOWAS	Economic Community of West African States
ECRC	Country-level Resilience Capacities
ET	evapotranspiration
EVI	Enhanced Vegetation Index
FANRPAN	Food, Agriculture and Natural Resources Policy Analysis Network
FANTA	Food and Nutrition Technical Assistance
FAO	Food and Agriculture Organization
FAOSTAT	FAO Corporate Statistical Database
FEWS-NET	Famine Early Warning Systems Network
FIES	Food Insecurity Experience Scale
FSP	food security pillars
FVC	food value chains
GAE	government agriculture expenditure
GDP	gross domestic product
GPS	Global Positioning System
HSC/HSCI	Health Systems Capacities Index
HVC/HVCA	household value chain/household value chain analysis
HVI	Health Vulnerability Index
IFPRI	International Food Policy Research Institute
IGAD	Intergovernmental Authority on Development
IISD	International Institute for Sustainable Development
ILO	International Labour Organization
IMF	International Monetary Fund
IPC	Integrated Food Security Phase Classification
IYCF	Infant and Young Child Feeding
JSR	Joint Sector Review
LSMS	Living Standards Measurement Study
LST	Land Surface Temperature
$MRCS^{GHS}$	Malabo Referenced Resilience Capacities Score to Global Health Shocks
NAFSIP	National Agriculture and Food Security Investment Plan
NAIP	National Agriculture Investment Plan

NDVI	Normalized Difference Vegetation Index
NEPAD	New Partnership for Africa's Development
NPCA	NEPAD Planning and Coordinating Agency
OECD	Organization for Economic Co-operation and Development
OxCGRT	Oxford Covid-19 Government Response Tracker
PCA	principal component analysis
PPP	purchasing power parity
PSNP	Productive Safety Net Program
RCI	Resilience Capacity Index
RCS^{GHS}	Resilience Capacities Score to Global Health Shocks
REC	Regional Economic Community
ReSAKSS	Regional Strategic Analysis and Knowledge Support System
RF	CAADP Results Framework
RIMA-II	Resilience Index Measurement and Analysis II
RSP	remote sensing product
SADC	Southern African Development Community
SAM	social accounting matrix
SARIMA	Seasonal Autoregressive Integrated Moving Average
SDG	Sustainable Development Goals
SME	small and mid-size enterprise
SSA	Africa south of the Sahara
UNCTAD	United Nations Conference on Trade and Development
UNDESA	UN Department of Economic and Social Affairs
UNDP	United Nations Development Programme
UNICEF	United Nations Children's Fund
UNSTATS	United Nations Statistics Division (UNSD)
USAID	United States Agency for International Development
USDA	United States Department of Agriculture
VC/VCA	value chain/value chain analysis
WDI	World Bank World Development Indicators
WEO	World Economic Outlook
WFP	World Food Programme
WHA	World Health Assembly
WHO	World Health Organization
WTO	World Trade Organization

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Foreword

The COVID-19 pandemic has posed unprecedented challenges in Africa and across the globe. In addition to its health effects, which as of November 2021 had resulted in hundreds of thousands of confirmed deaths in Africa and millions in the world, the pandemic has had grave ramifications for poverty and hunger. In Africa, COVID-19 interrupted the longest period of sustained economic growth in the continent's history. Although a recovery is expected to begin in 2021, the crisis has reversed years of progress in improving livelihoods and reducing child undernutrition.

The pandemic also exacerbated new and existing challenges. In the years before the crisis, economic growth had decelerated, and the prevalence of undernourishment had begun to increase after a decade and a half of improvement. The continent thus faces the urgent need not only to rebound from the severe impacts of the pandemic but to strengthen its growth recovery and get back on track to sustainably raise incomes and end hunger.

The pandemic has also slowed the continent's progress in advancing toward the goals of the 2014 Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods. Africa's agriculture sectors and food systems more broadly are key to ensuring the continent's food security as well as its economic recovery. In addition to marking the second year of the pandemic, 2021 saw the United Nations Food Systems Summit, which aimed to catalyze action to transform food systems and progress toward the Sustainable Development Goals (SDGs). Ensuring productive, resilient, and sustainable food systems will be critical to accelerate recovery from the impacts of COVID-19 and put the continent on a path to achieving the SDGs and the Malabo Declaration commitments.

The 2021 Annual Trends and Outlook Report (ATOR) focuses on building resilient African food systems after COVID-19. It examines emerging data on the impacts of COVID-19 on African economies and food systems, reviews the responses of African countries to the pandemic, and advances the discussion on methodologies to measure the impacts of and resilience to shocks. Although the report is centered around COVID-19, its lessons are applicable beyond the current crisis. The pandemic, a uniquely wide-ranging challenge that combined features of previous health, economic and food price shocks, reminds us of the breadth of risks and challenges that food systems must continue to withstand into the future. The report argues for a broader conceptualization of resilience that encompasses climate risks as well as the wider range of shocks that threaten progress toward transformed food systems and economies.

2021 also marked the preparation of the third continental Biennial Review process to assess progress towards the goals and targets of the Malabo Declaration. The third Biennial Review report will be presented at the 35th African Union Summit in early 2022, during which African leaders will discuss approaches to accelerating recovery from the pandemic and advancing progress toward achieving the Malabo Declaration goals by 2025. We hope that this report will help leaders, practitioners and partners to design strategies to ensure a sustainable and inclusive recovery that results in stronger food systems in the years to come.

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Executive Summary

Africa faces enormous challenges to overcome the negative impacts of the COVID-19 pandemic. The crisis has profoundly affected health, livelihoods, and food security in Africa, disrupting the continent's growth trajectory, reversing progress on improving incomes, and exacerbating long-term challenges including large numbers of poor and hungry people. The pandemic has exposed vulnerabilities and highlighted the need to ensure that post-COVID-19 food systems are more inclusive and resilient to future shocks. The 2021 Annual Trends and Outlook Report (ATOR) focuses on evidence to inform strategies to build more resilient African food systems after COVID-19. The report begins with an assessment of the impacts of COVID-19 on different aspects of Africa's food systems through a variety of avenues. The subsequent chapters examine the responses of African governments to the crisis, and in particular their expansion of social protection programs to mitigate negative impacts on households. The report then discusses tools, methodologies and approaches to measure the impacts of COVID-19 and similar crises and to assess the resilience of individuals, communities and countries. As the monitoring and evaluation report of the Comprehensive Africa Agriculture Development Programme (CAADP), the ATOR also reviews the continent's progress toward the CAADP Malabo Declaration goals and targets, which has been severely affected by the pandemic. All sections of the report discuss the implications of their findings in terms of accelerating the recovery from COVID-19 and preparing to respond effectively to future shocks.

Impacts of COVID-19 on African Countries

The COVID-19 pandemic had serious impacts on multiple aspects of African food systems through a variety of drivers. These drivers included changes in global trade, with reductions in traded volume and changes in prices of many of the commodities imported and exported by African countries; domestic measures taken to mitigate the spread of the disease, which in many cases affected people's ability to engage in economic activity; and changes in individual behavior taken to reduce exposure. The impacts of the pandemic on economic growth, incomes and employment, trade, and food prices had resulting effects on nutrition and food security which are likely to persist for years to come.

Economic and Agricultural Growth and Employment

GDP per capita in Africa as a whole declined by around 5 percent from 2019 to 2020, marking a sharp break with the steady—albeit decelerating—economic growth of the previous two decades. The growth decline reflects a sharp drop in employment, particularly employment in the informal sector. The corresponding declines in household incomes are expected to have resulted in significant increases in poverty and hunger.

These impacts of COVID-19 on economic growth were transmitted through a number of channels, including reductions in economic activity at the domestic and global levels. In addition to lockdown measures implemented in African countries, those carried out in the rest of the world significantly affected global trade. Declines in export volumes and in the prices of many African countries' main export commodities contributed to growth reductions, but countries with more diversified export baskets are expected to have suffered less severe impacts, underlining the importance of longer-term efforts to increase African countries' trade competitiveness and expand their range of exports.

Although many economic sectors experienced drops in output, agriculture appears to have been less affected by the crisis. In contrast to overall economic growth, Africa's agricultural growth remained positive in 2020. Globally, employment in agriculture is thought to have remained fairly stable, unlike many other sectors. Simulations suggest that other food system components will be more strongly affected by COVID-19 than agricultural production. In particular, food service businesses were strongly impacted by closures and other lockdown measures. The food service and food processing industries are also highly vulnerable to decreases in demand due to income losses among consumers.

Intra-African Agricultural Trade

The movement restrictions, border closures, and other COIVD-19 containment measures implemented by African countries severely impacted intra-African trade, particularly informal cross-border trade. Although data on informal trade is scarce, available estimates suggest steep declines in 2020, including in informal trade of food and agricultural products. Formal trade was also negatively affected by the pandemic, but data suggests that formal agricultural trade was less affected than non-agricultural trade, and that trade rebounded in the second half of 2020 after declines in the early months of the pandemic. Both formal and informal intra-African trade play vital roles in ensuring food security, supporting household incomes, stabilizing regional food markets, and reducing price volatility. Intra-African trade can help to buffer the impacts of local shocks and should therefore be protected and promoted during times of crisis. During health shocks such as COVID-19, it is important for countries to identify health measures that can be implemented in markets and at borders without affecting their operations. Advancing the implementation of the African Continental Free Trade Area (AfCFTA) to enhance intra-African trade should be central to longer-term strategies to increase the resilience of markets and food systems.

Food Prices

Governments in Africa and around the world attempted to slow the spread of COVID-19 through various measures including lockdowns, movement restrictions, closures of schools and businesses, market restrictions, and, in some cases, border closures. These measures altered the supply of and demand for foods, which in turn affected food prices. Impacts on prices were highly location-specific: the pandemic and related restrictions resulted in sharp increases in staple food prices compared to pre-pandemic projections in some areas and steep declines in others. Price behavior was influenced by factors including the location of markets in surplus or deficit areas, countries' pre-pandemic roles in regional food supplies, and the perishable or nonperishable nature of commodities. Both upward and downward price swings can be disruptive, with price increases making food less affordable for consumers and price decreases affecting farmers' ability to purchase inputs and make investments. In order to maintain price stability during crises, governments must carefully design and implement lockdown measures to ensure that their impacts on market functioning and domestic and cross-border trade is as limited as possible. Mechanisms should be put in place to monitor food prices, particularly during crises, to allow for early identification of disruptions. Support for producers or consumers may be necessary to ensure continued food supply and allow vulnerable populations to access food. One-size-fits-all responses should be avoided due to the importance of location characteristics in determining price behavior.

Nutrition and Food Security

Despite growth in agricultural production during 2020, food insecurity worsened markedly, with over half of Africans estimated to have been affected by either moderate or severe food insecurity during 2020. Many consumers were unable to access food in sufficient quantities due to market disruptions and to income losses. The number of undernourished people in Africa is projected to have increased by 46 million people between 2019 and 2020, with much of the increase taking place in western and eastern Africa. Child malnutrition is also expected to have risen significantly in 2020. The impacts of COVID-19 reversed previous steady progress in reducing child malnutrition; however, undernourishment had already risen slightly in the years prior to 2020, a trend which was exacerbated by the pandemic. The effects of the pandemic on nutrition are expected to endure beyond 2020. In particular, malnutrition in children can affect their long-term development.

Although the effects of the crisis on nutrition and food security were widely felt, impacts were more severe among more vulnerable households and communities. Due to differences in pre-existing patterns of vulnerability and uneven impacts of crises on food security, governments should consider increasing monitoring efforts and readying interventions for quick deployment in more vulnerable areas. At the household level, pre-crisis poverty and exposure to negative health, employment and price shocks are among the factors affecting susceptibility to declines in food security due to COVID-19, underlining the importance of social protection to alleviate the effects of shocks.

Strategic Responses of African Countries to COVID-19

In an effort to mitigate the harmful impacts of the pandemic on incomes, employment and food security, African governments implemented a range of emergency policy responses. These included different types of transfers to households and businesses—including cash transfers, in-kind transfers of food or agricultural inputs, subsidies, and tax exemptions—as well as changes in regulations, including the application or relaxation of price, import, and export controls. In particular, governments greatly expanded social protection programs in order to protect populations from the negative effects of the pandemic. This is a welcome development and demonstrates broadly shared awareness of the importance of social protection in preventing welfare losses and maintaining assets in times of crisis. Emerging literature from several African and non-African countries suggests that social protection programs instituted in response to COVID-19 had positive impacts on health, risk reduction behavior, food security, and business revenue. However, the coverage of social protection in Africa remained limited, and many of the newly introduced programs were of short duration, with nearly 30 percent of new cash transfer programs consisting of a single payment. Targeting of support was also a challenge in several countries for which data is available. In some areas, targeting was regressive, with the poorest households less likely to receive assistance than those better off. Even where targeting was progressive, large shares of poor households were not covered by social protection.

African countries must scale up social protection programs to improve coverage, both in normal times and in times of crisis. To do this, additional funding needs to be mobilized. The international community should adhere to its commitments for development assistance to fund social protection, and recent proposals for the creation of global COVID-19 contributions or global social protection funds should be pursued. However, African governments must also raise the level of funding from domestic sources in order to increase the predictability and sustainability of protection programs—during global crises such as COVID-19, external funding is prone to reductions when it is most needed. Countries should strengthen taxation systems to increase compliance and reduce leakages and unrecorded financial flows, while ensuring that systems are progressive and do not overly burden poor households.

Governments should also improve the design of social protection programs, particularly in terms of targeting. Targeting could be strengthened by developing and maintaining unified national databases of potential recipients, as has been done successfully in other regions. Governments should expand their use of digital technologies in implementing and monitoring programs. The adoption of digital technologies to track and deliver transfers has been shown to improve both the ability of protection programs to meet beneficiaries' needs and their cost-effectiveness.

Finally, governments should implement different types of social protection to increase coverage and meet a variety of objectives. There is great need to develop labor market interventions that cover informal workers, who were the most vulnerable to employment losses and were often not reached by social protection. To ensure timely responses to crises, countries should develop shock-responsive social protection systems than can be scaled up or down rapidly as shocks occur. However, in addition to their roles as safety nets in times of crisis, social protection programs should serve as long-term development tools to help households seize economic opportunities and sustainably increase their standards of living. Social protection programs for different populations and different purposes should be better coordinated and integrated with overall development strategies.

Measurement Issues

The wide-ranging impacts of the COVID-19 pandemic have also underlined the continuing challenges faced by African countries in generating evidence to understand the effects of crises and guide policy responses. Innovations including analytical methodologies, tools and frameworks as well as the use of emerging technologies must be developed and deployed in order to increase the availability of data and knowledge. While emerging measurement methodologies are important to gauge the impacts of COVID-19, they also present great potential to contribute to policymaking and development planning on an ongoing basis.

Crop Production

Collecting crop production data in Africa has long posed challenges. Traditional field work methods are costly, require significant time before data can be made available, and become more difficult to carry out during crises such as COVID-19. However, data is especially needed during crises in order to anticipate potential production disruptions in time to prepare responses. Near real-time data on biophysical indicators are important to monitor crop conditions and develop production estimates in advance of harvests for planning purposes. New technologies and analytical approaches have the potential to greatly increase the availability of timely, accurate crop production data. Remote sensing data on biophysical parameters such as rainfall and vegetation conditions combined with machine learning techniques allow for cost-efficient estimation of agricultural production well before harvest periods.

In order for African countries to take advantage of the potential of emerging data-gathering technologies, expertise in remote sensing and machine learning must be fostered through broad capacity strengthening initiatives. Public-private partnerships to support entrepreneurship and create jobs in science and technology can create incentives for students to enter emerging fields and contribute to building national capacities.

Resilience

Resilience, usually defined as the ability of an individual, household, area or country to maintain wellbeing despite shocks, is an important concept for both development and humanitarian response strategies. Several methodologies to estimate resilience prior to shocks have been proposed, based on the conviction that if resilience can be measured, governments can use that information to inform the targeting of social protection, both prior to and after shocks, and plan interventions to increase resilience levels.

The need to boost resilience to climate shocks has gained increasing attention, and strengthening the resilience of livelihoods and production systems to climate risk is one of the commitment areas of the 2014 Malabo Declaration. The emphasis on climate is important due to the increasing frequency of negative weather and climate shocks and adverse changes in climate which are already affecting agricultural production in Africa. However, the pandemic has demonstrated the range of shocks that households, communities and food systems are subject to, and resilience measures must accordingly go beyond climate to take other types of shocks into account. Newly developed resilience metrics that measure countries' health system capacities can be used to identify the countries that may be most susceptible to global health shocks, and can complement or be combined with existing resilience metrics. Incorporating measures of country health system capacity and other country-level factors adds valuable information to improve the accuracy of resilience estimations.

The resilience of food value chains is another important area for measurement. Consumer-focused value chain analysis carried out through a resilience lens can help to identify sources of risk and ensure that value chains meet consumers' needs and safeguard food security during times of crisis.

Dietary Patterns

Ensuring healthy and well-nourished populations requires more than just sufficient calorie availability. Awareness has broadened in recent years of the importance of diet quality in terms of micronutrient consumption and dietary diversity. In addition to visible forms of undernourishment, African countries experience high rates of hidden hunger, or micronutrient deficiencies, as well as growing rates of overweight and obesity. A focus on the quality of diets is necessary to better understand the drivers of these types of malnutrition and guide efforts to improve nutrition. The disruptions in food availability, food prices, and incomes caused by the COVID-19 pandemic are likely to have resulted in changes in diet composition, with implications for nutrition and health. A variety of indexes and tools have been developed to assess the quality of diets; efforts to evaluate diet quality during the COVID-19 period should also consider complementary factors that have bearing on nutrition and health and are likely to have been affected by the pandemic. In particular, dietary diversity was affected by disruptions in access to food. In some cases, the pandemic was associated with lifestyle changes and reductions in physical activity as well as increases in anxiety; these also have important implications for health, and their measurement serves as an important complement to the assessment of dietary patterns. Improvements in diets and other health-related behavior can be promoted through large-scale behavioral change communication (BCC) techniques, which have proven successful at contributing to improvements in feeding practices and nutrition outcomes. BCC interventions can be carried out through in-home or clinic-based interpersonal counseling, community-based mass media such as radio programs, or other community education events.

Concluding Remarks

In the years prior to the pandemic, Africa was making progress toward the goals and targets of CAADP and the Malabo Declaration, although improvements in some areas—such as reducing undernutrition—had slowed or stopped. COVID-19 has sharply exacerbated existing challenges and presented new ones. Putting the continent back on track toward sustainable growth will require concerted efforts to overcome the negative impacts of the crisis on growth, poverty reduction and nutrition and to increase the ability of Africa's food systems to support livelihoods and provide sufficient healthy food for all. The 2021 ATOR has highlighted several areas for action, including facilitating the functioning of markets and trade, strengthening social protection programs, and enhancing data and knowledge systems to incorporate new data sources, methodologies, and indicators. Efforts on these fronts and others will help to accelerate the recovery from COVID-19 and increase the resilience of food systems against future shocks.

CHAPTER 1

Introduction: Building Resilient African Food Systems After COVID-19

John M. Ulimwengu, Mark A. Constas, Éliane Ubalijoro,
and Julia Collins

Overall Context

The COVID-19 pandemic has quickly spread across the world over the last two years, causing a significant number of deaths—more than 4.55 million as of October 2021—and hospitalizations as well as economic disruption. This global crisis has triggered a transformation toward a new, elusive "normal that may take years to fully materialize despite the amazingly fast discovery and deployment of vaccines, and more recently, the progress of COVID-19 treatments in clinical trials. The World Health Organization established a global target of 10 percent vaccination by the end of September 2021; although many developed countries have fully vaccinated 50–75 percent of their populations, African vaccination rates have only reached 4.4 percent (Mwai 2021).

Many past pandemics have left behind a trail of heavy damage (Gurara, Fabrizio, and Wiegand 2020): mortality; worse health and education outcomes that depress future earnings; the depletion of savings and assets that force businesses to close—especially small enterprises that lack access to credit—and cause irrevocable production disruptions; and debt overhangs that depress lending to the private sector. The panic caused by diseases can also lead to significant social and economic losses. The Black Death, for example, killed between 75 million and 200 million people worldwide between 1348 and 1350. During that period, it contributed to a 29 percent cumulative decline in GDP and an 8 percent increase in the price of gold. Because of labor scarcity, real farm wages in England cumulatively rose by 116.2 percent. During the 1918-1919 Spanish flu pandemic, around 40 million people were killed worldwide. In the United States, cities with higher influenza mortality rates experienced higher real wage increases. In the United Kingdom, the real wages of construction workers in London cumulatively increased by 34.2 percent, while real GDP in the country declined by 6 percent (Millas 2020).

The same pattern of economic loss seems to be emerging with the COVID-19 pandemic. Across the globe, the immediate priority for policymakers has been to address the health crisis and contain short-term economic damage. As a result, the global economy is now facing its greatest recession since the last financial crisis of 2008–09. According to the World Bank (2020), the pandemic was expected to have triggered recessions in most countries in 2020, with average incomes falling in the largest share of countries since 1870. The International Monetary Fund (2020) forecast that the global economy could decline by 4.4 percent in 2020; global trade was projected to fall in 2020 by more than 10 percent and oil prices were projected to drop by 32 percent. Later estimates suggested that the global economy declined by 3.1 percent in 2020 and is set to recover by 5.9 percent in 2021. In Africa south of the Sahara, growth declined by 1.7 percent in 2020 and is recovering at a projected rate of 3.7 percent (IMF 2021); however, the decline in per capita terms was greater and is expected to have resulted in significant increases in poverty and hunger.

While the COVID-19 pandemic is a systemic disruption affecting every country in the world, low-income developing countries (LIDCs) have been hit the hardest by external shocks. These countries have also suffered severe domestic contractions from the spread of the virus and the lockdown measures to contain it (Gurara, Fabrizio, and Wiegand 2020). Since March 2020, LIDCs have been at the center of an exceptional confluence of external shocks: a sharp contraction in real exports; lower export prices, especially for oil; decreased inflows of capital and remittances; and reduced tourism receipts.

As noted by the World Bank (2020), leaders must enact wide-ranging reforms to strengthen longer-term drivers of growth after the current crisis. The early effects of the pandemic have shown that achieving the goal of sustainable healthy diets for all will require food systems—at the local, country, and global levels—that are resilient and capable of withstanding challenges posed by climate, health, political, economic, and all other shocks. The 2021 United Nations Food Systems Summit (UNFSS) clearly signals that food and nutrition security must be considered from a systems framework. Post-UNFSS efforts to transform African food systems must not neglect attention to the effects of the COVID-19 pandemic, which have exposed significant vulnerabilities and will have long-lasting impacts on many areas of food systems. The present ATOR supports these efforts by focusing the discussion on both food and nutrition security and the stresses of COVID-19.

Expected Impacts of COVID-19 on African Food Systems

Even before the COVID-19 pandemic, the state of food and nutrition security was a major problem in Africa. The pandemic has exacerbated already high levels of poverty and vulnerability. Concern is growing that the direct and indirect effects of the pandemic could be greater in Africa than the rest of the world as a result of the continent's much weaker institutions and health system capacity, large number of poor and vulnerable people, greater exposure to the world trade cycle, high dependence on demand from advanced economies, and more pronounced vulnerability to climate change impacts. Shadmi and colleagues (2020) highlight the inequitable spread of COVID-19 among poor and vulnerable populations due to the high prevalence of chronic conditions or poor access to high-quality public health and medical care. In this context, it is very likely that the state of food and nutrition security will deteriorate following the COVID-19 pandemic, with the poor (especially the urban poor), people living in remote areas, migrant and informal sector workers, people in humanitarian crisis and conflict areas, and other vulnerable groups likely to face the worst consequences.

Decreased access to food resulting from limited physical access to markets will likely contribute to the negative impacts of COVID-19 on food security, particularly in the early stages of the crisis when lockdown measures were the most restrictive. Retail food outlets such as grocery stores remained operational in most countries, but informal outdoor markets were often closed or subject to limited hours. This likely limited poor consumers' access to food, particularly perishable food, and reduced their purchasing power by forcing them to shop at more expensive outlets (Devereux, Béné, and Hoddinott 2020).

At times, informal food traders were also prevented from operating, posing additional barriers to food access for poor consumers. Informal traders often play an important role in meeting the needs of poor consumers, due to their ability to sell in small quantities, lower prices, provide credit, and operate close to consumers. In South Africa, small-scale traders were initially prevented from operating but later permitted to operate with restrictions, which increased the cost of transit for consumers to buy food (Wegerif 2020).

The Permanent Interstate Committee for Drought Control in the Sahel (CILSS) documented significant market closures in West Africa. Although market operations largely resumed in the months after the crisis began, there were still market closures as of July 2020. As of the end of April 2020, around 40 percent of agricultural markets in Senegal, Burkina Faso, and Chad had been closed, with lower closure rates in other West African countries; all countries showed disruptions to market activities even where markets were open. In some districts in Guinea, Chad, and Nigeria, all livestock markets were closed (CILSS 2020b). By July 2020, the situation had improved markedly, but disruptions and closures continued to affect crop and livestock markets in most West African countries (CILSS 2020a).

Policy Responses to COVID-19

Overall, African governments responded quickly to limit the spread of COVID-19, imposing lockdowns and sanitary measures to combat the disease. These actions, among other factors, may have contributed to Africa's relatively low death rates from the pandemic (Soy 2020). However, these actions also imposed serious economic consequences. Indeed, in addition to the effects on access to food, movement restrictions affected trade and other sectors. In some countries, governments shut down urban food markets partially or completely and banned or relocated informal traders, reducing access to food for poor consumers who depend on these sources the most (Resnick 2020a; Wegerif 2020).

In some cases, efforts to address the crisis did not sufficiently prioritize the agricultural sector. In a review of COVID-19 policy responses from developing countries across the globe, Resnick (2020b) reports that governments tended to provide less support to agricultural production than to other areas of the economy. In addition, the cross-ministerial COVID-19 response teams established in many countries often exclude Ministries of Agriculture.

The devastating effects of the COVID-19 crisis on livelihoods and incomes have prompted governments around the world to expand social protection in an effort to protect food security. Gentilini and colleagues (2020) find that nearly all African countries scaled up social protection programs in response to the crisis. However, coverage remains lower in Africa than in other world regions. As of July 2020, ongoing and planned social protection programs in Africa south of the Sahara were estimated to reach 11 percent of the population in countries with available data, which represents a 3 percent increase from pre-pandemic coverage. While this is a major increase, it is still by far the lowest rate among all developing regions, for which average coverage rates reach 38 percent.

Case for Building Resilient African Food Systems Post-2020

Building resilient African food systems is part of the seven commitments of the 2014 Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods. Indeed, in

2014, African Union (AU) Member States committed to: (1) re-commit to the principles and values of the Comprehensive Africa Agriculture Development Programme (CAADP) process; (2) enhance investment finance in agriculture; (3) end hunger by 2025; (4) halve poverty through agriculture by 2025; (5) boost intra-African trade in agricultural commodities and services; (6) enhance resilience to climate variability; and (7) strengthen mutual accountability for actions and results.

However, the commitment on resilience is limited to preparedness in responding to present and future climate variabilities and shocks. It focuses on social protection for rural and vulnerable groups. Given increasing climate vulnerabilities, Resilience and Livelihoods was selected as the overall theme of the 2019 Biennial Review report. While the focus on resilience is welcome, the COVID-19 pandemic demonstrates that disruptions take many forms, and efforts to build resilience should consider a range of risks and shocks in addition to those related to climate.

As shown by Savary and colleagues (2020), the vulnerability of food systems may be analyzed over time and across food security components. Disruptions in the food system may be scaled to consider impacts in the short (0–3 months), medium (3–12 months), and long term (1 year or more). Similarly, a food system's vulnerability to a shock such as COVID-19 may differ between stages of the system. Food systems include the range of activities involved in producing, processing, distributing, marketing, preparing, consuming, and disposing of goods that originate from agriculture, forestry, or fisheries, as well as a variety of ecosystem services with different levels of resilience to shocks. Resilience manifests in varying degrees and may differ across multiple levels and scales (Tendall et al. 2015). Even if a food system is resilient at the macro level, the ability to absorb shocks and disruptions can be distributed unevenly within the system. Moreover, specific communities within a region or a country may be more vulnerable than others due to socioeconomic disparities.

The 2021 Annual Trends and Outlook Report (ATOR) focuses on providing research-based evidence to support the design of post-COVID-19 recovery measures that strengthen the resilience of African food systems. This report explores the vulnerability of African food systems to COVID-19 by (1) assessing the impact of COVID-19 on food and nutrition security, (2) reviewing policy responses across the continent, (3) identifying measurement issues critical to the establishment of strategies to build resilient food systems at national and subnational levels, and (4) reporting progress on the CAADP agenda.

Impacts of COVID-19 on African countries are examined in four chapters. In chapter 2, Torero examines the impacts of COVID-19 and related containment measures on food security, nutrition, and agricultural trade in Africa. The chapter shows that formal trade in food and agricultural products rebounded in the second half of 2020 after sharp declines in the early months of the pandemic. However, hunger has increased alarmingly since 2019, with the number of undernourished people in Africa expected to increase by 46 million in 2020. An additional 800 million people, or 60 percent of the continent's population, were expected to be affected by moderate or severe food insecurity. Global- and regional-level projections confirm the enormous challenges of eradicating hunger and malnutrition by 2030.

The measures implemented by African governments to control the spread of COVID-19—including business and school closures, movement and market restrictions, and border closures—affected both the supply of and demand for food. In chapter 3, Yade and colleagues explore the impacts of the pandemic on staple food prices by comparing projected prices with actual 2020 prices for a range of local commodities and markets in 12 African countries. The authors find that the price behavior of staple foods differed markedly between areas, with sharp price increases in some markets and steep declines in others. These differences are related to market and commodity characteristics, as well as countries' roles in cross-border food trade. The findings underline the importance of tailoring policy responses to location-specific characteristics and designing health-related measures carefully to avoid impeding market functionality and the movement of food within and between countries.

In chapter 4, Fofana and colleagues shift the focus to global market changes, examining the impacts of COVID-19-related changes in global primary commodity prices and trade volumes on African food systems. Focusing on 23 countries with available data, the authors use computable general equilibrium modeling to translate price and trade volume changes into effects on agricultural production and input use, food processing industries, agricultural and food trade, food consumption, and the macroeconomic environment. The chapter shows that negative impacts were lower in countries with more diversified export baskets, underlining the need for countries to diversify trade to remain resilient to global shocks. Among the different food system components examined, food processing industries were by far the most vulnerable to negative impacts of the pandemic, as demand for their products is sensitive to declines in income.

Although the COVID-19 pandemic has affected every country in the world, impacts on health and food security vary considerably between locations and households. Chapter 5 examines patterns of vulnerability to the impacts of COVID-19 in western and central Africa at the community and household levels. Ulimwengu, Magne Domgho, and Collins use data on location characteristics to derive an index of vulnerability to the health and food security impacts of COVID-19 at the subnational level, and they use household survey data from Mali to examine the drivers of vulnerability to negative food security impacts at the household level. The authors find that levels of vulnerability differ markedly between as well as within countries, underlining the need for decision-makers to monitor local effects closely and be prepared to intervene in areas with high levels of vulnerability.

The section on **responses of African countries to COVID-19** is composed of three chapters. To mitigate negative impacts in the early months of the pandemic, African governments implemented a range of emergency economic support measures, including direct transfers, in-kind support, and regulatory measures. In chapter 6, Tadesse and Tefera use a descriptive mixed methods approach to assess the performance of African countries in designing and implementing emergency policy responses. The chapter combines public data on economic support measures with data from interviews with policymakers in 17 African countries to assess the responsiveness and implementation performance of countries' economic support policies and to identify best practices for improving emergency response performance.

Chapters 7 and 8 focus on African countries' social protection responses to the pandemic. In chapter 7, Duchoslav and Hirvonen review emerging literature on the effectiveness of social protection programs in combating the negative impacts of COVID-19. They find indications that social protection positively affected health, risk reduction behavior, business revenue, and food security in some cases. The authors then analyze the targeting effectiveness of social protection in Ethiopia, Malawi, and Nigeria, comparing pre-pandemic wealth levels with the distribution of social assistance during the pandemic. The chapter shows that targeting effectiveness varied between countries, and that in all cases, large shares of the poorest households did not receive assistance. These findings suggest a need to both increase the resources available for social protection and improve the targeting of support.

In chapter 8, Benammour and colleagues describe how African governments employed social protection to mitigate the adverse impacts of the pandemic on households. Despite substantial expansion in social protection programs, coverage remained generally low and many of the newly introduced programs were of limited duration. The authors review evidence from the literature on the impacts of COVID-19 on incomes and food security, finding that very large shares of households in both rural and urban areas saw declines in income and increases in in food insecurity. The chapter highlights key aspects of social protection programs that should be strengthened to aid Africa's recovery from the impacts of COVID-19 and continued economic development.

Measurement issues related to assessing the impacts of the pandemic are covered over five chapters. In chapter 9, Ly, Dia, and Diallo demonstrate the use of emerging methodologies to assess crop production before harvest periods. The availability of high-quality and timely agricultural data for Africa has long been a challenge for decision-makers, and access to data becomes even more problematic during crises such as the COVID-19 pandemic, when up-to-date information is most needed to monitor food supplies. The chapter illustrates the potential for remote sensing data and machine learning techniques to produce detailed crop production forecasts at the pixel level, allowing for early identification of areas that may experience production fluctuations.

Chapters 10 and 11 focus on resilience measurement methodologies. While many efforts to measure resilience focus on climate risks, the pandemic has demonstrated that global health shocks also have the potential to severely affect wellbeing. In chapter 10, Constas, Wohlgemuth, and Ulimwengu develop an indicator to measure countries' capacities to respond to global health shocks. The authors first construct a health systems capacity index and an economic resilience capacity index for African countries using health systems performance and macroeconomic data. Rankings on these indexes are used to derive a resilience capacities index for global health shocks, which can be used to identify countries in the greatest need of assistance to avoid the severe impacts of health shocks on their populations. Chapter 11 builds on and extends the health systems capacity index constructed in chapter 10, combining it with other macro (country-level) indicators and micro (household-level) resilience data from 11 African countries. Authors d'Errico, Jumbe, and Constas then use their approach to explore the determinants of food security resilience. The authors find that incorporating macro indicators with micro resilience capacity measures adds valuable information about factors contributing to resilience. The analysis also suggests that countries with stronger health systems have higher resilience capacities and are less likely to suffer from food insecurity.

The impacts of the pandemic on food prices and access to markets are likely to have repercussions for the quality of diets. The measurement of dietary patterns is essential for monitoring and responding to changes in diet composition. In chapter 12, Kwofie, Kwofie, and Ngadi examine different approaches for assessing dietary patterns and diet quality indexes, and they highlight measurement strategies that should be adopted to evaluate the impact of COVID-19 on diets. The chapter provides insight into the design of behavioral change communication strategies to improve diets during the pandemic and the recovery period.

Value chain analysis is a key tool for assessing the resilience of food value chains to shocks such as the pandemic and identifying ways to ensure food security in the face of crises. In chapter 13, Ellis, Kwofie, and Ngadi argue for a consumer-focused approach to value chain assessment that emphasizes linkages with food security. The authors propose a framework for consumer-centered value chain analysis and outlines a methodology for identifying criteria and indicators to assess value chain performance.

The last section of the report considers **progress toward CAADP goals**. In addition to compiling research on key development topics, the ATOR serves as the official CAADP monitoring and evaluation report. Accordingly, in chapter 14, Tefera, Collins, and Makombe review progress in CAADP implementation as well as the status of countries, regions, and the continent as a whole regarding the CAADP Results Framework indicators. The chapter also reviews emerging evidence on how the COVID-19 pandemic has affected Africa's progress on the indicators discussed.

The 2021 ATOR intends to support reflection on how to build resilient African food systems after COVID-19. As we begin the recovery from this global crisis, efforts must be made to ensure that the new normal is more sustainable and leaves no one behind. The contributions offered in the present volume provide insights and opportunities to better understand how to build resilience across the continent. By presenting a range of empirical findings and offering a selection of newly developed analytical strategies, the authors have helped advance our knowledge of resilience and drawn attention to areas where additional work is needed.

CHAPTER 2

Africa: Food Security and Agricultural Trade During the COVID-19 Pandemic

Maximo Torero[1]

1 Section 2 of this paper was developed with Carlo Cafeiro and Anne Kepple from FAO and is based on FAO et al. (2021). Section 3 was developed with Andrea Zimmermann from FAO.

Introduction

The COVID-19 pandemic has affected all the countries in the world, transforming lives and economies. Many governments imposed containment measures to curb the spread of the COVID-19 virus. Those measures included various forms of restrictions on the movement of people, closures of businesses, and curtailment of public and private services. The virus containment measures lowered infection rates and pressure on health systems but also affected economic activity worldwide.

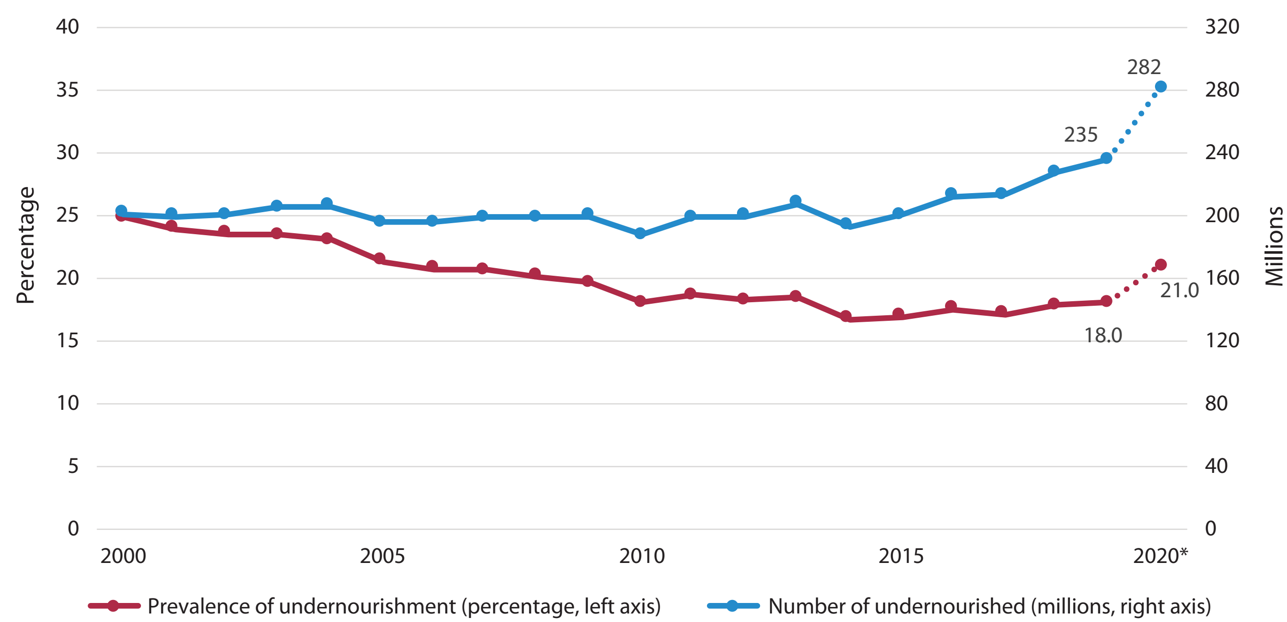
Global growth contracted by an estimated 3.3 percent in 2020. The economic output of Africa south of the Sahara is expected to have declined by 1.9 percent from 2019 to 2020. However, in per capita terms, the region is estimated to have suffered a steeper downturn of –4.5 percent, compared to –4.4 percent for the world as a whole (IMF 2021). African countries, like those in other regions, greatly expanded social protection programs to respond to the crisis; however, limited resources mean that large numbers of vulnerable people could not be reached (see Duchoslav and Hirvonon, and Benammour et al., chapters 7 and 8 in this volume). As a result of income losses and market disruptions, consumers are having difficulty accessing food, which has affected food and nutrition security.

Some of the impact on African economies and food security was transmitted through trade in food and agriculture. The food and agriculture industries play an important role in many African countries. Exports of agricultural commodities constitute an important means to generate income, provide employment, and sustain livelihoods. At the same time, high population growth, rapid urbanization, and low agricultural productivity have boosted demand for agricultural and food imports. Today, most net food-importing developing countries are located in Africa.

Although the agriculture and food sector was generally exempted from lockdown measures, widespread movement restrictions and business closures still led to disruptions in value chains and trade. In Africa, these induced a decline in exports and imports at the beginning of the pandemic, when the first lockdown measures were imposed. While disruptions of trade in staples remained limited, trade in beverages, fishery products, and nonfood commodities such as cotton and cut flowers was more severely affected. In general, trade in all commodities resumed in the second half of 2020.

This chapter provides an overview of the impact of COVID-19 on African economies, food and nutrition security, and agricultural trade. The next section reviews the estimated impacts of the pandemic on food insecurity and malnutrition. The following section assesses impacts on Africa's agricultural trade. The final section concludes.

FIGURE 2.1—PREVALENCE OF UNDERNOURISHMENT AND NUMBER OF UNDERNOURISHED PEOPLE IN AFRICA, 2000–2020



Source: FAO et al. (2020).
* Projected values for 2020 are illustrated by dotted lines.

TABLE 2.1—PREVALENCE OF UNDERNOURISHMENT IN AFRICA, 2000–2020										
	2000	2005	2010	2015	2016	2017	2018	2019	2020*	Change 2019–2020
World	13.0	12.4	9.2	8.3	8.3	8.1	8.3	8.4	9.9	+1.4
Africa	24.8	21.3	18.0	16.9	17.5	17.1	17.8	18.0	21.0	+3.0
Northern Africa	9.2	8.5	7.3	6.1	6.2	6.5	6.4	6.4	7.1	+0.7
Africa South of the Sahara	28.9	24.6	20.6	19.4	20.1	19.5	20.4	20.6	24.1	+3.5
Eastern Africa	39.9	33.0	28.4	24.8	25.6	24.9	25.9	25.6	28.1	+2.4
Middle Africa	41.4	36.8	28.9	28.7	29.6	28.4	29.4	30.3	31.8	+1.5
Southern Africa	5.8	5.0	6.2	7.5	7.9	7.3	7.6	7.6	10.1	+2.4
Western Africa	16.9	14.2	11.3	11.5	11.9	11.8	12.5	12.9	18.7	+5.8

Source: FAO et al. (2020).
Note: Changes are in percentage points. The 2020 value is a projection.

Food Insecurity

Of all the world's continents, Africa has the highest prevalence of undernourishment and food insecurity. About one in five people (21 percent of the population) were facing hunger in Africa in 2020 [2]—more than double the proportion of any other region, based on the prevalence of undernourishment (Sustainable Development Goal [SDG] Indicator 2.1.1). Of the total number of undernourished people in the world in 2020 (768 million), more than one-third (282 million) lived in Africa.

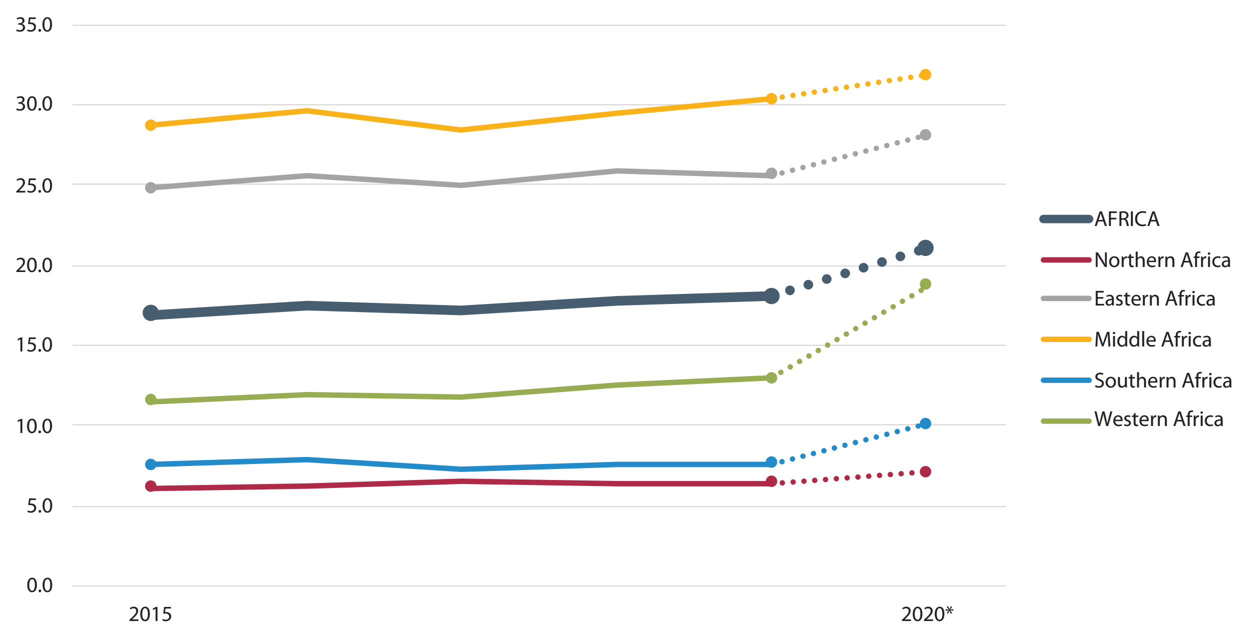
After a long trend of decreasing prevalence and a relatively unchanging number of undernourished people, both began to rise in Africa in 2014 (Figure 2.1). New estimates show the sharpest increase in undernourishment ever observed in a single year—from 2019 to 2020—for the continent. Compared with 2019, 46 million more people in Africa were affected by hunger in 2020.

The estimates show enduring and troubling regional inequalities (Table 2.1). The proportion of the population in northern Africa affected by hunger in 2020 (7.1 percent) is much smaller compared with almost all the subregions of Africa south of the Sahara, except for southern Africa (10.1 percent). In the other subregions, the prevalence ranges from 18.7 percent in western Africa to 31.8 percent in middle Africa. The largest number of undernourished people—more than 125 million—live in eastern Africa.

The prevalence of undernourishment increased from 2019 to 2020 in all the subregions in Africa (Figure 2.2). The sharpest increase of 5.8 percentage points in just one year was in western Africa, corresponding to 24.6 million more people (Table 2.2). If confirmed, this estimated increase would be further evidence of the trends noted by the Food and Agriculture Organization of the United Nations and the World Food Programme in 2020 for several countries in this subregion (FAO and WFP 2020), signaling the need for heightened attention to prevent further deterioration as the situation

2 All food insecurity data for 2020 presented in this section are projected values and subject to some uncertainty; findings should be considered with caution (FAO et al. 2020).

FIGURE 2.2—RECENT TRENDS IN THE PREVALENCE OF UNDERNOURISHMENT IN AFRICA AND SUBREGIONS OF AFRICA, 2015–2020



Source: FAO et al. (2020).
* Projected values for 2020 are illustrated by dotted lines.

evolves. Large increases of 2.4 percentage points in one year occurred also in eastern Africa and southern Africa, corresponding to 13.8 and 1.7 million more people, respectively. The smallest increase (1.5 percentage points) occurred in middle Africa, where the prevalence nonetheless remains the highest on the continent.

Projections for the number of undernourished globally and at regional levels confirm the enormous challenge of eradicating hunger by 2030. However, the evolution from 2020 to 2030 in terms of numbers of undernourished people is quite different across regions. A significant increase is forecast for Africa, where the number is projected to reach 300 million people, placing it on par with Asia by 2030 (Figure 2.3). Africa is projected to be the region with the highest number of undernourished people

TABLE 2.2—NUMBER OF UNDERNOURISHED PEOPLE IN AFRICA, 2000–2020

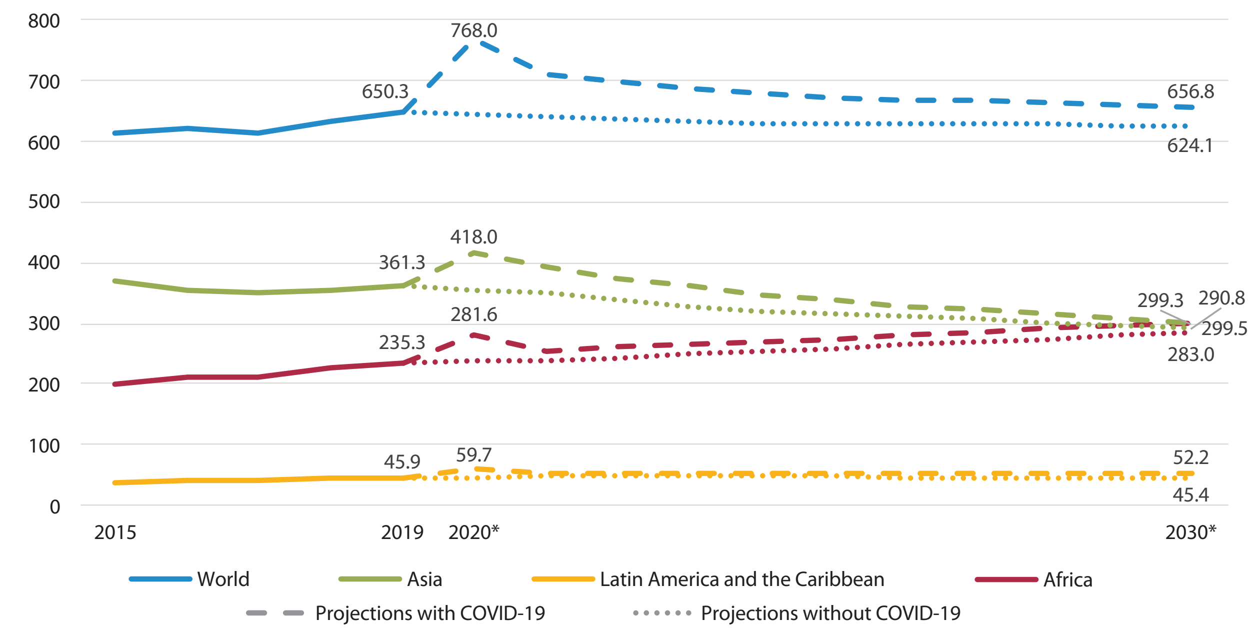
	2000	2005	2010	2015	2016	2017	2018	2019	2020*	Change 2019–2020
World	800.3	810.7	636.8	615.1	619.6	615.0	633.4	650.3	768.0	+117.8
Africa	200.9	195.0	187.4	199.7	212.0	212.3	227.1	235.3	281.6	+46.3
Northern Africa	15.7	15.8	14.8	13.6	14.2	15.0	15.1	15.5	17.4	+1.9
Africa South of the Sahara	185.1	179.2	172.6	186.1	197.8	197.3	212.0	219.8	264.2	+44.3
Eastern Africa	102.7	97.3	96.3	96.5	102.5	102.3	109.6	111.3	125.1	+13.8
Middle Africa	39.8	41.2	38.0	44.3	47.1	46.5	49.7	52.9	57.1	+4.2
Southern Africa	3.0	2.7	3.6	4.7	5.1	4.7	5.0	5.1	6.8	+1.7
Western Africa	39.6	38.0	34.7	40.5	43.2	43.8	47.8	50.6	75.2	+24.6

Source: FAO et al. (2020).
Note: Totals may differ from the sum of subregions due to rounding and nonreported values. The 2020 value is a projection.

even in the absence of the COVID-19 pandemic.

Beyond hunger, in 2020, nearly 60 percent of the population of Africa, or almost 800 million people, were affected by moderate or severe food insecurity based on the Food Insecurity Experience Scale (SDG Indicator 2.1.2). Nearly 26 percent (more than 345 million people) faced severe food insecurity. A sharp increase from 2019 to 2020 is seen for the continent, as well as across all subregions (Table 2.3). Moderate or severe food insecurity increased significantly in western Africa, from 54.2 percent in 2019 to 68.3 percent in 2020 (an increase of 62.3 million people). The subregion has the highest prevalence of food insecurity now, surpassing eastern Africa (65.3 percent), which experienced a

FIGURE 2.3—PROJECTED TRENDS IN THE PREVALENCE OF UNDERNOURISHMENT IN THE WORLD AND REGIONS



Source: FAO et al. (2020).
* Projected values.

TABLE 2.3—PREVALENCE OF FOOD INSECURITY IN AFRICA, BASED ON THE FOOD INSECURITY EXPERIENCE SCALE, 2014–2020

	Prevalence of severe food insecurity (%)							Prevalence of moderate or severe food insecurity (%)						
	2014	2015	2016	2017	2018	2019	2020	2014	2015	2016	2017	2018	2019	2020
World	8.3	8.1	8.3	8.7	9.6	10.1	11.9	22.6	22.8	23.6	24.9	25.9	26.6	30.4
Africa	17.7	18.3	19.8	20.5	20.6	21.9	25.9	47.3	48.0	50.9	52.5	52.7	54.2	59.6
Northern Africa	10.2	9.0	10.4	10.6	9.3	8.8	9.5	29.7	26.4	30.0	33.1	31.1	28.9	30.2
Africa South of the Sahara	19.4	20.4	22.0	22.7	23.2	24.9	29.5	51.4	53.0	55.8	57.0	57.6	59.9	66.2
Eastern Africa	23.7	24.1	25.8	25.3	25.0	26.0	28.7	57.7	58.1	62.2	62.1	61.6	63.4	65.3
Middle Africa	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	35.8	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	70.0
Southern Africa	18.9	18.9	19.0	19.0	19.1	19.2	22.7	43.8	43.9	44.0	44.1	44.2	44.3	49.7
Western Africa	8.6	10.8	12.9	15.3	16.8	19.6	28.8	39.2	42.8	45.5	48.7	50.6	54.2	68.3

Source: FAO et al. (2020).
Note: n.a. = not available, as data are available only for a limited number of countries, representing less than 50 percent of the population in the region.

TABLE 2.4—NUMBER OF FOOD INSECURE PEOPLE IN AFRICA, BASED ON THE FOOD INSECURITY EXPERIENCE SCALE, 2014–2020

	Number of severely food insecure people (millions)							Number of moderately or severely food insecure people (millions)						
	2014	2015	2016	2017	2018	2019	2020	2014	2015	2016	2017	2018	2019	2020
World	604.5	598.4	620.2	656.8	731.3	779.9	927.6	1,645.5	1,680.1	1,762.9	1,881.6	1,978.7	2,049.9	2,368.2
Africa	203.5	215.9	240.1	254.7	262.9	286.7	346.6	545.0	567.2	617.8	653.3	671.8	708.6	798.8
Northern Africa	22.4	20.2	23.7	24.6	22.0	21.2	23.4	65.1	59.1	68.6	77.0	73.7	69.8	74.5
Africa South of the Sahara	181.0	195.7	216.5	230.1	241.0	265.5	323.3	479.8	508.1	549.2	576.3	598.1	638.8	724.4
Eastern Africa	89.9	94.0	103.2	104.2	105.6	113.0	127.9	218.7	226.3	248.9	255.4	260.5	575.0	290.9
Middle Africa	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	64.3	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	125.7
Southern Africa	11.7	11.9	12.1	12.3	12.6	12.8	15.3	27.2	27.7	28.1	28.6	29.0	29.5	33.5
Western Africa	29.6	38.0	46.8	56.9	63.9	76.7	115.7	134.0	150.5	164.4	180.7	192.8	212.0	274.3

Source: FAO et al. (2020).
Note: n.a. = not available, as data are available only for a limited number of countries, representing less than 50 percent of the population in the region.

smaller increase, but remains the subregion with the highest number of people (291 million) suffering from moderate or severe food insecurity (Table 2.4).

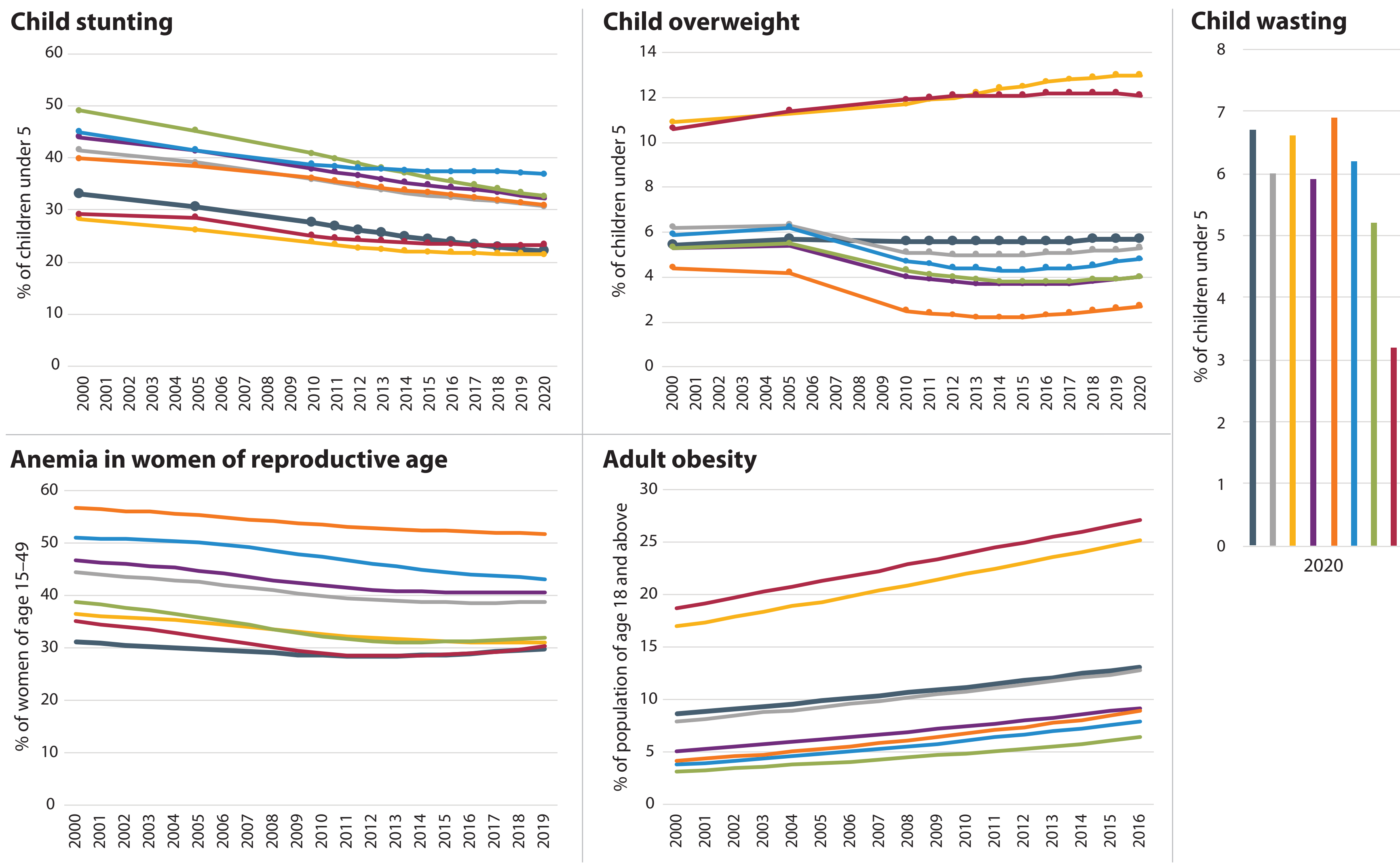
Severe food insecurity in those two subregions showed upward trends. It increased sharply in western Africa from 19.6 to 28.8 percent between 2019 and 2020 (equivalent to 49 million more people), but much less so in eastern Africa, from 26 to 28.7 percent (an increase of slightly less than 15 million people). Moderate increases were seen in southern Africa, where the prevalence of moderate and severe food insecurity rose from 44.3 to 49.7 percent (from 29.5 to 33.5 million people) and severe food insecurity increased from 19.2 to 22.7 percent (from 12.8 to 15.3 million people). Much smaller increases of around 1 percentage point were observed in northern Africa, where food insecurity affected 30.2 percent of the population (or 74.5 million people) in 2020, with one-third facing severe food insecurity (9.5 percent of the population, equivalent to 23.4 million people).

The State of Nutrition

Due to the physical distancing measures taken to contain the spread of the COVID-19 pandemic, data on nutrition outcomes were limited in 2020. Consequently, the latest estimates do not account for the effects of the COVID-19 pandemic. Nevertheless, Figure 2.4 presents the trends for Africa for four SDG Target 2.2 nutrition indicators—child stunting, child wasting, child overweight, and anemia in women of reproductive age (15–49 years)—as well as adult obesity, which is part of the Global Action Plan for the Prevention and Control of Noncommunicable Diseases adopted by the World Health Assembly (WHA) in 2013.

The prevalence of stunting among children under five years of age in Africa was 30.7 percent in 2020, higher than the global average of 22 percent. This is down from 32.8 percent in 2015 and from 41.5 percent 20 years ago. The downward trend was observed in all the subregions of Africa, with the most notable progress in eastern Africa. In 2020, the prevalence in Africa south of the Sahara (32.3 percent) was more than 10 percentage points higher than in northern Africa (21.4 percent). Within Africa south of the Sahara, middle Africa was the most affected, with a prevalence of 36.8 percent, followed by eastern Africa (32.6 percent), western Africa (30.9 percent), and southern Africa (23.3 percent). In 2020, 37 percent of the world's 149 million children under five years of age affected by stunting—about 55 million—lived in Africa south of the Sahara.

FIGURE 2.4—PREVALENCE OF SELECTED INDICATORS OF MALNUTRITION IN AFRICA AND SUBREGIONS OF AFRICA



Source: Data for stunting, wasting, and overweight are based on *UNICEF-WHO-World Bank: Joint Child Malnutrition Estimates—Levels and Trends (2021 Edition)*, https://data.unicef.org/topic/nutrition/, www.who.int/nutgrowthdb/estimates, https://datatopics.worldbank.org/child-malnutrition. Data for anemia are based on the WHO Global Health Observatory database, 2021, accessed April 26, 2021, www.who.int/data/gho/data/themes/topics/anaemia_in_women_and_children. Data for adult obesity are based on the WHO Global Health Observatory database, 2017, accessed April 19, 2021, www.who.int/data/gho/data/indicators/indicator-details/GHO/prevalence-of-obesity-among-adults-bmi-=-30-(age-standardized-estimate)-(-).

* Wasting is an acute condition that can change frequently and rapidly over the course of a calendar year. This makes it difficult to generate reliable trends over time with the input data available and, as such, this report provides only the most recent global and regional estimates.

The percentage of children under five years of age affected by wasting in Africa was 6 percent in 2020 (12.1 million children), lower than the global average of 6.7 percent. Across different subregions, wasting affects 5.9 percent of children in Africa south of the Sahara (6.9 percent in western Africa, 6.2 percent in middle Africa, 5.2 percent in eastern Africa, and 3.2 percent in southern Africa) and 6.6 percent in northern Africa. In 2020, nearly one-quarter of the world's 45.4 million wasted children—about 10 million children—lived in Africa south of the Sahara.

Since 2010, the child overweight trend in Africa had remained stagnant around 5 percent, but it began to tick upward in recent years, reaching 5.3 percent in 2020 (nearly 11 million children under five years of age). Although this is still lower than the global average of 5.7 percent, the prevalence was much higher in northern Africa and southern Africa, with 13 and 12.1 percent, respectively. the trend has been on a rapid rise, especially in northern Africa. In other subregions, while the prevalence is lower (4 percent in eastern Africa, 4.8 percent in middle Africa, and 2.7 percent in western Africa), it has been on the rise since 2015.

The prevalence of anemia in women of reproductive age in Africa has been decreasing slowly since 2000 but showed a slight increase in recent years. In 2019, 38.9 percent of African women ages 15–49, or nearly 123 million women, were affected by anemia. This is higher than the global average of 29.9 percent. The prevalence is the highest in western Africa at 51.8 percent, followed by middle Africa (43.2 percent), northern Africa (38.9 percent), eastern Africa (31.9 percent), and southern Africa (30.3 percent). Since 2015, none of the subregions of Africa has made significant progress toward reducing the prevalence of anemia among women of reproductive age.

Like the global trend, the prevalence of adult obesity continued to rise in Africa and all its subregions between 2012 and 2016. Obesity among adults 18 years of age and older increased from 11.5 percent (65.5 million) in 2012 to 12.8 percent (81.5 million) in 2016, which is slightly lower than the global average of 13.1 percent. Southern Africa and northern Africa had the highest prevalence of 27.1 percent and 25.2 percent, respectively, representing more than one-fourth of the adult population. In 2016, the prevalence of adult obesity in other subregions was below 10 percent (6.4 percent in eastern

TABLE 2.5—ASSESSMENT OF PROGRESS TOWARD SELECTED GLOBAL NUTRITION TARGETS

	Child stunting (%)			Child overweight (%)			Child wasting (%)		Anemia in women of reproductive age (%)			Adult obesity* (%)		
	2012	2020	2030	2012	2020	2030	2020	2030	2012	2019	2030	2012	2016	2025
World	26.2	22.0		5.6	5.7		6.7		28.5	29.9		11.7	13.2	
Africa	34.5	30.7		5.0	5.3		6.0		39.2	38.9		10.4	11.8	
Northern Africa	22.7	21.4		12.0	13.0		6.6		31.9	31.1		22.5	25.4	
Africa South of the Sahara	36.6	32.3		3.8	4.0		5.9		41.2	40.7		6.9	8.0	
Eastern Africa	38.9	32.6		4.0	4.0		5.2		31.4	31.9		4.3	5.2	
Middle Africa	38.0	36.8		4.4	4.8		6.2		46.1	43.2		5.5	6.6	
Southern Africa	24.3	23.3		12.1	12.1		3.2		28.5	30.3		23.2	25.6	
Western Africa	34.9	30.9		2.3	2.7		6.9		52.9	51.8		6.4	7.7	

Legend: On track; Off track–some progress; Off track–no progress; Off track–worsening; Assessment not possible

Source: UNICEF, WHO, and World Bank (2021); NCD-RisC (2017). Data for anemia are based on the WHO Global Health Observatory database (2021). Data for adult obesity are based on the WHO Global Health Observatory database (2017).

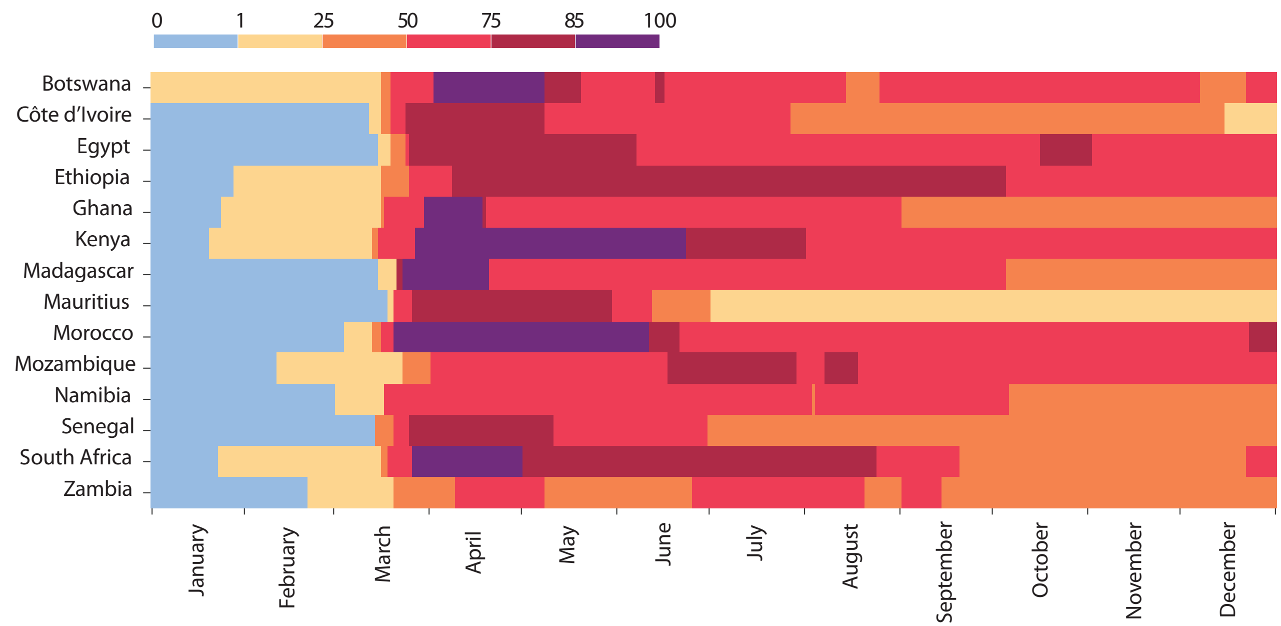
* There is no official target for adult obesity for 2030.

Africa, 7.9 in middle Africa, and 8.9 in western Africa), but it is projected to rise based on historical trends.

With respect to SDG Target 2.2 and the WHA global nutrition targets, estimates regarding levels of malnutrition in 2030 are characterized by a greater level of uncertainty this year than in the past, as with the projections for hunger. The estimates of progress toward these targets presented in Table 2.5 do not account for the effect of the COVID-19 pandemic, do not give weight to the more recent trends, and do not factor in future potential change in trends.

Africa as a whole is off track for all four SDG 2.2 nutrition targets (stunting, wasting, and overweight among children under five, and anemia in women of reproductive age). All subregions have shown progress toward the stunting target since 2012 but not enough to achieve the 2030 target (Table 2.5). For child wasting and overweight, and anemia in women, most subregions are making no progress. All subregions are off track to meet the 2025 WHA target to halt the rise in adult obesity by 2025.

FIGURE 2.5—OXFORD COVID-19 STRINGENCY INDEX, SELECTED COUNTRIES, 2020



Source: Data based on Hale et al. (2020); visualization by University of Oxford.

Patterns of Agricultural and Food Trade During the COVID-19 Pandemic in 2020

Trade in agricultural and food products is crucial for the economies and food security of many African countries. Exports of commodities such as cocoa, coffee, fruits, and vegetables generate income, while imports of staples such as cereals, dairy products, meat, and fats and oils provide energy and complement diets (FAO and AUC 2021).

While the World Trade Organization (WTO) estimated a 9.2 percent contraction of world merchandise trade due to COVID-19 impacts (WTO 2020a), global trade in agricultural and food products was only marginally affected. Particularly for food products for which demand is inelastic, trade continued to occur despite lockdowns; much of global trade in nonperishable staples is characterized by bulk shipments and automated processes (WTO 2020a; Schmidhuber and Qiao 2020). However, some disruptions in agricultural and food trade were observed at the very beginning of global movement restrictions (WTO 2020b). African countries for which early data were available reported sizable declines in agricultural exports and imports in the early months of the pandemic (FAO 2021).

COVID-19 containment measures of African countries and of their trading partners worldwide affected agricultural and food trade. Countries in Africa started imposing strict lockdown measures at the end of March 2020 (Figure 2.5). The most stringent measures were phased out by July, but none of the countries considered in this analysis had returned to full normality by the end of 2020. Restrictions on the movement of people followed similar patterns in many countries, notably developed countries, which are among Africa's main trade partners (FAO and AUC 2021; Malabo Montpellier Panel 2020).

The virus containment measures imposed by most countries in the world affected both export and import value chains. Agricultural and food production, processing, trade, and distribution were affected through restrictions on the movement of people, business closures, and in some cases, trade restrictions. Increasing unemployment, declining incomes, and the closure of the hospitality and tourism sectors in many countries led to shifts in demand and consumption patterns: decreased consumption of food away from home, including restaurants and other food services, drove declines in demand for beverages and other high-value food products, while home consumption and consumption of staple foods increased (FAO 2021).

Concerns over trade and value chain disruptions at the beginning of the pandemic led many countries to impose policy measures to limit potentially adverse impacts on food security and safety. Several African countries applied measures such as temporary export restrictions; relaxation of import barriers on specific or all foods to increase or stabilize domestic supply; measures to facilitate trade procedures; and temporary import restrictions or additional certification requirements in response to fears over possible COVID-19 transmission through the importation of food products. Measures to provide more targeted support to farmers and consumers included input subsidies, the expansion or release of food stocks, and the implementation or expansion of

TABLE 2.6—POLICY MEASURES AFFECTING WHEAT AND WHEAT FLOUR, MAIZE, RICE, MEAT AND DAIRY, AND VEGETABLE OILS

	Border Measures			Domestic Measures			
	Export restrictions	Lowering export duties	Lowering import restrictions/ subsidizing imports	Domestic market controls*; stock release/ food aid	Food reserves	Market price support/ producer subsidy	Non-product-specific producer subsidy
Wheat and flour							
Net importing countries	Algeria, Angola		Chad, Morocco, South Africa		Egypt		
Maize							
Net importing countries	Algeria, Angola, Sudan		Chad, Kenya	Rwanda, Nigeria			
Rice							
Net importing countries	Algeria, Angola, Mali		Chad, South Africa	Côte d'Ivoire, Gambia, Madagascar, Mali, Rwanda, Senegal		Côte d'Ivoire	Senegal
Meat and dairy markets							
Net importing countries	Algeria, Angola, Mali		South Africa				
Vegetable oils							
Net importing countries	Algeria, Angola		Chad, Mauritania, South Africa	Rwanda			

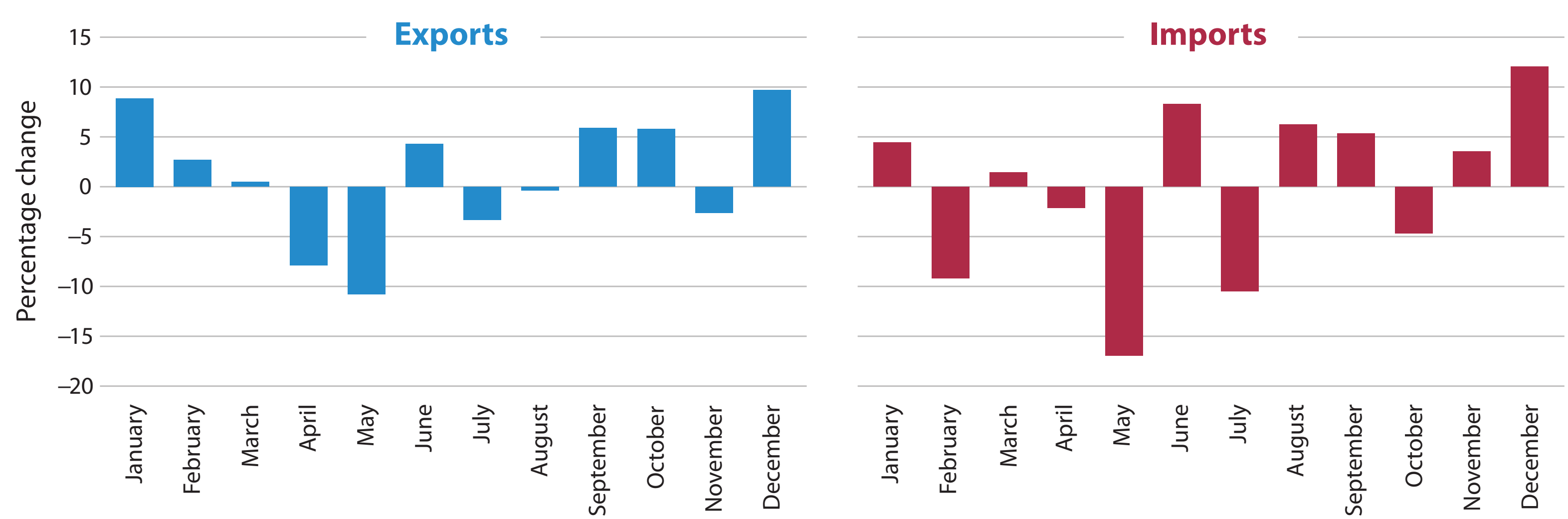
Source: Adapted from FAO (2021).
* Only reported if, in the sources, wheat and/or wheat flour, maize, rice, meat and dairy, and vegetable oils were explicitly listed among the food products upon which domestic market controls were applied.

price control mechanisms (FAO 2021). Table 2.6 presents the list of countries applying these measures.

In April and May 2020, when most countries in the world had imposed strict lockdown measures, agricultural and food export values of the aggregate of 14 African countries fell compared with the average of the same months in 2018 and 2019 (Figure 2.6).[3,4] Similar to global-level patterns, this decline was followed by a rebound effect in June (FAO 2021). In the second half of 2020, agricultural and food exports of the African countries tended to be higher in value terms than the average of 2018 and 2019.

The development of import values in 2020 was relatively more volatile. Import values of the aggregate of the African countries considered in the analysis had dropped already in February. By May 2020, they were down 15 percent compared with average values in the previous two years. Imports showed a strong rebound effect in June but declined again in July 2020. On

FIGURE 2.6—PERCENTAGE CHANGE IN AGRICULTURAL AND FOOD EXPORT AND IMPORT VALUES, AFRICA, JANUARY TO DECEMBER 2020 COMPARED TO THE SAME MONTH AVERAGE IN 2018 AND 2019



Source: Estimates based on Trade Data Monitor, accessed March 2021.

3 The analysis considered 14 African countries: Botswana, Côte d'Ivoire, Egypt, Ethiopia, Ghana, Kenya, Madagascar, Mauritius, Morocco, Mozambique, Namibia, Senegal, South Africa, and Zambia. These countries were estimated to account for nearly 40 percent of Africa's total population, around 48 percent of total gross domestic product, 45 percent of total exports, and 57 percent of total imports as of 2020 (based on World Bank 2021). The monthly trade data were used as reported by these countries at the end of March 2021. Trade data are subject to frequent revisions and can only give an indication of the changes in trade patterns in 2020 compared with those of the previous years. Data on trade of African countries, especially intra-African trade, are scarce in general, and official statistics do not reflect informal trade, which constitutes a large share of intra-African trade (Malabo Montpellier Panel 2020). The data include exports to and imports from trading partners as reported by the 14 countries, including trading partners that are not among the reporting countries. All monthly data in 2020 were compared with the average of the same time period in 2018 and 2019 to account for some volatility in these years.

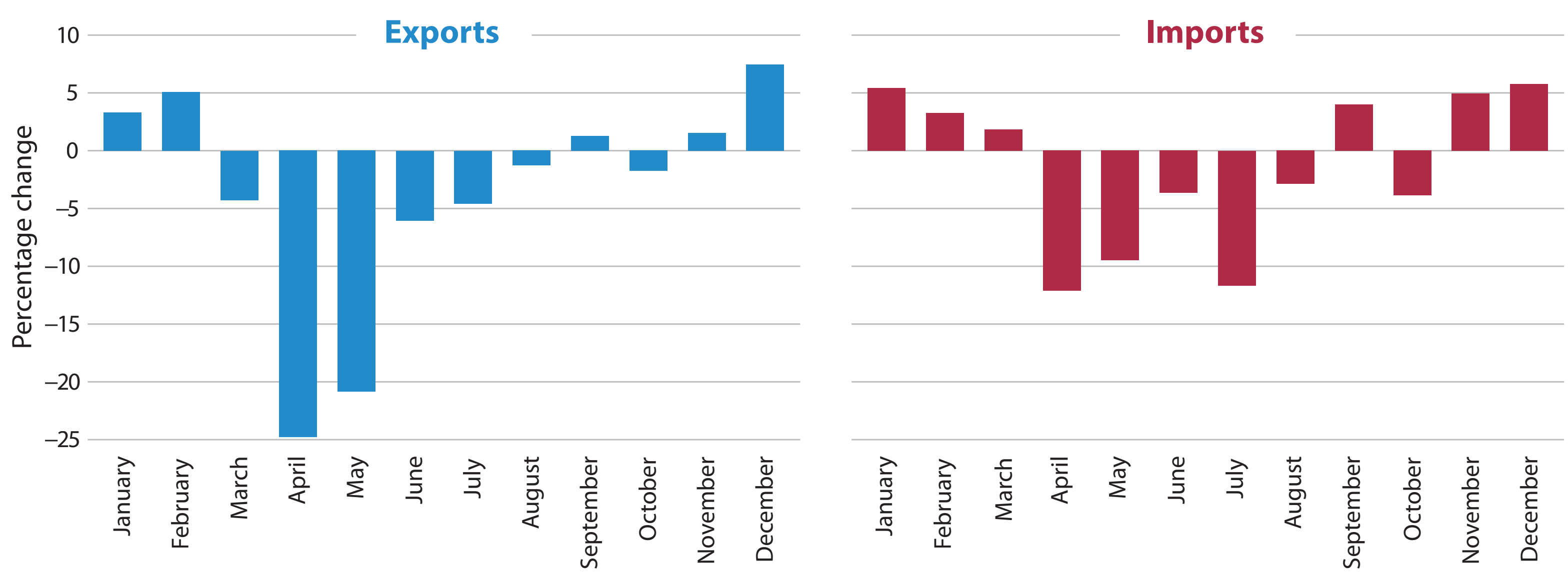
4 Trade in agriculture and food includes all products covered by the World Trade Organization Agreement on Agriculture, Annex 1, plus fishery products.

average, import values remained above prepandemic levels in the second half of 2020.

Export and import values reflect both changes in traded quantities and variations in export and import prices. They can give an indication of overall trade developments, measured in value terms. The FAO Food Price Index shows a steep decline in global food prices from January to May 2020, followed by a sharp increase in prices through the end of the year. Average price levels in 2020 were below those of 2018 and 2019 between March/April and August (FAO 2021). In addition to changes in prices and in volumes of trade with partners, part of the effect of the COVID-19 pandemic and related containment measures on trade in agricultural and food products was induced by complete disruptions of trade flows. In fact, the number of export flows, or export "links," of specific goods between two specific trading partners had shrunk by 25 percent already in April 2020 compared with the same month average in 2018 and 2019 (Figure 2.7). [5] That number was still down by more than 20 percent in May 2020 and remained subdued through June and July. The number of export flows did not deviate much from the pre-COVID average between August and November but increased by around 7 percent in December 2020.

The number of import flows of the African countries considered in the analysis declined by more than 10 percent in April and slightly less than 10 percent in May 2020 relative to the average number of

FIGURE 2.7—PERCENTAGE CHANGE IN THE NUMBER OF EXPORT AND IMPORT FLOWS OF AGRICULTURAL AND FOOD PRODUCTS, AFRICA, FROM JANUARY TO DECEMBER 2020 COMPARED TO THE SAME MONTH AVERAGE IN 2018 AND 2019



Source: Estimates based on Trade Data Monitor, accessed March 2021.

5 Export and import flows are also referred to as "export/import links" or "active export/import lines." They are counted at the Harmonized System six-product level and by bilateral trade flow. The number of export/import links is a simple measure of export/import diversification (Cadot, Carrère, and Strauss-Kahn 2010). A higher number of export/import links indicates a larger variety of products traded and/or more trade partners.

import flows in 2018 and 2019 (Figure 2.7). In July 2020, it was again more than 10 percent lower, while relatively little variation was observed between August and October. More import flows than the average of previous years were recorded in November and December 2020.

Moreover, the number of intraregional import flows of countries in Africa south of the Sahara showed a relatively sharper decline than import flows from other regions in the first phase of the pandemic and related containment measures. The relative resilience of extra-African imports might reflect the global orientation of African trade (FAO 2021). Much of Africa's trade and transport infrastructure is adapted to facilitate external trade (Fleshman 2009). In addition, although official statistics do not capture informal trade, available data suggest that informal intra-African trade also declined sharply in early 2020 compared to previous years. Informal trade accounts for a significant share of intra-African trade, but its exact magnitude is unknown. Bouët, Laborde, and Seck (2021) summarize findings from several informal trade monitoring efforts in western and eastern Africa that suggest informal cross-border trade declined precipitously in the early months of the pandemic due to border closures and increased screening of travelers.

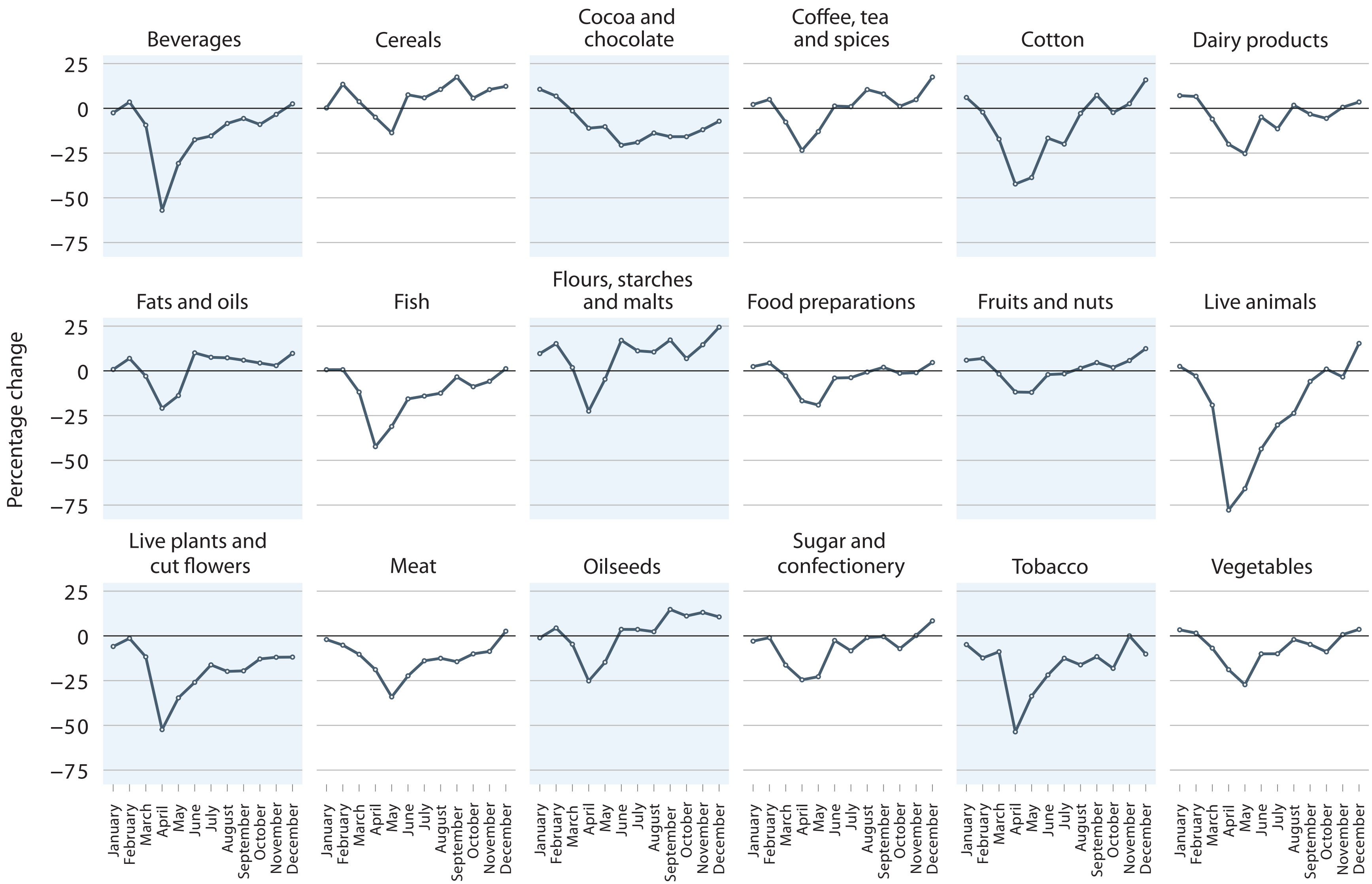
African exports and imports of products that did not immediately affect food security—unlike staples and foods important for a healthy diet—showed a relatively sharp decline at the beginning of lockdowns; Figure 2.8 shows the changes in the number of export links by commodity group.[6] This was similar to global-level patterns. Demand for beverages and fishery products declined rapidly at the beginning of the pandemic, which was partly attributed to the closure of bars, cafés, and restaurants in many countries (Cranfield 2020; Eftimov et al. 2020; FAO 2020). Similarly, demand for cut flowers decreased as a result of florist and cemetery closures and restrictions on social gatherings (Coluccia et al. 2021; FAO 2021; Vickers et al. 2020). Policy restrictions in some countries affected trade and demand for live animals, fishery products, and alcoholic beverages (FAO 2021; Sikuka 2020), while exports and imports of cotton and tobacco were mainly affected by trade disruptions and declining demand (Muhammad, Smith, and Yu 2021; TextileFuture 2020; Voora, Larrea, and Bermudez 2020).

In general, markets had recovered already in the second half of 2020 and trade in all commodities resumed.

The aggregate effects, particularly the decline in trade links during April and May 2020, show some variation that was likely caused by the restrictions imposed to curb the spread of the COVID-19 virus. However, exports and imports of agricultural and food products may have evolved differently at the country level. A distinct feature of trade for many African countries is a strong reliance on exports of a handful of primary agricultural commodities such as cocoa, coffee, fruits, and vegetables and imports of staples such as cereals. Examples in Box 2.1 illustrate that trade disruptions caused by the pandemic did not necessarily exert a strong impact on exports and imports of products that are crucial for export earnings and food security in some African countries.

6 Changes in import links and export and import values follow largely similar patterns.

FIGURE 2.8—PERCENTAGE CHANGE IN THE NUMBER OF EXPORT LINKS OF AGRICULTURAL AND FOOD PRODUCTS, AFRICA, FROM JANUARY TO DECEMBER 2020 COMPARED TO THE SAME MONTH AVERAGE IN 2018 AND 19, BY COMMODITY GROUP



Source: Estimates based on Trade Data Monitor, accessed March 2021.

BOX 2.1—COMMODITY-SPECIFIC DEVELOPMENTS IN CÔTE D'IVOIRE, ETHIOPIA, MADAGASCAR, AND NAMIBIA

Based on four selected countries, this box sheds light on trade developments of a few product categories that are important to generate export earnings in some African countries. It also looks at developments in cereals imports of the four countries.

The countries were selected from different subregions in Africa and represent different country income groups. Côte d'Ivoire is a lower-middle-income country located in western Africa; Ethiopia is a low-income country in eastern Africa; Madagascar is a low-income island country in eastern Africa; and Namibia is an upper-middle-income country located in southern Africa.

Côte d'Ivoire is the world's largest producer and exporter of cocoa beans. Cocoa exports account for more than 50 percent of Côte d'Ivoire's total agricultural exports and play an important role in the domestic economy of the country.1 Compared with trade in other commodities, African exports of cocoa and cocoa products were generally not strongly affected by the pandemic (Figure 2.8). Export values of cocoa and cocoa products from Côte d'Ivoire were lower between February and April 2020 than the average of the same months in 2018 and 2019. However, they recovered strongly in May and remained above average levels throughout the rest of the year 2020 (Figure 2.9). The number of export links remained almost stable.

Côte d'Ivoire is classified as a lower-middle-income food-deficit and net food-importing developing country, with rice being the main staple imported. Overall cereals imports of Côte d'Ivoire were relatively volatile throughout 2020 (Figure 2.9). Both cereals import values and links dropped in February and May 2020 relative to previous years. In particular, the cereals import values ranged from a decline of more than 60 percent in February and a rise of more than 90 percent in November 2020 compared with the 2018 and 2019 average in each month.

In Ethiopia, coffee is the most important export commodity. Ethiopian exports in the slightly broader category of "coffee, tea, and spices" were not strongly affected by the pandemic and related containment measures. The number of trade links dropped in March and April but remained above average levels in the second half of 2020 (Figure 2.9). Export values were above average in the first half and slightly below average in the second half of 2020.

Vanilla makes up the largest share of exports from Madagascar. Vanilla exports appear to have been affected by the pandemic. Export values in the category "coffee, tea, and spices," which includes vanilla, were almost 40 percent below average from January to March 2020. In April 2020, they further declined, with a drop of almost 60 percent, compared with the 2018 and 2019 average (Figure 2.9). The number of export links were also below average and dropped again in April 2020. Both values and the number of links surged in May 2020. While values remained volatile throughout the rest of the year, the number of export links remained more stable above-average values.

Both Ethiopia and Madagascar are low-income food-deficit and net food-importing developing countries. They also depend on the import of cereals. Cereals imports in Ethiopia and Madagascar were volatile in 2020 without following a clear pattern, especially in value terms (Figure 2.9).

Namibia is an upper-middle-income net food-importing developing country. It exports mainly diamonds, gold, and copper. Its agricultural exports are dominated by fish and fishery products. Both the number of export links and export values of fish and fishery products declined in April 2020 compared with those of previous years (Figure 2.9). Export links were more than 20 percent lower in April 2020 than the average of 2018 and 2019; export values were 40 percent lower than they were in the same month in 2018 and 2019. After the drop in April, the number of export links and values remained subdued until November and increased to above average levels only in December 2020.

Namibia imports a wide range of products not clearly dominated by any specific category. For consistency, Figure 2.9 shows the development of Namibia's cereals imports in 2020 compared with average values in 2018 and 2019. While the number of import links tended to remain below average levels, cereals import values were first above average and then dropped to 60 percent below average levels in June 2020. Import values remained low through September and increased again in October 2020.

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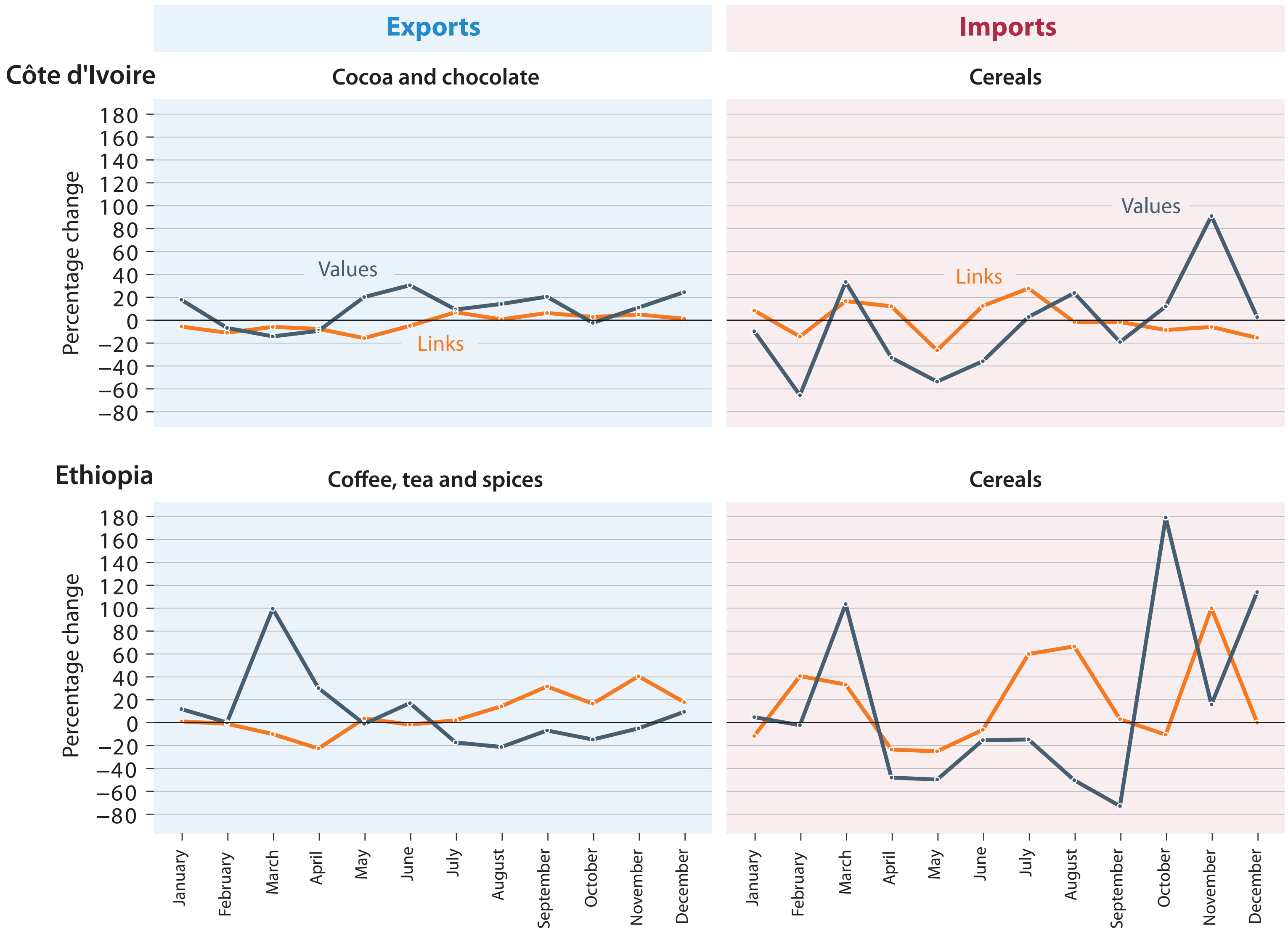
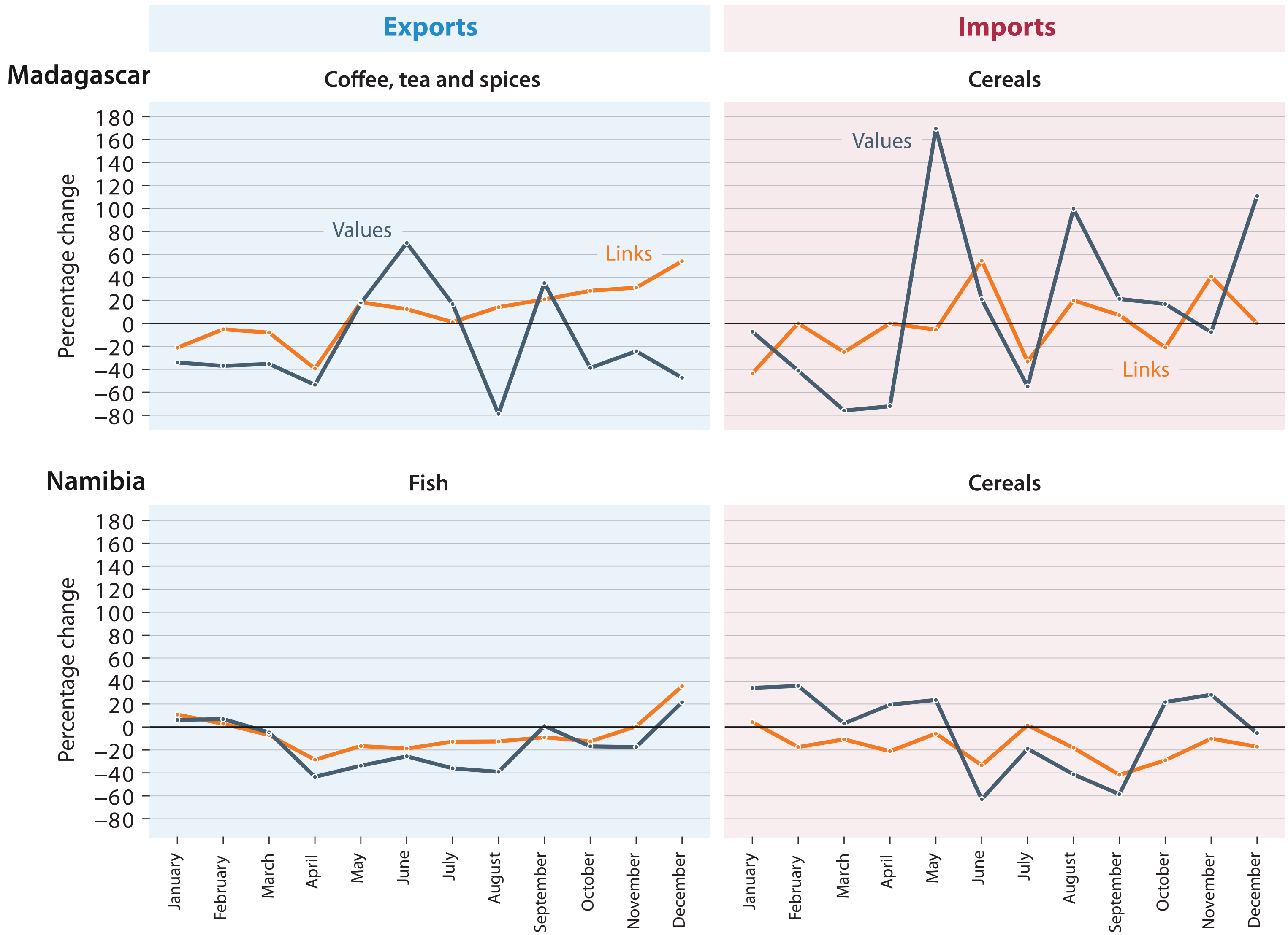
1 General trade patterns based on export and import shares in this section were retrieved from The Atlas of Economic Complexity (https://atlas.cid.harvard.edu/).

FIGURE 2.9—PERCENTAGE CHANGE IN EXPORT AND IMPORT VALUES AND LINKS, SELECTED COUNTRIES AND COMMODITIES, JANUARY TO DECEMBER 2020 COMPARED TO THE SAME MONTH AVERAGE IN 2018 AND 2019 *(continued on next page)*



Source: Estimates based on Trade Data Monitor, accessed March 2021.

FIGURE 2.9—PERCENTAGE CHANGE IN EXPORT AND IMPORT VALUES AND LINKS, SELECTED COUNTRIES AND COMMODITIES, JANUARY TO DECEMBER 2020 COMPARED TO THE SAME MONTH AVERAGE IN 2018 AND 2019 *(continued from previous page)*



Source: Estimates based on Trade Data Monitor, accessed March 2021.

Conclusion

The COVID-19 pandemic and the measures adopted by countries around the world to contain it affected the global economy, food and nutrition security, and trade in agricultural and food products. While trade in food and agriculture proved relatively resilient, African countries were hit hard by deteriorating macroeconomic conditions, increased unemployment, and declining incomes that exacerbated acute and chronic food insecurity.

In Africa, following a long trend of decreasing prevalence of undernourishment and a relatively unchanging number of undernourished people, new estimates showed the sharpest increase in hunger in a single year from 2019 to 2020. The prevalence of undernourishment increased from 2019 to 2020 in all subregions of Africa. Compared with 2019, 46 million more people in Africa were affected by hunger in 2020. The numbers show deep regional inequalities, with the largest number of undernourished people living in eastern Africa.

Projections of the number of undernourished people globally and at the regional level confirm the enormous challenge of eradicating hunger by 2030. A significant increase in hunger is forecast for Africa from 2020 to 2030, with an estimated 300 million people undernourished, on par with Asia. By 2030, Africa is projected to have the highest number of undernourished people even without considering the impact of the COVID-19 pandemic.

Beyond hunger, nearly 60 percent of the population of Africa—amounting to almost 800 million people—was affected by moderate or severe food insecurity in 2020. Nearly 26 percent (more than 345 million) faced severe food insecurity. A sharp increase from 2019 to 2020 is seen for the continent, as well as across all subregions.

Africa as a whole is off track for all four SDG 2.2 nutrition targets. All subregions have shown progress toward the stunting target since 2012, but not enough to achieve the 2030 target. For child wasting and overweight, and anemia in women, most subregions are making little progress. All subregions are off track to meet the 2025 WHA target to halt the rise in adult obesity by 2025.

Disruptions in African exports and imports of agricultural and food products remained limited to a short period in the first half of 2020. Whereas trade in staples was only minimally affected, exports and imports of some other product categories declined more sharply during that period. Such categories included beverages and fishery products, which were affected by changes in consumption patterns and, partly, policy restrictions. Disruptions in value chains and dwindling demand contributed also to decreasing trade in non-food commodities such as cotton, cut flowers, and tobacco. In the second half of 2020, trade resumed and remained at or even exceeded prepandemic levels.

As the COVID-19 virus continues to mutate and vaccination rollout in many developing countries remains sluggish, economic recovery is uncertain. This situation will likely further aggravate existing problems in many African countries, hinder development, and deepen their dependence on external assistance for food. It has resulted in grim projections for meeting the SDG food and nutrition security targets in the next 10 years, given the enormous challenges.

CHAPTER 3

The Impact of COVID-19 on Staple Food Prices: Location Matters

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Anatole Goundan, Paul Guthiga, Maurice Taondyandé,
Sunday Odjo, and Sibusiso Nhlengethwa

Introduction

This chapter summarizes the findings from analyses conducted by AKADEMIYA2063 on local staple food market dynamics during the COVID-19 pandemic in Africa. With the outbreak of the highly contagious virus in Africa in March 2020, various measures were implemented by African governments to contain its spread. These measures included bans on public gatherings and markets; restrictions on movement within and between countries; closures of schools, restaurants, and hotels; and curfews. All these measures were likely to cause market disruptions and revenue losses for vulnerable groups by disrupting supply and demand of agricultural staples, either directly or indirectly. The objective of these analytical studies is therefore to generate evidence on how the various COVID-19 response measures have affected food supply and demand patterns in Africa, taking into account the locational characteristics (that is, whether an area is urban or rural, has a surplus or deficit of the commodity in question, and is in a coastal or landlocked country) and whether the commodity is perishable or nonperishable. Such evidence can then be used to inform efforts to anticipate and respond to food crises arising from infectious disease outbreaks and the measures implemented to limit their spread.

Although pandemics like COVID-19 are not common, other major infectious disease outbreaks have been experienced in the recent past, including, for example, Ebola, severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MERS), and HIV/AIDS, among others (Verikios et al. 2011). Whenever they occur, they disrupt human lives and livelihoods, especially those of rural populations that depend heavily on agriculture and other primary sectors of the economy (Cabore et al. 2020; Phillipson et al. 2020). Sickness associated with pandemics affects the ability of rural populations to carry out normal agricultural activities that contribute to production. In addition, disease containment measures such as restrictions on movement of people and goods, restrictions on market operations, social distancing, and self-isolation, which are common during pandemics, curtail labor mobility, reduce productivity, disrupt supply chains, depress demand for agricultural commodities, impede the proper functioning of agricultural markets for inputs and outputs, and affect prices (Sumo 2019; Awotide et al. 2015; Boisvert, Kay, and Turvey 2012). Studies conducted on the impacts of the Ebola outbreak in West Africa, for example, showed that farms experienced shortages of agricultural labor for planting and harvesting as communities stayed away from agricultural fields, resulting in reduced yields and production (Bowles et al. 2016; de la Fuente, Jacoby, and Lawin 2020). In addition to constraining labor supply, movement restrictions also affect the timely supply of agricultural inputs and the movement of agricultural commodities from points of production to points of consumption. In urban areas, closures of hotels and restaurants and restrictions on agricultural market operations also affect demand. These effects are transmitted and expressed through changes in the demand for and the supply and prices of agricultural commodities.

The emergence and spread of COVID-19 and the measures implemented to contain it have raised concerns regarding the pandemic's effects on food security at the global, regional, and local levels. There is a growing body of literature globally on the impact of the COVID-19 pandemic on agricultural systems. However, most of these studies have focused on the global level or on select countries, the majority of which are outside Africa. At the global level, these studies report that food consumption has remained unchanged during the pandemic due to the inelastic demand for most agricultural commodities (Elleby et al. 2020; World Bank 2020; Ezeaku, Asongu, and Nnanna 2020; Falkendal et al. 2021).

In many developing countries, however, the pandemic has led to supply disruptions, agricultural commodity price disruptions due to interrupted supply and depressed demand, income losses, and rising food insecurity (Elleby et al. 2020; World Bank 2020; Varshney, Roy, and Meenakshi 2020; Aday and Aday 2020; Tamru, Hirvonen, and Minten 2020; Singh et al. 2020; Surni et al. 2021). The impact of COVID-19 on agricultural markets is highly dependent on local conditions in a country, the commodity in question, the status of the market systems, the capacity of local and national governments to respond to the pandemic, and the trade flows between countries, among other factors. Location characteristics—such as whether the area is urban or rural, surplus or deficit—determine the impact of the pandemic on agriculture prices. Furthermore, commodity characteristics (whether perishable or nonperishable) also determine the direction and magnitude of the price effect of the pandemic. As shown by Varshney, Roy, and Meenakshi (2020) in a study conducted in India, the impact of COVID-19 on agricultural markets differs by commodity (whether perishable or nonperishable) and period of analysis. This finding highlights the need to situate the studies in a local context, to capture nuances that could influence how a pandemic affects agricultural markets and ultimately food security.

Against this background, this chapter assesses the findings of analyses conducted in Benin, Burkina Faso, Kenya, Lesotho, Malawi, Mali, Mozambique, Nigeria, Rwanda, Senegal, Uganda, and Zambia that examined the effects of COVID-19-related market disruptions on staple food prices in different contexts. The analyses focused on domestic markets for local staple foods such as millet, cassava, white maize, and local rice, which tend to behave differently during times of crisis than global markets for major commodities such as imported rice, wheat, or yellow maize. Local staple food markets tend to be rather segmented from global food markets and are therefore less affected by global market shocks (Minot 2011). However, in some cases the local commodities examined are also extensively traded with neighboring countries, meaning that their prices are affected by disruptions to cross-border as well as domestic markets and transport. The analyses focused on price data at a granular, community level. They included descriptive analyses of the data, characterizing trends over time, assessing volatility, identifying spikes, comparing actual with predicted prices, examining geographic differences within and between countries, and investigating price transmission between markets.

The rest of this chapter is organized as follows: the next section describes the methodology and the data used for the analyses, while the third section provides a summary of the main findings of the analyses grouped by urban versus rural areas, deficit versus surplus areas, coastal versus landlocked countries, and perishable versus nonperishable food products. The fourth section draws conclusions and provides recommendations.

Methodology and Data

The COVID-19 pandemic has affected almost all countries, with varied consequences. To limit these impacts, different governments have implemented a variety of policies, including the closure of markets, hotels, schools, and borders. These actions are not without effect on the supply and demand of food. Indeed, these policy measures will have a direct impact on the price of these products, given the deficit or surplus situation of each market. In surplus areas, one would expect that various lockdown measures would negatively affect agricultural commodity prices, mainly due to a decrease in demand. In deficit locations, in contrast, staple food prices would be expected to increase due to limited supply locally. However, prices in cities may not increase if the decreases in demand due to the closure of schools and hotels and reductions in exports are large enough compared to the demand from households. Therefore, market connection and typology and policy options may influence price behavior. Only empirical investigation can help identify how various measures have impacted staple food prices in various contexts.

To analyze staple food price behavior before and during the COVID-19 pandemic, we modeled price trends in the absence of the pandemic and compared them to the actual prices observed during early and mid-2020, when many countries had instituted lockdowns and movement restrictions in response to the disease. As usual in a time series framework, seasonal autoregressive integrated moving average (SARIMA)[1] models were considered to extract price trends and to predict their dynamics over the lockdown period. A seasonal model was preferred since price data used were collected on a weekly or monthly basis. Therefore, there was a need to account for seasonal effects in order to obtain more accurate price forecasts. Interested readers can refer to the brief description of SARIMA models in the appendix. More technical details are available in Box et al. (2015) and Hyndman and Athanasopoulos (2018).

The use of SARIMA models to predict future prices of agricultural goods is not new. Various authors have used this approach to model agricultural commodity price trends in order to anticipate their future dynamics. For example, Marchezan and Souza (2010), Ohyver and Pudjihastuti (2018), and Darekar and Reddy (2017a) used these models to study rice prices. Similarly, Punitha (2007), Badmus and Ariyo (2011), and Kibona and Mbago (2018) have analyzed the future trend of maize prices using ARIMA models. Other commodities analyzed by the ARIMA models are tea (Ansari and Ahmed 2001), cotton (Özer and İlkdoğan 2013; Darekar and Reddy 2017b), onion (Darekar et al. 2015; Darekar, Pokharkar, and Datarkar 2016), wheat (Darekar and Reddy 2018), palm oil (Razali and Mohamad 2018), and green gram (mung bean) (Chaudhari and Tingre 2014).

For the empirical part of this work, we consider a set of 12 African countries from three subregions: eastern, southern, and western Africa. For each country,

1 When there are not enough price observations (less than five consecutive years of observations), the double difference approach is used to test whether observed prices in 2020 were different from what had been observed in the past.

up to two commodities were analyzed. The choice of countries was driven by data availability. For most of the countries, retail price data used in the study were obtained from the country's market information system. For Nigeria, we used data from the Famine Early Warning Systems Network (FEWSNET) created by the United States Agency for International Development (FEWSNET 2020). For each country, we selected one of the most important locally produced and consumed commodities. Table 3.1 presents the list of countries, commodities, and periods considered in the analysis. For a majority of countries, maize is one of the most important staples for the population's consumption. Maize or maize flour was considered for 9 of the 12 countries: Benin, Burkina Faso, Kenya, Lesotho, Malawi, Mali, Mozambique, Rwanda, and Zambia. We analyzed rice prices in Mali, while millet was the focus staple studied in Senegal. In Nigeria, we considered gari, which is roasted cassava granules. The last commodity considered in this study is the cooking banana (plantain) locally named matooke in Uganda.

TABLE 3.1—COMMODITIES, NUMBER OF MARKETS, AND PERIODS CONSIDERED BY COUNTRY

Country	Commodity	Number of markets considered	Period considered
Benin	Maize	12	2010–2020
Burkina Faso	Maize	27	2010–2020
Kenya	Maize	10	2011–2020
Lesotho	Maize flour	10	2015–2020
Malawi	Maize	23	2016–2020
Mali	Maize	22	2010–2020
Mali	Rice	15	2014–2020
Mozambique	Maize	11	2016–2020
Nigeria	Gari	8	2012–2020
Rwanda	Maize	5	2013–2020
Senegal	Millet	28	2010–2020
Zambia	Maize	10	2017–2020
Uganda	Matooke	4	2010–2020

Source: Authors.

For each country, price data were available for a set of representative markets. However, only markets with sufficient data points to satisfy the requirements of the models were considered in our analysis. The number of markets considered in each country is reported in Table 3.1. For each market for which enough observations were available, the best SARIMA model was selected among candidate models using a variety of forecast accuracy measures (further details are provided in the Appendix).

Finally, due to the number of countries and markets, we needed to find an easy way to communicate our findings, especially for policymakers. Therefore, we considered the average discrepancy (percent) between observed prices and the in-sample price prediction. The average percentage absolute error was around 5 percent. Therefore, we assumed that a price deviation of 5 percent or less, in absolute terms, is not significantly different from zero. Whenever the price gap is between –5 and 5 percent, we conclude that there is no difference between actual and predicted prices.

Main Findings and Lessons Learned

The results from these analyses are summarized in the sections that follow. Results are grouped according to whether the markets are rural or urban, located in deficit or surplus areas, and located in coastal or landlocked countries, and whether the commodities are perishable or nonperishable. The authors' local knowledge of the markets as well as responses from the in-country contacts who facilitated data access were useful in understanding which areas were generally deficit or surplus areas.

Urban Versus Rural Areas

An analysis of price trends for various commodities in urban and rural areas under COVID-19 is important for purposes of intervention planning. The differentiation is necessary because COVID-19 responses may affect prices in urban and rural areas differently owing to various factors (income per capita, own production of commodities, population, availability of substitute commodities, etc.) related to demand and supply of the commodities. This section presents price dynamics for urban and rural markets for maize flour (Lesotho), maize (Malawi, Kenya, Rwanda, and Mali), and millet (Senegal). This analysis provides insights into the differential effects of COVID-19 responses on price dynamics in those markets.

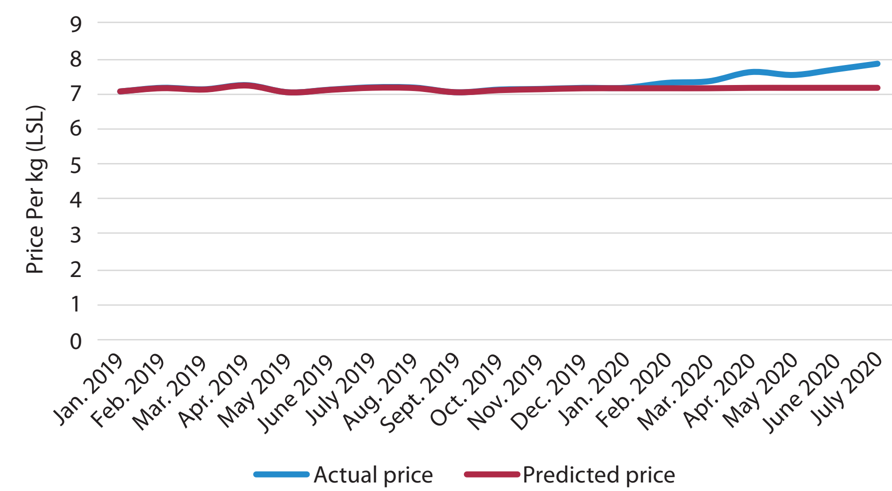
In Lesotho, the study focused on prices of maize flour in the following rural markets: Butha-Buthe, Mafeteng, Mohale's Hoek, Mokhotlong, and Qacha's Nek. It also focused on the following urban markets: Berea, Leribe, Maseru, and Quthing. The results presented in this chapter are for Butha-Buthe (a rural market) and Maseru (an urban market). Figure 3.1 shows the average observed prices for maize flour in the rural areas and those forecasted by the model. The prices observed were higher than expected (implying that COVID-19 restrictions led to a price increase in rural markets). The effect of COVID-19 restrictions also led to price increases in urban markets (Figure 3.2). For food import–dependent Lesotho, the general price increase speaks to the effect of a slowdown in commodity flows from South Africa. The differential effect between urban and rural markets is likely due to the effects of Lesotho's own movement restrictions during the COVID-19 pandemic, as rural areas must import maize food commodities from the urban centers, which receive the products first from abroad.

Although Lesotho produces maize locally, it is a net importer. During the COVID-19 crisis, informal cross-border trade was restricted,[2] which may have contributed to increased transaction costs for transporting maize to rural areas, leading to higher prices. There is a role for food policy to facilitate rural and urban market integration in order to reduce transaction costs and ensure that commodities reach the rural poor at affordable prices. The price increases seen in urban and rural areas of Lesotho during the COVID-19 pandemic are in line with previous findings by the High Level Panel of Experts on Food Security and Nutrition (HLPE 2020) as well as Espitia, Rocha, and Ruta (2020), who noted that there had been localized positive price changes due to the pandemic, especially in countries that depend on food imports to meet food requirements.

Malawi is a net exporter of maize grain. It is clear from Figures 3.3 and 3.4 that price forecasts differed from average observed prices for both urban and rural markets. The international travel restrictions announced toward the end of March and in April 2020, as well as the increase in awareness about the dangers of COVID-19 among many consumers and producers, reduced the movement of food within and across borders, leading to too much supply of food at low demand over that period. Awareness of the dangers of COVID-19

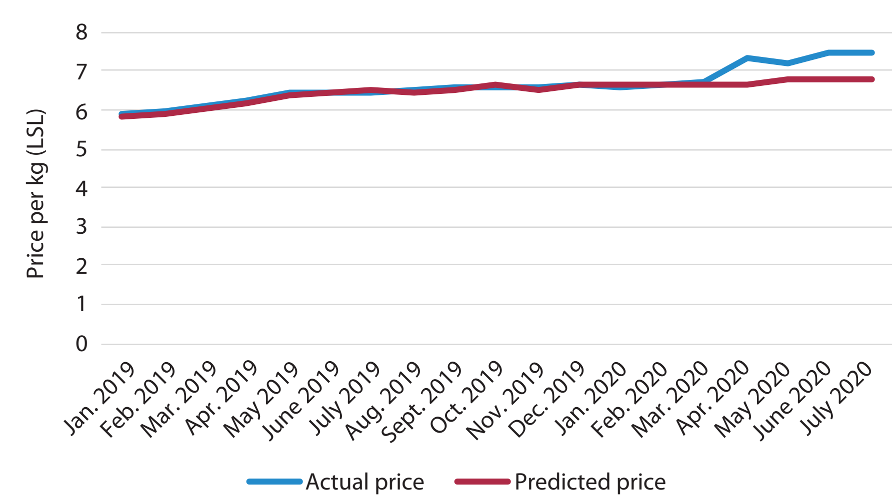
2 https://www.maserumetro.com/news/business/informal-cross-border-trade-severely-injured/

FIGURE 3.1—ACTUAL AND PREDICTED MAIZE FLOUR PRICE TRENDS IN RURAL MARKETS, LESOTHO (PRICE PER KG)



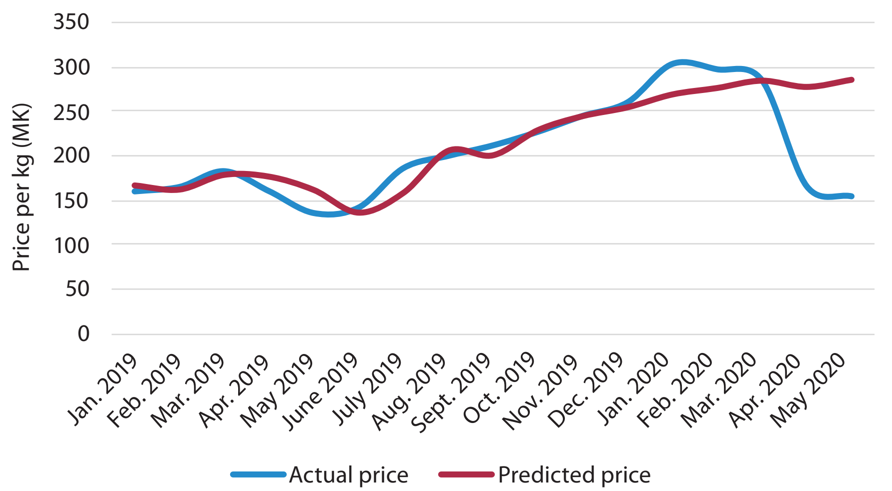
Source: Authors' computation based on data from Lesotho Bureau of Statistics.
Note: LSL = Lesotho loti.

FIGURE 3.2—ACTUAL AND PREDICTED MAIZE FLOUR PRICE TRENDS IN URBAN MARKETS, LESOTHO (PRICE PER KG)



Source: Authors' computation based on data from Lesotho Bureau of Statistics.
Note: LSL = Lesotho loti.

FIGURE 3.3—ACTUAL AND PREDICTED MAIZE PRICE TRENDS IN URBAN MARKETS, MALAWI (PRICE PER KG)



Source: Authors' computation based on data from WFP (2020).
Note: MK = Malawi kwacha.

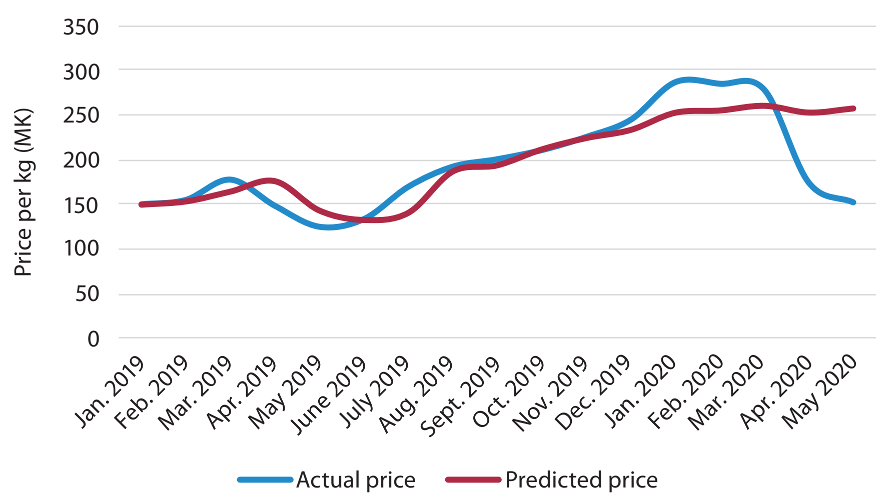
led consumers and food suppliers to reduce the number of times they visited markets to purchase or sell goods.

After March 2020, the observed prices were much lower than the prices predicted by our models, despite adjusting for seasonality. The price drop in urban centers appeared to be more than the decrease in prices in rural centers over the period, perhaps because the (demand reducing) internal travel restrictions were likely to be experienced first and more in urban centers than in rural areas, leading to surpluses of food in urban centers and depressing prices more.

In Kenya, a comparison of the observed prices and those predicted by our models for an urban market in Nakuru (Figure 3.5) suggests that measures taken to control the spread of COVID-19 may have depressed prices, especially during the months of March and April and after June, where the observed prices trended lower than predicted prices. This result concurs with the findings from Malawi.

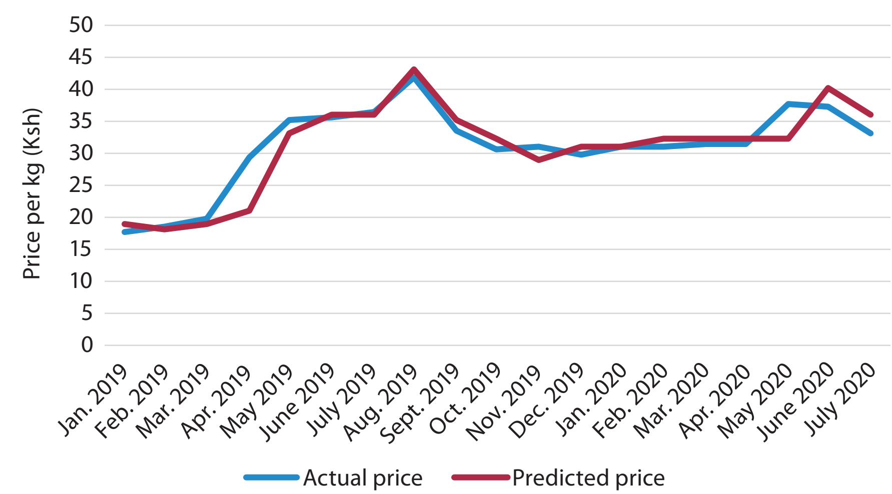
Again, within Kenya's rural market in Kipkaren (Figure 3.6), the prices of maize during the COVID-19 period trended slightly below those predicted by our models between January and June 2020, again implying that COVID-19 restrictions had depressed demand for maize. Unlike in the urban market of

FIGURE 3.4—ACTUAL AND PREDICTED MAIZE PRICE TRENDS IN RURAL MARKETS, MALAWI (PRICE PER KG)



Source: Authors' computation based on data from WFP (2020).
Note: MK = Malawi kwacha.

FIGURE 3.5—ACTUAL AND PREDICTED MAIZE PRICE TRENDS IN NAKURU (URBAN MARKET), KENYA (PRICE PER KG)



Source: Authors' computation based on data from WFP (2020).
Note: Ksh = Kenyan shillings.

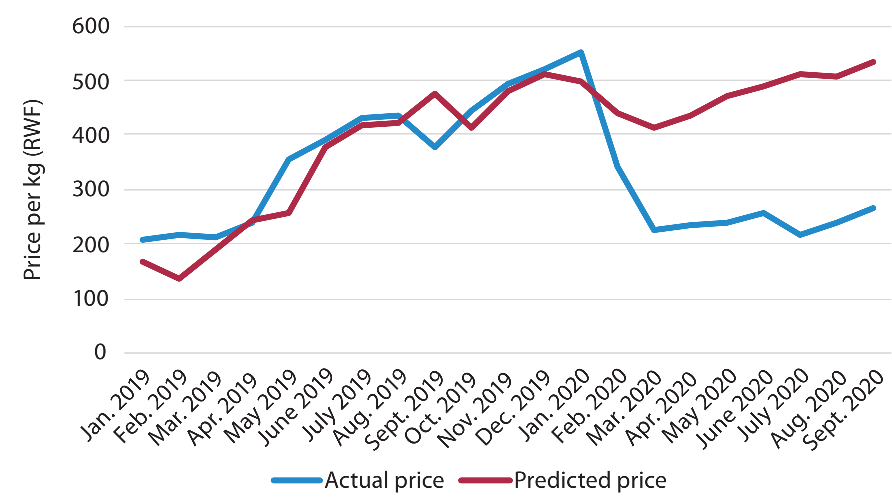
Nakuru, prices nevertheless seemed to recover in Kipkaren, perhaps as restrictions eased and demand recovered as well.

In both the urban and rural markets analyzed in Kenya, there was a general downward trend in maize prices that was more persistent in the urban market of Nakuru than in the rural market of Kipkaren. This finding also concurs with the findings in Malawi and Lesotho, where urban markets appeared to be associated with lower prices as compared to rural markets during the COVID-19 period. This is likely a manifestation of the speed with which (demand depressing) restrictions were enforced in urban areas as compared to rural areas.

In Rwanda, maize prices were analyzed for Kibungo (a rural market) (Figure 3.7) and Kimironko (an urban market located in Kigali) (Figure 3.8). There was a clear difference in the effect of COVID-19 restrictions on prices in the urban market compared to the rural market. The rural Kibungo market saw a larger decline in the price of maize compared to expected prices over the same period. It is likely that the Kibungo market experienced a reduction in demand for its maize, leading to price reductions.

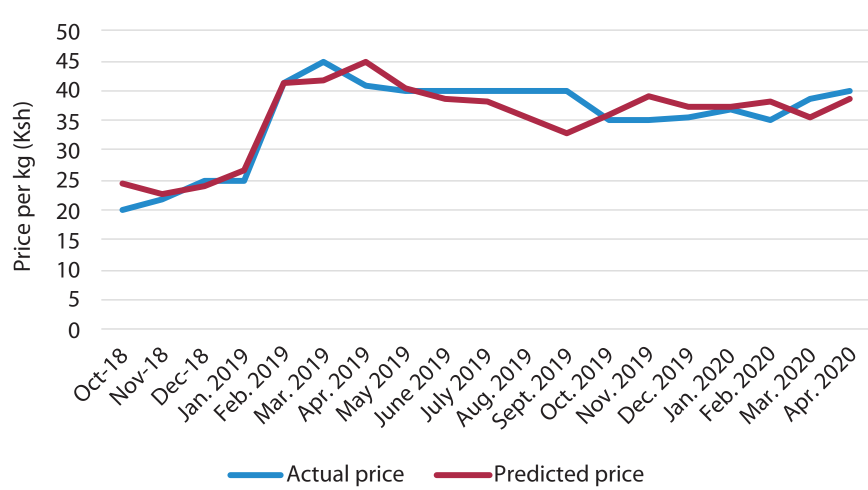
By contrast, the urban Kimironko market in Kigali, in the center of the

FIGURE 3.7—ACTUAL AND PREDICTED MAIZE PRICES IN KIBUNGO (RURAL MARKET), RWANDA (PRICE PER KG)



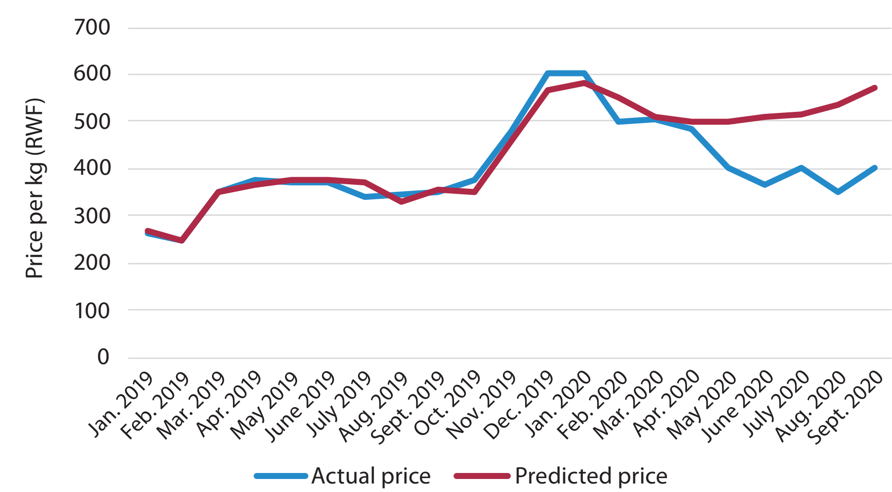
Source: Authors' computation based on data from the Ministry of Agriculture and Animal Resources, Rwanda.
Note: RWF = Rwandan francs.

FIGURE 3.6—ACTUAL AND PREDICTED MAIZE PRICE TRENDS IN KIPKAREN (RURAL MARKET), KENYA (PRICE PER KG)



Source: Authors' computation based on data from WFP (2020).
Note: Ksh = Kenyan shillings.

FIGURE 3.8—ACTUAL AND PREDICTED MAIZE PRICES IN KIMIRONKO (URBAN MARKET), RWANDA (PRICE PER KG)



Source: Authors' computation based on data from the Ministry of Agriculture and Animal Resources, Rwanda.
Note: RWF = Rwandan francs.

country, recorded a decline in maize prices relative to predicted prices from March onward (Figure 3.8), but the reduction was markedly smaller than that observed in the rural Kibungo market.

In Senegal, many of the markets registered sharp price increases compared to the prices that would have held in the absence of COVID-19 restrictions. For example, following the imposition of COVID-19 restrictions, the actual prices in St. Louis, an urban market located in a millet deficit area, increased until June 2020 (Figure 3.9). This suggests that market restrictions denied urban centers the needed stocks of millet, leading to price increases.

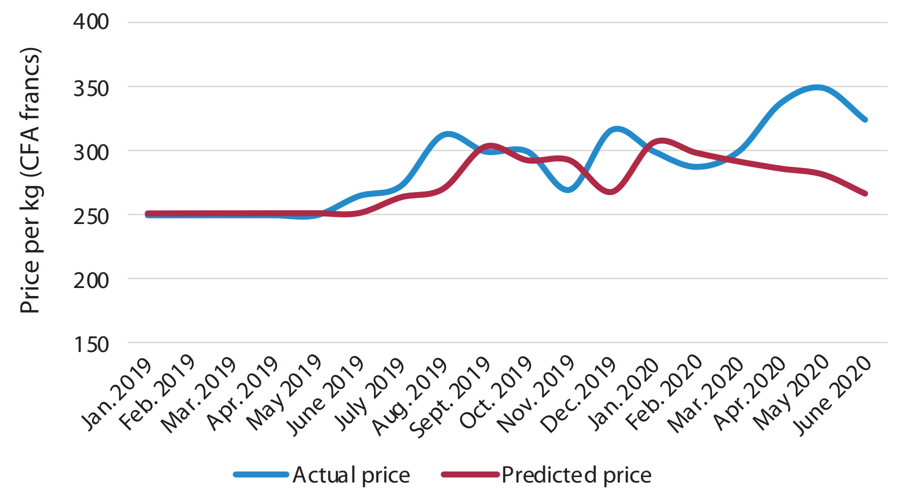
By creating an artificial shortage of staple foods, the restrictions imposed in response to COVID-19 disrupted the arbitrage mechanism across markets, resulting in a more generalized upward trend in prices, not just in deficit areas but also in some surplus areas. To the extent that some markets registered price increases, these results corroborate the findings by Elleby et al. (2020) and the World Bank (2020), which found that the pandemic had led to supply disruptions, agricultural commodity price disruptions, income losses, and rising food insecurity in a number of African countries.

In Mali, maize prices in Niono, a rural surplus market, increased compared to predicted prices after August 2020 but were not markedly different from predictions between January 2020 and July 2020 (Figure 3.10).

This increase in prices after August cannot be attributed solely to the COVID-19 pandemic, especially since the restrictive measures had been lifted at the beginning of June. It can be explained by both an increase in demand and an anticipation of reduced harvests. Indeed, the disruptions on the international market caused by climatic phenomena led neighboring countries (Guinea, Mauritania, and Senegal) to increase their imports of maize from Mali after the lifting of the sanctions imposed by the Economic Community of West African States during Mali's August 2020 coup d'état. The rise in prices was also influenced by the introduction of maize into the national food security stock and government purchases to support vulnerable households. On the supply side, the boycott of cotton cultivation by producers resulted in lower fertilizer quantities provided by the government-owned cotton enterprise to the producers, and this in turn reduced the availability of fertilizer for maize.[3] The reduced availability of

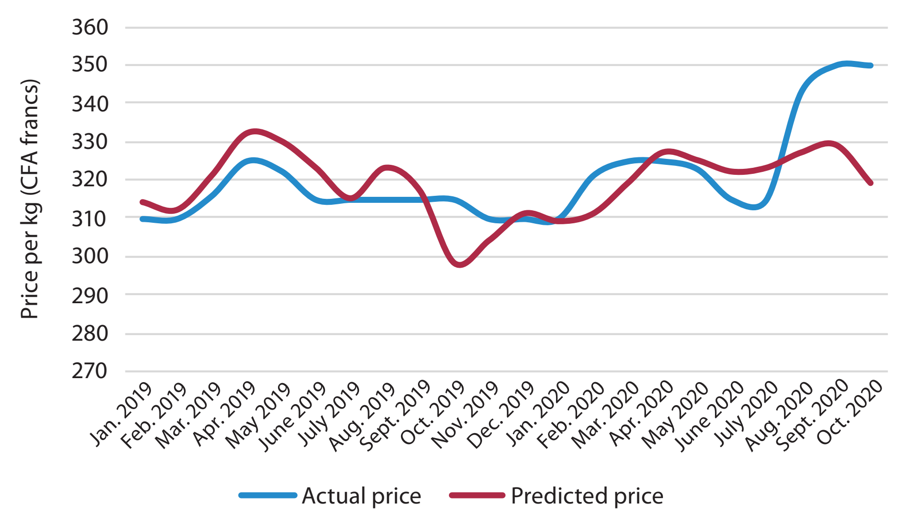
3 In Mali, there is no input distribution facility for maize production. However, cotton producers divert a part of the fertilizer distributed by the cotton company for maize production. Thus, a high share of the fertilizer used for maize originates from the cotton company.

FIGURE 3.9—ACTUAL AND PREDICTED MILLET PRICES IN ST. LOUIS (URBAN MARKET), SENEGAL (PRICE PER KG)



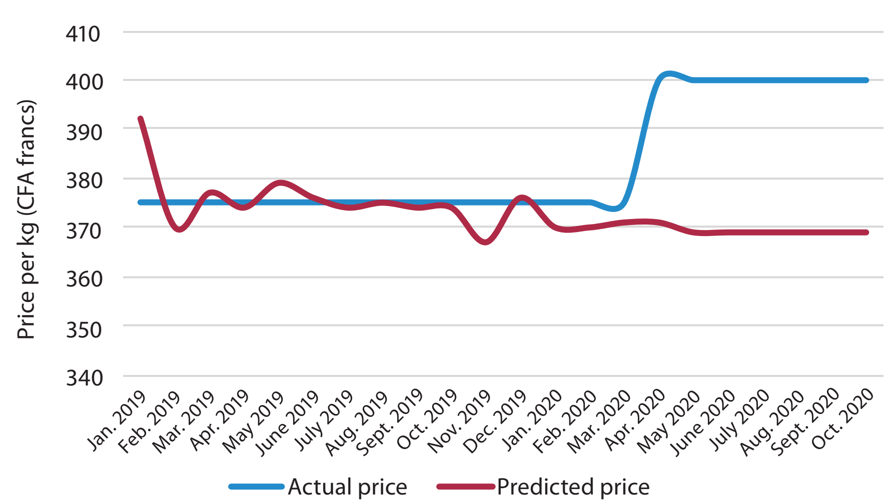
Source: Authors' computation based on data from the Senegalese Market Information System of the Food Security Commission (SIM/CSA).

FIGURE 3.10—ACTUAL AND PREDICTED MAIZE PRICES IN NIONO (RURAL MARKET), MALI (PRICE PER KG)



Source: Authors' computation based on data from Agricultural Market Watch (OMA).

FIGURE 3.11—ACTUAL AND PREDICTED MAIZE PRICES IN KOULIKORO BA (URBAN MARKET), MALI (PRICE PER KG)



Source: Authors' computation based on data from OMA.

fertilizer negatively affected maize yields, even if the cultivated area increased.

Similarly, the observed prices in the Koulikoro Ba maize market, which is located in the city of Koulikoro, were consistently higher during the COVID-19 period compared to those predicted by the model (Figure 3.11).

The consistently higher-than-expected prices again indicate that urban markets faced supply pressure as movement was restricted, such that although demand was also likely affected, the impact of restrictions on supply had a larger effect, leading to rising prices. This, again, corroborates the findings by Singh et al. (2020) and Surni et al. (2021), who found that the COVID-19 pandemic led to a disruption in agricultural commodity prices through supply chain disruptions.

Deficit Versus Surplus Areas

Another interesting grouping of the markets is based on the levels of domestic supply relative to demand for a given commodity. In this section, the prices of maize in Burkina Faso, Mali, Kenya, Malawi, Mozambique, Rwanda, and Zambia; millet in Senegal; gari in Nigeria; and matooke in Uganda are analyzed in terms of the distinction between deficit and surplus areas.

As would be expected, restrictions that emerged at the beginning of the pandemic in March 2020 to limit the movement of people affected the movement of goods, making it difficult for food products to flow uninterrupted from production areas to markets in deficit areas and across borders with neighboring countries. In theory, such market restrictions should induce a downward trend in prices, below their predicted levels, in surplus areas, as there would be too few purchasers, while the opposite would be expected in deficit areas, due to lack of supply.

Deficit Areas

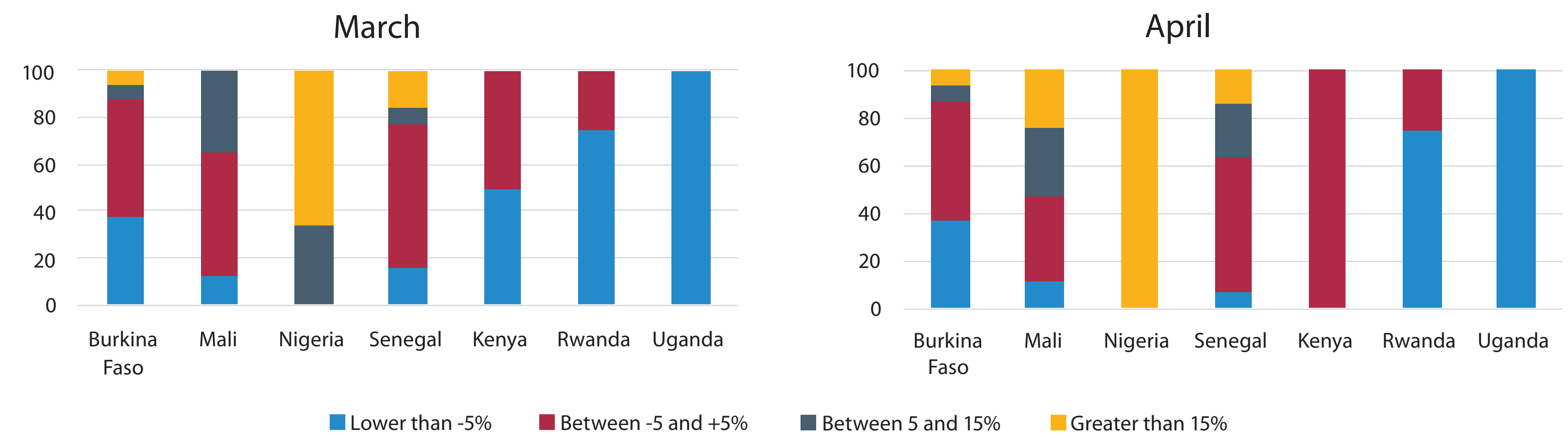
In deficit areas, the extent to which prices may change would depend on access to surplus areas and on changes in demand from particular groups like schools, universities, restaurants, and hotels, which were operating at an unusually low level during the lockdown period. A comparison of deficit-area markets in western and eastern Africa reveals a differential effect of COVID-19 restrictions on prices across the regions. For instance, it appears from Figure 3.12 that price trends in eastern Africa were in general negative or increased by less than 5 percent, while in western Africa, some markets experienced price increases of between 5 and 15 percent and even more.

In western Africa, the price increases at the beginning of the pandemic (March and April 2020) were modest in most markets (that is, below 5 percent), except in Nigeria, where substantial price increases (over 15 percent) were observed in two-thirds of the markets in March and in all markets from April to July.

It is noteworthy that price increases were more significant in Senegal than in Burkina Faso and Mali after one month of lockdown in April 2020. This might be explained by the fact that even in normal years Senegal has a deficit in millet, the staple food. This commodity is primarily imported from Mali. The situation worsened in Senegal in May, when price increases of more than 5 percent were observed in around three out of four markets (72 percent). Prices in deficit areas in the country rose steadily from March until June.

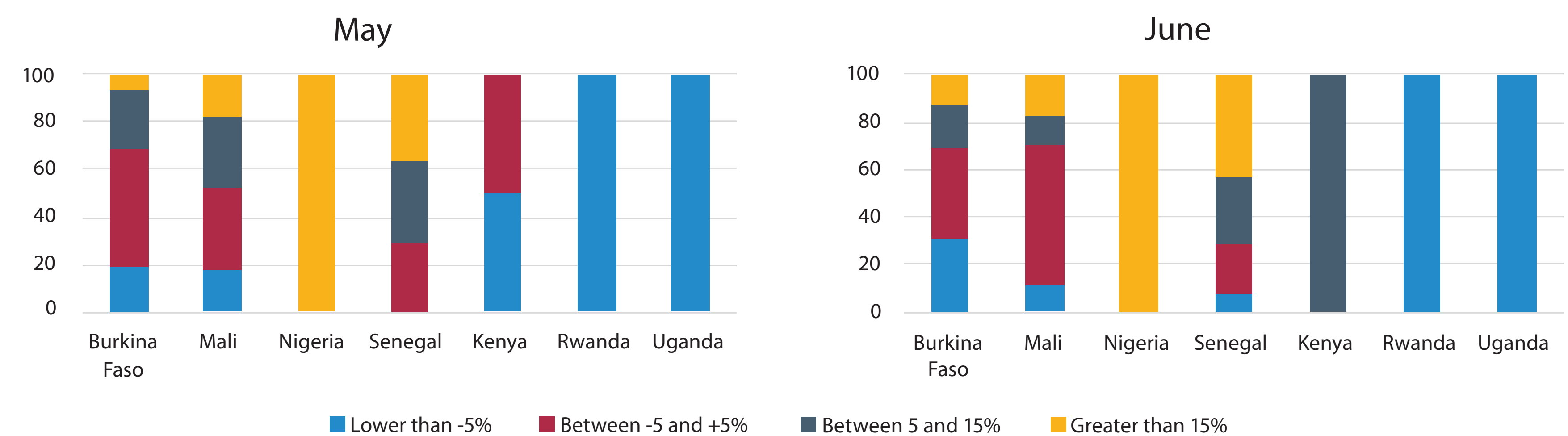
In June 2020, with the end of lockdown, price increases were less than 5 percent in around 70 percent of the markets in Burkina Faso and Mali, while in Senegal price increases of more than 15 percent were observed in nearly one market out of two (47 percent) in the deficit areas (Figure 3.13). A drop in demand caused by the economic crisis following the onset of the pandemic could explain this trend in Burkina Faso and Mali. The increased

FIGURE 3.12—PROPORTION OF MARKETS IN DEFICIT AREAS ACCORDING TO THE LEVEL OF DEVIATION FROM PRICE PREDICTIONS (IN PERCENT) IN MARCH–APRIL 2020



Source: Authors' computation based on price data from country bureaus of statistics or agricultural market information systems.

FIGURE 3.13—PROPORTION OF MARKETS IN DEFICIT AREAS ACCORDING TO THE LEVEL OF DEVIATION FROM PRICE PREDICTIONS (IN PERCENT) IN MAY–JUNE 2020



Source: Authors' computation based on price data from country bureaus of statistics or agricultural market information systems.

supply in deficit areas induced by the decrease in cross-border exports due to border closures could also explain the price drop in deficit areas. In Senegal, the concentration of millet production in the groundnut basin (the major groundnut producing area in central Senegal), the dependance on imports from neighboring countries in normal years, and the significant number of urban markets with huge demand in deficit areas might explain the longer delay in those markets' return to normality.

The behavior of staple food prices in eastern Africa is quite similar to that observed in southern African countries, but it differs from what is observed in deficit areas in western Africa.

In March 2020, in eastern Africa, price decreases of more than 5 percent were observable in 50 percent of markets in Kenya, 75 percent of markets in Rwanda, and all markets in Uganda. The same situation prevailed in Rwanda and Uganda from April to July, with price drops of more than 5 percent in almost all markets in deficit areas.

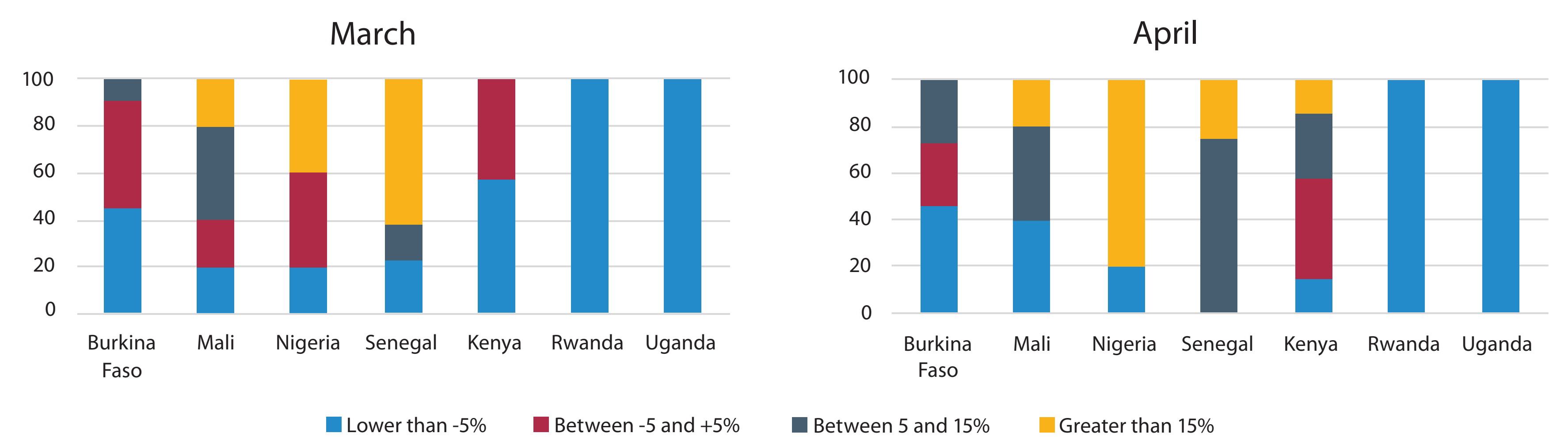
In Kenya, prices were more or less stable, with price changes between –5 and 5 percent in all considered markets in April. Only in June were the price increases higher than 5 percent in all markets. In May as well as in July, prices decreased or increased less than 5 percent.

Surplus Areas

In March 2020, prices showed normal or decreasing trends compared to predictions in Burkina Faso and Kenya. However, in Mali and Senegal, and to a lesser extent in Nigeria, most markets were already reporting prices that were higher than predicted. Indeed, the share of markets located in surplus areas with prices more than 5 percent higher than predicted was 60 percent in Mali, 77 percent in Senegal, and 40 percent in Nigeria (Figure 3.14).

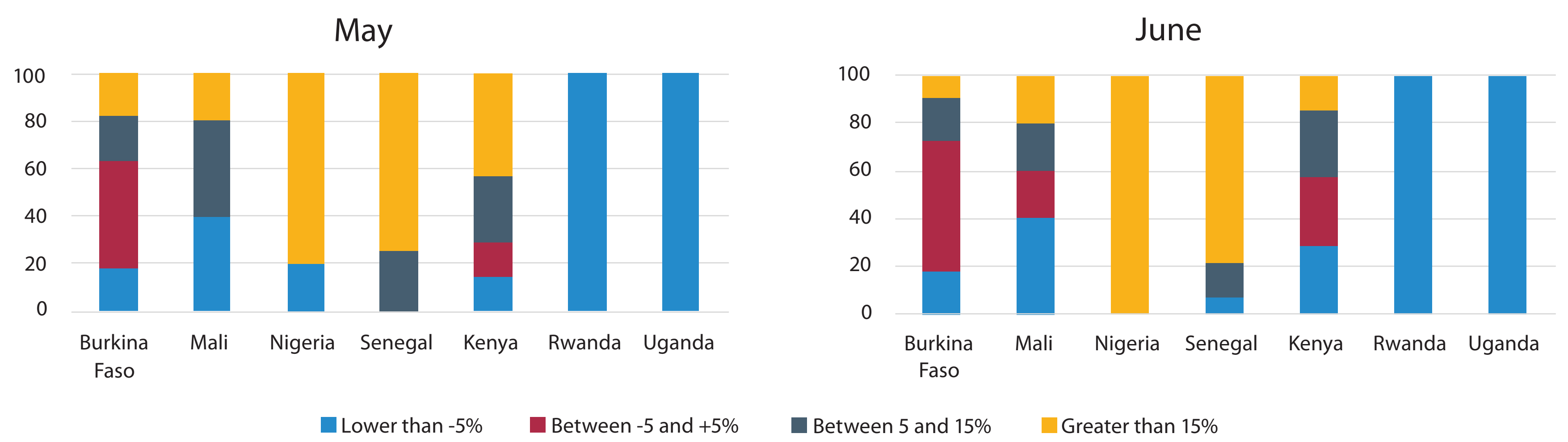
The restrictive measures implemented by the countries started impacting markets as early as April, but these effects differed. In Burkina Faso, Nigeria, Senegal, and Kenya, market prices increased despite restrictions on movement. The proportion of markets with prices at least 5 percent higher than predicted was 100 percent in Senegal (versus 77 percent in March), 43 percent in Kenya (versus 0 percent in March), and 80 percent in Nigeria (versus 40 percent in March). In Senegal, the expected imports from Mali were disrupted with

FIGURE 3.14—PROPORTION OF MARKETS IN SURPLUS AREAS ACCORDING TO THE LEVEL OF DEVIATION FROM PRICE PREDICTIONS (IN PERCENT) IN MARCH–APRIL 2020



Source: Authors' computation based on price data from country bureaus of statistics or agricultural market information systems.

FIGURE 3.15—PROPORTION OF MARKETS IN SURPLUS AREAS ACCORDING TO THE LEVEL OF DEVIATION FROM PRICE PREDICTIONS (IN PERCENT) IN MAY–JUNE 2020



Source: Authors' computation based on price data from country bureaus of statistics or agricultural market information systems.

the closure of borders, and movement restrictions in general contributed to increased prices during the lean season. In Mali, prices fell in some markets in surplus areas due to falling demand. In fact, in 20 percent of markets where prices were more or less equivalent to the predictions, prices declined by more than 5 percent compared to predictions.

In May 2020, the upward price trend in surplus areas was accentuated in Mali, Senegal, Kenya, and, to a lesser extent, Burkina Faso.

With the lifting of restrictive measures in June 2020 in most countries, the pressure observed in markets in surplus areas decreased in some countries. In Burkina Faso, 73 percent of the markets in surplus areas analyzed showed declining price trends, compared to 64 percent in April (Figure 3.15). Similar trends were observed in Mali and Kenya, with, respectively, proportions of 60 and 40 percent in April and 57 and 29 percent in June. However, prices remained high in Nigeria and Senegal. The increase in demand after the reopening of the markets or the negative expectations of traders could explain this trend. Similar price increases have also been reported by other studies. For example, a study by Mogues (2020) reported that consumer food prices saw an appreciable increase globally in the three months beginning in mid-February 2020, underscoring the negative effect on markets of the reduced supply of food commodities.

In Rwanda, measures taken by the government to control and contain the spread of COVID-19 had the unintended effect of disrupting maize prices. The containment measures made it difficult for maize to flow uninterrupted from production markets to consumption markets and across borders with neighboring countries. The closure of hotels and restaurants, which are major demand points for the staple, exacerbated the situation. The decline in actual prices relative to predicted prices continued even into the month of July 2020, despite some relaxation of the initial measures. The same measures taken by the government of Uganda also led to a decline in the price of matooke relative to predicted prices.

In Malawi, Mozambique, and Zambia, restrictions on people's movement resulted in reduced maize demand (as consumers reduced the number of trips to markets), which in turn led to a drop in prices. The price decrease is also related to the fact that COVID-19 restrictions coincided with the maize harvesting season. The price effect of decreased demand as a result of COVID-19 restrictions, along with the onset of the harvest season, led to excess supply and thus to generally lower prices. This result is understandable considering that Malawi, Zambia, and Mozambique are net exporters of maize and rely on cross-border trade. Maize harvests were not substantially reduced by the COVID-19 pandemic in 2020 because the first cases emerged long after the growth season had commenced. In Senegal, the price increase is explained by the fact that the markets were not well supplied during the lockdown period.

In summary, two different patterns appear when comparing pandemic-related staple food price trends in deficit and surplus areas across the three subregions of western, eastern, and southern Africa. In western Africa, prices increased in the deficit areas of all considered countries during the lockdown period. Prices fell with the lifting of restrictions in Burkina Faso and Mali, while the pressure on prices remained significant in Senegal and Nigeria. In contrast, in eastern and southern Africa, where cross-border trade is more important than in western Africa, a general downward trend was observed for deficit as well as for surplus areas throughout the considered period, with some exceptions. Indeed, cross-border sales to neighboring countries in these subregions may have played a significant role in determining pre-COVID-19 price behavior across the country, not just in border areas, and declines in cross-border trade due to the COVID-19 crisis may have contributed to lower prices. The potential negative impact from the observed decline in prices shows the critical importance of transborder trade for smallholder farmers and small businesses. When trade across the borders stopped, the exporting markets quickly found themselves with too much maize and low demand, leading to declining prices.

Coastal Versus Landlocked Countries

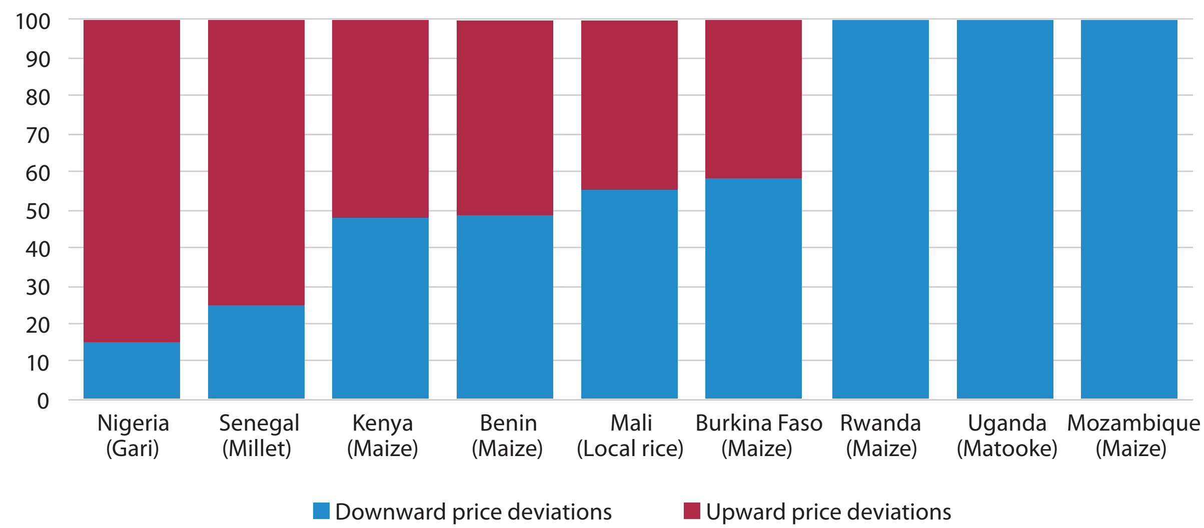
A market's location within a coastal area or far from an ocean is an important factor in determining the effects of COVID-19 restrictions on market prices. Supply chain disruptions are likely to affect coastal and landlocked African food import–dependent countries to varying degrees due to differing levels of exposure to international trade. The effects of COVID-19 on international food prices were relatively moderate (Nagle and Baffes 2020) and could have helped to stabilize local food prices in coastal countries. Landlocked countries are likely to be affected more significantly, given their less direct connections with world markets. Among the sample of countries under analysis, Benin, Kenya, Mozambique, Nigeria, and Senegal are coastal countries that trade directly with the rest of world, while Burkina Faso, Lesotho, Malawi, Mali, Rwanda, Uganda, and Zambia trade with the rest of world through the ports of neighboring coastal markets and thus incur higher trading costs than coastal countries.

Fewer price deviations attributable to COVID-19 would be expected in coastal countries, as these countries can more easily mitigate price hikes resulting from domestic production and market disruptions through direct imports. In contrast, landlocked countries would be expected to experience more price hikes due to longer delays in supplying domestic markets from world markets via regional port infrastructure.

However, this anticipated dichotomy has not been confirmed by the distribution of price deviations across the sample of countries. The highest price deviations were observed among both coastal and landlocked countries, as were the lowest price deviations. For instance, an upward price deviation as high as 113.5 percent was observed for gari in Nigeria, a coastal country, and a downward price deviation as high as 48 percent was reached for matooke in Uganda, a landlocked country. This does not imply that access to the sea is not important for trade, but it does suggest the importance of considering commodity characteristics in the analysis. The downward movement of matooke prices may be explained by the fact that Uganda is the sole major producer of this commodity, and trade restrictions led to excess supply, thus leading to low prices. The results also suggest that price deviations—both upward and downward—were highest for commodities that are less internationally traded, like gari and matooke, than for commodities that are traded across borders in higher volumes.

The actual evolution of food prices seems to have been governed by a combination of other more determining factors. Figure 3.16 shows that between March and July 2020, the prices of the commodities under analysis deviated upward from their predicted levels more often in coastal countries than in landlocked countries. However, this is also likely because many of the coastal

FIGURE 3.16—PROPORTION OF MARKETS WITH DOWNWARD/UPWARD PRICE DEVIATIONS BETWEEN MARCH AND JULY 2020 IN STUDY COUNTRIES (PERCENT)



Source: Authors' computation based on price data from country bureaus of statistics or agricultural market information systems.

areas in focus were surplus producers of the commodities. In Rwanda and Uganda (landlocked countries) but also in Mozambique (a coastal country), observed prices deviated consistently downward in all localities analyzed throughout March–July 2020. In Nigeria, in 85 percent of cases, the observed prices of gari deviated upward in the same period.

Overall, the prices of staple foods counterintuitively deviated downward in landlocked countries and upward in coastal countries during the period of COVID-19-related transport and trade restrictions. This result indicates that landlocked countries have been able to counter the cost effects associated with their remoteness and indirect connections with world import markets. However, the price increases in coastal countries seem to reflect the additional cost effects of delays and losses associated with international transport and world trade restrictions.

Perishable Versus Nonperishable Commodities

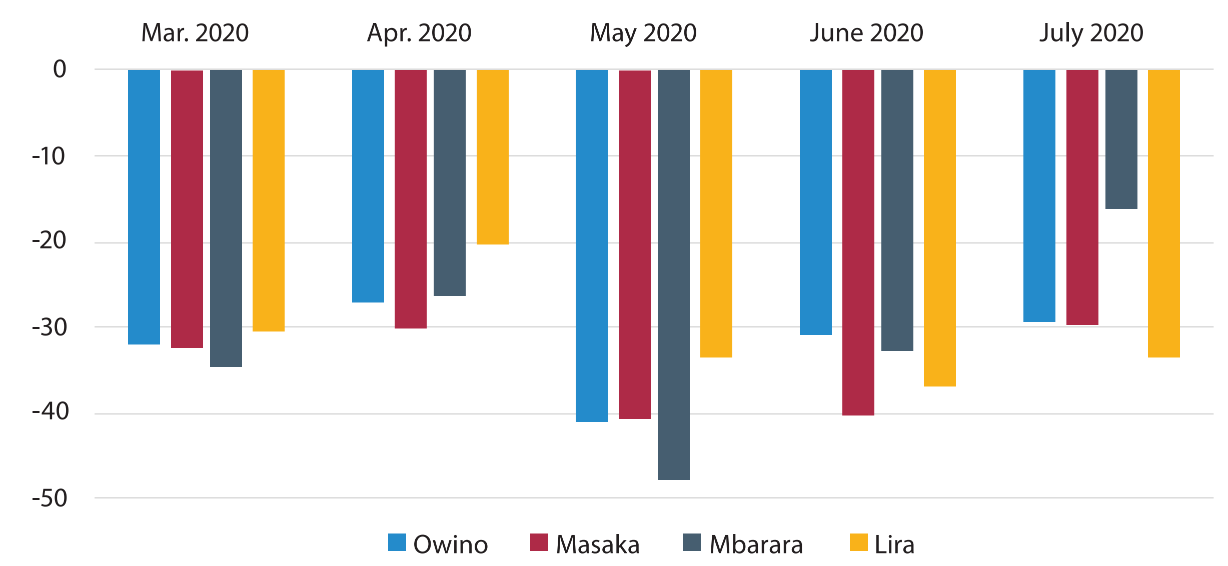
This section summarizes the findings of a comparative analysis of the impact of the COVID-19 pandemic and measures taken by governments to control it on the wholesale and retail prices of perishable and non-perishable staple food commodities across six countries in Africa. The nonperishable staple commodities consist mainly of cereals, including millet (in Senegal), maize flour (in Lesotho), and maize grain (in Malawi, Kenya, and Burkina Faso). The perishable staple food considered was matooke (in Uganda).

Perishable food commodities cannot be stored or hoarded because they will spoil and go to waste. In essence, the market-period supply curve of a perishable commodity is perfectly inelastic, or a vertical straight line. This implies that demand for perishables determines the price. If demand is disrupted and shifts downward, the price will consequently fall. However, the supply of a nonperishable good is elastic, and therefore the impact of disruption to supply and demand is less determinate. Sellers of nonperishable commodities can hold back and wait until the price of the good rises, but sellers of perishable commodities do not have this option.

Holding other factors constant, the COVID-19 pandemic and the restrictions that accompanied it were expected to affect prices of perishable and nonperishable staples differently. In a situation in which the disruption affects the demand side (for example, closure of hotels and restaurants), the price of perishable staples can collapse. In contrast, disruption in the flow of nonperishable staples, controlling for other factors, could have a differentiated effect: producing areas would experience declining prices due to accumulating supplies, while deficit areas would experience rising prices. In this section, we present the results of a comparison between actual monthly prices and predicted prices (prices that we expect would have prevailed in the absence of the pandemic), based on seasonal patterns and historical price data.

Matooke is the primary staple food commodity in Uganda. It is highly perishable and hence vulnerable to any market disruption. Analysis conducted in five markets across the country showed that COVID-19-related restrictions led to a sharp decline in matooke prices (Guthiga, Kirui, and Karugia 2020). As shown in Figure 3.17, prices in retail markets were observed to range between 16 and 48 percent below the predicted long-term prices over the March–July 2020 period. The closure of main demand centers (restaurants, educational institutions, etc.) led to a decline in demand and a sharp drop in prices. The restrictions on movement and partial closure of borders also affected the export of matooke to neighboring countries. The dynamics of local matooke prices are illustrated in Figure 3.18 for one of the markets in Kampala (Owino), which shows actual prices falling below long-term predicted prices in both production and consumption areas.

FIGURE 3.17—PERCENTAGE DIFFERENCE BETWEEN ACTUAL AND PREDICTED MATOOKE PRICES IN UGANDA (MARCH–JULY 2020)



Source: Authors' computation based on data from Farmgain Africa (2020).

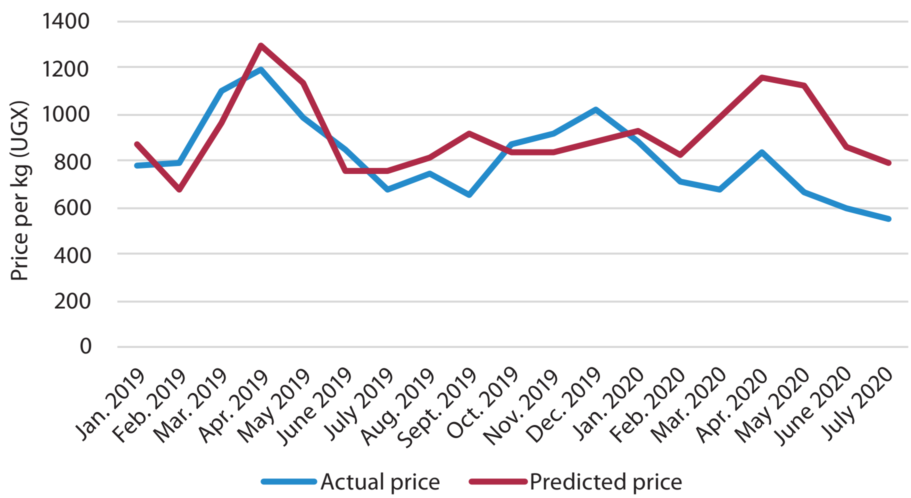
The impact of COVID-19-related restrictions on the price behavior of nonperishable cereals varied across countries in southern, eastern, and western Africa. Millet and maize surplus markets in western Africa experienced decreases in prices, while deficit markets experienced increased prices (Taondyande et al. 2020). Maize markets in southern Africa (Malawi and Mozambique) exhibited similar trends of depressed prices, primarily in border area markets, albeit with more variation across markets (Matchaya et al. 2020). The differential effects of COVID-19 containment measures and restrictions on perishable and nonperishable commodities are also supported by other empirical studies, including Varshney, Roy, and Meenakshi (2020), who found that the impact of COVID-19 on agricultural markets differed depending on whether the commodity was perishable or nonperishable. Similarly, Mogues (2020) found that the magnitude and the direction of price changes differ depending on many factors, including product storability.

Figure 3.17 shows that in all markets studied in Uganda, the prevailing matooke prices were much lower than the predicted prices, underscoring the fact that COVID-19 containment measures disrupted demand and led to low prices for surplus matooke markets.

Figure 3.18 presents evidence in support of the findings presented in Figure 3.17. The overwhelming conclusion from this analysis is that prices for matooke declined significantly during the COVID-19 pandemic.

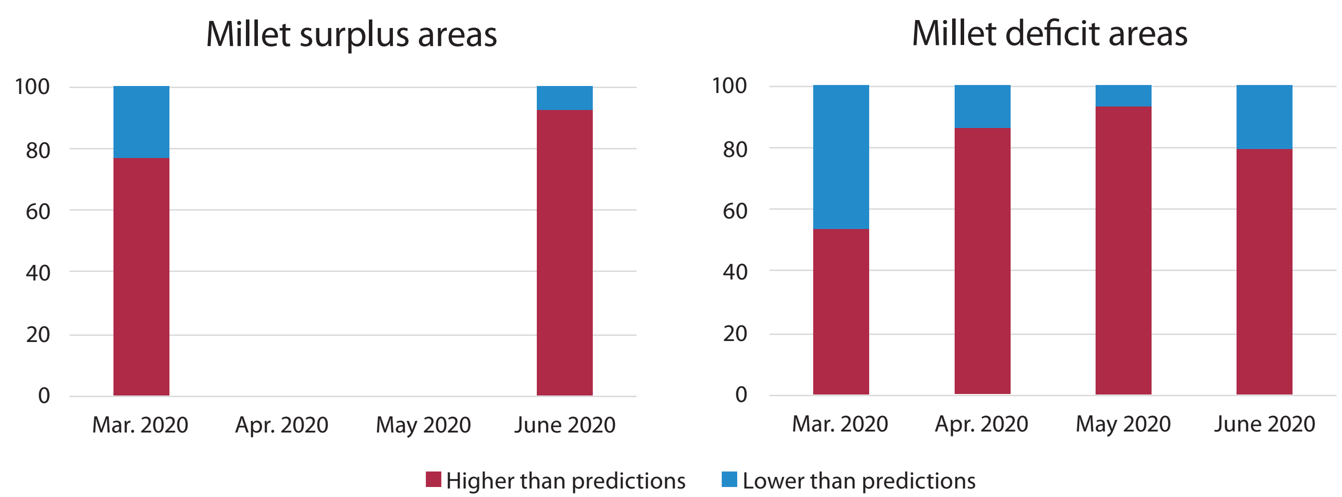
In Senegal, government measures to control the spread of COVID-19 pushed millet prices in deficit areas far above their predicted levels. The same increase was observed in surplus area markets and was sustained even in June, following

FIGURE 3.18—ACTUAL AND PREDICTED MATOOKE PRICES IN OWINO MARKET, UGANDA (PRICE PER KG)



Source: Authors' computation based on Farmgain Africa (2020).
Note: UGX = Ugandan shillings.

FIGURE 3.19—SHARE OF MARKETS WITH HIGHER-THAN-PREDICTED MILLET PRICES IN DEFICIT AND SURPLUS AREAS IN SENEGAL (PERCENT)



Source: Authors' computation based on data from SIM/CSA.

the easing of restrictions. A similar pattern was observed with maize prices in Burkina Faso. The general upward trend in prices means that poor and vulnerable households experienced an erosion of purchasing power and pressure to adjust staple food demand and consumption (Figures 3.19 and 3.20).

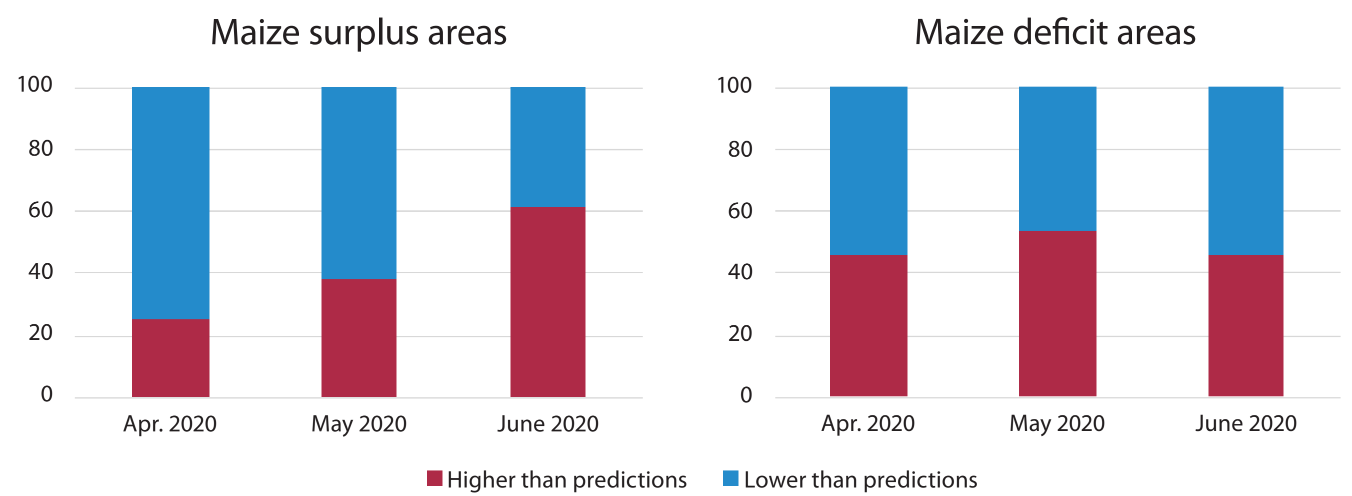
In southern Africa, the behavior of maize prices over the COVID-19 restriction period differed notably between countries. For countries that are generally maize deficit and depend on imports from neighbors, there was a general increase in maize prices due to reduced supply caused by the closure of borders. For example, the restrictions on movement within Lesotho and South Africa may have reduced the supply of food commodities in Lesotho, leading to price increases above the long-term predicted levels in both rural and urban areas (Figures 3.1 and 3.2). This is because Lesotho relies heavily on maize imports from South Africa.

In Malawi, a different pattern of behavior was observed for maize prices; at the onset of the harvesting period in the first quarter of the year, market demand for food commodities was dampened by increased supplies of food in markets, combined with government actions taken domestically and in neighboring countries in response to COVID-19 spread. As shown in Figure 3.21, maize prices were lower in both urban and rural markets compared to the predicted prices.

In Kenya, restrictions enacted to limit the movement of people led to a higher-than-predicted increase in maize prices in the majority of retail markets, as maize supply was restricted over that period. Figure 3.22 shows that the proportion of markets recording higher-than-predicted prices increased steadily from March to July 2020.

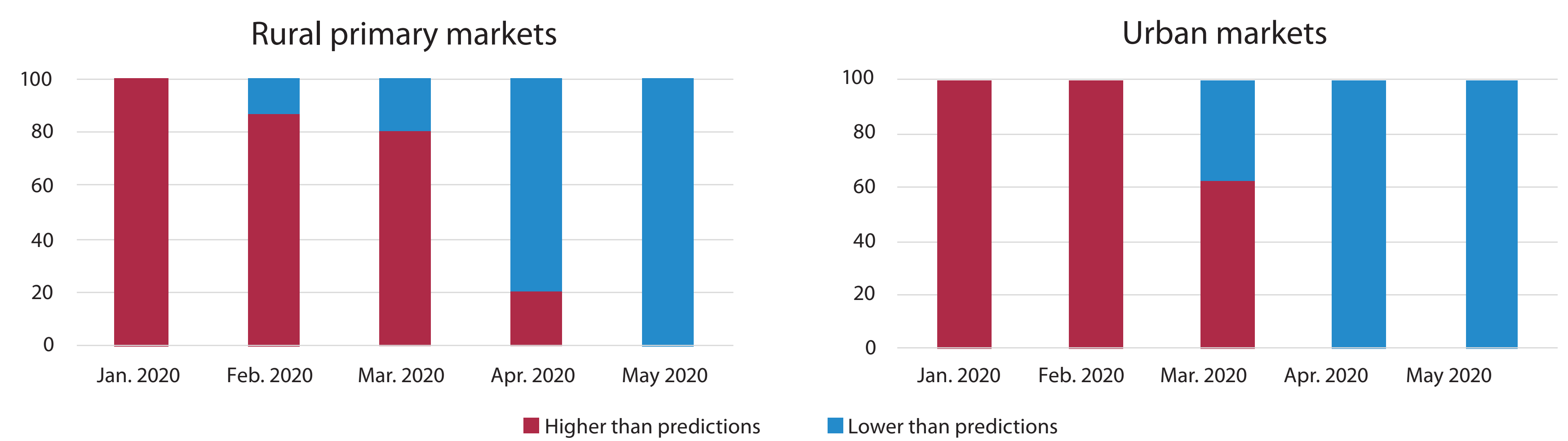
In theory, disruptions in supply and demand would be expected to have different impacts

FIGURE 3.20—SHARE OF MARKETS WITH HIGHER-THAN-PREDICTED MAIZE PRICES IN DEFICIT AND SURPLUS AREAS IN BURKINA FASO (PERCENT)



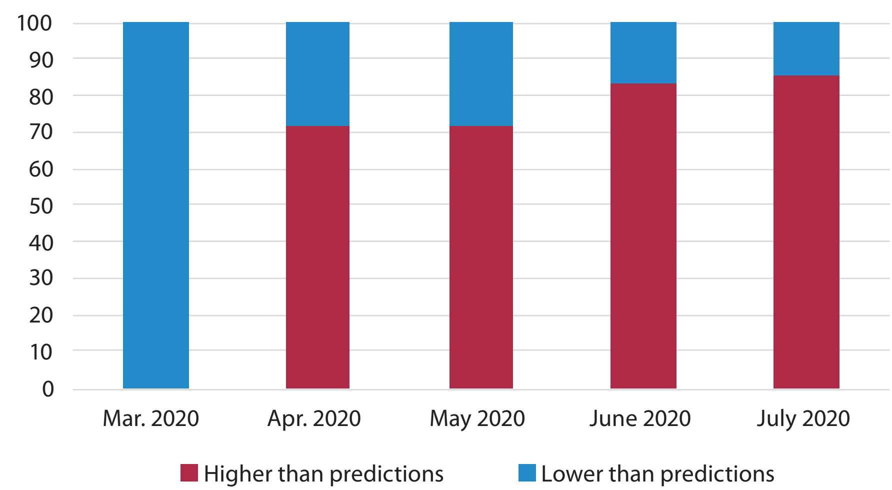
Source: Authors' computation based on data from the Agricultural Market Information System of the National Food Security Stock Management Society of Burkina Faso (SIM/SONAGESS).

FIGURE 3.21—SHARE OF MARKETS WITH HIGHER-THAN-PREDICTED MAIZE PRICES IN RURAL AND URBAN AREAS IN MALAWI (PERCENT)



Source: Authors' computation based on data from WFP (2020).

FIGURE 3.22—SHARE OF RETAIL MARKETS WITH HIGHER-THAN-PREDICTED MAIZE PRICES IN KENYA (PERCENT)



Source: Authors' computation based on WFP (2020).

on the price behavior of perishable and nonperishable commodities. In practice, however, the effects are less distinct due to confounding factors. In this section, we observed that disruption of demand for perishable matooke led to a near collapse of its price in Uganda. The impact of disruption on cereals was, however, a bit more nuanced across countries. In general, these results appear to be supported by literature on restrictions imposed for COVID-19 and other diseases, such as Ebola. For example, in a study in Liberia, Sumo (2019) also found that diseases that require social distancing and other containment measures to limit their impact reduce productivity, disrupt supply chains, depress demand for agricultural commodities, impede the proper functioning of agricultural markets for inputs and outputs, and affect prices.

Conclusions

The objective of this chapter was to present evidence on the effects of COVID-19 restriction measures on food systems by studying the dynamics of food prices over time. The findings reveal that the crisis has exposed the structural vulnerabilities of food import–dependent countries linked through food price dynamics. After the pandemic's onset, many markets in western Africa experienced noticeable price increases due to the impact of lockdown restrictions on supply. In southern and eastern African markets, however, prices were generally lower than expected (except in Lesotho). Prices were also generally lower in urban markets than in rural ones, even in countries that experienced a general increase in prices. Analyzing specific commodities adds further complexity: for example, while maize prices generally declined in both urban and rural markets in Kenya and Malawi, this downward trend was more persistent in urban markets. In Rwanda, however, maize prices declined more in the rural market under observation than the urban one.

A comparison of staple food prices across deficit and surplus areas within different African subregions also illustrates distinct patterns. During the lockdown period, prices increased in deficit areas in western Africa. Prices remained high in Senegal and Nigeria after restrictions were lifted, but fell in Burkina Faso and Mali. In eastern and southern Africa, where cross-border trade is more important, prices instead declined in both deficit and surplus areas (with some exceptions). Trade with neighboring countries may have significantly affected price behavior across the country, not just in border areas. The decline in prices and subsequent potential for negative impacts also highlights the importance of transborder trade for smallholder farmers and small businesses.

Due to higher costs and longer procurement delays for delivering goods inland, prices were expected to increase more in importing, landlocked countries than in coastal ones. However, this assumption was disproven by the finding that prices of local staple foods trended downward in landlocked countries and upward in coastal ones. This result does not refute the importance of coastal access for trade, but it highlights the need to consider commodity characteristics. For example, in landlocked Uganda, where the price of matooke fell by as much as 48 percent, excess supply resulting from lower demand and export restrictions may explain the significant price deviation.

In theory, the prices of perishable and nonperishable foods would be affected differently by disruptions to supply and demand. However, the analysis shows that the effects on price behavior are less distinct than expected due to confounding factors. While disruption to demand in Uganda for perishable matooke led to a near collapse in its price, the impacts on nonperishable cereals were more nuanced across countries.

Policy Implications

This study has demonstrated that during crises, a good understanding of how local staple food markets behave and close tracking of changes in food prices at the community level must be key elements of any strategy to protect livelihoods, especially those of the poor and most vulnerable members of society. The following recommendations are suggested by the study:

1. Blanket policy responses and interventions will not be effective in addressing the effects of crises such as the COVID-19 pandemic. Interventions should be based on a good understanding of how different factors compound to affect staple food price behavior at the local level.
2. Countries should institute a mechanism to track and analyze food prices to avoid large-scale market disruptions by enabling early identification of affected areas.
3. Countries must put measures in place to facilitate intra-regional trade, especially during crises or shocks. This study shows the importance of intra-regional trade in stabilizing local food prices.
4. Policy responses to control a pandemic such as COVID-19 must consider the differentiated effects on staple food demand and supply. Measures should ensure that producer prices remain remunerative to safeguard continued supply while consumer prices allow the poor and vulnerable to access food. Targeted support to food production and distribution services, accompanied by consumer support interventions, can stabilize food prices. These interventions were especially critical after the disruptions experienced in the early days of COVID-19, when countries were still learning how to cope with the crisis.
5. Measures implemented by countries to control the spread of a disease such as COVID-19 should be designed and implemented in ways that avoid large-scale disruptions of market operations, especially of essential commodities such as staple foods. Infection-control protocols could be enforced while allowing market operations to continue unhindered.
6. Large-scale disruption of market activities can be avoided by engaging with local market players to design interventions that help control the spread of the disease but also allow intra-regional trade and movement of food commodities from surplus to deficit regions within a country.
7. The response to outbreaks such as COVID-19 should include carefully considered commodity price stabilization as well as a drive toward building food system resilience (for instance, through diversification). Such an approach would have limited the micro- and macroeconomic effects of the pandemic in each of the countries studied.

Appendix

SARIMA Model

The objective of this section is to briefly describe the model used to extract trends in commodity prices in order to forecast their future values. The seasonal autoregressive integrated moving average (SARIMA) models were considered for this exercise.

These models have six components and are expressed as ARIMA(p,d,q)(P,D,Q)$_m$, where

- p is the number of autoregressive terms,
- d is the number of nonseasonal differences needed for stationarity, and
- q is the number of lagged forecast errors in the prediction equation (moving average part).
- P is the number of the seasonal autoregressive terms,
- D is the number of seasonal differences needed for stationarity, and
- Q is the number of seasonal moving average terms.

Let Y be the time series of interest.

- If $d = 0$: $y_t = Y_t$.
- If $d = 1$: $y_t = Y_t - Y_{t-1}$.
- If $d = 2$: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$.

The general mathematical formulation of an ARIMA(p,d,q) is

$$y_t = \mu + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t,$$

where y_t denote the d^{th} difference of Y, ε_t is an error term and μ is a constant, φ are the autoregressive parameters, and θ stand for the moving average's parameters.

Once the model order has been identified (that is, the values of p, d, and q), its estimation can be performed using the maximum likelihood estimator. Due to differences in the algorithms implemented in the software used, results are likely to differ from one software program to another.

A seasonal ARIMA (SARIMA) model is an extension of the usual ARIMA to include additional seasonal terms. For monthly data, an ***ARIMA(1,1,1)(1,1,1)$_{12}$*** should look as follows:

$$(1-\varphi_1 \boldsymbol{B})(1-\delta_1 \boldsymbol{B}^{12})(1-\boldsymbol{B})(1-\boldsymbol{B}^{12})Y_t = (1-\theta_1 \boldsymbol{B})(1-\vartheta_1 \boldsymbol{B}^{12})\varepsilon_t,$$

where $\boldsymbol{B}$ stands for time lag operator.

The first step to identify the most reasonable ARIMA is to visualize various representations of the series at hand. The most popular graphs are those of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots are a useful visual tool in choosing the order parameters for the ARIMA model. PACF plots can be used to identify the autoregressive (AR) part of the ARIMA, while ACF plots are useful for the moving average (MA) part of the model. Four series are of interest: (1) observed data, (2) first difference data, (3) first seasonal difference data ($Y_t - Y_{t-12}$ for monthly data), and (4) both trend and seasonality difference. The visualization of the ACF/PACF plots of these various series helps to identify whether there is a need to differentiate the observed data regarding trend or seasonality, or what will be the right order for the nonseasonal/seasonal AR and MA parts of the model.

From the previous step, several models are eligible. Once those models have been estimated, it is important to conduct further steps to find the best model to use for forecasting. Two properties are crucial for any time-series forecasting models: (1) residuals must be uncorrelated, and (2) residuals should have zero mean. ACF and PACF plots can be used to test whether residuals are uncorrelated. If they are not, the model needs to be improved by adding additional terms in the AR part or MA part. When residuals do not have zero mean, forecasts are biased. The issue with non-zero mean of residuals is easily resolved by changing the model specification or adding the observed residuals mean to the forecasts. However, solving the autocorrelation issue is very challenging empirically. One way to solve this issue is to add AR terms when there are positive autocorrelations and to add MA terms for negative autocorrelations.

When multiple models are found, it is critical to check whether they will be accurate in forecasting. Several metrics exist in the literature to assess forecasting accuracy. Since forecasting is the main objective of time series analysis, forecast accuracy measures are preferable to information criteria measures (Akaike information criterion [AIC], Bayesian information criterion [BIC], etc.). Forecast accuracy measures include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean absolute deviation (MAD), etc. More details on these measures are available in Adhikari and Agrawal (2013). For the forecasting accuracy exercise, one needs to split the sample in two parts: a training sample used for the Box-Jenkins methodology and the test sample used to compute the forecast performance metrics. The best model is the one with the best forecast accuracy.

CHAPTER 4

Impact of COVID-19-Related Global Trade Disruptions on African Food Systems

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and Leysa M. Sall

Introduction

The COVID-19 pandemic is affecting national economies through several channels including global primary commodity trade and market disruptions. Countries have been affected by many of the measures taken to adapt to and control the spread of the disease.[1] Measures enacted in response to the pandemic have had a major impact on both the demand for and the supply of commodities. They have reduced the availability of air cargo and shipping services, induced changes in port and airport operations, and impacted international trade and market access conditions. On the demand side, the net effect is likely to be negative in the short term, with a decrease in the global population's propensity to consume and a decrease in intermediate consumption by firms.

The global economic shock of the COVID-19 pandemic drove most commodity prices down, according to the World Bank's Commodity Markets Outlook report (2021a). Prices of energy and base metal products were much lower in 2020 compared with pre-pandemic projections for the same year. Prices for agricultural and food products were rather mixed, with increases in projected prices for some commodities and decreases for others. In addition, the analysis covered the effects of the changes in trade volumes of the primary commodities. The pandemic has caused a decline in trade volume for all primary commodities (Verschuur, Koks, and Hall 2021). The ultimate impact of global price and trade changes on economies and livelihoods for each country depends on the magnitude of individual commodity price and volume changes and a country's exposure to the global market relative to the composition of the basket of primary commodities it trades internationally.

The structure of external trade shows that African countries mostly export raw materials and import finished products. Exports of most African countries are highly dependent on primary commodities such as energy, metal, and agricultural commodities (DESA/UNSD 2021). Thus, the COVID-19 global trade shock is likely to affect national economies primarily through the export of commodities.

Against this background, the analysis aims to contribute to the understanding of the impacts of external shocks on African food systems and to generate evidence for effective policy responses to future crises. It focuses exclusively on one of the many channels through which the pandemic is impacting national economies: the global trade and market disruptions associated with primary commodities. More specifically, the objective of this chapter is to assess the effects of changes in international prices and traded volumes of primary commodities on the food systems in select African countries.

The term food systems refers to the set of actors—including producers, processors, traders, and consumers—who interact within an institutional framework governing activity with potential environmental and health effects (Béné 2020). African countries are dealing with the immediate consequences of the COVID-19 pandemic while rebuilding for the future. Building a more resilient and sustainable food system is critical not only for better preparedness in future crises, but also for addressing future nutritional, health, and environmental challenges. This is even more compelling for African countries because economic performance in developing countries is more sensitive to the recurrence of natural disasters (droughts, floods, storms, and earthquakes, among others) than in developed countries (Loayza et al. 2012; Panwar and Sen 2019). Thus, the long-term impacts of the COVID-19 pandemic on food systems may be most heavily felt in low- and middle-income countries with fragile health systems and economies (Ali et al. 2020).

To assess the food system, we identify five of its components that are easily measurable through proxies: agricultural production and input use, food processing industries, agricultural and food trade, food consumption, and the macroeconomic environment. The impact assessment of the global trade disruptions on African food systems employs existing single-country computable general equilibrium (CGE) models. For each country, the latest social accounting matrix (SAM), accessible through the database of the African Growth and Development Policy Modeling Consortium (AGRODEP), is used to calibrate the model. The SAM is updated to the latest available year (currently 2019 or 2018, depending on the country) to reflect the recent structure of each country's economy. Data from the World Development Indicators database are used to

1 These measures range from states of emergency to curfews, border closures to changes in border protocols, quarantines, additional travel documentation requirements, and reduced labor due to business closures.

update the macrostructure of the national economies. Data from the United Nations Commodity Trade Statistics Database (UN Comtrade) are used to reflect the most recent trade structure of the economies available for 2019. The analysis focuses on 23 African countries for which a disaggregated SAM allows us to identify the above components of the food system. The impact of the COVID-19 pandemic is assessed by comparing a pre-COVID-19 scenario with a COVID-19 scenario. The former is based on previously existing commodity price forecasts while the latter uses the latest estimates. A commodity-specific price and trade volume scenario is built for every country based on changes in international prices and traded volumes of primary commodities and the composition of its external trade basket. The scenarios are used to assess the impacts of COVID-19-related global trade disruptions on the country's food systems.

Following this introduction, the second section provides a brief description of African food systems' characteristics and performance. Next, the third section presents the key characteristics of African trade of primary commodities. The fourth section presents the analytical framework, including the data used to carry out this analysis. Then, the fifth section describes the baseline and COVID-19 scenarios built and implemented for each of the selected African countries. The sixth section presents and discusses the results of the COVID-19-related global trade shocks on food systems in the selected African countries. Finally, the seventh section summarizes the chapter and offers policy recommendations.

Overview of African Food Systems

The characteristics and performance of food systems can be assessed in many ways. This section presents relevant macroeconomic indicators to give an aggregated overview of food system drivers. To this end, the analysis critically compares the status of African food systems with the global food system in three main components related to (1) agricultural production and food supply, (2) agricultural and food trade, and (3) food demand and consumption. African food systems can be characterized as having low productivity, exports driven by low-value products, and high levels of food insecurity.

Agriculture represents a sizable share of the economies in Africa, averaging 15.7 percent of the gross domestic product (GDP) compared with a global average of 4.0 percent in 2019 (Table 4.1). This makes agriculture a key sector of the continent's growth strategy. Agricultural production per capita in constant value is estimated at US$243[2] in Africa as compared with a value of $544 at the global level. While the value of agricultural production per capita in Africa is less than half of the global average, the caloric supply per capita in Africa is closer to the global average (2,604 kcal and 2,929 kcal per day, respectively). The relatively low value of the food supply in Africa can be explained by low labor productivity, compared with the rest of the world, and the predominance of high-caloric-content and low-value commodities in the food supply basket. Indeed, agricultural productivity in Africa is less than half that of the world as a whole. Agricultural value added per worker in constant value is estimated at $1,488 in Africa, as compared with a global average of $3,720. The low agricultural productivity on the continent is partially due to the low adoption of agricultural technologies. As the data in Table 4.1 indicate, the average use of inorganic fertilizer per hectare of arable land in Africa is lower than the global average. In addition, the proportion of irrigated land in Africa is three times lower than the global average. The food manufacturing industry is an important segment of the food supply chain, with a share of 2.7 percent of GDP in Africa as compared with a global average of 2.4 percent (Table 4.1). The annual growth rate of the food manufacturing industry in Africa (0.4 percent) is far less than the global average (5.4 percent). On the other hand, the annual growth rate of African agriculture (average of 1.6 percent per capita over the decade from 2009 to 2018) is close to the global average (1.7 percent per capita over the same period).

Agricultural and food trade is also a major driver of food systems because both imports and exports directly influence the level, composition, and cost of domestic food supplies. Trade in food products represents a significant proportion of African external trade, accounting for 12.3 percent of total exports and 11.3 percent of total imports. However, due to the limited quality of transportation infrastructure, international trade in food products remains less than optimal. Indeed, in 2018, Africa scored 2.2 on a scale of 5 in terms of the quality of transport and trade infrastructure, compared with the global average of 2.7 (Table 4.1). Recently, African exports of food and agricultural products have increased more than the global average, driven by the increase in volumes.

2 All dollar figures in this chapter refer to US dollars.

TABLE 4.1—OVERVIEW OF AFRICAN FOOD SYSTEMS, COMPARING VALUES FOR AFRICA AND THE WORLD

	Indicator	Africa	World
Agricultural production and food supply	Value-added agriculture, forestry, and fishing – share of GDP (%)	15.7	4
	Value-added agriculture, forestry, and fishing per capita – annual growth 2009–2018 (%)	1.6	1.7
	Value-added manufacture of food, beverages, and tobacco products – share of GDP (%) (b)	2.7	2.4
	Value-added manufacture of food, beverages, and tobacco products per capita – annual growth 2009–2018 (%)	0.4	5.4
	Agriculture gross production value per capita (constant 2014–2016 $) (b)	242.8	543.7
	Food supply (kcal/capita/day) (b)	2,604	2,929
	Agriculture, forestry, and fishing, value-added per worker (constant 2010 $) (a)	1,488.1	3,720.1
	Fertilizer use, nutrient nitrogen (N) use (kg/ha)	15.9	69.8
	Fertilizer use, nutrient phosphate (P2O5) use (kg/ha)	6.4	28
	Fertilizer use, nutrient potash (K2O) use (kg/ha)	3.7	24.2
	Arable land area equipped for irrigation (%)	6.9	24.7
Food trade	Food imports (% of merchandise imports) (a)	11.3	8.1
	Food exports (% of merchandise exports) (a)	12.3	8.6
	Logistics performance index: Quality of trade- and transport-related infrastructure (1=low to 5=high) (a)(b)	2.2	2.7
	Agricultural export value index (2014–2016 = 100)	109	107
	Agricultural export unit/value index (2014–2016 = 100)	82	98
	Agricultural export quantity index (2014–2016 = 100)	134	109
	Agricultural import value index (2014–2016 = 100)	102	107
	Agricultural import unit/value index (2014–2016 = 100)	92	96
	Agricultural import quantity index (2014–2016 = 100)	111	112
Food demand and consumption	Rural population (% of total population) (a)	59.3	44.3
	Total population growth (annual %) (a)	2.7	1.1
	Rural population growth (annual %) (a)	1.7	0.1
	Urban population growth (annual %) (a)	3.7	1.9
	Gross national income, value $ per capita	1,819.70	11,291.90
	Households and NPISHs final consumption expenditure (% of GDP) (a)	67.1	57.6
	Households' final consumption expenditure (annual % growth) (a)	1.4	2.4
	Consumer prices, general indices (2015 = 100)	150.8	113
	Consumer prices, food indices (2015 = 100)	154.7	111.6
	Food price inflation (annual %)	8.2	4.4

Source: FAO (2021) ; World Bank (2021b).

Note: NPISHs = nonprofit institution–serving households; (a) = Africa south of the Sahara for 2019 from the World Development Indicators (World Bank 2021b); (b) = 2018 values from the same source.

Indeed, the unit value index of African exports has recently declined while the quantity index has increased over the same period. The opposite has been observed in the rest of the world, where imports have increased more than in Africa, driven by increases in both value and quantity.

Household final consumption expenditures represent a significant share of GDP in Africa—67.1 percent, compared with the global average of 57.6 percent (Table 4.1). In Africa, food purchases exceed 50 percent of the total household final consumption expenditure in general, and food ranks as the top category of household expenditures; for example, in 2016, the household food budget was estimated at 58.9 percent in Nigeria and 52.2 percent in Kenya (USDA 2021). In contrast, households in most industrialized countries spend less than 20 percent of their total consumption budget on food and nonalcoholic beverages (for example, 6.3 percent in the United States and 10.6 percent in Germany). According to Smith and Subandoro (2007), households spending between 50 and 65 percent of their income on food are considered to have medium levels of food insecurity and those spending between 65 and 75 percent and more than 75 percent are considered highly and very highly food insecure, respectively. The cost of food is relatively higher and increases faster in Africa than elsewhere, with a food consumer price index of 154.7, compared with 111.6 for the global average. Considering the average household consumption expenditure growth (1.4 percent for Africa and 2.4 percent for the world) and population growth (2.7 percent for Africa and 1.1 percent for the world), consumer expenditure growth is primarily driven by population growth in Africa and by income growth in the rest of the world. Several studies show that globalization, trade facilitations, and rapid urbanization have led to major shifts in the availability, affordability, and acceptability of different types of food, all of which is changing food systems rapidly (Kennedy, Nantel, and Shetty 2004; Gillespie and van den Bold 2017).

Africa's Primary Commodity Trade

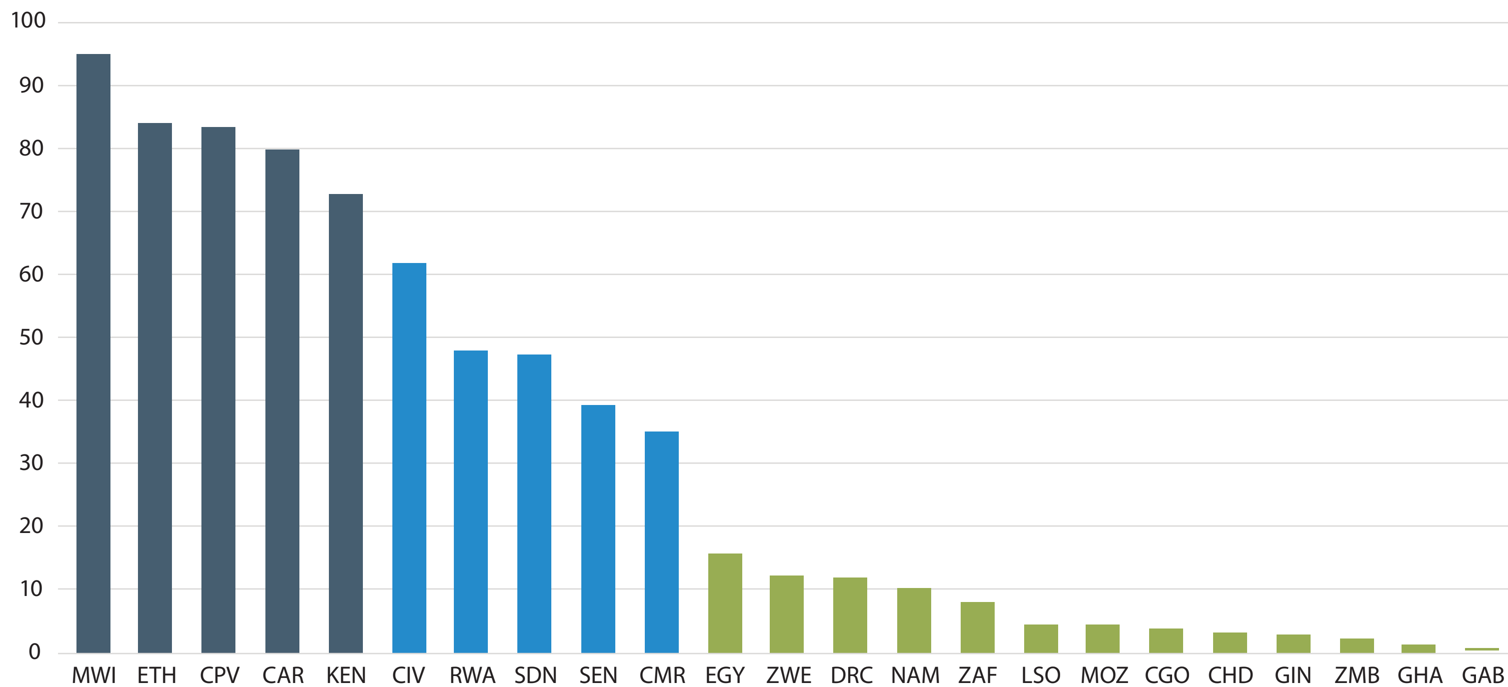
African countries mostly export raw materials and import finished products.[3] Exports of most African countries are highly dependent on primary commodities such as energy, metal, and agricultural products. Primary commodities account for more than 50 percent of total exports in most African countries, according to data retrieved from UN Comtrade (Figure 4A.1). In contrast, primary commodities contribute less than 50 percent of total imports in most African countries (Figure 4A.2). Thus, the COVID-19-related global trade shock is likely to affect national economies primarily through the export of commodities.

The composition of the primary commodity export basket is computed using data from UN Comtrade. Figure 4.1 indicates a low contribution of agricultural commodities in the primary commodity export baskets of most of the selected African countries. Among the 23 countries, only 5 can be identified as agriculture-dominated exporting countries (Cabo Verde, Central African Republic, Ethiopia, Kenya, and Malawi). In these countries, agricultural commodities contribute more than 70 percent of the total exports of primary commodities. Conversely, 13 countries are identified as energy- and mineral-dominated exporting countries (Chad, Congo, Democratic Republic of the Congo, Egypt, Gabon, Ghana, Guinea, Lesotho, Mozambique, Namibia, South Africa, Zambia, and Zimbabwe). In these countries, agricultural commodities account for less than 20 percent of the total export of primary commodities. The remaining countries are considered mixed agriculture- and nonagriculture-exporting countries (Cameroon, Côte d'Ivoire, Rwanda, and Senegal). These countries are exporting large proportions of both agricultural and nonagricultural commodities.

Figure 4A.3 shows the most important commodities exported by the selected countries with their relative contributions to total exports of primary commodities. The figure displays countries according to the grouping discussed above, from agriculture-dominated exporting countries on the left to energy- and mineral-dominated exporting countries on the right. It indicates a mix of agricultural, energy, and mineral commodities in the primary export baskets of the selected African countries. The export baskets are dominated by a limited number of commodities, reflecting low diversification of the primary commodity export baskets. Exports are concentrated in a few commodities, making countries more vulnerable to market disruptions and international shocks. For instance, a single commodity makes up two-thirds of the total exports of primary commodities in Cabo Verde (fish), Central African Republic (wood), Chad (petroleum), Congo (petroleum), Gabon (petroleum), Malawi (tobacco), and Zambia (copper).

3 According to our computation of data from UN Comtrade (DESA/UNSD 2021).

FIGURE 4.1—PERCENTAGE SHARE OF AGRICULTURE IN TOTAL EXPORTS OF PRIMARY COMMODITIES



Source: Authors, based on data from DESA/UNSD (2021).

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon.

Analytical Framework

The impact of COVID-19-related disruptions of the primary commodity trade and markets on African food systems is assessed in 23 African countries using single-country CGE models.[4] Countries are selected based on the availability and accessibility of a recent SAM that captures several segments of the food supply chain: production, processing, trade, and consumption. Based on these criteria, the following countries are covered by the analysis: Cabo Verde, Cameroon, Central African Republic, Chad, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Egypt, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Malawi, Mozambique, Namibia, Rwanda, Senegal, Sudan, South Africa, Zambia, and Zimbabwe.

As with most CGE models, the model developed to assess the impact of COVID-19-related trade disruptions on African food systems is grounded in the Walrasian small open economy framework. Individual national economies are interconnected to the global economy through the international trade of products and the flows of revenue and capital.

4 The single-country CGE models were developed under the African Union's Comprehensive Africa Agriculture Development Programme (CAADP).

The constant elasticity of transformation relationship specifies the trade-off between the national and international markets for exported commodities. The Armington assumption is used to model imported products as imperfect substitutes for locally produced goods and services. Finite elasticity is assumed for export supply, meaning that the export supply curve describes an upward slope that entails an endogenous export free on board price effect in addition to the quantity effect. In the same vein, we introduce a finite elasticity for import demand to capture the endogenous import cost, insurance, and freight and quantity effects. However, the international price remains exogenous for any given product; that is, we make the small country assumption.

An extended linear expenditure system represents consumption and saving behaviors. The function depicts a nondiscretionary expenditure component related to autonomous (or exogenous) consumption and a discretionary expenditure component associated with induced (or endogenous) consumption. The production technology is represented by a multilevel nested constant elasticity of substitution function combining production factors (labor and capital) and intermediate inputs.

The labor market is segmented according to the categorization of laborers in each SAM. To reflect the massive layoffs that suddenly occurred with the COVID-19 lockdown and the substantial increase in unemployed people, the imperfect labor markets are set to be demand driven while real wage rates are held fixed. The government budget is balanced through changes in its primary savings, or its gross revenue net of its current expenses. The provision of public services and public transfers increases at exogenous rates according to the country's precrisis fiscal policy. Public expenses remain endogenous through the prices of factors and inputs used in the delivery of these services. The external current account balance is held fixed while the exchange rate equilibrates revenues and expenses. The model is savings driven, and the weighted average market equilibrium price for goods and services—the economywide price index—is set as the numeraire, or reference price.

The SAMs are updated with data through the year 2019 to reflect the recent structure of the economies. Data from the World Development Indicators database are used to update the macroeconomic structure of the economies. Data from UN Comtrade are used to reflect the most recent trade structure of the economies. The updated SAMs are used to calibrate the CGE models. This requires the use of additional economic and demographic data and elasticities parameters available through the ReSAKSS Toolbox (AU and NEPAD 2018).

To address the impact of the COVID-19-related global trade shock on the food system, five components of the system based on the characterization suggested by Béné (2020) are used: agricultural production and input use, food processing industries, agricultural and food trade, food consumption, and the macroeconomic environment.

The impact on agricultural and food production and processing is captured through the volume of production, cost of inputs, value addition, and job creation (Table 4A.1). For every indicator, an aggregate value is computed for activities and entities throughout the food supply chain, including agricultural production, food processing industries, and food services and distribution.

The effects of the COVID-19-related global trade shock on agricultural and food trade are assessed through changes in export and import volumes for agricultural and food products and services. Similar to the production and processing component of the supply chain, an indicator for the overall trade in agricultural and food products and services is considered as well as the individual components. Increasing exports of the overall agricultural and food goods and services is likely to strengthen the trade component of the food systems. On the other hand, increasing imports of the overall agricultural and food commodities does not necessarily improve the performance of the food systems because of the adverse effects of increased competition with local producers and reduced availability of foreign currencies for nonfood imports.

The consumption component of the systems is captured by the food expenditures in constant value and the food consumption price for agricultural products, processed food, and food services. Because of data limitations, the analysis does not include other aspects of the consumption component of the food systems.

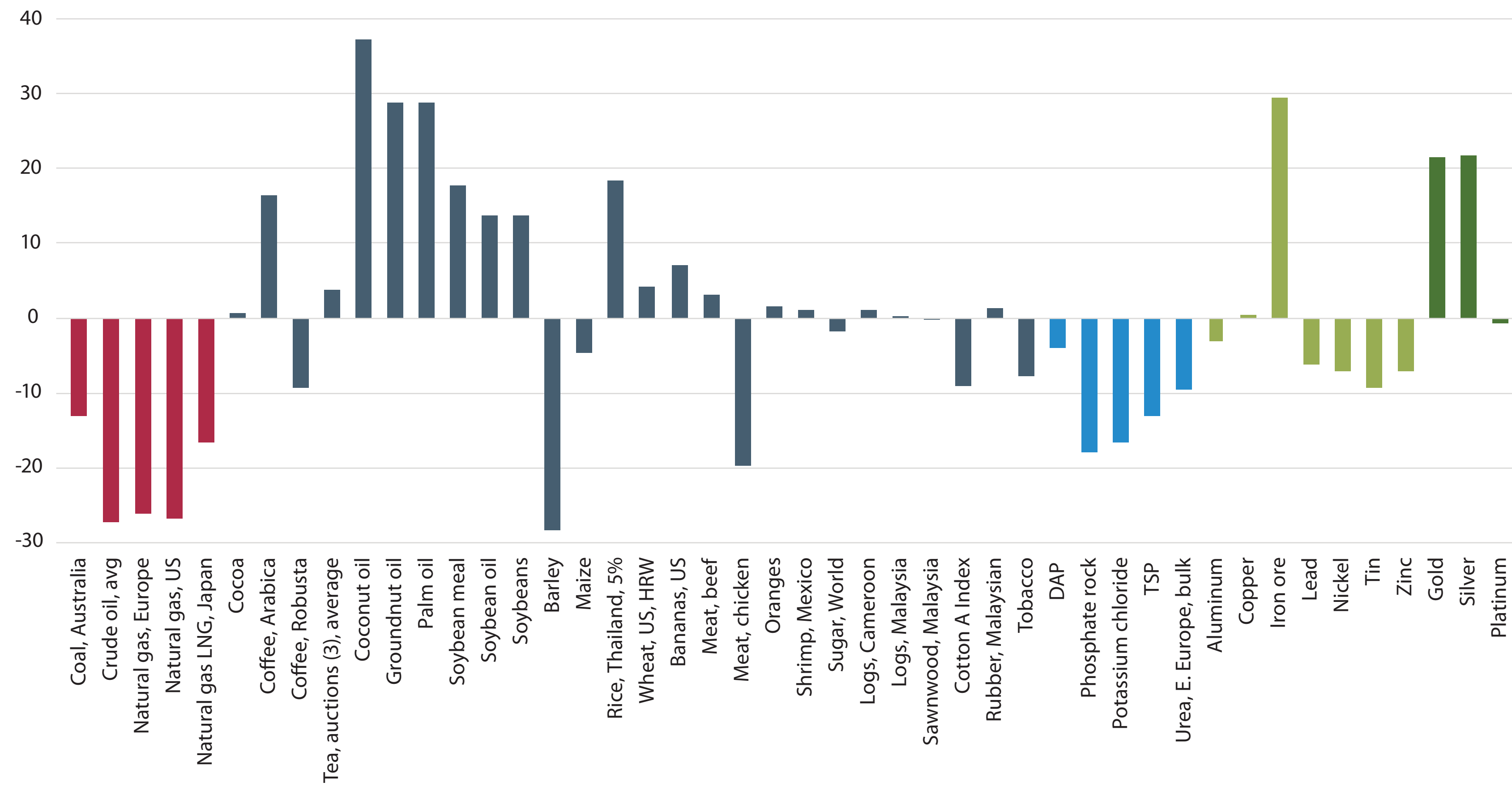
In addition, household income, economywide job creation, consumer price index, and GDP are considered in assessing the macroeconomic impact of the COVID-19-related global trade shock. The first three indicators are computed at the national level as well as disaggregated for urban and rural areas. In total, 41 indicators are used to assess the effects of COVID-19-related global trade disruptions on African food systems (Table 4A.1).

Because this assessment framework identifies several indicators, we compute a score to appreciate the impact of the COVID-19-related global trade shock on African food systems. The score measures the proportion of indicators adversely impacted by the shock. An indicator is adversely impacted by the COVID-19-related global trade shock when the changes observed under the COVID-19 scenario are less than those observed under the baseline. Thus, the higher the score, the higher the adverse effects of the pandemic on the food systems, and vice versa.

Simulation Scenarios

The COVID-19-related global trade and market disruptions associated with primary commodities are simulated through two scenarios: the baseline scenario and the COVID-19 scenario. These scenarios are built around the changes in the

FIGURE 4.2—CHANGES IN PRIMARY COMMODITY PRICES BETWEEN 2019 AND 2020, PERCENTAGE POINT DIFFERENCE BETWEEN ESTIMATED AND PREDICTED PRICES FOR 2020



Source: World Bank (2021a).

Note: LNG indicates liquefied natural gas; Tea, auctions (3) indicates tea, average 3 auctions; HRW indicates Hard Red Winter; DAP indicates diammonium phosphate; TSP indicates triple superphosphate.

international prices and traded volumes of primary commodities. To build the scenarios, we identify key primary commodities exported and imported by the selected countries.

International Price Shock

The baseline scenario uses the predicted prices for 2020 from the World Bank as of October 2019, before the onset of the COVID-19 pandemic (World Bank 2021a). The COVID-19 scenario is based on the estimated prices for 2020, also made available by the World Bank. In both scenarios, the changes in international prices are computed by comparing the 2020 prices with the 2019 prices.

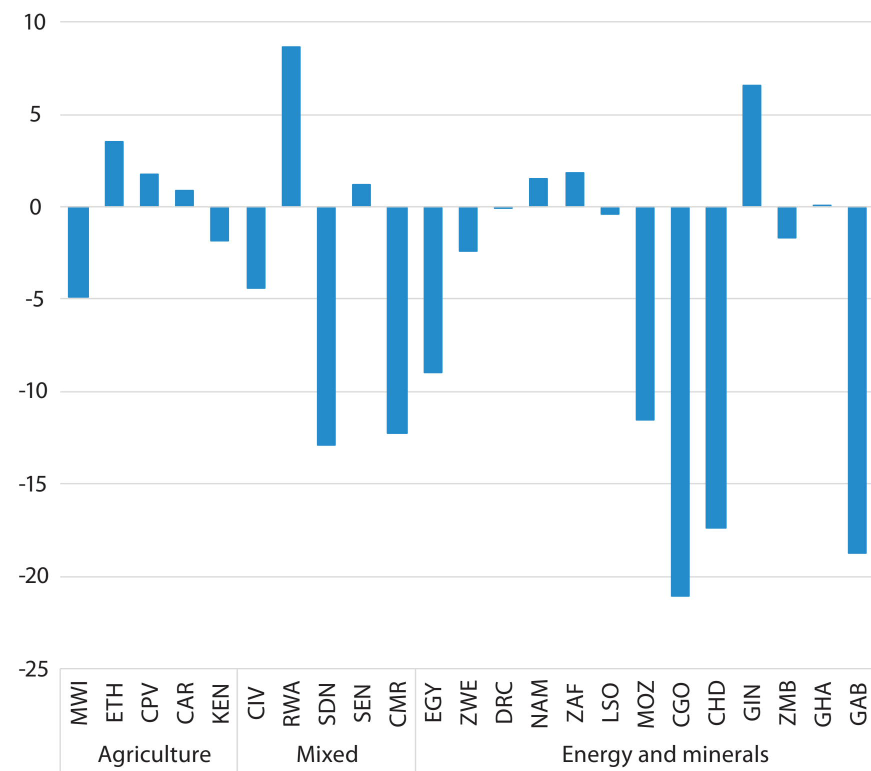
The global economic shock of the COVID-19 pandemic drove most commodity prices down, according to the World Bank's Commodity Markets Outlook report (Figure 4.2) (World Bank 2021a). Prices of energy and base metal products were much lower in 2020 compared with pre-pandemic projections for the same year. Energy product prices declined by as much as 27.3 percentage points (pp) for petroleum products and 16.6 pp for natural gas. In contrast, prices for agricultural and food products were rather mixed, with, for example, increases in projected prices for commodities like coconut oil (37.3 pp), palm oil (28.9 pp), groundnut oil (28.7 pp), or rice (18.4 pp), and a decrease for barley (28.3 pp). International prices for precious metal products were forecast to rise by close to 21.8 pp for silver and 21.6 pp for gold.

The composition of primary commodity export and import baskets ultimately determines the magnitude of the global price and volume shocks that affect individual countries. Figures 4.3 and 4.4 show the price shocks affecting individual countries. Countries are displayed according to the grouping discussed above, from agriculture-dominated exporting countries on the left to energy- and mineral-dominated exporting countries on the right. In the agriculture-dominated exporting countries, the changes in the average export price of primary commodities are closely linked to the changes in the average export price of agricultural commodities, except in the Central African Republic. The energy-dominated exporting countries—Chad, Congo, Gabon, and Mozambique—experienced a greater fall in average export prices of primary commodities than did the other group of countries. Overall, the changes in primary commodity prices are less important for agriculture-dominated exporting countries than for energy- and mineral-dominated exporting countries.

Trade Volume Shock

In addition to the global price shock, the analysis captures the effects of changes in trade volumes of primary commodities as a consequence of the COVID-19 pandemic. High-frequency shipping data are used to measure the impact of the COVID-19 pandemic on trade volumes (Verschuur, Koks, and Hall 2021).

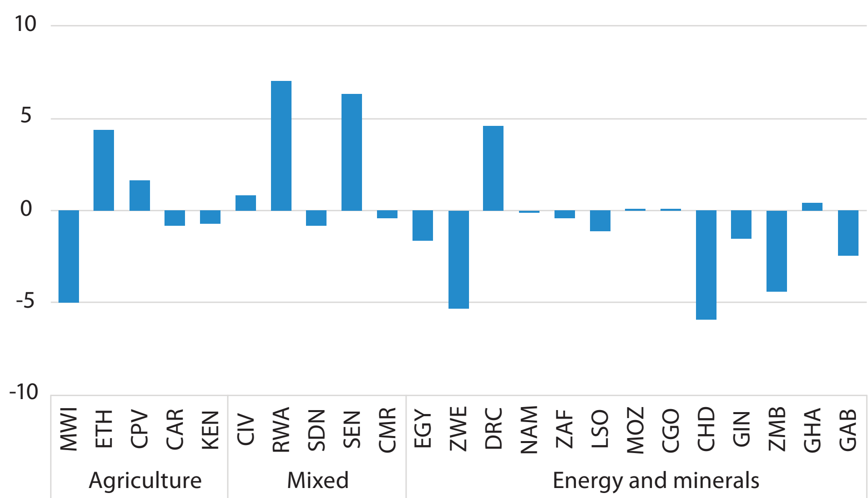
FIGURE 4.3—CHANGES IN AVERAGE EXPORT PRICES OF PRIMARY COMMODITIES BETWEEN 2019 AND 2020 FOR SELECTED AFRICAN COUNTRIES (PERCENTAGE)



Source: Authors' computation from World Bank (2021a).

Note: Percentage point variation between October 2019 and April 2021 forecasts by the World Bank. MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon. Countries are grouped into agriculture-dominated exporting countries, energy- and mineral-dominated exporting countries, and mixed agricultural and nonagricultural exporting countries.

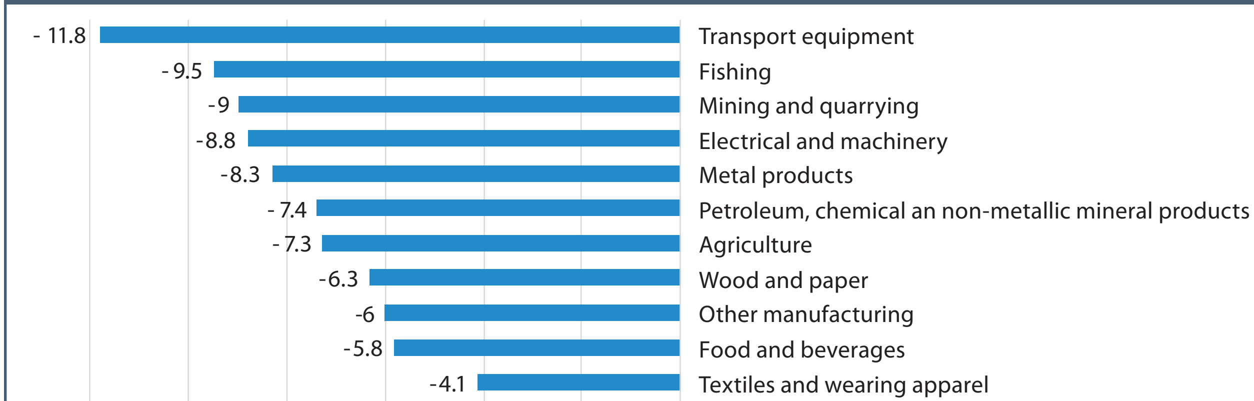
FIGURE 4.4—CHANGES IN AVERAGE EXPORT PRICES OF AGRICULTURAL COMMODITIES BETWEEN 2019 AND 2020 FOR SELECTED AFRICAN COUNTRIES (PERCENTAGE)



Source: Authors' computation from World Bank (2021a).

Note: Percentage point variation between October 2019 and April 2021 forecasts by the World Bank. MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon. Countries are grouped into agriculture-dominated exporting countries, energy- and mineral-dominated exporting countries, and mixed agricultural and nonagricultural exporting countries.

FIGURE 4.5—SECTOR-SPECIFIC PERCENTAGE CHANGES IN GLOBAL TRADE OF COMMODITIES BETWEEN 2019 AND 2020



Source: Authors' computation from Verschuur, Koks, and Hall (2021).

Changes in the daily global trade of commodities between 2019 and 2020 are recorded for aggregate groups of commodities.

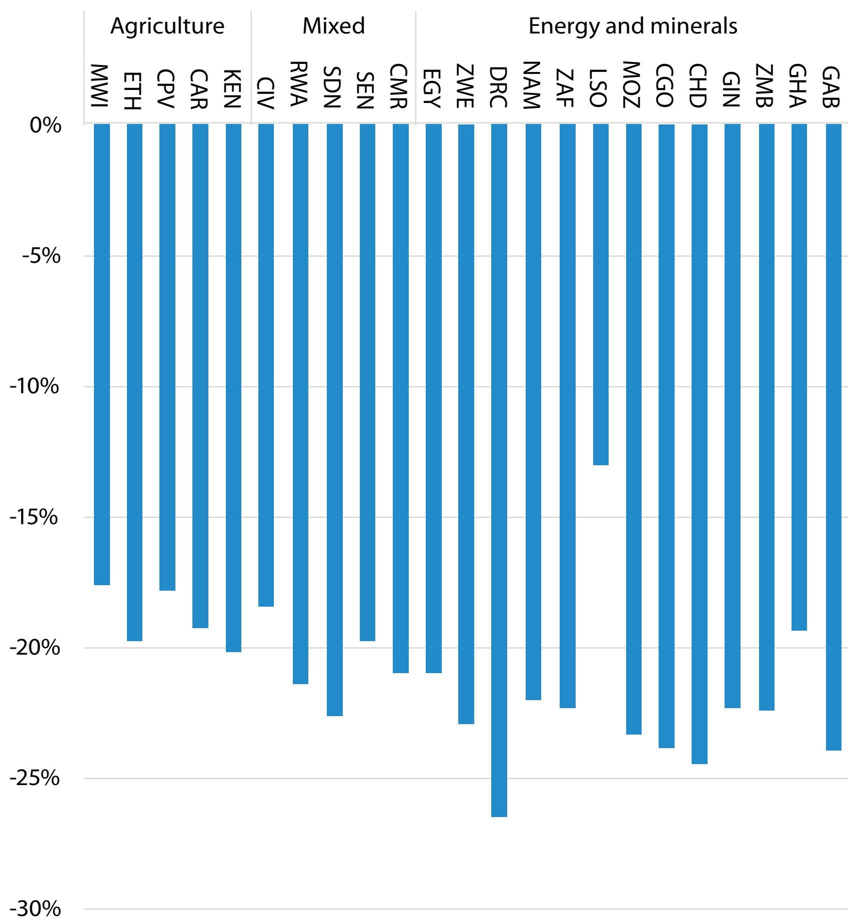
The pandemic has caused a decline in trade volume for all primary commodities (Figure 4.5). Traded volumes of mining and quarrying products and petroleum products declined by 9.0 percent and 7.4 percent, respectively, between 2019 and 2020. Similarly, traded volumes of fish and agricultural products fell by 9.5 percent and 7.3 percent, respectively. However, a modest decline was recorded for the traded volumes of food and beverages (5.8 percent).

Similar to international prices of commodities, the changes in country-specific import and export volumes depend on the structure of a country's external trade. The average changes in export volumes by country are shown in Figures 4.6 and 4.7. The average volumes of export for primary commodities decreased for all selected countries between 2019 and 2020, with declines ranging from 13 to 27 percent. As expected, agriculture-dominated exporting countries experienced a smaller decline in the average export volumes of primary commodities, compared with the energy- and mineral-dominated exporting countries.

Results and Discussion

The COVID-19-related disruptions affecting global supply chains of primary commodities, including agricultural and food commodities, can significantly impact African economies and food systems. Changes in prices received for primary commodity exports or paid for imports translate into gains or losses of foreign exchange earnings by African countries. Changes in the availability of cargo or the operation of airports and seaports also affect the cost and volume of goods shipped. Individual economies are affected based on their degree of exposure to shocks in different primary commodity markets, which in turn depends on the bundle of primary goods that countries sell to or buy from foreign markets. Changes in exported and imported quantities, as well as related prices, are transmitted to domestic producers and consumers, resulting in changes in production activities and

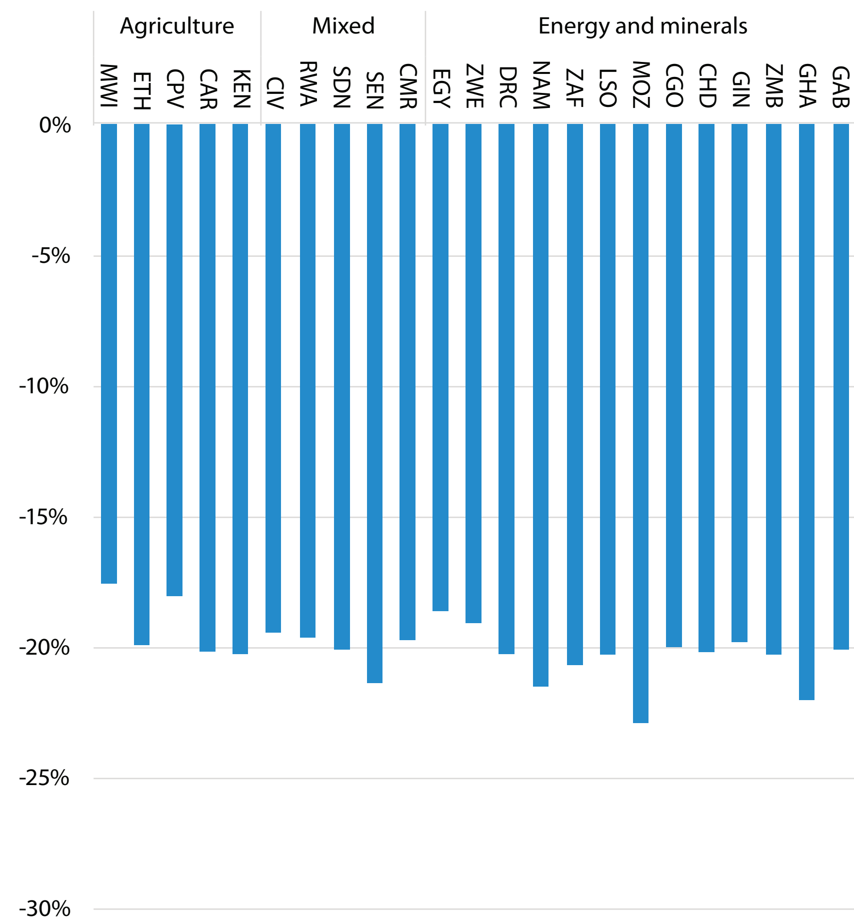
FIGURE 4.6—CHANGES IN AVERAGE EXPORT VOLUMES OF PRIMARY COMMODITIES BETWEEN 2019 AND 2020 FOR SELECTED AFRICAN COUNTRIES (PERCENTAGE)



Source: Authors' computation from Verschuur, Koks, and Hall (2021).

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon. Countries are grouped into agriculture-dominated exporting countries, energy- and mineral-dominated exporting countries, and mixed agricultural and nonagricultural exporting countries.

FIGURE 4.7—CHANGES IN AVERAGE EXPORT VOLUMES OF AGRICULTURAL COMMODITIES BETWEEN 2019 AND 2020 FOR SELECTED AFRICAN COUNTRIES (PERCENTAGE)

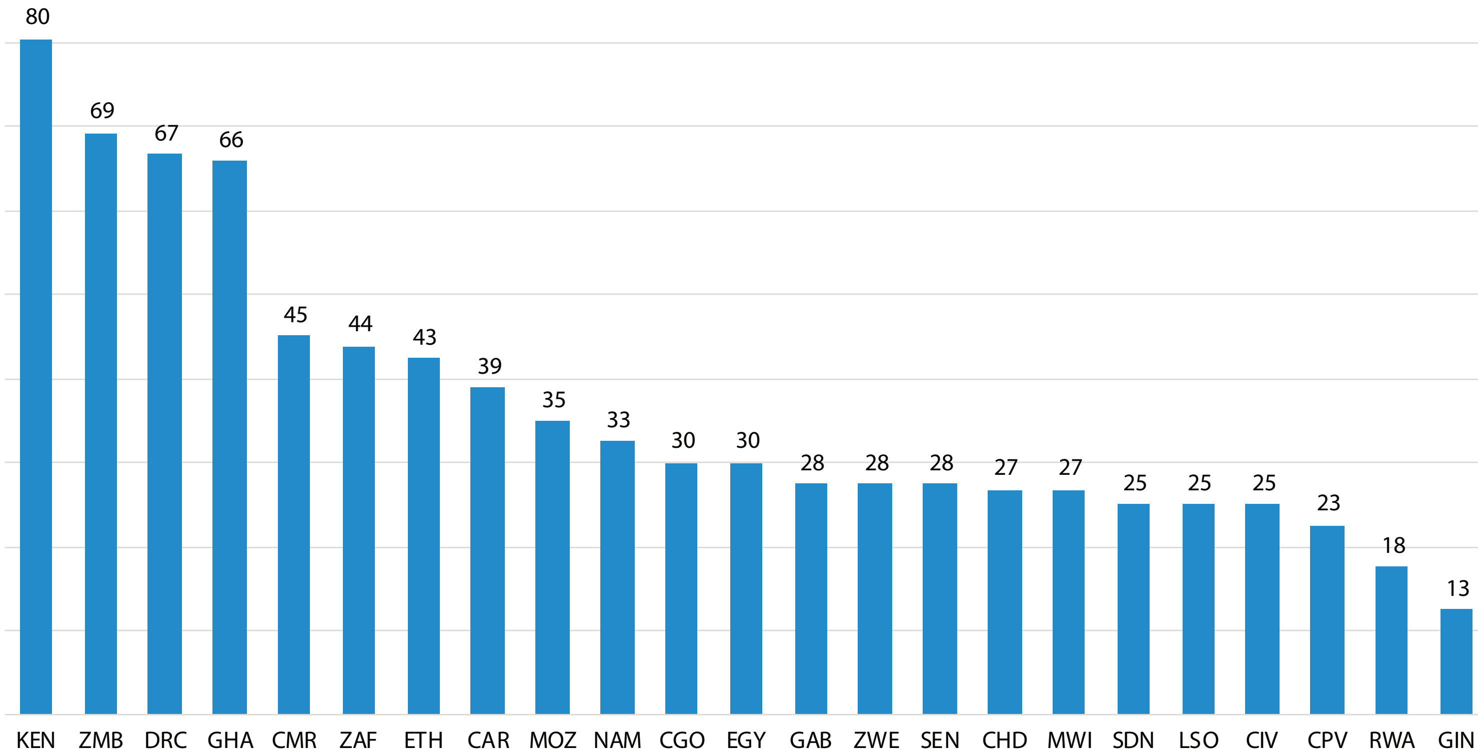


Source: Authors' computation from Verschuur, Koks, and Hall (2021).

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon. Countries are grouped into agriculture-dominated exporting countries, energy- and mineral-dominated exporting countries, and mixed agricultural and nonagricultural exporting countries.

demand for both agricultural and nonagricultural products. Ultimately, these changes affect the pace of growth and available incomes, and thus livelihoods. The final impact depends on the ability of domestic producers and consumers, and the economy in general, to adjust to changing market conditions.

FIGURE 4.8—SENSITIVITY OF FOOD SYSTEMS TO COVID-19-RELATED GLOBAL TRADE SHOCK, SCORE IN PERCENTAGE, COMPUTED FOR SELECTED AFRICAN COUNTRIES

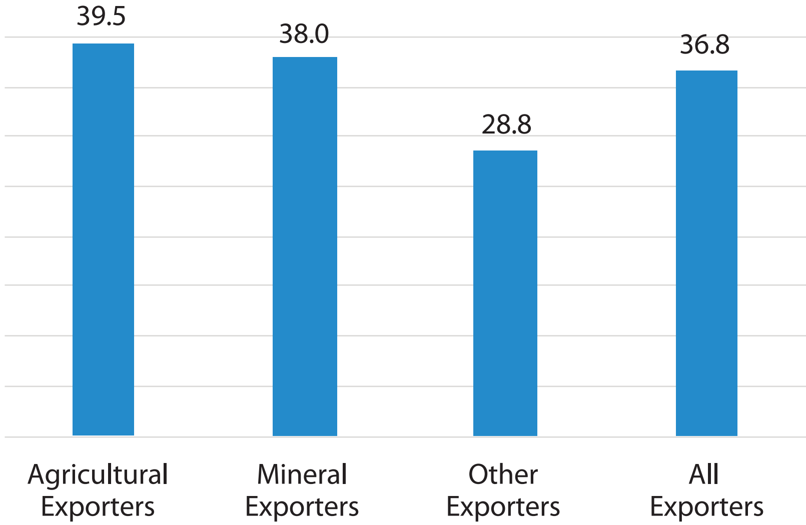


Source: Authors' simulation results.

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon.

The COVID-19-related global trade disruptions have adversely affected the food systems in the 23 African countries covered by this analysis (Figure 4.8). In accordance with the construction of the score, the higher the score, the higher the adverse effects of the trade shock on the food systems. Kenya shows the highest score (80 percent) indicating that the COVID-19-related global trade shock has adversely affected the country's food systems more than any other country covered by the analysis. Three other countries show a relatively high score: Zambia (69 percent), Democratic Republic of the Congo (67 percent), and Ghana (66 percent). However, more than half of the selected countries (13 out of 23) show a relatively low score of 30 percent or less. Guinea (13 percent) and Rwanda (18 percent) recorded the lowest scores. Countries are affected by both price and volume shocks. The fall in prices and volumes of energy products primarily affected the first group of countries (Democratic Republic of the Congo, Ghana, and Kenya). Moreover, the prices of copper, tea, and cocoa increased slightly but

FIGURE 4.9—IMPACT OF COVID-19-RELATED GLOBAL TRADE SHOCK ON AFRICAN FOOD SYSTEMS, AVERAGE SCORE IN PERCENTAGE, COUNTRIES GROUPED BY EXPORTS



Source: Authors' simulation results.

Note: Agricultural Exporters = agriculture-dominated exporting countries; Mineral Exporters = energy- and mineral-dominated exporting countries; Other Exporters = mixed agricultural and nonagricultural exporting countries.

not enough to compensate for the decline in their traded volumes, which also contributed to decreased export revenues in the Democratic Republic of the Congo, Ghana, Kenya, and Zambia. The surge in gold prices helped mitigate the adverse effects of the pandemic on food systems in Guinea and Rwanda. These countries generate a large share of their export revenues from gold exports.

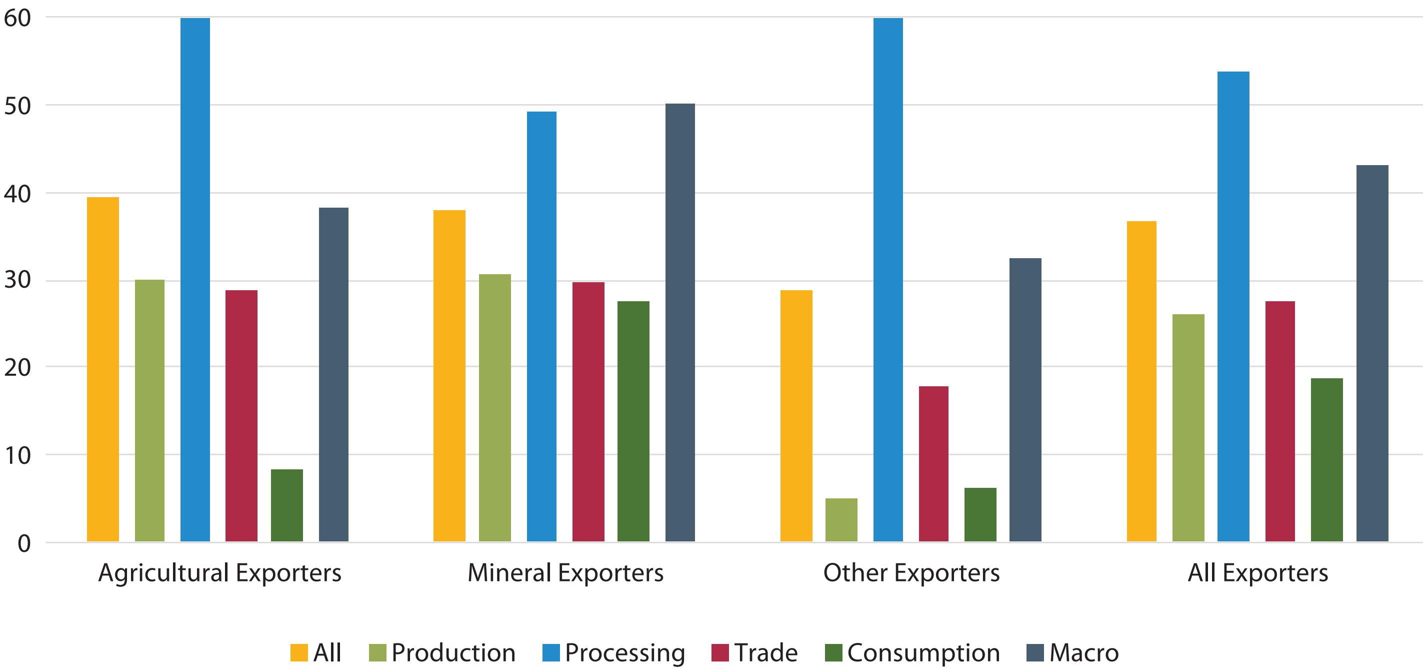
Overall, the countries covered by the study have an average score of 36.8 percent, but this shows some heterogeneity. Indeed, when we look at the scores of countries grouped according to the composition of their primary commodity export basket (Figure 4.9), the food systems of the more diversified exporting countries are less affected by the COVID-19-induced global trade shock (28.8 percent), compared with both agriculture-dominated exporting countries (39.5 percent) and energy- and mineral-dominated exporting countries (38.0 percent). Thus, these results indicate that a diversified export basket is an important factor that contributes to strengthening Africa's food systems against the adverse effects of external shocks.

The analysis now turns to assessing and comparing the effects of the global trade shock on the components of food systems. The food system is assessed through the following five components: production and input use, processing industries, agricultural and food trade, consumption, and macroeconomic environment. In this regard, the simulation results indicate that food processing is by far the most sensitive component of the systems to the COVID-19-related global trade shock (Figure 4.10). The explanation lies in the fact that processed food and food services industries are relatively more sensitive to changes in households' incomes (that is, they have higher income elasticity) as compared with agrifood products. Indeed, the deterioration of the macroeconomic environment due to the recurrence of the COVID-19-related shock reduced employment and household income, resulting in a sharp decline in demand for processed food and food services. Indeed, this result is consistent with the findings of Van Hoyweghen and colleagues (2021), who investigate the impact of the COVID-19 pandemic on the fruit and vegetable supply chain in Senegal, using trade statistics and survey data collected through online questionnaires and telephone interviews with smallholder farmers, agro-industrial companies, agricultural workers, traders, importers, and consumers. By comparing COVID-19 effects between modern and traditional value chains, they found that the large fresh fruit and vegetable companies in Senegal were hardly affected by the pandemic.

The consumption component is relatively less sensitive to the COVID-19-related global trade shock. This may seem less surprising when we consider the nondiscretionary component of household consumption expenditures and the relative rigidity in food consumption habits. Empirical evidence suggests that the rational behavior of households is to keep the consumption of food and other necessities constant in response to health risks and shocks (Somi et al. 2009). Wagstaff (2007) found that households are likely to reduce their food expenditures following a health shock, but by less than they reduce expenditures on nonfood items such as housing and electricity.

Moreover, consistent with the previous results (Figure 4.9), we observe that the group of countries with relatively diversified primary commodity exports has food system components that are less sensitive to the COVID-19-related global trade shock, particularly in production, consumption, and trade (Figure 4.10).

FIGURE 4.10—SENSITIVITY TO COVID-19-RELATED GLOBAL TRADE SHOCK, AVERAGE SCORE IN PERCENTAGE, BY COUNTRY GROUPS AND ALONG THE FOOD SYSTEM CHAIN



Source: Authors' simulation results.

Note: Agricultural Exporters = agriculture-dominated exporting countries; Mineral Exporters = energy- and mineral-dominated exporting countries; Other Exporters = mixed agricultural and nonagricultural exporting countries.

To further investigate the impact of the COVID-19-related global trade shock on African food systems, we adopt another grouping of African countries to control for the changes in the export prices of agricultural and primary commodities. Because the above results are primarily driven by the price shock, by grouping countries according to the size of the price shock we expect to better understand the effects of factors unrelated to price. This new grouping allows us to identify three groups of countries, as presented by Table 4.2.

In the first group (designated G.1 in the table), we observe a decline in net export prices for agricultural commodities, as well as for primary commodities in general. However, nonagricultural commodity prices decline more than agricultural commodity prices. Here, we seek to know why countries in this group show heterogeneity in the sensitivity of their food systems even though they experienced the same price shock. As the prices of energy products decline more than the prices of agricultural commodities, these countries compensate for the loss of external revenues from energy products by increasing their export revenues from agricultural products. Thus, this mechanism favors the agricultural sector and contributes to mitigating the adverse impact of the pandemic on food systems in the energy-dominated export countries (Chad, Congo, Egypt, Gabon, and Sudan). In the agriculture-dominated export countries, such as Kenya, this compensation mechanism is limited and dominated by the direct price effects of the pandemic on agricultural and food commodities. The impact of the COVID-19-related global trade shock is also high for Cameroon for the same reason.

The second group (G.2) is characterized by higher declines in the net export price of agricultural products relative to nonagricultural products. In this group, Zambia and Ghana record the highest adverse impacts. These countries are primarily affected by the agricultural price shocks—lower export prices for Zambia and higher import prices for Ghana.

The last group (G.3) is characterized by increasing mineral prices with a relatively higher average mineral price compared with average agricultural price, with the exception of the Democratic Republic of the Congo. In this group, the food systems are primarily impacted indirectly through the exposure of the mineral economy to global trade. For instance, in Guinea (the country with the lowest score), although the prices of agricultural exports have fallen, the increasing price of mineral products allows the country to mitigate the direct negative effects of the shock on its food systems. In contrast, the opposite trend is observed in the Democratic Republic of the Congo, where the increase in agricultural export prices is not enough to compensate for the decline in mineral export prices. In the mineral-dominated export countries such as Guinea and the Democratic Republic of the Congo, the indirect effects surpass the direct effects of the COVID-19-related global trade shock.

TABLE 4.2—COVID-19-RELATED GLOBAL TRADE SHOCK, EXPORT AND IMPORT PRICE SHOCKS, AND IMPACT SCORE FOR SELECTED AFRICAN COUNTRIES, PERCENTAGE CHANGE BETWEEN 2019 TO 2020

Group	Country	Impact Score	Agriculture		All Primary	
			Export Price	Import Price	Export Price	Import Price
G.1—Decline in net export prices of nonagricultural commodities greater than that of agricultural commodities	KEN	80.5	-0.7	0.0	-1.8	0.0
	CMR	45.0	-0.4	6.6	-12.2	0.1
	EGY	30.0	-1.7	3.1	-9.0	-2.5
	GAB	27.5	-2.5	0.6	-18.8	1.6
	CHD	26.8	-6.0	0.5	-17.4	1.8
	SDN	25.0	-0.8	2.2	-12.9	-8.0
G.2—Decline in net export prices of agricultural commodities greater than that of nonagricultural commodities	ZMB	71.8	-8.0	0.8	-0.9	7.8
	GHA	65.9	0.4	10.5	0.1	5.3
	MOZ	35.0	0.1	4.1	-11.5	-10.8
	MWI	26.8	-5.1	2.7	-4.8	-1.6
	CIV	25.0	0.8	6.1	-4.4	-4.0
G.3—Increase in net export prices of mineral products greater than that of agricultural products	ZAF	44.0	0.0	2.0	2.0	-5.0
	CAR	39.0	-1.0	1.0	1.0	-6.0
	NAM	33.0	0.0	1.0	2.0	1.0
	ZWE	28.0	-5.0	0.0	-2.0	-5.0
	SEN	28.0	6.0	8.0	1.0	-7.0
	GIN	13.0	-2.0	6.0	7.0	-3.0
	DRC	67.0	4.6	3.0	-0.1	1.0
	ETH	43.0	4.0	4.0	4.0	2.0
	LSO	25.0	-1.1	-4.0	-0.4	-9.0
	CPV	23.0	2.0	1.0	2.0	-2.0
	RWA	18.0	7.0	5.0	9.0	0.0

Source: Authors' computation from simulation results.

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon.

Conclusion

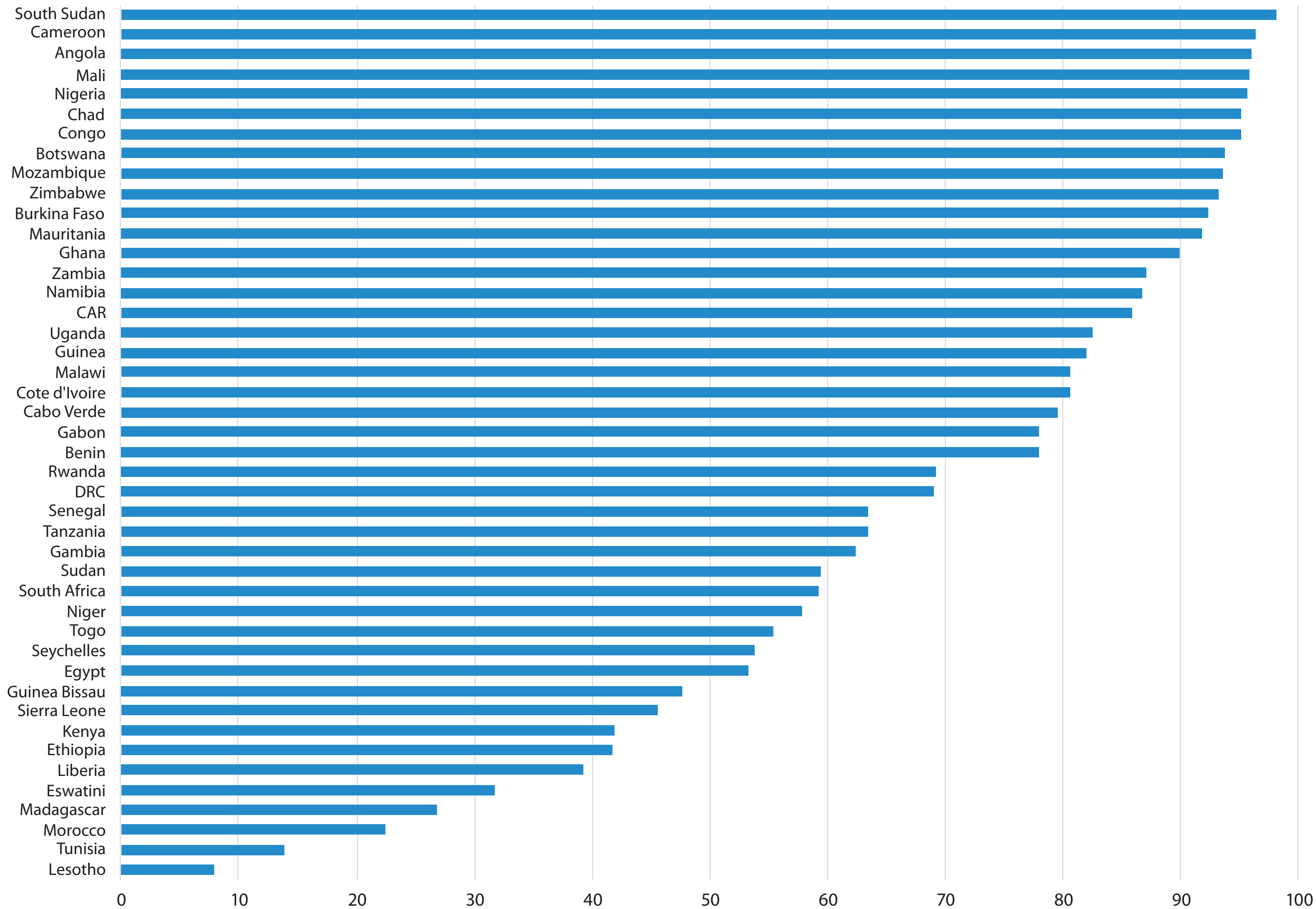
The COVID-19 health crisis and government responses to limit the spread of the virus have resulted in major disruptions in global trade and markets. In this study, we analyze the effects on the food systems in select African countries, focusing on the changes in global prices and market access of primary commodities. The analysis uses country-specific CGE models calibrated to SAMs that capture the most recent structure of each national economy. Because the assessment framework considers several indicators, a score is computed to evaluate the impact of the COVID-19-related global trade shock on African food systems. The score measures the proportion of indicators adversely impacted by the shock.

Our findings indicate that the COVID-19-related global trade shock had a moderate impact on the food systems in the selected African countries, with an average score of 37 percent. In other words, out of the 943 metrics defining the food systems in the selected African countries, 347 metrics were adversely affected by the COVID-19-related global trade shock associated with primary commodities. However, this average value masks a significant disparity among countries. Indeed, it has been demonstrated that countries with a diversified export basket—combining agricultural, energy, and mineral products—are less adversely impacted by the global trade shock than are other countries. As a result, a well-diversified export basket is key to strengthening the resilience of Africa's food systems to external shocks. These findings are even more compelling in relation to African economies that display a low contribution of agricultural commodities to their primary commodity export baskets, as well as a low degree of diversification across primary commodity export baskets.

The consumption component is substantially less responsive to the global trade shock due to the relative rigidity of food consumption habits. In contrast, the food processing industry is by far the most vulnerable component of the system to the global trade shock caused by the COVID-19 pandemic. This can be explained by the industry's higher sensitivity to households' income variations. Multiple governments offered relief packages in support of the food industry to mitigate the adverse impact of the pandemic. Takeout orders, delivery, and online grocery shopping grew substantially during the pandemic. Actors across the food value chain have been embracing digital technologies as a way to mitigate the adverse impact of the health crisis. Government policies aimed at transforming and strengthening the resilience of the food system are important in terms of not only its preparedness for future crises but also its adaptability to the rapid changes in food consumption habits.

Appendix

FIGURE 4A.1—PERCENTAGE SHARE OF PRIMARY COMMODITIES IN TOTAL EXPORTS, 2019

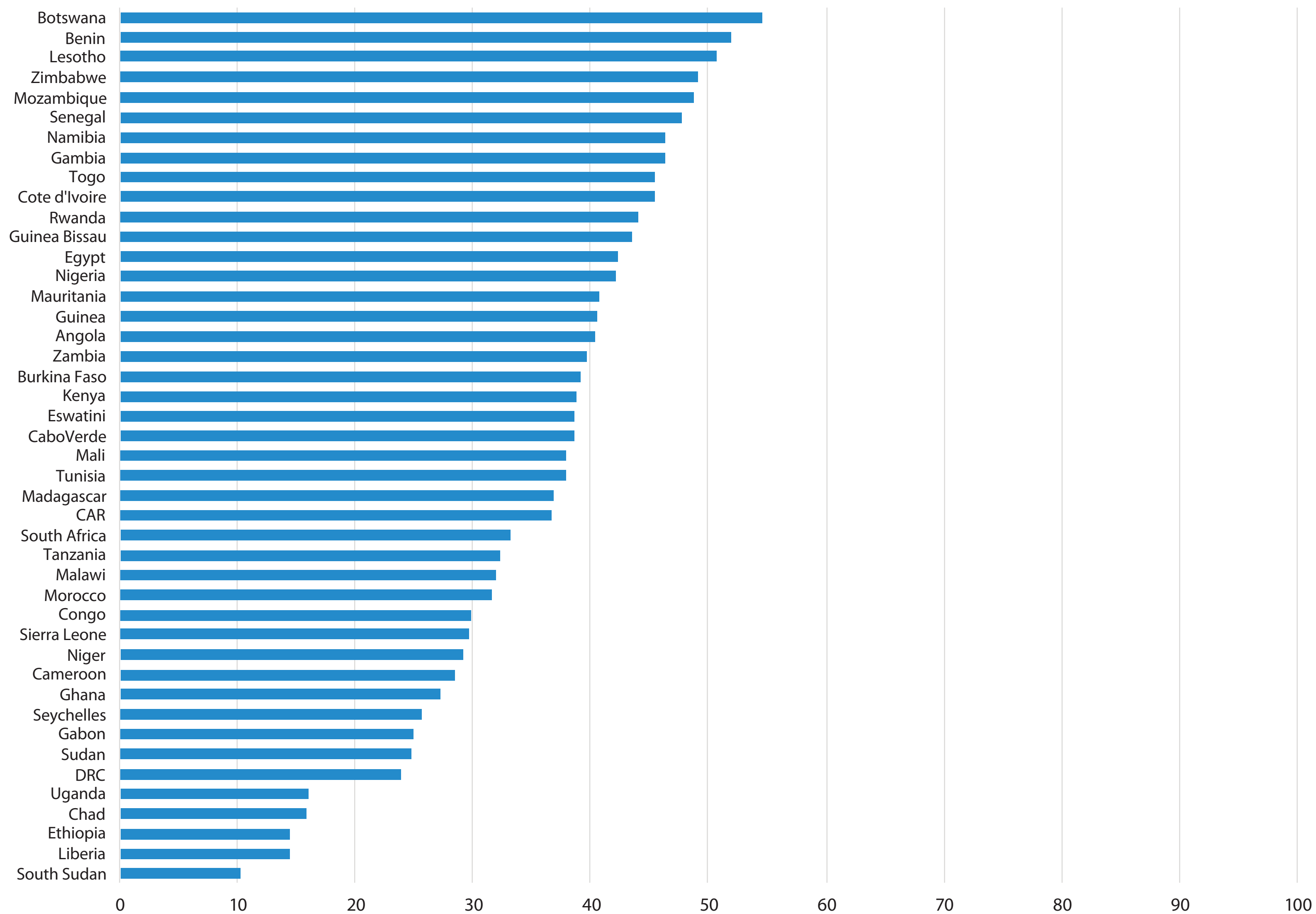


Source: Authors, based on data from DESA/UNSD (2021).

Note: CAR = Central African Republic; DRC = Democratic Republic of the Congo.

Appendix continued

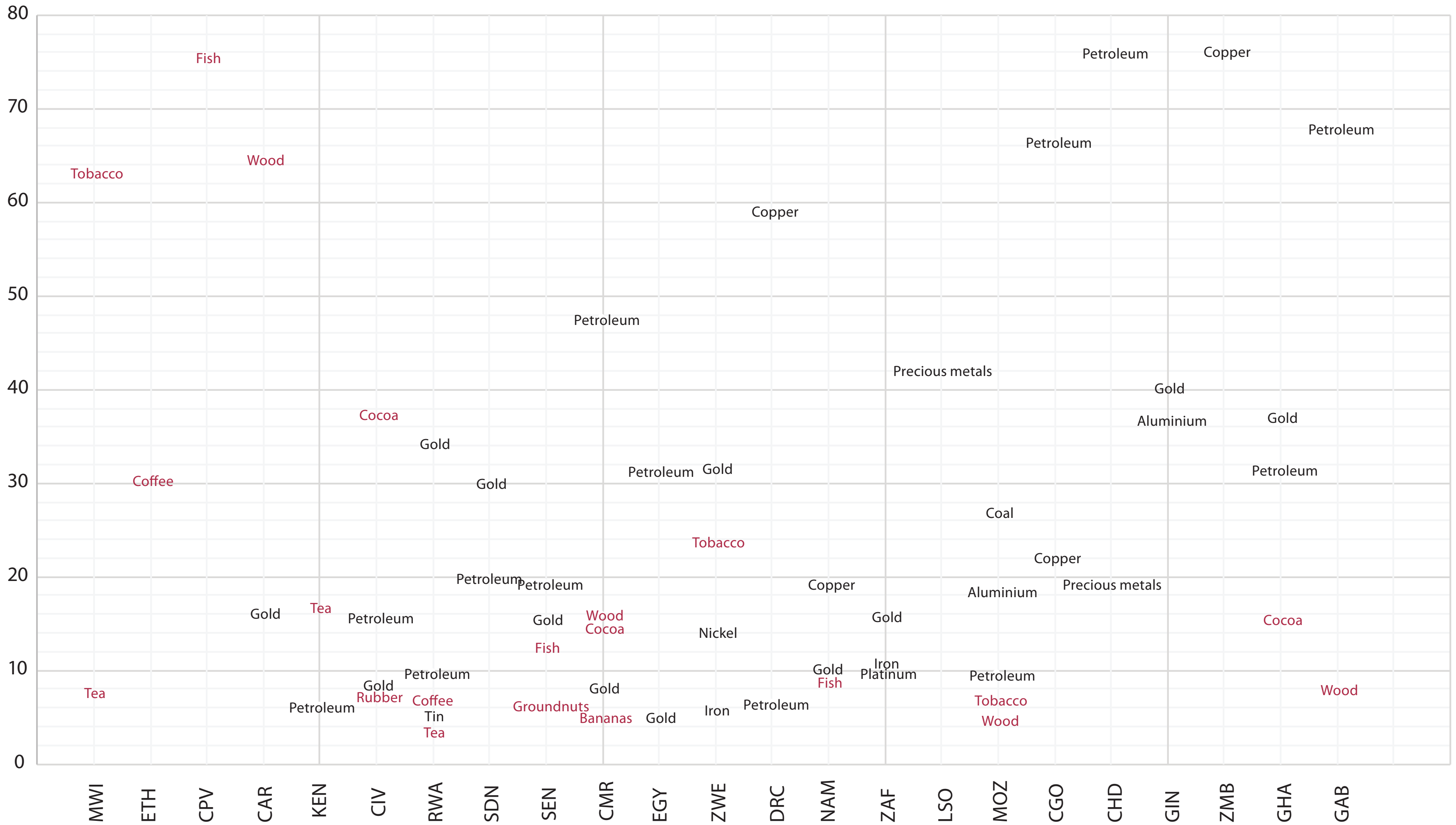
FIGURE 4A.2—PERCENTAGE SHARE OF PRIMARY COMMODITIES IN TOTAL IMPORTS, 2019



Source: Authors, based on data from DESA/UNSD (2021).

Note: CAR = Central African Republic; DRC = Democratic Republic of the Congo.

FIGURE 4A.3—PERCENTAGE SHARE OF SELECTED PRIMARY COMMODITIES IN THE EXPORT BASKET OF SELECTED AFRICAN COUNTRIES



Source: Authors, based on data from DESA/UNSD (2021).

Note: MWI = Malawi; ETH = Ethiopia; CPV = Cabo Verde; CAR = Central African Republic; KEN = Kenya; CIV = Côte d'Ivoire; RWA = Rwanda; SDN = Sudan; SEN = Senegal; CMR = Cameroon; EGY = Egypt; ZWE = Zimbabwe; DRC = Democratic Republic of the Congo; NAM = Namibia; ZAF = South Africa; LSO = Lesotho; MOZ = Mozambique; CGO = Congo; CHD = Chad; GIN = Guinea; ZMB = Zambia; GHA = Ghana; GAB = Gabon.

TABLE 4A.1—LIST OF INDICATORS TO ASSESS THE IMPACT OF COVID-19-RELATED GLOBAL TRADE DISRUPTIONS ON AFRICAN FOOD SYSTEMS

Component	Indicator
Agricultural production	Value-added agricultur
	Value-added agriculture
	Value-added manufact
	Value-added manufact
	Agriculture gross prod
Food processing	Food supply (kcal/capita/day) (b)
	Agriculture, forestry, and fish
	Fertilizer use, nutrientha)
	Fertilizer use, nutrient p
	Fertilizer use, nutrient
Food services	Arable land area equ
	Food imports (% of m
	Food exports (% of merchan
	Logistics performance index: Quality of tr
	Agricultural export value index (2014–2016 = 100)
Aggregate supply of agricultural and food products	Arable land area equ
	Food imports (% of m
	Food exports (% of merchan
	Logistics performance index: Quality of tr
	Agricultural export value index (2014–2016 = 100)

Component	Indicator
Trade	Agricultural export unit/value index (2014
	Agricultural export quantity index (2014–2016 = 100)
	Agricultural import value index (2014–2016 = 100)
	Agricultural import unit/value index (2014–2016 = 100)
	Agricultural import quantity index (2014–2016 = 100)
	Rural population (% of total population) (a)
	Total population growth (annual %) (a)
	Rural population growth (annual %) (a)
Consumption	Urban population growth (annual %) (a)
	Gross national income, value $ per capita
	Households and NPISHs final consumption e
	Agricultural export quantity index (2014–2016 = 100)
	Agricultural import value index (2014–2016 = 100)
	Agricultural import unit/value index (2014–2016 = 100)
	Agricultural import quantity index (2014–2016 = 100)
	Rural population (% of total population) (a)
	Total population growth (annual %) (a)
	Households' final consumption expenditure (
	Consumer prices, general indices (2015 = 100)
	Consumer prices, food indices (2015 = 100)
	Food price inflation (annual %)

Source: Authors' computation from simulation results.

CHAPTER 5

Assessing the Vulnerability of West and Central African Countries to COVID-19

John M. Ulimwengu, Léa Magne Domgho, and Julia Collins

Introduction

As of October 2021, the effects of the COVID-19 pandemic in African countries are still unfolding. The early stages of the pandemic were characterized by apparent lower illness and mortality rates in Africa compared to the other world regions, although significant underreporting of COVID-19 cases and deaths in Africa is likely. [1] However, the economic effects of the pandemic and the measures taken to combat it were expected to impact African countries severely, worsening poverty and hunger and erasing recent economic gains (Bouët, Laborde, and Seck 2021). A "third wave" of the pandemic in mid-2021 saw rapidly escalating health effects and a return to lockdowns and other mitigation efforts in many countries (Mwai 2021). The crisis is expected to have severe impacts on food security in Africa as in other regions, due to food supply chain disruptions, income loss, school closures, and other factors (HLPE 2020).

The health, economic, and food security effects of the pandemic vary greatly between and within countries. Underlying characteristics of households and regions influence their vulnerability to shocks and ultimately determine the severity of the impacts they experience from the crisis. Due to limited national resources, pandemic responses must prioritize the locations where the effects are likely to be particularly devastating. Therefore, efforts to identify the most vulnerable households and communities are essential to targeting those most in need of assistance.

In the literature, vulnerability has emerged as a development concept because of the recognition that poverty and food insecurity are dynamic in nature and reflect the exposure of households, communities, and countries to risk (Naudé, Santos-Paulino, and McGillivray 2009). Vulnerability is generally defined as the susceptibility of an individual, household, community, or country to fall below a threshold welfare level in response to an adverse shock (Naudé, Santos-Paulino, and McGillivray 2009; Barrett and Constas 2014; Moret 2018). Therefore, vulnerability is related to the concept of resilience but can be differentiated as a measure more focused on short-term reactions to specific hazards than on longer-term capacity to maintain or improve well-being (Barrett and Constas 2014). Efforts to assess vulnerability incorporate both exposure to shocks or hazards and ability to respond to these shocks—as stated by Moret (2017, 7), "Risk + Response = Vulnerability." The literature emphasizes that vulnerability must be considered in relation to a particular outcome—for example, economic vulnerability, vulnerability to negative impacts of climate change, etc. Vulnerability measurements cannot be standardized; rather, vulnerability assessments should be appropriate to the context (Nkonde, Masuku, and Manyatsi 2014; Moret 2018).

In this chapter, we examine vulnerability to the negative effects of COVID-19 among select West and Central African countries at the community level and assess the impact of COVID-19 vulnerability on food security at the household level. In the following section, we describe subnational vulnerability hot spots in 10 West and Central African countries by examining the underlying conditions at the first administrative division level that are expected to render these areas particularly vulnerable to the pandemic. In the third section, we examine the impact of vulnerability to COVID-19 on food security at the household level in Mali using five rounds of COVID-19-specific Living Standards Measurement Study (LSMS) surveys from the World Bank (World Bank 2020). The final section discusses the implications and presents key recommendations.

Identification of Vulnerability Hot Spots

Methodology and Data

To identify areas at particular risk for food insecurity and negative health effects arising from the COVID-19 crisis, we developed a vulnerability index based on multiple indicators. We classify subnational areas—usually at the level of the first administrative division—according to their vulnerability with respect to two sub-indexes grouping similar indicators, as well as to the combined index. Our basic approach is similar to the approaches followed in other studies; these include the Household Vulnerability Index developed by the Food, Agriculture and Natural Resources Policy Analysis Network (FANRPAN) to measure vulnerability to shocks and stressors such as climate change and the effects of HIV/AIDS based on the households' access to different types of assets and services (Nkonde, Masuku, and Manyatsi 2014). The Local Vulnerability Index developed

1 For example, *The Economist* estimates that Africa's cumulative COVID-19 fatalities as of October 2021 may be up to 800 percent higher than official counts—a greater level of underreporting than that of any other continent. However, Africa's mortality rates including estimated deaths are still lower than estimated mortality rates in most other continents (*Economist* 2021).

by Naudé, McGillivray, and Rossouw (2009) for magisterial districts of South Africa similarly assesses each district's vulnerability in different domains, including economic, environmental, and demographic and health vulnerability, before deriving a composite index.

Several COVID-19-specific subnational vulnerability analyses have been carried out for the United States. Nayak et al. (2020) and Neelon et al. (2021) examine associations between COVID-19 infection and death rates and the US Centers for Disease Control and Prevention's (CDC) Social Vulnerability Index, a composite index based on four subthemes (socioeconomic status, household composition and disability, minority status and language, and housing type and transportation). A notable initiative to create a COVID-19-specific subnational vulnerability index for African countries was carried out by Surgo Ventures, using indicators reflecting seven themes, including socioeconomic status, population density, and epidemiological and health system factors, to develop theme scores and overall vulnerability scores for each area (Surgo Ventures 2021). Our index differs from other efforts in that we include a food security theme, incorporating a food security sub-index to capture vulnerability to the deterioration of food security due to the pandemic, in addition to examining vulnerability to health-related impacts.

Similar analyses can be carried out for individual countries or for regions; here we examine a group of 10 West and Central African countries [2] for which sufficient data are available. All localities are classified into vulnerability categories based on their relationship to the regional average; thus, we rely on relative vulnerability benchmarks as opposed to absolute levels of vulnerability.

Our vulnerability index attempts to identify areas at highest risk for negative health and food security impacts induced by COVID-19. We generate sub-indexes that reflect two dimensions of vulnerability: (1) an area's ability to care for infected people, as reflected by the quality of health systems, and (2) its susceptibility to negative food security impacts from the crisis. Under (1), we include two indicators of access to healthcare—the share of women receiving assistance from a medical professional during their last childbirth and the share of women reporting that distance to a medical facility constitutes a major obstacle. Indeed, limited access to healthcare can exacerbate the health impacts of the COVID-19 crisis. Under (2), we use the prevalence of stunting in children under the age of five, an indicator of chronic food insecurity, as well as average food expenditure per capita (in purchasing power parity). Communities and households suffering from chronic food insecurity are likely to have fewer resources to withstand additional shocks.

Notably, the index does not attempt to predict which locations will experience higher infection rates. For countries or regions with sufficient data, a third sub-index could be developed to identify areas with higher susceptibility to infection; based on emerging knowledge about risk factors related to COVID-19 infection rates, this sub-index would likely include variables related to density, connectivity, and population mobility (Rice et al. 2021; Zhang et al. 2021; Matheson et al. 2020). We cannot implement this type of analysis in the current study due to the lack of relevant data at the subnational level (with the exception of population density).

Data sources include Demographic and Health Surveys (DHS), Living Standards Measurement Study (LSMS) surveys, and other national household budget surveys. Data available for the most recent year were used; years range from 2013 to 2018. A complete list of data sources for each country is provided in

TABLE 5.1—SUMMARY STATISTICS, FOOD SECURITY AND HEALTH SYSTEMS SUB-INDEX VARIABLES

Variable	Obs.	Mean	Standard deviation	Min.	Max.
Food security sub-index					
Average food expenditure per capita (PPP)	139	984.53	511.02	367.00	3,316.50
Stunting rate in children under five (percent)	139	0.32	0.13	0.11	0.66
Health systems sub-index					
Share of women 15–49 receiving assistance from a doctor, nurse/midwife, etc., at last birth (percent)	139	0.55	0.30	0.04	1.00
Share of women 15–49 for whom distance to a health facility is a major problem (percent)	139	0.38	0.19	0.02	0.84

Source: Authors' construction based on national data sources (see Appendix Table 5.A1).
Note: Max. = maximum; min. = minimum; obs. = number of observations; PPP = purchasing power parity.

2 Benin, Burkina Faso, Cameroon, Chad, Ghana, Mali, Niger, Nigeria, Senegal, and Togo.

Appendix Table 5.A1. Table 5.1 presents summary statistics of the indicators used to construct the two sub-indexes.

The regional analysis shown in this chapter relies on indicators that were available for all countries in the region, which significantly limits the number of indicators used. Analysis carried out at the country level could potentially include other indicators available for the country—for example, the food security and health systems sub-indexes could be enriched with additional indicators, and data on age structure and preexisting medical conditions such as diabetes and high blood pressure could be used to construct another sub-index on factors related to more severe health outcomes of COVID-19.

Based on the indicators listed above, we use principal component analysis (PCA) to generate scores for each location for the strength of health systems and severity of food insecurity. Vulnerability sub-indexes are then constructed by assigning each score to one of four categories, with thresholds based on the mean and standard deviation of scores for all locations. The thresholds are designed such that approximately 25 percent of observations fall into each category, assuming a normal distribution. Prior to PCA, indicators are transformed such that higher values correspond to greater vulnerability (for example, lower levels of healthcare access and food security). Categories are constructed as follows:

$$
\begin{array}{ll}
I_{ik} \geq \bar{I}_k + 0.67 * std(I_k) & :3 = \textit{Much more vulnerable,} \\
\bar{I}_k + 0.67 * std(I_k) \leq I_{ik} < \bar{I}_k & :2 = \textit{More vulnerable,} \\
\bar{I}_k \leq I_{ik} < \bar{I}_k - 0.67 * std(I_k) & :1 = \textit{Less vulnerable, and} \\
I_{ik} < \bar{I}_k - 0.67 * std(I_k) & :0 = \textit{Much less vulnerable,}
\end{array}
$$

where $\bar{I}_k$ represents the mean and $std(I_k)$ represents the standard deviation over all countries of the k^{th} indicator, and I_{ik} represents the i^{th} observation of the k^{th} indicator. A category score of 3 indicates the highest level of vulnerability relative to the regional average, and a category score of 0 represents the lowest level of vulnerability.

Following the classification of scores to generate sub-indexes for health systems and food insecurity, a composite vulnerability score for each location is calculated by averaging the score for each indicator. The composite vulnerability score is then classified into one of the same four categories according to the first method outlined above.

It should be noted that assigning weights to indicators with respect to their respective contribution to vulnerability is not obvious. Our approach is based on other similar indexes (for example, the CDC index) that involve grouping similar indicators into sub-indexes and then combining sub-indexes with equal weight into a composite index. This composite index should be viewed as an initial ex ante attempt to identify areas with the potential to be particularly vulnerable, but it needs to be refined as more analysis becomes available on the importance of different drivers of vulnerability. The composite index provides a summary of performance in different dimensions of vulnerability but may mask differences in vulnerability with regard to food insecurity versus vulnerability with regard to health systems. Thus, for targeting purposes, the sub-indexes may be more informative than the combined index.

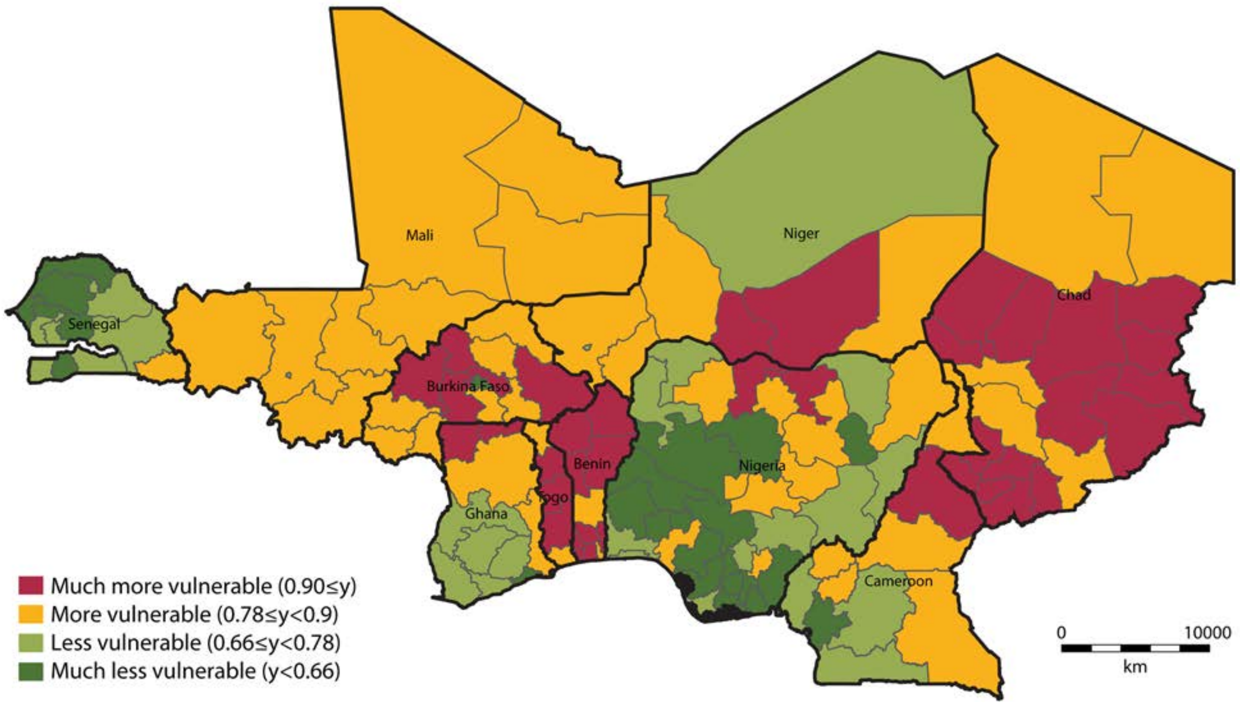
Another important limitation of the index is its silence regarding which areas are likely to suffer from high COVID-19 caseloads. Higher infection rates are clearly likely to affect vulnerability with respect to health outcomes; they can also plausibly influence vulnerability to food insecurity, although even areas with low infection rates are likely to suffer from food insecurity resulting from lockdowns and other measures taken to prevent the spread of the virus. However, the relationship between COVID-19 infection rates and outcomes is likely to be complex, as areas suffering from high infection rates also tend to be those with stronger health systems (Zhang et al. 2021; Muchangi 2021).

Results

Subnational Vulnerability in West and Central Africa

In this section we present the results of the vulnerability classification for select West and Central African countries for the two sub-indexes as well as for the combined vulnerability index. Figure 5.1 shows the food security sub-index, constructed from the prevalence of stunting in children under age five and household food expenditures per capita (purchasing power parity). Northern Nigeria, southern Niger, northern Chad, and several regions of Burkina Faso and Cameroon have the highest stunting rates in the region, while per capita food expenditures are lowest in Togo and Benin as well as areas of Burkina

FIGURE 5.1—FOOD SECURITY VULNERABILITY SUB-INDEX



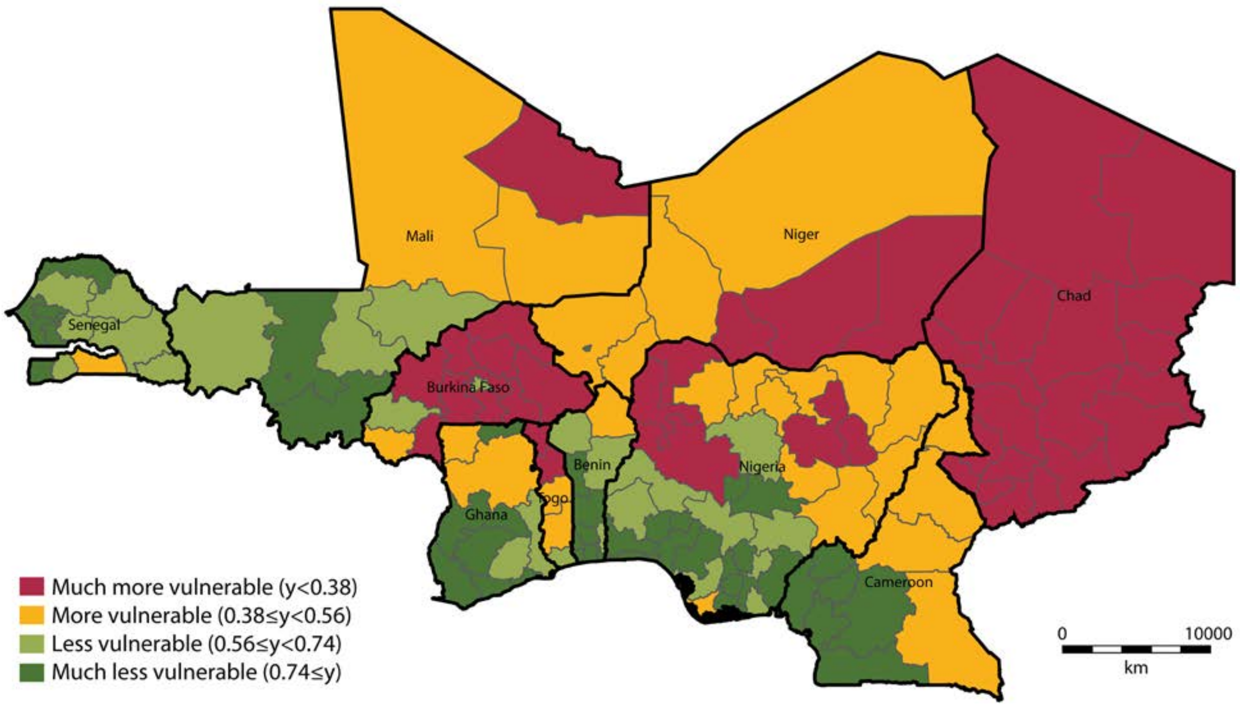
Source: Authors' construction based on national data sources (see Appendix Table 5.A1).

Faso, Ghana, Niger, Nigeria, Cameroon, and Chad. The sub-index suggests that vulnerability with respect to food insecurity is highest in some Sahelian areas—parts of Burkina Faso, northern Ghana, northern Nigeria, southern Niger, northern Cameroon, and Chad—as well as Togo and Benin. Senegal and southern and central Nigeria show the lowest vulnerability.

Figure 5.2 presents the classified health systems sub-index, based on indicators of access to medical services: the share of women receiving assistance from a medical professional during childbirth and the share of women reporting that distance to a health facility presents major problems. For both indicators, access to health services is generally higher in the western and southern areas of the West and Central Africa region. For the combined health systems sub-index, areas in the highest vulnerability category include nearly all regions of Chad (except for the capital, N'Djamena); most regions of Burkina Faso; and parts of southern Chad, northern Nigeria, northern Mali, and northern Togo.

Figure 5.3 shows the composite vulnerability index for the selected countries. Most regions of Chad as well as parts of Burkina Faso and southern Niger are classified as much more vulnerable than the regional average, reflecting

FIGURE 5.2—HEALTH SYSTEMS VULNERABILITY SUB-INDEX

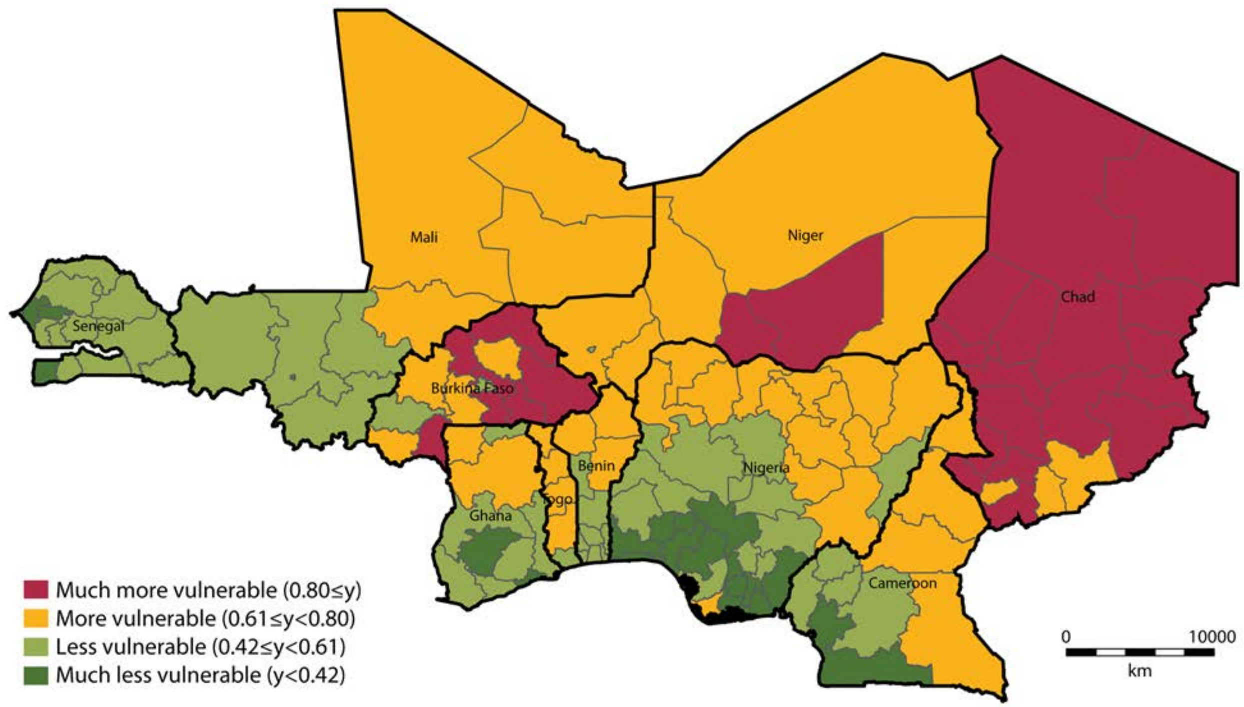


Source: Authors' construction based on national data sources (see Annex Table 5.A1).

their lower performance on both health systems and food security indicators. The lowest levels of vulnerability are found in Senegal as well as in southern areas of Mali, Ghana, Togo, Benin, Nigeria, and Cameroon. Most countries in the region have fairly low intra-country variations in vulnerability levels with respect to the regional average, while Burkina Faso, Cameroon, Ghana, and Nigeria have at least two regions or states in each of three vulnerability categories.

There are some commonalities across the indicators, with eastern and southern areas of the region performing better on most indicators as well as on the composite vulnerability index. Chad and Burkina Faso stand out as the countries with the largest share of regions in the highest vulnerability category, while Senegal is the only country with no regions in the two highest categories. Differences between countries and areas within the region seem to be associated with overall levels of development. The areas identified as more vulnerable than the regional average have fewer resources to absorb shocks. It bears repeating that these areas are not necessarily those more likely to experience high COVID-19 infection rates; however, infected people in vulnerable regions may experience more severe health impacts due to lower access to healthcare,

FIGURE 5.3—COMPOSITE VULNERABILITY CLASSIFICATION



Source: Authors' construction based on national data sources (see Appendix Table 5.A1).

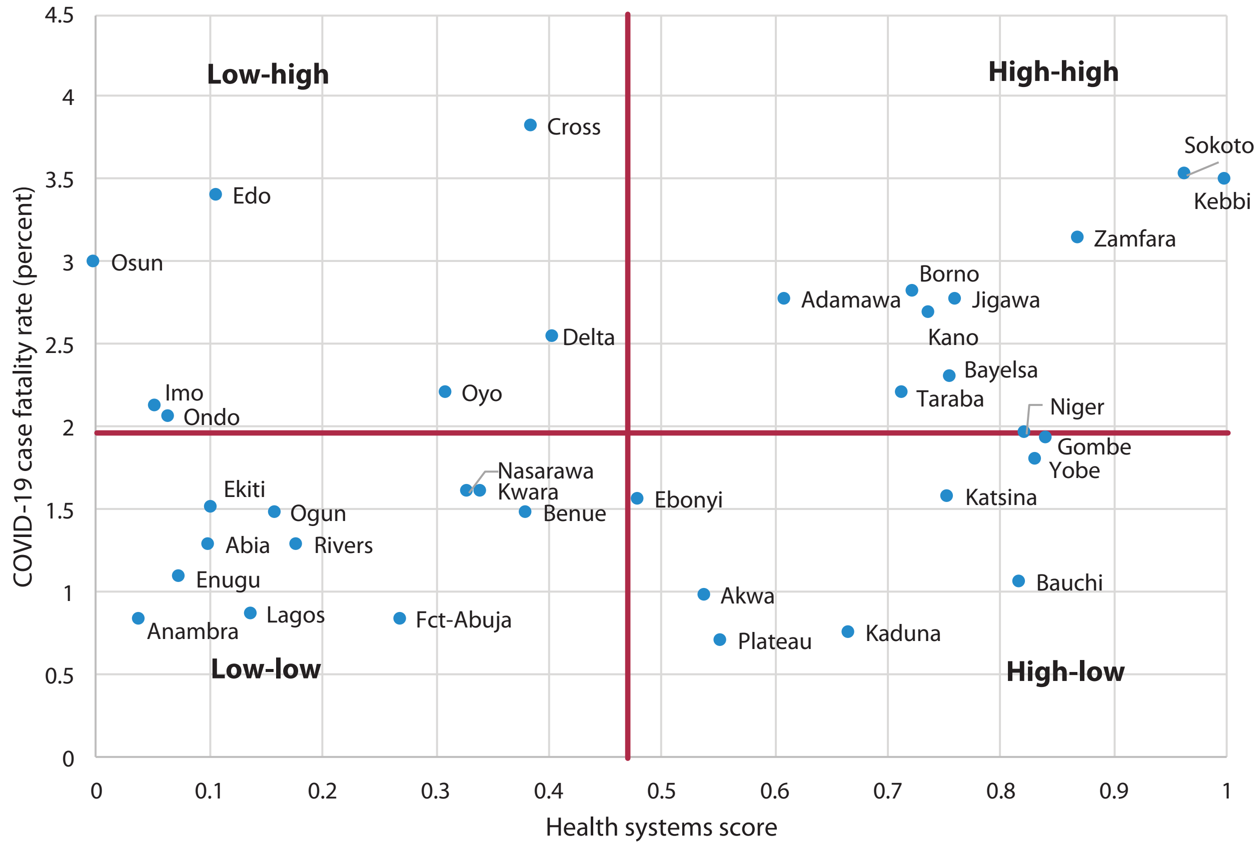
and the populations of these regions may be more severely affected by the economic impacts of lockdowns, movement restrictions, and other measures taken to limit the spread of the disease.

Outcomes of Vulnerability

An important next step for the analysis would be to validate the vulnerability index with outcome data. While updated subnational data reflecting the period after the onset of COVID-19 are not yet available in most cases, in this subsection we explore simple correlations between the vulnerability index and selected outcome data for illustrative purposes. By design, the vulnerability index is developed to identify areas most at risk for severe impacts of COVID-19. Data on COVID-19-related hospitalizations and deaths would be relevant to assess the severity of health impacts, while data on changes in food security status would be required to evaluate impacts on food security.

Unfortunately, data on COVID-19 hospitalization or mortality rates are not available at the subnational level for most of the countries of analysis. An exception is Nigeria, which releases weekly reports on COVID-19 cases and deaths by state. COVID-19 case fatality rates are expected to be correlated with the quality of health systems, preexisting health conditions, and, potentially, food security to the extent that undernutrition is linked to lower immune system function and worse health outcomes (Kurtz et al. 2021). Unfortunately, subnational data on preexisting conditions are unavailable for Nigeria. We find that case fatality rates for Nigerian states as of late September 2021 are moderately positively correlated with the health systems score (0.311), but uncorrelated with the food security score (0.028). In Figure 5.4, we compare health systems sub-index scores for Nigerian states with data on COVID-19 case fatality rates.[3] The vertical and horizontal lines indicate the average health systems score and mortality rate, respectively. The majority of Nigerian states fall into either the lower left-hand quadrant, with lower than average vulnerability scores and fatality rates, or the upper right-hand quadrant, with higher than average vulnerability and fatalities. This association suggests that areas with poorer health systems may have experienced greater mortality impacts; however, more rigorous analysis would be required to establish causality, and any findings should be treated with caution, given likely significant underreporting of COVID-19 cases and deaths.

FIGURE 5.4—HEALTH SYSTEMS VULNERABILITY AND COVID-19 CASE FATALITY RATES, NIGERIA



Source: Authors' construction based on NCDC 2021 (COVID-19 case fatality rates) and other national data (health systems score—see Appendix Table 5.A1).

Note: Case fatality rates are cumulative as of September 26, 2021. Kogi state is not shown due to very low recorded COVID-19 cases. FCT = Federal Capital Territory.

Comparable data on food security at the subnational level prior to and during the COVID-19 crisis are very limited. However, data based on the Cadre

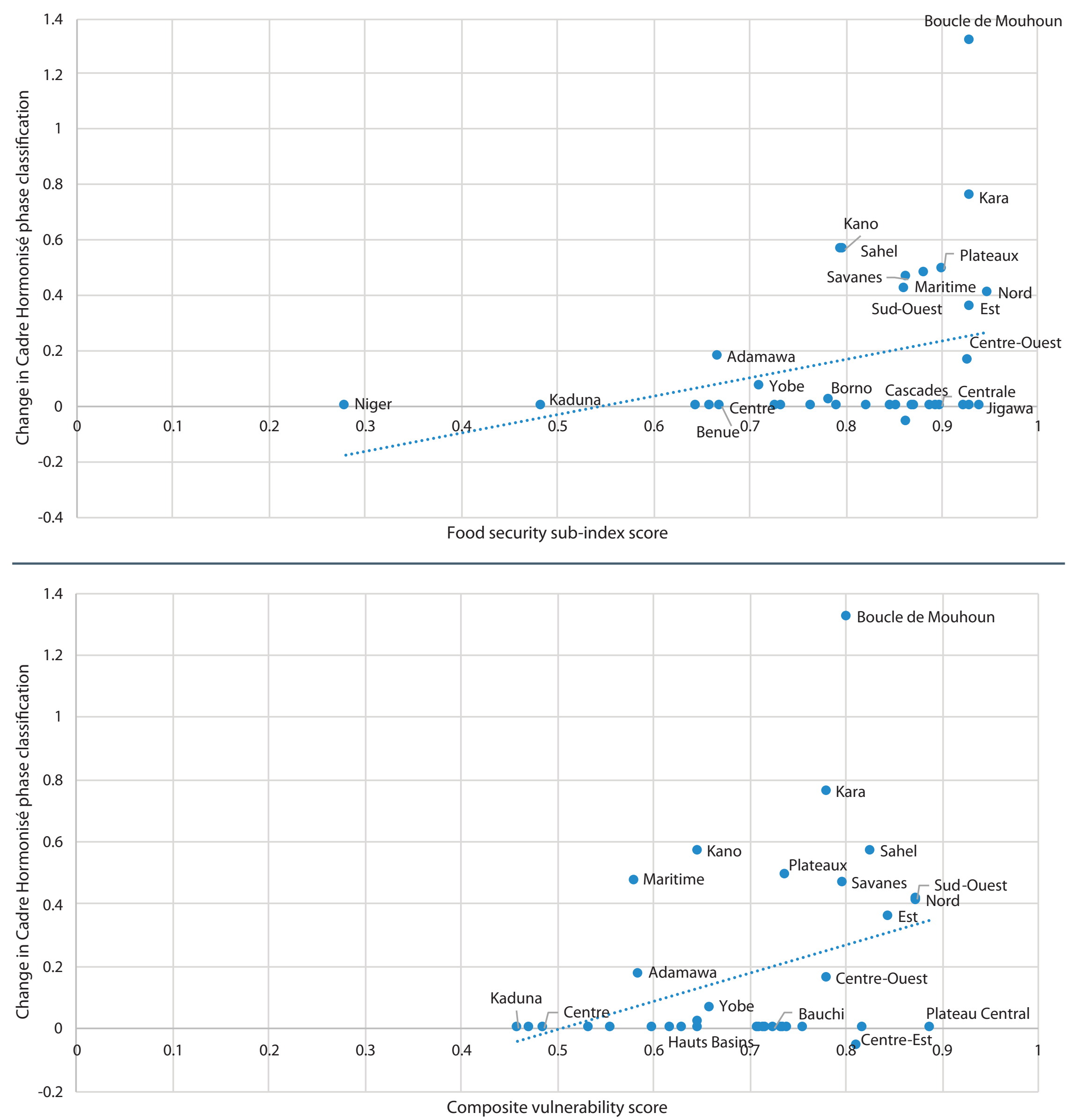
3 The health systems scores are shown before classification into four categories in order to preserve variation between states.

Harmonisé (CH, Harmonized Framework) indicator developed for select West African countries can provide important insight into changes in food security at the subnational level during the COVID-19 period. The CH phase classification is a composite indicator developed by the Permanent Interstate Committee for Drought Control in the Sahel (CILSS) and its technical partners[4] to monitor the current and projected food and nutrition security situation in the Sahel and West Africa. It includes indicators related to dietary diversity, livelihood strategy changes, observed coping strategies, nutrition status, and mortality (CILSS 2019).

In March 2020, CH projections were carried out for a number of West African countries for the period of June–August 2020. Updated estimations for the same period were completed in July 2020 for Burkina Faso, Togo, and 17 northern and central Nigerian states, taking into account the current effects of the COVID-19 crisis. Differences between the March 2020 projections and the July 2020 updates reflect the impact of current events on food security, including the pandemic and related lockdown measures. Of the 35 subnational areas covered, 14 showed increases in the CH phase classification, indicating

4 Partners include Action Against Hunger, the Food and Agriculture Organization of the United Nations, the Famine Early Warning Systems Network, the Integrated Food Security Phase Classification Global Support Unit, the International Federation of Red Cross and Red Crescent Societies, the Joint Research Centre of the European Commission, Oxfam, Save the Children, UNICEF, and the World Food Programme.

FIGURE 5.5—CHANGE IN FOOD INSECURITY VERSUS VULNERABILITY (FOOD SECURITY SUB-INDEX AND COMPOSITE INDEX), BURKINA FASO, TOGO, AND NORTHERN NIGERIA, MID-2020



Source: Authors' construction based on FSNWG–West Africa 2021 (Cadre Harmonisé data) and national sources (vulnerability index—see Appendix Table 5.A1).

Note: The y-axis shows the difference between the March 2020 Cadre Harmonisé (CH) projections for June–August 2020 and the July 2020 updates. Increases in the CH phase classification indicate decreases in food security. CH data at the second administrative division level were aggregated to the first administrative division level using population-weighted averages. Increases in food security sub-index and composite vulnerability scores (measured on the x-axes) correspond to greater vulnerability. Some data labels were omitted for legibility.

declines in food security; only 1 area showed a (small) improvement in food security. Nearly all (12 out of 14) of the areas showing declines in food security were classified as "more" or "much more" vulnerable than the regional average on the food security sub-index. Areas with larger declines in food security, as measured by the CH, also tended to have higher vulnerability levels, as measured by both the food security sub-index and the composite vulnerability index. Figure 5.5 compares changes in CH classification with vulnerability scores prior to classification into the four categories.

These findings are suggestive of an association between higher levels of vulnerability and food insecurity during the early months of the pandemic. However, more rigorous analysis is required to establish causality, pending data availability.

Impact of Vulnerability to COVID-19 on Food Security at the Household Level

LASSO Model

In this section, we turn to the household-level analysis of the impact of vulnerability to the pandemic on food security. Given the number of variables involved and the lack of consensus on an exhaustive list of COVID-19 determinants affecting food security, we decided to use the LASSO (least absolute shrinkage and selection operator) algorithm. To illustrate the impact of vulnerability to COVID-19 on food security, we implement a double selection model at the household level using the LASSO machine learning algorithm. In other words, we assume that the probability of being food insecure is a function of a set of vulnerability variables that are themselves determined by household and location characteristics. Following Belloni, Chernozhukov, and Wei (2016), the model takes the following form:

$$\mathrm{E}[y|\boldsymbol{d}, x] = G(\boldsymbol{d}\alpha' + \beta_0 + x\beta'), \qquad (1)$$

where $G(a) = \exp(a)/\{1 + \exp(a)\}$, $\boldsymbol{d}$ contains the J covariates of interest, and x is the p controls.

Initially introduced by Tibshirani (1996), LASSO estimates the parameters by finding the minimum of a cost function of the following form:

$$Q_L = \frac{1}{N}\sum_{i=1}^{N} w_i f(y_i, \beta_0 + x_i\beta') + \lambda \sum_{j=1}^{p} \theta_j |\beta_j|, \qquad (2)$$

where N is the number of observations, w_i are observation-level weights, $f(\cdot)$ is the model likelihood contribution, $\lambda \geq 0$ is the LASSO penalty parameter, and θ_j are coefficient-level weights.

Data Description

This section is based on longitudinal household data from the World Bank's LSMS-supported High-Frequency Phone Survey on COVID-19 in Mali. The dataset includes five rounds collected in May, June, July, September, and October 2020. The survey period corresponds to the pastoral lean season (April–June) and the agricultural lean season (July–October) (FEWS NET 2013). These data were designed to be representative at the country and regional levels as well as at the urban and rural levels. The survey covers 12 topics that provide detailed and relevant information on prices and food security, income, and socioeconomic indicators to assess the welfare impact of the pandemic. The survey also includes variables related to employment, access to basic services, shocks and coping strategies, income loss, behavior, and social distancing. Data on governance and sociopolitical crisis cover the period up to July. As presented in Table 5.1, data sample sizes range between 1,718 and 1,935 households.

In Mali, the first cases of COVID-19 were reported on March 25, 2020, in a context marked by a worsening security crisis. As of October 25, 2020, the country had recorded 3,490 positive cases, with peaks of over 80 and 50 confirmed cases per day in June and October, respectively (Mali, Ministry of Health and Social Affairs 2020). After the survey period, the COVID-19 situation worsened, intensifying during November 2020–January 2021 and again in March–April 2021, when daily cases reached a new peak of 413. Infection rates had declined again by June 2021, with daily average new cases in the single digits (HERA 2021).

We carry out two versions of the analysis. In the first estimation, y is a binary variable equal to 1 if the household reported having experienced food insecurity due to COVID-19; in the second, the dependent variable is reported food insecurity not due to COVID-19. Vector ***d*** includes variables (poverty status, access to health services, access to the Internet, population density, and negative shocks) that capture household vulnerability to the pandemic. Finally, the controls (x) include household demographics (age, gender, size, location), governance, perception of government responses to the pandemic, and political environment. The vector ***d*** variables were selected based on their potential to reflect households' vulnerability to negative effects of COVID-19 on food security.

Table 5.2 reports summary statistics of variables of interest used in our analysis. Poverty status, which is defined here by households' subjective assessments of their status, varies between 25.5 percent at the beginning of the pandemic and 26.6 percent in October 2020. As mentioned above, following Carletto, Zezza, and Banerjee (2013) and Bellemare and Novak (2017), we defined COVID-19-related food insecurity by using variables related to the households' self-reported ability to eat nutritious or healthy food.[5] In the questionnaire, households that reported not being able to eat nutritious or healthy food were asked whether this was specifically due to the COVID-19 crisis. Households that replied affirmatively are considered to be food insecure due to COVID-19, while households that reported food insecurity but answered that it was not due to COVID-19 are considered to have been food insecure in the absence of the COVID-19 crisis.

Over the five rounds of the survey, the results show a significant decrease in households considered to be food insecure both in the absence of COVID-19 and due to the COVID-19 crisis. Indeed, household food insecurity was the highest at the beginning of the pandemic (just over 43 percent

TABLE 5.2—DESCRIPTIVE STATISTICS OF VARIABLES OF INTEREST

Variable	Round 1 (N = 1,718)	Round 2 (N = 1,935)	Round 3 (N = 1,897)	Round 4 (N = 1,792)	Round 5 (N = 1,761)
Food insecurity due to COVID-19 (1 if food insecure because of COVID-19, 0 if no)	43.3 (0.496)	36.0 (0.480)	27.5 (0.447)	28.0 (0.449)	28.2 (0.450)
Food insecurity in the absence of COVID-19 (1 if food insecure, 0 if no)	43.6 (0.496)	39.9 (0.490)	31.1 (0.463)	31.6 (0.465)	31.9 (0.467)
Poverty (1 if poor, 0 if no)	25.5 (0.436)	26.7 (0.442)	26.4 (0.441)	26.2 (0.439)	26.6 (0.442)
Illness of an income-earning household member (1 if yes, 0 if no)	10.1 (0.301)	10.0 (0.300)	10.3 (0.304)	10.1 (0.301)	10.2 (0.303)
Loss of employment (1 if yes, 0 if no)	11.9 (0.324)	11.9 (0.324)	12.2 (0.327)	12.5 (0.331)	12.5 (0.330)
Bankruptcy of a nonfarm family business (1 if yes, 0 if no)	6.7 (0.254)	6.7 (0.251)	7.0 (0.254)	6.8 (0.251)	6.9 (0.253)
Increase in price of major food items consumed (1 if yes, 0 if no)	25.7 (0.437)	25.8 (0.438)	25.6 (0.437)	25.0 (0.433)	25.0 (0.433)
Need access to COVID-19-related services (1 if yes, 0 if no)	2.2 (0.148)	2.4 (0.154)	2.5 (0.155)	2.5 (0.155)	1.1 (0.106)
Need access to maternal health services (1 if yes, 0 if no)	15.2 (0.359)	15.1 (0.358)	15.1 (0.358)	15.1 (0.358)	14.4 (0.351)
Need access to child health services other than COVID-19 (1 if yes, 0 if no)	32.6 (0.469)	34.1 (0.474)	34.0 (0.474)	33.9 (0.474)	38.0 (0.486)
Need access to adult health services other than COVID-19 (1 if yes, 0 if no)	31.0 (0.463)	32.0 (0.467)	31.8 (0.466)	31.9 (0.466)	35.6 (0.479)
Access to the Internet (1 if yes, 0 if no)	74.7 (0.435)	74.2 (0.438)	74.0 (0.439)	73.9 (0.439)	74.0 (0.438)
Sample weight (used as proxy for population density)	1,405.44	1,243.72	1,242.74	1,298.27	1,310.97

Source: Authors' calculations based on Mali Living Standards Measurement Study–Integrated Surveys on Agriculture High-Frequency Phone Survey 2020 rounds (World Bank 2020).

Note: The first values listed are means, and the values in parentheses are standard deviations.

5 The question used to assess food insecurity is "You or other members of your household, have you been in a situation where you could not eat foods that are nutritious and good for your health because you did not have enough money or other ways to get food?" The same question format was used consistently in the first four rounds of the panel survey. For the final cycle, we assume that the numbers do not change between rounds four and five.

in May for both categories) but decreased in October to 31.9 percent for those insecure prior to COVID-19 and 28.2 percent for those insecure due to the pandemic.

Our findings suggest that more than 30 percent of the population had access to child health services, compared to 15 percent for maternal health services. Less than 3 percent of households had access to health services related to COVID-19. There was a slight increase in access to child health services (vaccination) during the period under consideration.

Between 10 and 12 percent of households have experienced the loss of either employment or an income-earning family member due to the COVID-19 pandemic. The proportion of households negatively affected by the bankruptcy of a nonfarm family business, an increase in the price of major food items consumed, or the illness of an income-earning household member was roughly stable over the five survey rounds. In terms of health services, the proportion of households with access to child or adult health services (other than COVID-19) and COVID-19-related services (testing, diagnosis, treatment) remained more or less the same throughout the period under consideration. The results also indicate that more than 7 in 10 Malian households have access to the Internet. This proportion remained stable over the period under consideration.

Table 5.3 presents a summary of unconditional transition probabilities from one state of food security to the other between survey rounds. Overall, the probability of staying in the same state is approximately 59–70 percent for food secure households, as compared to 34–43 percent for food insecure households. However, it is worth noting that the dynamics are different from one round to another. In future analysis, it will be interesting to explore the relationship between household characteristics and food security transition probabilities. In the current study, we account for only household and location attributes that ultimately determine the negative effects of COVID-19 on food security at the household level and that may be more complex than one would expect.

TABLE 5.3—UNCONDITIONAL TRANSITION PROBABILITIES FOR FOOD SECURITY

Food security status	From round 1 to 2		From round 2 to 3		From round 3 to 4		From round 4 to 5	
	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure	Food secure	Food insecure
Food secure	0.593	0.407	0.656	0.345	0.656	0.345	0.697	0.303
Food insecure	0.567	0.433	0.623	0.377	0.623	0.377	0.656	0.344

Source: Authors' calculations based on World Bank 2020.

Note: Unconditional transition probabilities refer to probabilities of entering a different food security status, independent of any other factors. The row categories represent status in the first of two subsequent rounds, and the column categories represent status in the second of the subsequent rounds. For example, 0.593 is the share of households that were food secure in round 1 that also reported being food secure in round 2.

Results

Estimation results are reported in Table 5.4. For the sake of parsimony, we discuss only the results of variables of interest (matrix d in equation 1). In total we had 40 control variables, but the LASSO algorithm selected only 23.[6] The first two columns of Table 5.4 present the results for food insecurity as aggravated by COVID-19, while the last two focus on food insecurity in the absence of COVID-19.

Overall, the results between the two specifications are qualitatively the same, which is probably due to the short period of time examined (five months). As expected, poverty status, negative shocks, access to the Internet, and population density have significant impacts on household food security.

In the literature, as pointed out by Naudé, Santos-Paulino, and McGillivray (2009), poverty status is often included in assessments of resilience and vulnerability; indeed, poverty status has a strong relationship with food and nutrition insecurity (see, for example, Siddiqui et al. 2020; Wight et al. 2014). Health variables such as access to maternal, child, and COVID-19-related health services are included to reflect households' access to medical services. Access to health services is an important factor in households' ability to respond to health shocks (FAO 2016), with medical services being particularly relevant for resilience to

6 We tested for overspecification by implementing the elastic net (Zou and Hastie 2005), which includes a penalty whenever covariates are correlated. More specifically, coefficient estimates from the elastic net are more robust to the presence of highly correlated covariates than are LASSO solutions. Results from the elastic net did not suggest overspecification or redundancy and indicated that variables are not correlated enough to require a robust estimation.

TABLE 5.4—ESTIMATION RESULTS, DRIVERS OF FOOD INSECURITY

Variable	Food insecurity exacerbated because of COVID-19		Food insecurity in the absence of COVID-19	
	Coefficient	Robust standard error	Coefficient	Robust standard error
Poverty (1 if poor, 0 if no)	0.4901***	0.0761	0.5072***	0.0759
Illness of an income-earning household member (1 if yes, 0 if no)	0.6989***	0.1004	0.6852***	0.1004
Loss of employment (1 if yes, 0 if no)	0.7997***	0.0882	0.7801***	0.0883
Bankruptcy of a nonfarm family business (1 if yes, 0 if no)	-0.0420	0.1288	-0.0072	0.1276
Increase in price of major food items (1 if yes, 0 if no)	0.1279*	0.0728	0.1196*	0.0728
Access to the Internet (1 if yes, 0 if no)	-0.4403***	0.0744	-0.4580***	0.0742
Assess to COVID-19-related services (1 if yes, 0 if no)	-0.0295	0.1906	-0.0451	0.1911
Assess to maternal health services (1 if yes, 0 if no)	0.0512	0.0859	0.0816	0.0856
Assess to child health services other than COVID-19 (1 if yes, 0 if no)	0.0613	0.0659	0.0687	0.0658
Population density	0.0455**	0.0235	0.0510**	0.0234
Number of observations	5,288		5,288	
Number of controls	40		40	
Number of selected controls	23		23	
Wald chi-squared (10)	221.6		224.9	
P-value	0.00		0.00	

Source: Authors' estimation results.
Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

health shocks such as COVID-19. However, in our results these variables are not significant. Most of the health access variables are too general[7] to capture the impact of COVID-19 in the short term. For example, for the COVID-19-related health services variable, only symptomatic respondents answered this question; however, they represent less than 3 percent of surveyed individuals.

Access to the Internet is expected to reflect households' ability to access information and overcome the effects of social distancing; in some cases, Internet access can permit household members with formal employment to protect their income sources by working from home during lockdowns. Our results suggest that the probability of being food insecure is much lower for households with Internet access compared to those without access to the Internet. While access to the Internet is higher among the non-poor (79 percent) than the poor (58 percent), the community at large is rather well serviced, with at least 75 percent of surveyed individuals having Internet access. This may be due to Mali's high mobile connectivity rate, with 125 mobile cellular subscriptions per 100 people as of 2020 (World Bank 2021).

Negative shocks such as illness of an income-earning household member, job loss, bankruptcy of a nonfarm family business, and increase in the price of a major food item increase the probability of households depleting their assets to cope, which ultimately threatens their food security standings. We found that households hit by illness of an income-earning family member, loss of employment, or increase in the price of a major food item consumed have a higher probability of becoming food insecure.

7 They are not specifically related to health conditions that put an individual at greater risk of contracting COVID-19 or of experiencing worse outcomes, such asthma, blood disorders, cancer, cerebrovascular disease, chronic obstructive pulmonary disease, chronic kidney disease, cystic fibrosis, diabetes, Down syndrome, heart disease, hypertension, use of corticosteroids or other immunosuppressive medications, solid organ or blood stem cell transplantation, neurological conditions, and obesity.

Finally, we include sample weight as a proxy for population density as an additional vulnerability variable that captures the level of social interaction with respect to social distancing measures. Higher population density is expected to increase the speed of COVID-19 contagion, therefore contributing to negative impacts on food security. Our findings confirm that higher population density is associated with negative impacts of COVID-19 on food security.

Conclusion and Recommendations

In this chapter we present two types of vulnerability analysis: we examine the vulnerability of subnational regions to the health and food security effects of COVID-19, and the vulnerability of households to the negative impacts of COVID-19 on food security. The subnational analysis suggests that while there are major differences in vulnerability between West and Central African countries, vulnerability can also vary markedly within countries, underlining the need for decision-makers to monitor local effects closely and be prepared to intervene in areas with high levels of vulnerability. While the impacts of COVID-19 are still unfolding, we find some evidence that higher levels of vulnerability may be associated with larger reductions in food security due to the pandemic. The household-level analysis examines the impact of drivers of vulnerability to COVID-19 on food security. Findings suggest that preexisting poverty, lack of access to the Internet, greater population density, and negative income and price shocks increase susceptibility to negative food security impacts.

Both types of analysis point to the importance of programs to help households absorb negative shocks. The effects of crises are not uniform; therefore, resource limitations require governments and donors to allocate assistance to the most vulnerable locations, households, and individuals. In cases of sudden and widely shared crises, geographic targeting may be the most efficient and effective approach.

As post-COVID-19 crisis data become more widely available, ex post analyses should be carried out to refine subnational vulnerability analyses to identify the areas or households at highest risk. This would help to inform regular and ongoing monitoring of vulnerability to future crises. Ongoing vulnerability monitoring efforts could include multiple indexes customized to different types of shocks. While many drivers of vulnerability are not dependent on the type of shock, other drivers may differ. For example, population density is often associated with better access to health systems and other services that help households adapt to shocks, but in the case of COVID-19, density increases household members' risk of contracting the disease through social interactions, which in turn may exacerbate the negative impact on food security and health.

Appendix

Table 5.A1—Data sources for subnational vulnerability analysis		
Country	**Indicator**	**Source**
Benin	Stunting, medical assistance, distance to health facility	DHS 2017–2018
Benin	Per capita food expenditure	EMICOV 2015 (PPP from WDI 2015)
Burkina Faso	Stunting, medical assistance, distance to health facility	DHS 2017
Burkina Faso	Per capita food expenditure	LSMS 2014 (PPP from WDI 2015)
Cameroon	Stunting, medical assistance, distance to health facility	DHS 2018
Cameroon	Per capita food expenditure	ECAM4 2014 (PPP from WDI 2014)
Chad	Stunting, medical assistance, distance to health facility	DHS 2018
Chad	Per capita food expenditure	ECOSIT4 2018 (PPP from WDI 2014)
Ghana	Stunting	Micronutrient survey 2017
Ghana	Medical assistance, distance to health facility	DHS 2014
Ghana	Per capita food expenditure	GLSS 7 2017 (report) (PPP from WDI 2017)
Mali	Stunting, medical assistance, distance to health facility	DHS 2018
Mali	Per capita food expenditure	ENSAN 2016 (PPP from WDI 2016)
Niger	Stunting, medical assistance, distance to health facility	DHS 2012
Niger	Per capita food expenditure	LSMS 2014 (PPP from WDI 2014)
Nigeria	Stunting, medical assistance, distance to health facility	DHS 2018
Nigeria	Per capita food expenditure	LSMS 2014 (PPP from WDI 2014)
Senegal	Stunting, medical assistance, distance to health facility	DHS 2017
Senegal	Per capita food expenditure	PAPA 2017 (PPP from WDI 2017)
Togo	Stunting	MICS 2017
Togo	Medical assistance, distance to health facility	DHS 2013
Togo	Per capita food expenditure	QUIBB 2015 (PPP from WDI 2015)

Note: DHS = Demographic and Health Surveys; ECAM4 = Quatrième Enquête Camerounaise auprès des Ménages; ECOSIT4 = Enquête sur les Conditions de Vie des Ménages et la Pauvreté au Tchad; EMICOV = Enquête Modulaire Intégrée sur les Conditions de Vie des Ménages; ENSAN = Enquête Nationale sur la Sécurité Alimentaire et Nutritionnelle; GLSS 7 = Ghana Living Standards Survey–Round Seven; LSMS = Living Standards Measurement Study; MICS = Multiple Indicator Cluster Surveys; PAPA = Projet d'Appui aux Politiques Agricoles; PPP = purchasing power parity; QUIBB = Questionnaire Unifié des Indicateurs de Base du Bien-être; WDI = World Bank World Development Indicators.

CHAPTER 6

Assessing African Economic Policy Responses to COVID-19

Getaw Tadesse and Wondwosen Tefera

Introduction

In early 2020, African governments adopted a wide range of containment and confinement measures to limit the spread of COVID-19 in the continent. The measures included border closures, suspension of international flights, closures of markets and schools, state-of-emergency declarations, total and partial lockdowns, restrictions on internal movement, imposition of curfews, and closures of nonessential businesses (UN-Habitat 2020; IMF 2020). To mitigate the adverse economic effects of these health measures, governments implemented various emergency economic supports and regulations. Several institutions have tracked the type and size of policy responses by African countries to ease the adverse impacts on agricultural development, food security, finance, and trade (Laborde and Parent 2020; Bisson and Hambleton 2020). These studies have explored the incidence and impacts of emergency responses with the objective of estimating the costs of COVID-19. Similarly, AKADEMIYA2063 has established analytical workstreams to monitor the impacts of COVID-19 on food production, markets, trade, and households (Badiane and Collins 2020). However, these studies have evaluated the overall impact of COVID-19 without disentangling the impacts of the health measures from those of the economic measures.

Unlike previous policy response studies (for example, Hale et al. 2020; IMF 2020; UN-Habitat 2020), which focus primarily on tracking policy responses and to some extent evaluating their political economy, this chapter aims to measure the performance of African countries in designing and implementing emergency policy responses, using a descriptive mixed methods approach. More generally, the study presented in this chapter seeks to explore the performance of countries in managing shocks. The study is motivated by the fact that the extent of public responses, the types of interventions chosen, the implementation strategies followed, and the speed of adoption are notably heterogenous (Hale et al. 2020). While some of the countries have relied on transfers, others have attempted to mitigate the pandemic's adverse effects by regulating markets and transactions. More importantly, some countries have applied innovative digital technologies to implement their responses, while others have continued to depend on conventional physical approaches, with significant implications for the performance of the responses in terms of both meeting the needs of beneficiaries and containing the public costs of implementation.

The chapter describes the sources of data and the analytical methods used to track performance before presenting the results on policy responses. The chapter focuses on the empirical measurement of COVID-19 policy planning and implementation performance in 17 African case study countries (Benin, Burkina Faso, Ethiopia, Gambia, Ghana, Kenya, Liberia, Lesotho, Madagascar, Malawi, Mali, Mozambique, Nigeria, Rwanda, Sierra Leone, Togo, and Zambia) using two major indicators: responsiveness and implementation performance. While the responsiveness indicator measures the planning capacity of countries in responding to emerging shocks such as COVID-19, the implementation performance indicator measures the effectiveness and innovativeness of countries in implementing emergency responses across four sectors: food, seed, fertilizer, and trade. The chapter also examines the interaction between policy response performance and price changes, based on previous studies on the impacts of COVID-19 on food prices, to demonstrate the importance of policies and their effective implementation in shielding households, markets, and economies from the adverse impacts of COVID-19. The chapter further estimates the overall policy process performance of the countries, characterizes the six best-performing countries, and identifies best practices that can be replicated and scaled up to improve emergency policy process performance in Africa.

Data and Methods

Data

The data used for this study were obtained from two sources. The first is the Oxford COVID-19 Government Response Tracker (OxCGRT), which was launched by the University of Oxford's Blavatnik School of Government at the end of March 2020. It is the first tool ever used to track policy measures adopted by governments in responding to the coronavirus pandemic (University of Oxford 2021). The tracker collects data and information that is publicly available on several indicators such as economic policies, which include income support, debt relief, the provision of aid, and other indicators. The tool launched with 73 countries and expanded continuously to include policy response data from more than 180 countries around the world (Sant 2021). Of all the available indicators, we focus on the income support indicator, which provides data on direct cash payments delivered by governments to those who lost their jobs due to the pandemic. On an ordinal scale, the data tell whether and to what extent governments are replacing lost salaries. This indicator helps to verify our argument that although African governments were less responsive in supporting lost incomes, they were very responsive in supporting access to supplies and services for households and sectors that are vulnerable and economically critical. However, we also explored the overall economic support scores of the tracker. The raw data of the tracker are obtained from Hale et al. (2021) for the entire list of African countries.

The second major dataset used for this chapter is obtained from the AKADEMIYA2063 expert interviews conducted in September 2020 to track certain African governments' COVID-19 sectoral policy responses and their implementation. The expert interviews were conducted using a semi-structured online survey questionnaire designed specifically to track countries' responses and implementation performance. The questionnaire covers five sectors: food, seed, fertilizer, trade, and transportation. The transportation data are not used here, as the responses were too few. For each sector, three broad questions were covered: the type of responses; the timing, location, and beneficiaries of the responses; and the methods of implementing the responses. The questionnaire asked specific questions regarding the government's approach to mitigating the adverse effects of COVID-19 in each sector. Thus, the questions were designed to reflect self-reporting of attributions rather than causal inference with counterfactuals.

The questionnaire was distributed to purposely selected experts who have knowledge of policy actions and implementations in a specific sector in a country. Thus, different experts were interviewed for the different sectors, in most cases two or three experts in a country: one for food, seed, and fertilizer (mainly from the Ministry of Agriculture) and the other for trade or transportation or both (mainly from the Ministry of Trade). In some cases, where more than two responses were obtained from the same country and the same sector, we used the average response for each question. The experts were selected by Regional Strategic Analysis and Knowledge Support System node coordinators familiar with the knowledgeable persons for each sector.

The questionnaires were sent to experts in more than 30 African countries. However, full responses were received from only 17 countries from the three regions in Africa south of the Sahara: 9 from western Africa, 5 from southern Africa, and 3 from eastern Africa. Though the major countries and regions of Africa south of the Sahara are included in this sample, the number of countries is admittedly too few to represent the whole continent. However, since the purpose of the study is to track sector-level policy responses at the country level and identify best practices, we believe that this is a reasonable sample to allow us to make comparisons and draw lessons and indicative conclusions on emergency responsiveness and implementation performance.

Analytical Approach

To track and examine the sample countries' COVID-19 policy responsiveness (CPR) and program implementation performance (PIP), several indexes are developed based on the two datasets described above. The first indexes to measure CPR are the income support and overall economic support scores of the OxCGRT. The income support scores are based on the intensity of income support and are defined as "0" if a country did not support, "1" if it provided less than 50 percent of lost income, and "2" if it provided 50 percent or more of lost income. The scores are reported on a daily basis and hence the average scores are estimated for the period from March 2020 to February 2021. The average values are normalized to percentages by dividing by the maximum score, which is "2," for example, for income support. In this case, a country scores the maximum score (100 percent) for income support if it has provided 50 percent or more of the income lost and has done so throughout the full year (365 days). The economic support index is an aggregate of various economic response scores, including the income support index, debt relief index, etc., using simple averages (Hale et al. 2021).

Since the OxCGRT indexes mainly capture responses to support lost incomes due to job loss, which is a rare type of support in Africa, we instead regenerated a CPR index at the sector level—sector policy responsiveness (SPR)—that captures in-kind and regulatory responses to support lack of supplies and services due to the COVID-19 lockdowns, based on data from the experts' interviews. The SPR index for country i in sector j is coded as

$$SRP_{ij} = \frac{NR_{ij} + TR_{ij}}{20} 100,$$

where NR_{ij} refers to the number of response categories implemented. We divided responses into two categories: transfers and regulation. Transfers include in-kind free transfers of food, seed, and fertilizer as well as subsidies, transportation, storage, tax exemptions, and technical supports in all sectors, including trade. Regulation includes imposing or lifting price controls, export bans, informal trades, restricting marketplaces, etc. Thus, NR takes a value from 0 to 2, where "0" represents no response, "1" only one type of response, and "2" both regulatory and transfer programs.

TR_{ij} refers to the speed of the responses, categorized as "0" if there is no response; "1" if a country responded after May 2020; "2" if a country responded in March, April, or May 2020; and "3" if a country responded before March 2020. The speed of response may depend on several factors, including the level of COVID-19 cases and the production season of a country, especially for seed and fertilizer. Thus, we first evaluated the correlation of the countries' responses and the average caseload, and then we gauged the countries' provision of seed and fertilizer transfers against the planting time.

The higher the SPR index, the more responsive the country is in terms of both number of instruments used and timely action. If a country had both transfer and regulation programs and these programs were implemented before March 2020 in all four sectors, it scores a maximum value of 20 (NR_{ij} = 2 + TR_{ij} = 3) x 4). The SPR is normalized into percentages by dividing the scores to the maximum value 20 and multiplying by 100.

The PIP index is developed based on experts' responses to questions related to the timeliness, targeting effectiveness, and innovativeness of their countries' COVID-19 program supports. The PIP index for country i in sector j is computed as

$$PIP_{ij} = \frac{TE_{ij} + TD_{ij} + TF_{ij} + DT_{ij}}{37} 100,$$

where TE_{ij} denotes targeting effectiveness in country *i* for sector *j*. We assumed that targeting effectiveness depends on targeting stringency, which in turn depends on the number of criteria (location, commodity, economic status) applied to select beneficiaries (IPA 2020). We assumed that the higher the number, the more stringent and effective, and vice versa. Based on this rationale, we coded the targeting effectiveness of countries as "3" if a country targeted the program using two criteria, "2" if a country targeted using only one criterion, "1" if a country did not target the program, and "0" if a country did not respond at all. This definition applies for food, seed, and fertilizer programs. For trade programs, targeting effectiveness is coded based on the number of pre-identified trade flows supported by the program, such as (1) export of food/inputs, (2) export of nonfood items, (3) import of food/inputs, and (4) import of nonfood items. Unlike the number of criteria, for which larger values are better, targeting in trade programs is coded such that the fewer the trade flows targeted the better. Thus, trade program targeting effectiveness of countries is coded as "3" if a country provided support to a single prioritized trade flow, "2" if a country provided support for two trade flows, "1" if a country provided support to three or four trade flows, and "0" if a country did not implement any trade support program.

TD_{ij} refers to the time of delivery (speed of implementation), gauged against the time of implementation of COVID-19 containment measures for food support and against planting time for input supports. TD_{ij} also considers the sources of the transfers. We assume that countries that procure the food/inputs for in-kind transfers from the market and deliver the transfers on time are considered more effective than countries that use stocks for transfers. Thus, the timeliness of a country is coded from 0 to 3, with "0" if a country had no program in that sector, "1" if a country did not deliver on time (after the containment or planting time), "2" if a country delivered on time (before containment or planting time) but from stocks, and "3" if a country delivered on time by procuring from the market ahead of time. Swift market procurement helps countries to implement virtual reserves, which are more cost-effective than physical stocks (reserves) for emergency responses (von Braun and Torero 2008). TD_{ij} is measured only for food, seed, and fertilizer supports. It has less relevance for trade support. Thus, TD_{ij} also measures procurement effectiveness.

TF_{ij} denotes the use of a task force to implement COVID-19 policies in each sector. It is coded as "1" if a country used a task force and "0" otherwise.

DT_{ij} denotes the use of digital technologies (pre-identified digital and smart platforms, for example, warehouse vouchers) to monitor progress and deliver the transfers as well as implement the regulations. It is coded as "0" if a country did not adopt any policy, "1" if the country did not use any digital technologies, "2" if it used digital platforms for monitoring progress, and "3" if the country used warehouse receipt vouchers. These practices were selected based on literature that identifies them as promising best practices that increase the effectiveness of social protection programs (Tadesse 2018; Hidrobo et al. 2014). The use of e-commerce in African food systems remains very limited.

PIP_{ij} is gauged against the sum of the maximum ordinal score (37) for all indicators in all sectors. The maximum score for food, seed, and fertilizer is 10 ($TE_{ij} = 3 + TD_{ij} = 3 + TF_{ij} = 1 + DT_{ij} = 3$), and 7 is the maximum score for trade, as it has no score for TD_{ij}. A maximum of 100 percent implementation performance is achieved if a country scores the maximum in all sectors. The SPR and PIP indexes are compared across countries and sectors to track progress and performance.

An additional indicator—emergency response performance (ERP)—that summarizes the SPR and PIP indexes is also developed to identify best practices and lessons for potential scale-out and scale-up across the continent. ERP measures the relative performance of countries in designing and implementing emergency policy responses. It is estimated using a correlation-weighted performance score of four performance indicators: responsiveness, targeting effectiveness, timeliness, and innovativeness ($TF_{ij} + DT_{ij}$). We choose a correlation-weighted performance score mainly because, unlike a simple average, it helps to measure the systemic performance (or capacity) of a country by capturing policy consistency and synergy across all indicators and sectors. This means that a higher positive correlation among indicators signifies higher consistency and synergy, and thus higher policy design and implementation performance.

The correlation weighting factor is calculated using a principal component analysis (PCA) approach. PCA estimates the principal components of the data that retain the maximum information related to the correlations of the observed variables (indicators). However, PCA generates several components that capture all the possible correlations within a given dataset. In our case, we used the first principal component, as it captures the highest correlation of the data. According to Combes and Azema (2010), the choice of the number of components depends on the percentage of correlation explained by the components. The number of components that explain at least 60 percent of the correlation among the observed variables is sufficient to represent the dataset. In our dataset, 68 percent of the correlation among the four indicators is explained by the first component, confirming the sufficiency of the first component to represent the correlation among indicators and generate an overall policy process performance score.

Policy Responses to COVID-19

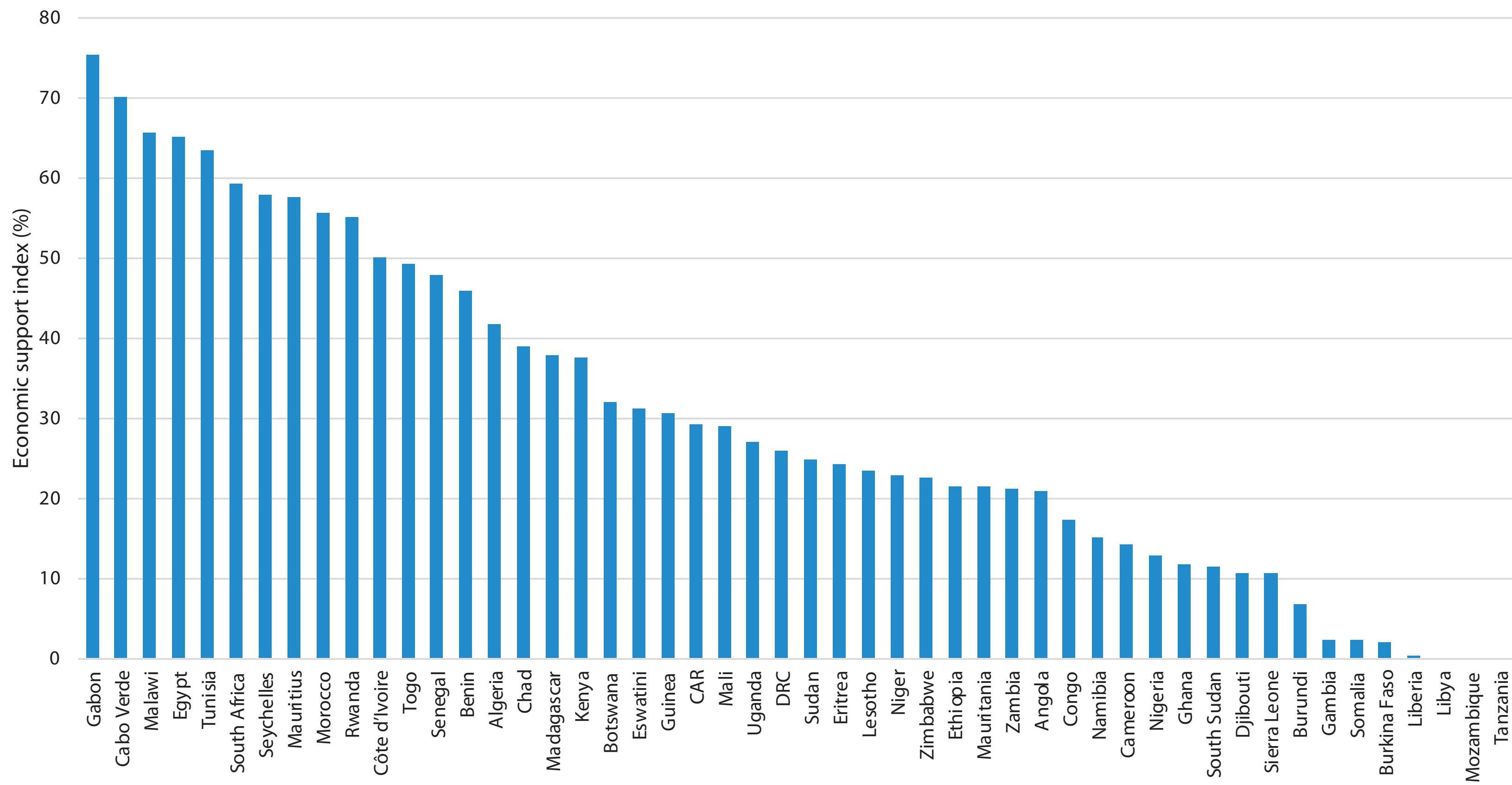
African governments have responded to the pandemic with two types of measures: health measures to contain the spread of the virus, and economic measures to support households and economic activity. The first group includes containment measures (closing schools, closing workplaces and marketplaces, canceling public events, confinement at home, etc.) but also sanitary measures (public information, testing, contact tracing, facial coverings, vaccination policy, etc.). The second group includes income support (salary payment), debt and contract relief for households, food transfers, agricultural input supports, fiscal measures, and trade facilitation.

Economic Support

Figure 6.1 shows the OxCGRT economic support index for African governments. The index is reported daily, and the figure shows the simple average of daily indexes from March 1, 2020, to February 28, 2021. A value of 0 means the country has no income support or debt relief, while a value of 50 percent can mean that the country has provided either income support or debt relief for 182.5 days out of the total 365 days in a year (half) or both income support and debt relief for 91.25 days in a year (one-quarter), or any other similar combination. The index shows the extent of support, and the higher the index, the more intensive the support provided by the country.

No African country is included in the 20 most responsive countries across the globe. The leading nations are mostly from Europe—with some from Asia (Japan, Israel, etc.) —and scored more than 75 percent. The maximum score for Africa is about 75 percent, represented by Gabon, followed by Cabo Verde and Malawi (Figure 6.1). Fourteen African countries scored above the global average of 45 percent. Of the 184 countries included in the global index, only 6 have a score of 0. Three of them are in Africa: Libya, Mozambique, and

FIGURE 6.1—AVERAGE COVID-19 ECONOMIC SUPPORT INDEX OF AFRICAN COUNTRIES FROM MARCH 1, 2020, TO FEBRUARY 28, 2021



Source: Authors' computation based on OxCGRT data reported in Hale et al. (2021).
Note: CAR = Central African Republic; DRC = Democratic Republic of the Congo.

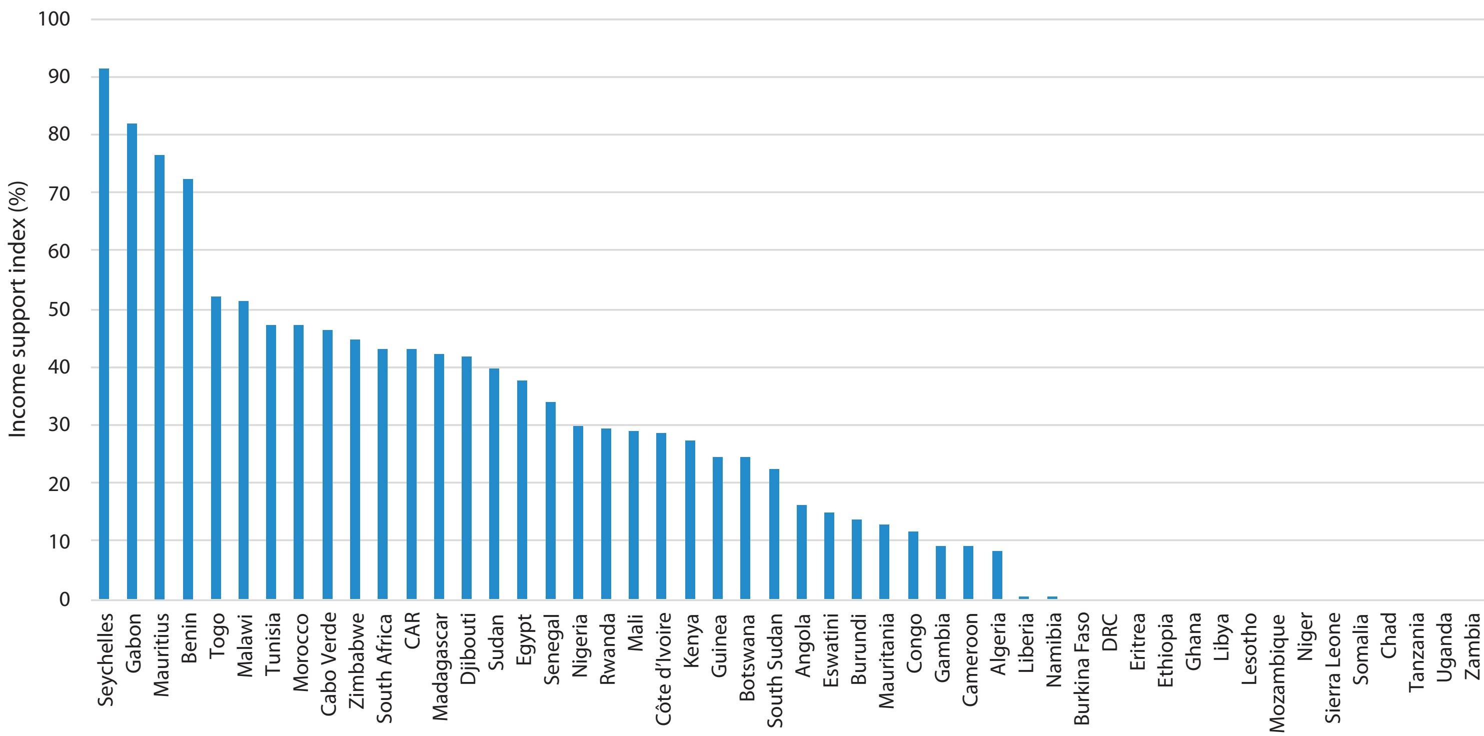
Tanzania. These countries did not provide either income support or debt relief as defined by the tracker.

We further assessed the extent of income support that those African countries have provided to employees to compensate for lost income. Figure 6.2 presents the income support index of African countries for the same period. Of the 50 African countries for which the tracker has data, only 35 provided income support. Seychelles, Gabon, Mauritius, and Benin were the most protective countries, with scores of more than 70 percent. These countries as well as Togo and Malawi covered more than 50 percent of lost salaries for a significant number of days during the year.

Sector Policy Responses

As shown in Figure 6.2, about 15 African countries provided no income support to mitigate lost income. This does not, however, mean that these countries did

FIGURE 6.2—THE EXTENT OF INCOME SUPPORT PROVIDED BY AFRICAN COUNTRIES TO EMPLOYEES AFFECTED BY COVID-19 RESTRICTIONS FROM MARCH 1, 2020, TO FEBRUARY 28, 2021



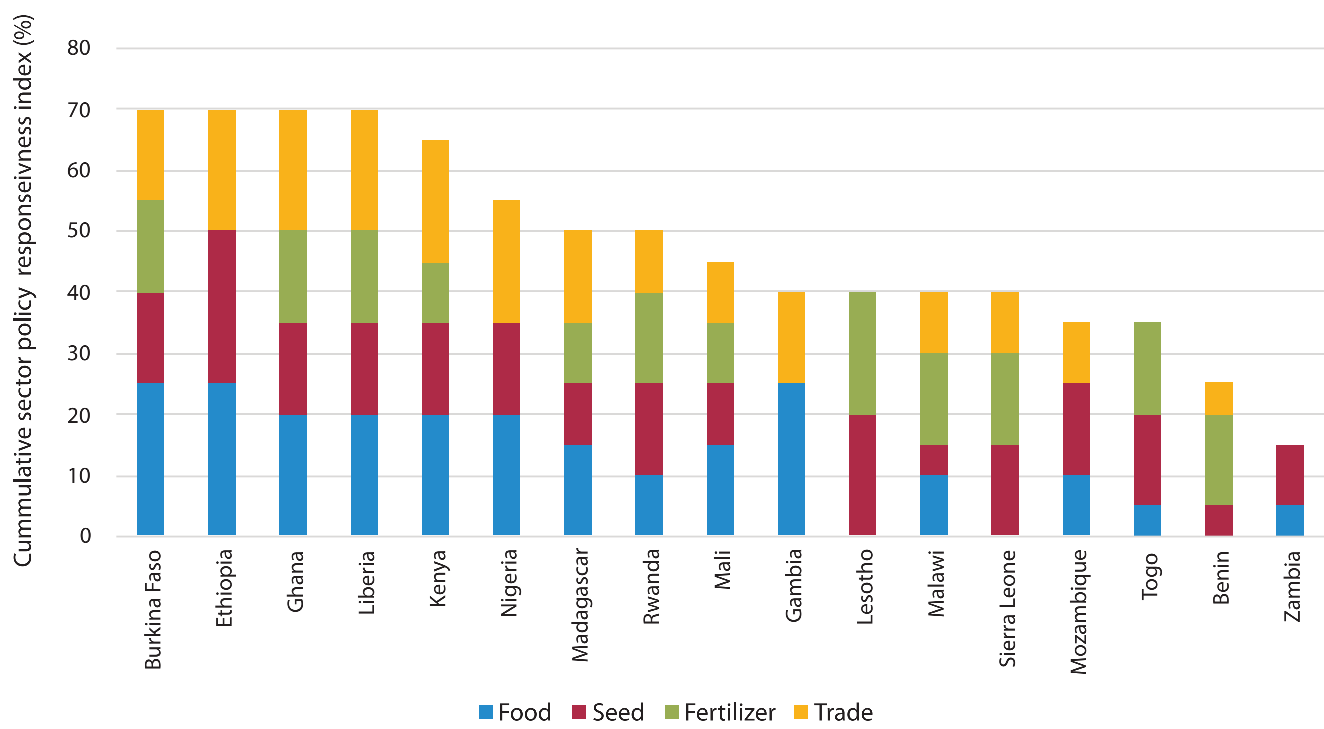
Source: Authors' computation based on OxCGRT data reported in Hale et al. (2021).
Note: CAR = Central African Republic; DRC = Democratic Republic of the Congo.

not support households and producers who faced lack of access to supplies and services due to the COVID-19 containment measures and restrictions. Instead, they supported vulnerable households, farmers, and businesses using sector-specific policy instruments through in-kind transfers and regulations. The in-kind transfers are made in the form of supplying food and providing inputs and services either free of charge or at a subsidized price. The regulatory supports are provided in the form of applying or relaxing price, import, and export controls, and enforcing safety standards. These regulatory supports may be intended, however, to protect households, farmers, and businesses from health shocks as well as income shocks.

Countries designing and implementing social protection measures attempt to achieve three important, usually conflicting, objectives (Zimmerman and Carter 2003; Devereux and Guenther 2009). These are (1) protecting vulnerable groups from welfare loss (consumption smoothing), (2) preventing beneficiaries and markets from experiencing disincentives (asset crisis) and distortion effects, and (3) promoting the productive capacity of marginalized groups that have been trapped by poverty. The prevention and promotion objectives are important for shocks that have long-term effects, whereas the welfare protection and cost minimization objectives are important even in the short term. Since the economic emergency responses are meant to mitigate the adverse effects of the COVID-19 health measures, the overall impacts of the responses should depend on their effectiveness in protecting short-term outcomes (food supply, input use, cost of trade) and minimizing the public costs of implementation.

The impact of the supports in protecting consumers, producers, and trade, however, depends on the extent of the policy responses, the effectiveness of the supports in addressing priority needs, and the innovativeness of the implementation process to deliver and monitor the supports. Thus, in this section, we will measure the responsiveness of government measures, while in the next section we will examine program implementation performance in terms of the targeting effectiveness, timeliness of delivering supports, and innovativeness of countries in implementing supports, using data from the experts' interviews.

FIGURE 6.3—THE INTENSITY AND DIVERSITY OF SECTOR-SPECIFIC SUPPORTS TO COUNTERACT THE ADVERSE EFFECTS OF COVID-19 BY A SAMPLE OF AFRICAN COUNTRIES

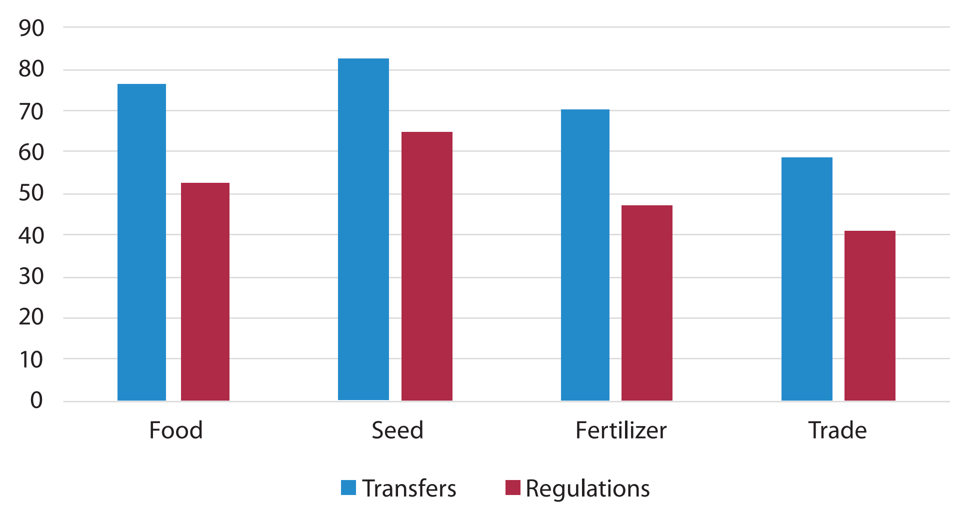


Source: Authors' computation using experts' interview data.

Using qualitative data collected from 17 countries, we assessed the responsiveness of African governments in the food, seed, fertilizer, and trade subsectors. Figure 6.3 shows the number (intensity) and diversity of sector-specific supports for a sample of 17 African countries measured using the method described above. If a country scores more than 10 percentage points in a sector, it implies that the country has adopted both regulatory and transfer programs for that specific sector.

The results suggest varying degrees of responsiveness across countries and sectors. Out of the 17 sample countries, Burkina Faso, Ghana, and Liberia were identified as very responsive countries, as they responded in all four sectors and scored a minimum of 15 percentage points in each sector. Five countries—Kenya, , Madagascar, Malawi, Mali, and Rwanda—supported all the sectors but with minimal degrees of responsiveness. Three countries—Benin, Lesotho, and

FIGURE 6.4—PERCENTAGE OF SAMPLE COUNTRIES USING TRANSFERS AND REGULATIONS



Source: Authors' computation using experts' interview data.

Sierra Leone—focused on supporting farmers and businesses, without providing any kind of support to food consumers. In contrast, Gambia supported only food consumers. With regard to instruments, many governments used transfers to support consumers and farmers, and regulations to support traders.

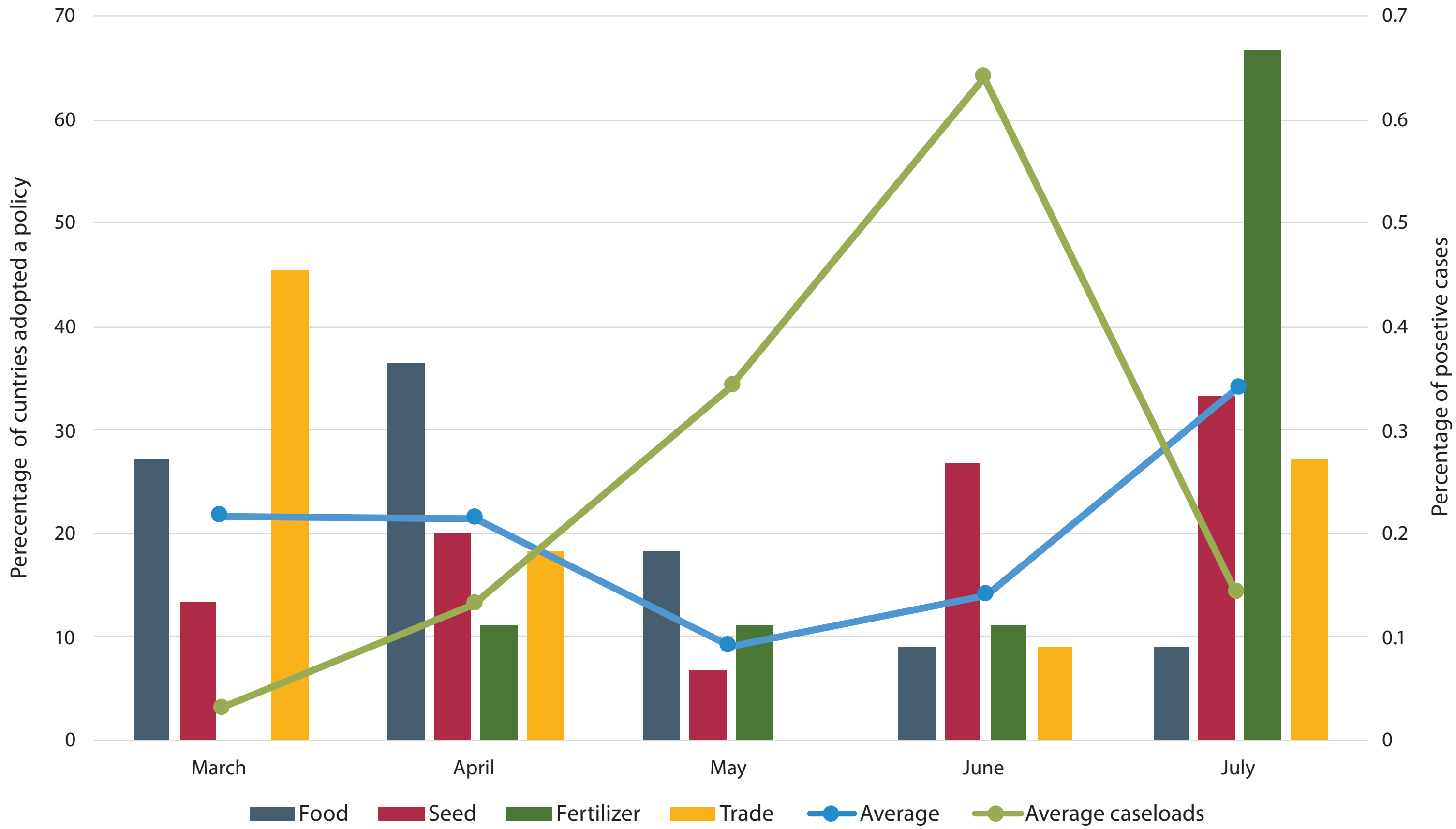
In general, even if many countries in Africa did not respond by providing direct income support, as reported in Figure 6.2, almost all of them have responded in the form of sector-specific in-kind transfers and regulations, with varying levels of intensity and diversity across sectors. More importantly, they implemented the supports at different times using different targeting and delivery approaches, which will have significant implications for the effectiveness of the supports. Below we first explain how we provide evidence on the extent of effectiveness for the sample countries.

Figure 6.4 presents the percentage of sample countries that used transfers and regulations to protect consumers, producers, and traders from the adverse effects of COVID-19. As expected, transfers are more prevalent than regulatory supports. This is particularly the case for the food and seed sectors. Surprisingly, a greater number of countries made transfers in the seed sector than in other sectors, suggesting that countries were worried about shortfalls in the harvest following confinement. Regulatory programs are usually supplemental support for the transfers. While transfers may target poorer households or traders, regulatory supports are intended to facilitate transactions hindered by confinement.

In addition to evaluating the number of policy instruments used to protect consumers, traders, and producers, we also assessed the timing of responses. Figure 6.5 shows the percentage of countries that implemented their first responses in five periods. More than one-third of the sample countries introduced food transfers and regulations in April 2020, while about one-fourth responded before March 31. Some countries responded as late as August or September. In terms of timing, countries were faster to act on trade than on other sectors. Close to half of the sample countries introduced trade measures before March 31, 2020. This is consistent with the fact that domestic containment policies in many African countries were introduced later than in trading partner countries and hence the trade policies were made in response to external restrictions (Hale et al. 2020; IMF 2020). The timing of policy responses for the seed and fertilizer sectors seems more related to the local planting time. Most countries intervened in seed and fertilizer distribution beginning in June 2020. Generally, the timing of responses varied greatly across countries and sectors. In an emergency, earlier responses are often considered to be the most effective. However, responses should be gauged relative to the timing of the shock and the demand for the supports.

Figure 6.5 also shows the average percentage of positive cases in the sample countries (green line) reported in each month. The comparison of the average policy response rate (blue line) and the average caseloads indicates that the policy responses are not highly correlated with COVID-19 caseloads. The average caseload increased from 0.03 percent in March 2020 to 0.64 percent in June, then sharply declined in July to 0.14 percent. However,

FIGURE 6.5—THE SPEED OF POLICY RESPONSES (PERCENTAGE OF COUNTRIES BY MONTH, 2020)



Source: Authors' computation using experts' interview data.

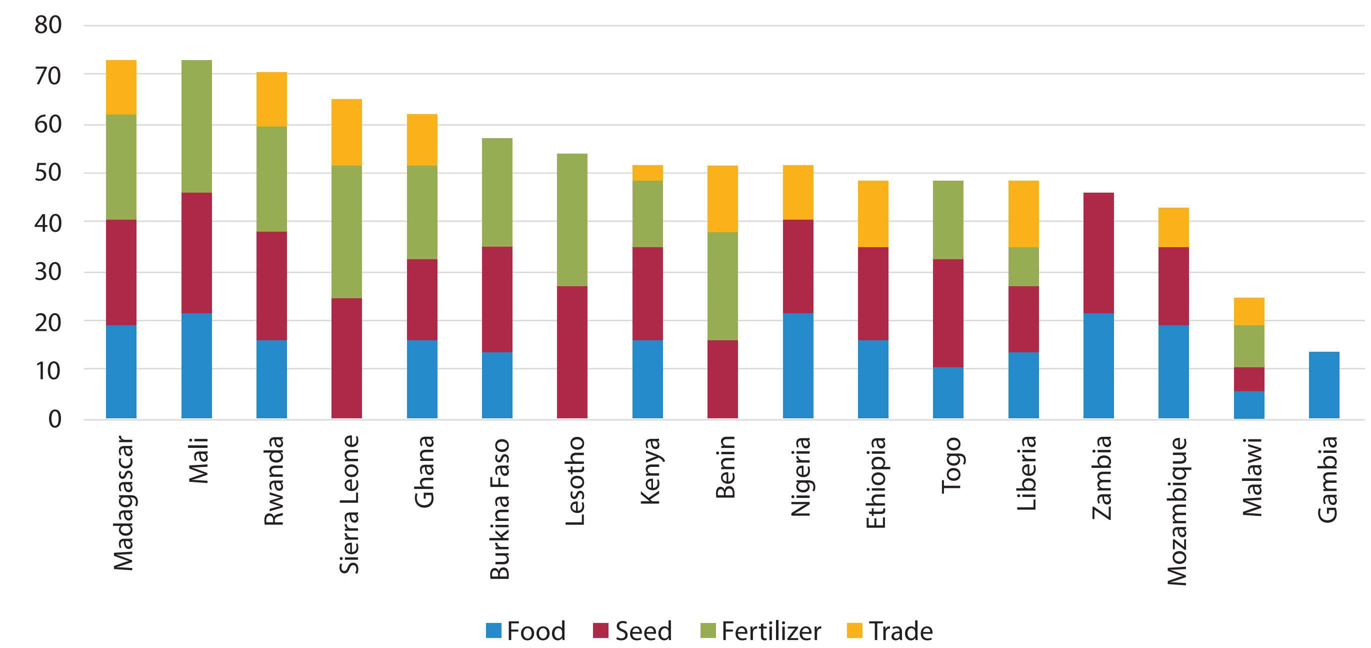
Note: "Average caseloads," which refers to the average percentage of positive cases in the total population of the sample countries, are measured against the secondary (right-side) vertical axis. All other percentages are measured against the primary (left-side) vertical axis.

the average response rate (percentage of countries that adopted a new policy) was higher in March and then declined before climbing in June and especially July. It seems that the countries' policy responses were influenced by two waves—the first being the outbreak of the pandemic in March and April, and the second being the high incidence rate in June that led to a response in July.

Program Implementation Performance

In this chapter, we define program implementation performance (PIP) as the effectiveness of countries in implementing sector-specific policies or programs designed to combat the adverse effects of COVID-19 restrictions. In principle, program performance, as opposed to program impact, is measured at the

FIGURE 6.6—PROGRAM IMPLEMENTATION PERFORMANCE INDEX, NORMALIZED TO 100 PERCENT



Source: Authors' computation using experts' interview data.

Note: The index values are from 0 to 1 but were converted to percentages by multiplying by 100.

process or output levels. At the output level, performance is usually measured by the quantity or size of outputs achieved by the programs, for instance, the number of people benefited, and the amount of food and seed distributed. Unfortunately, we do not have reliable data on the output variables. Instead, we measured the implementation performance at the process level, using qualitative information on targeting effectiveness, delivery timing, institutional arrangements, and the methods or technologies (innovations) used to implement the programs. The advantage of the process approach is that it helps to capture (proxy) not only output effectiveness but also cost-effectiveness. The methods used to deliver the program benefits determine the cost of a social protection program. Thus, we developed a sector-specific PIP index for each country.

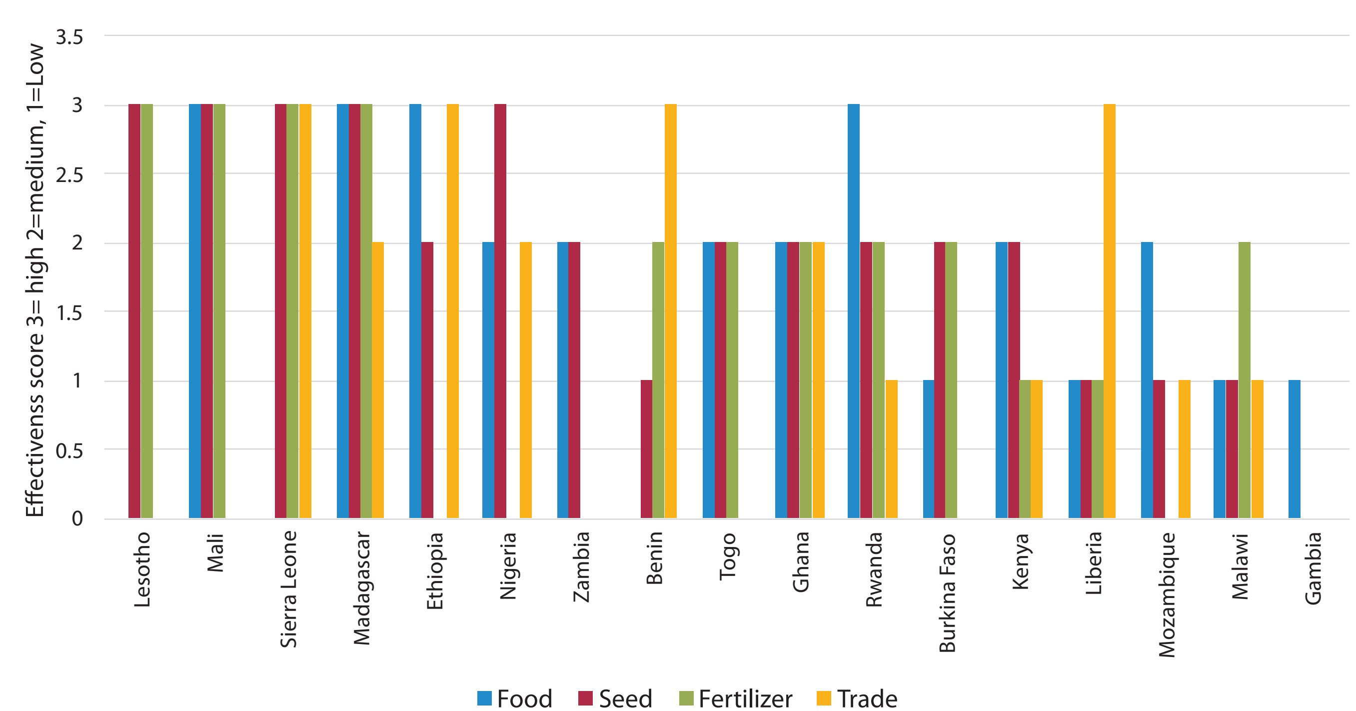
Figure 6.6 presents the PIP indexes (normalized to 100) of the sample countries across sectors. Of the 17 countries, only 7 received an overall PIP score of more than 50 percent. However, the overall score may obscure the implementation performance of a country within specific sectors. For example, Mali, Nigeria, and Zambia appear to be the most effective countries in implementing food support programs, as they used innovative warehouse vouchers to deliver foods to targeted households on time. Others, such as Ethiopia, Ghana, Kenya, Madagascar, and Mozambique also scored highly in implementation effectiveness of food programs. Similar variations are observed in the seed, fertilizer, and trade programs. To make the analysis more practical and shed light on the weaknesses and strengths of the sample countries, below we describe the countries that have done well in each of the three performance indicators used to construct the PIP index.

Targeting Effectiveness

In a social protection program, effective targeting of locations, commodities, and households is crucial to reach vulnerable groups and enhance social welfare (Cirillo and Tebaldi 2016). For example, in a food transfer program, focusing on staples or nutritious food items helps to reach the poor who depend on staples. Similarly, targeting urban residents during COVID-19 confinement helps to reach most consumers without access to food (IPA 2020). Targeting is also very important for other supports related to seed, fertilizer, and trade, as it ensures the prioritization of locations, commodities, and producers or firms that provide significant welfare effects at the national level. Effective targeting also helps to minimize market distortions and disincentives associated with transfers and regulations (Alderman 2001.). Therefore, we explored the targeting effectiveness of the sample countries in food, seed, and fertilizer transfers, as well as trade facilitation support in response to COVID-19 using the method described in the "Data and Methods" section. It is important to note that we do not have specific data on actual targeting efficiency, and hence we are unable to verify whether the transfers actually reached the target groups or not. But the use of a greater number of targeting criteria indicates how a country is trying to reach those most affected by the pandemic.

Figure 6.7 presents the targeting effectiveness scores for the sample countries by sector and ordered by average values. The results suggest varying levels of targeting effectiveness across sectors and countries. Input supports seem more targeted than food and trade supports. About half of the countries provided input supports to selected producers and commodities only. With regard to food transfers, Ethiopia, Madagascar, Mali, and Rwanda appear to be effective, as they prioritized beneficiaries across locations and economic statuses (Figure 6.7). Our survey data indicate that food transfers in these countries were targeted to urban

FIGURE 6.7—TARGETING EFFECTIVENESS SCORES OF SAMPLE COUNTRIES



Source: Authors' computation using experts' interview data.

Note: In cases of missing values, mainly due to a lack of policy response for one or more sectors, we assign the missing sector a score based on the average of scores for the sectors for which the country has complete data or responses. This is to allow comparison using the full dataset.

areas where COVID-19 containment had significant impacts on food supply in poor households, which is consistent with the recommendation of Innovations for Poverty Action (IPA 2020). Contrary to our expectations, the survey data also showed that about 29 percent of the sample countries did not specify (target) beneficiaries of food transfers. As expected, supports to trade were less targeted. Just three countries, Benin, Ethiopia, and Liberia, were able to provide the supports only for prioritized transactions—either for import or export of food and inputs, or of nonfood products. Generally, out of the 17 case study countries, Lesotho, Mali, and Sierra Leone had the most effectively targeted programs, while the policy responses of Gambia, Malawi, and Mozambique were less targeted or prioritized.

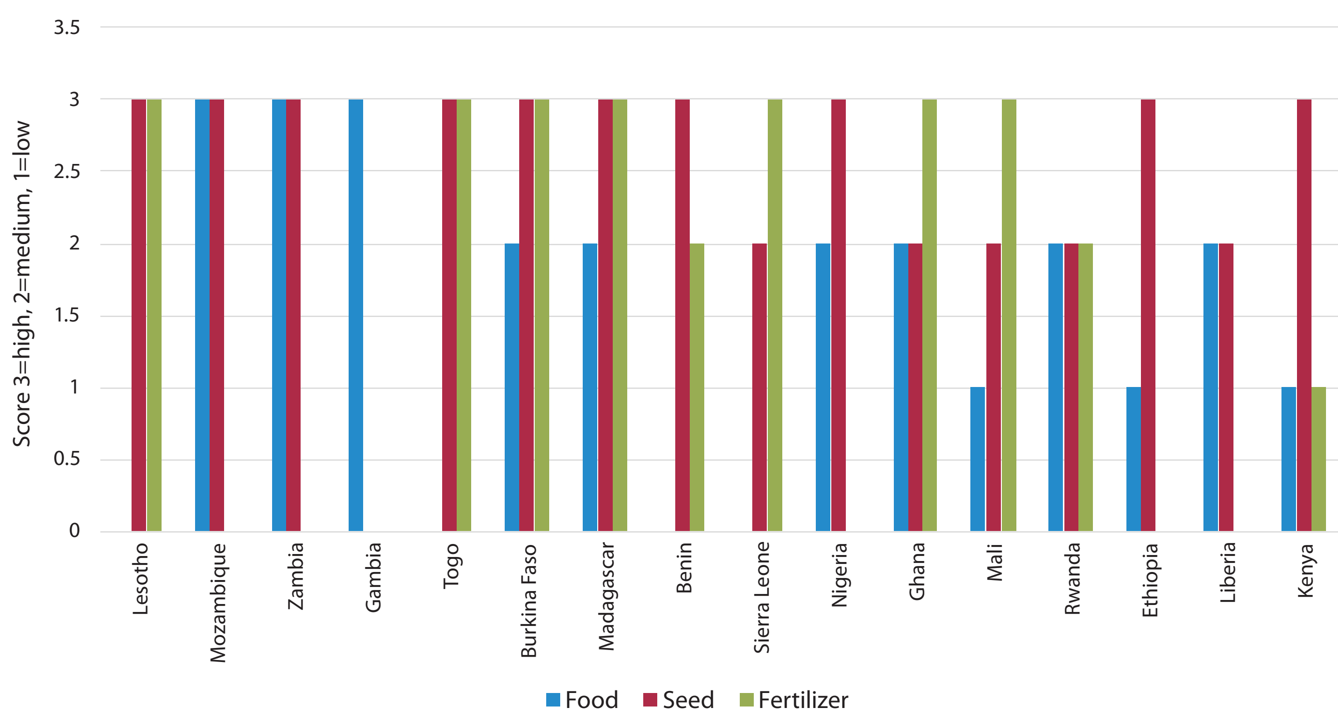
With regard to specific social groups, although most transfer programs during the pre-pandemic period targeted the poorest population only and failed to include informal workers, informal workers began to be included in social protection programs adopted in developing countries during the pandemic (Bilo et al. 2021). This is likely in response to the fact that the informal sector has been one of the hardest hit by the pandemic. A brief published by the International Labour Organization in September 2020 revealed that about 1.6 billion informal workers have been affected worldwide following the lockdown and containment measures that governments devised to combat COVID-19 (ILO 2020).

Timeliness of Delivery

Unlike with other policy actions, the effectiveness of an emergency response greatly depends on the timeliness, or time effectiveness, of delivery. Timeliness also depends on the sources of the transfers. We assessed the timeliness of sample countries' in-kind transfers of food, seed, and fertilizer using the effectiveness codes specified above.

The timeliness scores of sample countries are presented in Figure 6.8. As described above, the timeliness score is measured against containment time for food, and planting time for seed and fertilizer. The score also considers the sources (market or reserves) of the transfers. On average, countries such as

FIGURE 6.8—IMPLEMENTATION TIMELINESS SCORES FOR THE CASE STUDY COUNTRIES



Source: Authors' computation using experts' interview data.

Note: Implementation timelines scores are based on the extent to which a country implements the transfer or regulation in line with the time of containment for food and planting time for inputs.

Gambia, Mozambique, Lesotho, Togo, and Zambia rank higher than the others. However, these countries have implemented responses in only a few sectors.

Figure 6.8 also shows that seed and fertilizer transfers were timelier than food transfers. Most countries procured seed and fertilizer from markets and delivered them on time (before or at planting time). Similarly, most countries (9 out of 11) were able to deliver food transfers before or at the time containment measures were implemented, but most of these countries used foods from stocks. Only three countries (Gambia, Mozambique, and Zambia) were able to procure foods from markets ahead of time and deliver them on time. The use of virtual and physical food reserves is an important policy consideration in managing emergencies and risks (von Braun and Torero 2008). Keeping physical food reserves is usually costly but helps countries to deliver support on time. If a country depends on markets (virtual reserves) and is also able to deliver on time, this is considered the most effective policy response in terms of timeliness. However, from the sample countries' experience, it seems that unlike for transfers of farm inputs, reserves are critical to deliver food transfers on time.

Use of Task Forces and Digital Technologies

In addition to protecting consumer, farmer, and business welfare, governments are obliged to minimize the direct public cost of implementing social protection measures (Baird, McIntosh, and Ozler 2009; Devereux and White 2010). In many cases, the cost of implementation depends on the institutional arrangements and the types of technologies that are put in place to implement the emergency response. For example, the use of e-government resources for stakeholders coordination has significantly contributed to the effectiveness of program implementation (Ashaye and Irani 2019). An emergency-response task force assisted by information and communications technology can improve implementation effectiveness by enhancing accountability and mutual responsibility. The use of virtual platforms for monitoring progress and, more importantly, for procuring and delivering transfers is also critical not only to minimize the cost of implementation but also to increase the welfare effects of transfers. Innovations such as virtual platforms, warehouse vouchers, and smart subsidies, among others, facilitate timely implementation of the support as well as the effective targeting of households (Hidrobo et al. 2014). These innovations also reduce the costs of handling transfers. We assessed the innovativeness of sample countries using ordinal scores, as described above.

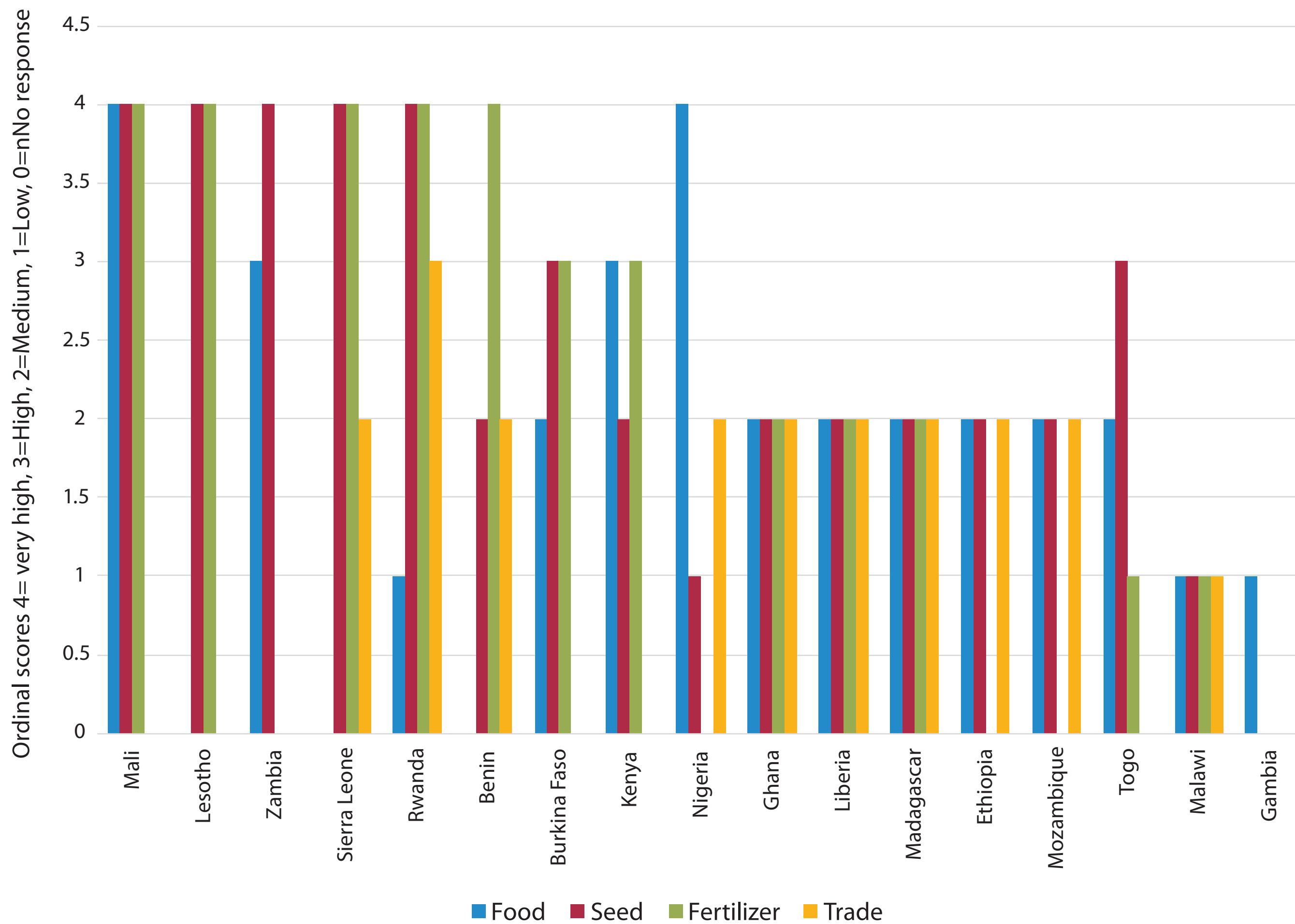
Figure 6.9 reports the ordinal scores of sample countries regarding policy implementation innovativeness (the use of task forces and digital technologies) across sectors (types of support), ordered by average scores from top to bottom. The results vary across types of economic support. In food support, only two countries (Mali and Nigeria) used warehouse voucher systems to procure and deliver transfers. Similarly, only two countries (Kenya and Zambia) used digital platforms to monitor the implementation of transfers from procurement to delivery. As explained earlier, these four countries could have been the most cost-effective ones regarding food emergency responses. Many countries organized task forces to oversee the implementation of food support.

Unlike for food support, many countries used warehouse voucher systems for input support. Lesotho, Mali, Rwanda, and Sierra Leone used voucher systems to transfer both seed and fertilizer. These countries are among the highest-ranking ones when it comes to innovativeness (Figure 6.9). As expected, many countries used only task forces for trade support implementation; the exception is Rwanda, which used both digital platforms and task forces for facilitating trade and monitoring the implementation of trade policies.

The high performance of some of the sample countries, such as Mali, might be surprising given reported issues with fertilizer distribution and cotton farmer boycotts due to the challenges of COVID-19 (Theriault, Tschirley, and Maredia 2021; Wangchuk 2021). However, our results show that the few responses implemented by the government perform reasonably well. Moreover, Mali performs best with certain indicators, such as innovativeness. The adoption of innovative approaches might have been promoted by external support rather than internal state capacity. Mali obtained support for several COVID-19 response projects from international donors (for example, the United States Agency for International Development) in 2020, and this may have helped the country to design quite innovative approaches to implement the responses.

A high level of innovativeness in implementing COIVD-19 responses may reduce the cost of implementation. However, it may not help to minimize embezzlement and corruption due to low governance capacity. This has been witnessed in many countries, which have shown high performance in many of the indicators discussed above but have performed poorly in the governance of transfers. For example, in Kenya the cash transfer program reached a very small proportion of those in need (Jerving 2021). The approach used to select recipients was not transparent and resulted in the exclusion of thousands of households that should have qualified for support. In Nairobi, the cash transfer program reached only 5 percent of the vulnerable population. Moreover, even though the program was intended to provide weekly cash transfers for several weeks, many households received transfers for periods as short as two to four weeks. To make matters worse, households that were in a better situation were allowed to benefit from the transfer program. Political leaders were alleged to have funneled some funds to friends, relatives, and supporters (Jerving 2021).

FIGURE 6.9—INNOVATIVENESS IN IMPLEMENTING COVID-19 RESPONSES



Source: Authors' computation using experts' interview data.

Note: Innovativeness scores are calculated by summing the ordinal scores of use of task forces and use of digital technologies for implementing and monitoring COVID-19 transfers and regulations ($TF_{ij} + DT_{ij}$).

Impacts and Best Practices

The Role of Policies for Mitigating COVID-19 Impacts

In this section, we explore the importance of policy responsiveness and implementation performance in shielding populations from the impacts of COVID-19, using the impact on local food prices as an example of an economic outcome. The policies were designed mainly to shield households and economies from welfare (consumption and production) shocks and macroeconomic instability. However, they could also affect markets by stabilizing prices, though we expect the impact on prices to be much smaller than the impacts on welfare and macroeconomic stability. Since we lack comprehensive and comparable data on the welfare and macroeconomic effects of COVID-19, we examined the impacts of COVID-19 on staple food prices in sample African countries that have shown varying levels of performance on policy responsiveness and implementation. The price impact studies were obtained from a series of analyses carried out by researchers at AKADEMIYA2063 and published as bulletins.[1] However, before we present the comparison of policy performance and COVID-19 effects on market prices, we summarize the typology of countries based on the two performance indicators presented above: the sector policy responsiveness (SPR) and program implementation performance (PIP) indexes.

Table 6.1 presents the typology of countries based on their food policy response performance indicators. Sample countries are divided into four groups. The first group consists of countries that were not responsive or were less responsive and less effective in implementing the programs. The second group includes countries that were effective in implementing the programs but were less responsive. The third group consists of countries that were responsive but less effective in implementing their responses. The fourth group includes countries that were responsive as well as effective in implementation. Table 6.1 is based on performance scores for food support programs. The typology may vary across sectors, as countries could perform better in some sectors than in others.

TABLE 6.1—TYPOLOGY OF COUNTRIES BASED ON FOOD SECTOR POLICY RESPONSIVENESS (SPR) AND PROGRAM IMPLEMENTATION PERFORMANCE (PIP) SCORES

Group 1	SPR	PIP	GROUP 2	SPR	PIP
Benin	0	0.0	Zambia	5	21.6
Lesotho	0	0.0	Mozambique	10	18.9
Sierra Leone	0	0.0	Rwanda	10	16.2
Togo	5	10.8	Madagascar	15	18.9
Malawi	10	5.4	Mali	15	21.6
Group 3	**SPR**	**PIP**	**GROUP 4**	**SPR**	**PIP**
Liberia	20	13.5	Ghana	20	16.2
Burkina Faso	25	13.5	Kenya	20	16.2
Gambia	25	13.5	Nigeria	20	21.6
			Ethiopia	25	16.2

Source: Authors' computation based on experts' interview data.

We used the typology presented above to examine the role of policy responses to protect food markets in the selected sample countries. We selected one country from each group, for which we obtained comparable price outcome indicators. As shown in Table 6.2, we explored the impact of COVID-19 on maize prices for Malawi, which has low scores for both SPR and PIP; Mozambique, which has a low score for SPR but a higher score for PIP; Burkina Faso, which has a high score for SPR and a low score for PIP; and Kenya, which shows high scores for both SPR and PIP. We assume that both large increases and large decreases in food prices are potentially harmful due to their effects on consumers and producers, and thus we look at the magnitude of impacts rather than their direction. We expect that successful COVID-19 response policies will result in lower-magnitude price changes.

1 For all AKADEMIYA2063 bulletins related to price impacts, see https://akademiya2063.org/food-price-tracking.php#bulletins.

TABLE 6.2—POLICY RESPONSE PERFORMANCE SCORES AND THE IMPACTS OF COVID-19 ON MAIZE PRICES IN SELECTED AFRICAN COUNTRIES

Country	Policy performance indicator scores		Average price impact due to COVID 19 (%)	
	SPR	PIP	Deficit areas	Surplus areas
Malawi	10	5.4	-50.0	-40.0
Mozambique	10	18.9	-30.0	-55.9
Burkina Faso	25	13.5	2.4	-0.4
Kenya	20	16.2	10.3	-0.3

Source: Authors' calculation based on AKADEMIYA2063 research bulletins (https://akademiya2063.org/covid-19.php).
Note: PIP = program implementation performance; SPR = sector policy responsiveness.

The result is vividly clear. Of the four countries, those that were responsive and effective in implementing the polices were able to stabilize food prices in both deficit and surplus markets. COVID-19 had higher-magnitude impacts on food markets in Malawi and Mozambique, which have lower overall scores (the sum of SPR and PIP). COVID-19 had less impact on food markets in Burkina Faso and Kenya, which had higher overall policy performance scores. Regarding the relative importance of responsiveness and implementation effectiveness, it seems that responsiveness has a better shielding effect for food markets than effectiveness. Burkina Faso, which has a higher responsiveness score, showed lower COVID-19 effects on food prices than Mozambique, which has a higher PIP score. We measure implementation effectiveness in terms of targeting, timeliness, and innovativeness, factors that are more important for welfare effects than for market-level effects. Thus, the superiority of responsiveness over implementation effectiveness in protecting markets from COVID-19 is not surprising.

Emergency Response Performance and Best Practices

To identify best practices in designing and implementing emergency policy responses, we developed a relative emergency response performance (ERP) score using a correlation-weighted performance score of the four performance indicators explained above: responsiveness, targeting effectiveness, timeliness, and innovativeness.

TABLE 6.3—THE SIX BEST-PERFORMING COUNTRIES IN TERMS OF EMERGENCY RESPONSE PERFORMANCE (ERP) SCORE

Sector	Country	ERP score	Sector	Country	ERP score
Food	Nigeria	1.82	Trade	Sierra Leone	1.93
	Mali	1.28		Liberia	1.93
	Zambia	1.16		Ghana	1.43
	Ethiopia	1.00		Nigeria	1.43
	Kenya	0.97		Ethiopia	1.29
	Ghana	0.92		Benin	1.29
Seed	Lesotho	1.96	Fertilizer	Lesotho	2.22
	Sierra Leone	1.44		Sierra Leone	2.22
	Togo	0.97		Mali	1.71
	Rwanda	0.86		Benin	1.42
	Nigeria	0.76		Rwanda	1.42
	Mali	0.70		Madagascar	1.08
Overall	Rwanda	0.85	Overall	Ghana	0.55
	Madagascar	0.70		Mali	0.52
	Sierra Leone	0.69		Kenya	0.44

Source: Authors' computation based on experts' interview data.

Table 6.3 presents the list of the six best-performing countries based on the ERP score in each sector. The overall (average) ERP score across all sectors indicates that Rwanda, followed by Madagascar and Sierra Leone, is the best-performing country among the sample countries. However, the list of best-performing countries varies across sectors.

Though the definition of best practices is always elusive and varies significantly depending on the context and type of practice (for example, technology versus policy, process versus outcome), best practices should meet certain common criteria: (1) they should be empirically tested and evidence should exist to verify their performance, and (2) they should be replicable or scalable. Thus, we defined best practices as policy options that have been practiced by many of the best-performing countries in terms of relative emergency response performance.

Table 6.4 shows the percentages of best-performing countries that adopted various policy options. The best practices depend on the type of emergency responses. For example, targeting using one priority criterion is associated with higher performance in food policy responses, while multiple criteria are needed to achieve higher performance in other sectors. For fertilizer response, reliance on markets for procurement has led to higher performance than use of stocks. Countries that use warehouse voucher systems for agricultural inputs perform better than others. Unlike other sectoral responses, almost all the countries performing best in trade response organized task forces to facilitate and monitor implementation of trade support in order to combat the adverse effects of COVID 19. This indicates that social protection measures should be designed and implemented based on the type of sector or economic agent that the measures aim to support.

TABLE 6.4—PERCENTAGES OF BEST-PERFORMING COUNTRIES PRACTICING POLICY OPTIONS

Policy option	Overall	Food	Seed	Fertilizer	Trade
Use of either transfers or regulation	34.29	33.33	16.67	33.33	33.33
Use of both transfers and regulation	65.71	66.67	83.33	66.67	66.67
Targeting using only one criterion	45.71	66.67	33.33	33.33	33.33
Targeting using multiple criteria	40.00	33.33	66.67	66.67	66.67
Use of stocks	31.43	33.33	50.00	33.33	n.a.
Market-based response	51.43	16.67	50.00	66.67	n.a.
Use of task force	42.86	33.33	0.00	16.67	100.00
Use of digital system for monitoring and evaluation	17.40	33.33	16.67	0.00	0.00
Use of warehouse vouchers	34.29	33.33	66.67	83.33	0.00

Source: Authors' calculation based on AKADEMIYA2063 research bulletins (https://akademiya2063.org/covid-19.php).
Note: n.a. = not applicable, "Overall" represents all the sectors together.

Conclusion

The purpose of this chapter is to explore the performance of African countries in designing and implementing policy responses to combat the adverse effects of COVID-19, and to identify best practices. To this end, we measured policy responsiveness and implementation performance and the roles of these factors in shielding markets and households from COVID-19 impacts. We also estimated a systemic performance indicator that qualitatively measures the relative capacity of a country in addressing emergency challenges and identified best practices that contributed to higher emergency response performance across sectors.

From the results presented in the chapter, we draw three major findings. First, although most African countries provided less direct income support to employees, almost all countries responded at the sector level by delivering in-kind support to vulnerable consumers, producers, and traders, for which targeting, timeliness, and cost-effectiveness are critical. However, the types and intensity of responses varied across countries and sectors. Second, effectiveness in implementing responses is as important as adopting a response to shield markets and vulnerable households from the adverse impacts of COVID-19. However, the effectiveness of countries in targeting and ensuring timely delivery of support and the use of innovative approaches is very low. Third, countries that adopt both transfer and regulatory supports as well as market-based responses score the highest in overall emergency response performance. However, the identified best practices vary across sectors, and it is unclear how index scores reflect real-world performance.

In general, the empirical analysis has indicated the need for a new way of thinking to enhance the performance of policy responses to threats that differ from conventional risks in terms of both coverage and consequences. Risks that cover the globe, limit the transfer of goods and services, and restrict physical contact require a different type of preparedness and innovative approaches for implementation. Thus, it is critical to identify and prioritize areas that are limiting the overall performance of a country's policy responses. Understanding the interconnectedness of policy processes is also very important. For instance, the use of warehouse vouchers has been an important innovation in implementing effective targeting using multiple criteria. Unlike the well-developed food supply chains in developed countries, where COVID-19 has revolutionized food systems through e-commerce, the extent of digital innovativeness in Africa is very much limited to warehouse receipt systems and the use of information and communications technologies for monitoring the delivery of food and other support transfers. This implies that African countries will need to mobilize their international e-commerce experience to improve the resilience of urban food systems.

The chapter assessed the implementation (process) performance of COVID-19 policy responses very qualitatively, with the objective of stimulating discussion among development researchers and practitioners rather than providing quantitative and exhaustive evaluations of the responses' effectiveness and impacts. Thus, further research is needed to verify the actual effectiveness and impacts of the policy interventions. The effectiveness study could focus on comparing the costs of implementation with the innovations adopted and the number of people benefitting from the programs using detailed data from program implementers. The impact evaluation could focus on estimating the welfare and resilience impacts of the interventions using data from program beneficiaries. The long-term community and market-level impacts of the responses could also be studied using comparable household and market-level data. The findings presented in this chapter can help to identify the impact pathways as well as the specific interventions to be evaluated. They can also serve as benchmarks to help select countries and/or to make comparisons across the case study countries, which are at different levels of COVID-19 policy response implementation.

CHAPTER 7

Delivery of Social Protection Programs to Combat COVID-19 in Africa

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Introduction

The COVID-19 pandemic has prompted governments across the world to introduce unprecedented lockdowns and other restrictions on mobility to slow the spread of coronavirus and to avoid overwhelming healthcare systems. While often necessary, these measures have led to well-documented disruptions in economic activity (World Bank 2020e). Consequently, many experts and international organizations have raised serious concerns about increased poverty and threats to food and nutrition security (Headey and Ruel 2020; Laborde et al. 2020; Laborde, Martin, and Vos 2020; Torero 2020). In April 2020, the World Food Programme warned that the number of acutely food insecure people in the world could double by the end of 2020 without concerted action (WFP 2020).

Alarmed by this unprecedented crisis, many governments have expanded their existing social protection programs or announced new measures (Gentilini et al. 2020). While there is now strong evidence that social protection programs can be effective in reducing poverty and improving food security (Andrews et al. 2018; Bastagli et al. 2019; Hidrobo et al. 2018), the evidence of their effectiveness during the ongoing pandemic remains limited. Therefore, in this chapter we try to understand the potential effectiveness of social protection measures taken by African governments during the COVID-19 pandemic in 2020 and review the available empirical literature on this topic. We then use case studies to examine the delivery of social protection during the pandemic. More specifically, we assess the targeting accuracy of social assistance (that is, noncontributory transfers to the poor) in three countries for which high-frequency phone survey data are available: Ethiopia, Malawi, and Nigeria.

Social Protection in Africa

The State of Social Protection in Africa Before the COVID-19 Pandemic

Over the last two decades, social safety net programs have become a mainstream policy tool to address poverty and food insecurity in Africa. These programs aim to reduce chronic poverty through cash or in-kind transfers to the poorest and most vulnerable people. The number of social safety net programs has more than doubled since 2000 (Hickey et al. 2018) and today, virtually all African countries implement at least one social assistance program (Beegle et al. 2018b).

This emerging policy focus is backed up by strong evidence that social assistance programs improve food security and build up assets, thus reducing the risk of chronic poverty (Andrews et al. 2018; Hidrobo et al. 2018). Moreover, investments in social protection programs can also contribute to economic growth by encouraging savings, creating community assets, and addressing credit market imperfections (Alderman and Yemtsov 2014; Filipski et al. 2016; Hirvonen et al. 2021).

Social assistance programs in Africa have traditionally had a strong focus on rural areas (Beegle et al. 2018a), where the majority of chronically poor people reside (World Bank 2016). In the context of the COVID-19 pandemic, lockdowns and other measures to limit the spread of the virus are likely to have stronger negative welfare effects in urban areas. This is because the livelihoods of urban residents are more likely to depend on sectors that are more adversely affected by travel bans and social distancing policies (Abay et al. 2020b). Recent national accounts data from Africa show that the sectors that are relatively more important for urban residents, such as the service and industrial sectors, have been those most negatively affected during the pandemic (Zeufack et al. 2021). Meanwhile, the agricultural sector—the sector that provides the livelihoods of most rural residents—actually expanded during 2020 (Zeufack et al. 2021). Consequently, the World Bank predicts that urban people are more likely to be pushed below the poverty line as a result of the pandemic (Nguyen et al. 2020). The limited focus on urban social protection before the pandemic meant that many African countries did not have a readily available social protection platform available in urban areas when the pandemic began. As noted by Gentilini and colleagues (2021), in this regard, the pandemic has highlighted an important vulnerability in social protection programming in Africa.

Social Protection Policy Measures During the Pandemic

Most African governments announced new measures during the pandemic or made adjustments to their existing social protection programs (Gentilini et al. 2020). For example, in July 2020, Zambia announced a new cash transfer scheme to assist vulnerable communities affected by the COVID-19 pandemic (UNICEF

2020b). With support from the World Bank, South Sudan expanded its South Sudan Safety Net Project to cover more poor and vulnerable households (World Bank 2020g). Meanwhile, the Moroccan government targeted cash transfers to workers employed in sectors negatively affected by the pandemic (Paul-Delvaux et al. 2020). A number of African countries also adjusted their social insurance programs (Gentilini et al. 2020). For example, South Africa established a new National Disaster Benefit Fund to compensate workers affected by the lockdown measures (South Africa 2020), and the Tunisian government provided additional support to those with small pensions (Kokas et al. 2020). Below, we discuss the available evidence of the effectiveness of social protection during the pandemic before focusing on three case studies in Ethiopia, Malawi, and Nigeria.

Evidence of the Effectiveness of Social Protection During the Pandemic

Background

Many of the existing social protection programs in Africa were designed to protect against chronic poverty and income shocks induced by natural disasters such as droughts and floods. The COVID-19 pandemic has been a very different type of shock, simultaneously affecting health outcomes, incomes, and food systems, as well as complicating the logistics of delivering assistance. Thus, an important question is whether traditional social protection approaches remain effective for shocks like the current pandemic (Banerjee et al. 2020). Unfortunately, careful research takes time, and just one year into the pandemic, evidence of the effectiveness of social protection programs against the negative impacts of the COVID-19 pandemic is still scarce. In this section, we review the emerging evidence on this question.

Review of the Available Evidence

Taking advantage of an experimental approach, Banerjee and colleagues (2020) studied the effectiveness of a universal basic income (UBI) scheme in rural Kenya during the pandemic. The authors found that the UBI scheme resulted in modest positive effects on food security as well as on physical and mental health. The UBI recipients were also more likely to adhere to social distancing measures and were less likely to visit hospitals during the pandemic. However, previous income gains facilitated by the UBI were wiped out during the pandemic.

Also in Kenya, Brooks and colleagues (2021) used an experimental approach to study the impact of a one-time cash transfer to female-led microenterprises located in a low-income suburb of Nairobi. The authors used Kenya's M-PESA mobile money service to provide a one-time cash transfer just before the COVID-19 infections in Kenya began to escalate. Measured against a control group, the group that received a one-time cash transfer substantially increased its inventory spending, revenues, and profits. The transfer also led to increased spending on personal protective equipment (PPE) as well as to the establishment of management practices to minimize the spread of the virus. However, this latter finding was applicable only to those who believed that the COVID-19 virus posed a serious health threat, thus highlighting the need to combine transfers with awareness creation.

Elsewhere, Abay and colleagues (2020a) used household survey data collected in August 2019 and during the pandemic in June 2020 to study the extent to which Ethiopia's rural Productive Safety Net Programme (PSNP) protected its beneficiaries against the negative effects of the pandemic. They found that self-reported food insecurity increased considerably in these areas during the first months of the pandemic but considerably less among households supported by the PSNP. While the prepandemic data on the PSNP showed that the program has been successful in improving food security and resilience (Berhane et al. 2014; Knippenberg and Hoddinott 2017), the new evidence implied that the PSNP could also protect against shocks induced by pandemics.

Evidence from non-African countries provides further support for the notion that social protection can be effective during pandemics. A new unconditional cash transfer program rolled out in Colombia during the pandemic and targeting poor households improved household food access and reduced the need for asset depletion and borrowing (Londoño-Vélez and Querubin 2020). In Bolivia, Bottan and colleagues (2021) found that a large-scale noncontributory pension program had sizable positive impacts on food security during the early months of the pandemic, particularly protecting poor households and those who lost their livelihoods.

Targeting of Social Protection During the Pandemic

Background

One of the key conditions for effective social protection programming is that the assistance be targeted at the right people. Therefore, to complement the evidence reviewed above, in this section, we provide some new analyses to assess the targeting accuracy of social assistance during the pandemic. To do so, we use data from high-frequency phone surveys collected by the World Bank in Ethiopia, Malawi, and Nigeria (World Bank 2020a; 2020c; 2020d). [2] In all three countries, the World Bank conducted at least five phone survey rounds after the pandemic was declared. The samples for these phone surveys were drawn from in-person surveys conducted before the pandemic. The prepandemic household surveys collected rich information about household demographics, including detailed data on the different types of durable assets owned by households. We applied principal components analysis methods to construct simple wealth indices that allowed us to rank households by quintiles based on their prepandemic wealth levels (Sahn and Stifel 2003). These wealth indices were constructed separately for rural and urban households. Table 7.1 profiles households in each quintile. In all countries, household literacy levels increased with wealth levels. There were no obvious patterns with respect to household size in Ethiopia and in Nigeria, but in Malawi, richer households were, on average, larger than poorer households. In all three countries, poorer households tended to have slightly higher dependency ratios than richer households. In Nigeria and Malawi, poorer households were more likely to be headed by females, but this was not the case in Ethiopia, where female-headed households were more equally distributed across wealth quintiles.

We then used the high-frequency phone survey data collected during the pandemic to calculate the share of households within each wealth quintile that reported receiving social assistance at any point during the pandemic. A progressively targeted program would have covered a large percentage of the poorest households and a small percentage of the wealthiest households. We conducted the targeting analyses separately for rural and urban areas, and we used sampling weights provided by the World Bank to correct for possible sampling biases in phone surveys resulting from unequal and nonrandom access to mobile phones.

Ethiopia Case Study

The first COVID-19 case in Ethiopia was confirmed on March 13, 2020. By the end of February 2021, more than 150,000 people had tested positive and more than 2,000 deaths were attributed to the virus (Ethiopia, Ministry of Health, and EPHI 2021). The overwhelming majority of the positive tests were in the capital, Addis Ababa (Ethiopia, Ministry of Health, and EPHI 2021). Figure 7.1 provides the timeline of policy measures compared with COVID-19 caseloads in Ethiopia.[3]

The first policy measures to limit the spread of the virus in Ethiopia were declared on March 16, just three days after the country's first confirmed case. The government of Ethiopia closed schools, banned all public gatherings and sporting activities, and encouraged physical distancing. Travelers from abroad were put into mandatory quarantines, bars were closed until further notice, and travel across land borders was prohibited. Several regional governments imposed further restrictions on public transportation and other vehicle movement between cities and rural areas.

A federal-level state of emergency was declared on April 8. Land borders were closed, except for cargo transportation. Face mask use was made compulsory in public spaces. Restrictions on cross-country public transportation and city transportation were also declared (for instance, public transportation vehicles were limited to half of their regular carrying capacity). Moreover, the government prohibited employers from laying off workers and property owners from evicting tenants or increasing rents during the state of emergency. Some administrative regions took even stricter measures by closing restaurants and limiting movement between rural and urban areas. However, unlike some other

2 Josephson and colleagues (2021) used these data to study socioeconomic impacts of the pandemic in selected African countries.

3 Confirmed case numbers depend on both the extent of testing and the quality of contact tracing. Therefore, the true caseload is likely to be higher than the confirmed caseload. Confirmed cases are thus a good illustration of trends, but not necessarily of levels.

TABLE 7.1—SELECTED HOUSEHOLD CHARACTERISTICS, BY ASSET QUINTILE

	Poorest	Poorer	Middle	Richer	Richest
Ethiopia, rural					
Household size, mean	4.9	4.8	4.5	5.0	4.8
Dependency ratio, mean	0.47	0.46	0.44	0.44	0.43
Head's age, mean	45.5	46.7	44.1	43.3	42.2
Female head, %	24.5	29.1	30.6	25.7	22.7
Literate, %	69.6	69.9	67.8	80.4	89.9
Malawi, rural					
Household size, mean	4.1	4.1	4.8	5.0	5.1
Dependency ratio, mean	0.47	0.42	0.46	0.45	0.39
Head's age, mean	42.1	36.3	41.4	45.7	46.0
Female head, %	46.4	26.7	25.3	25.9	21.5
Literate, %	80.1	90.2	94.3	92.9	98.1
Nigeria, rural					
Household size, mean	5.1	5.9	6.0	5.6	5.5
Dependency ratio, mean	0.46	0.46	0.44	0.43	0.38
Head's age, mean	51.8	49.5	49.6	50.3	49.3
Female head, %	25.5	16.7	20.6	19.2	14.9
Literate, %	67.9	83.9	90.4	93.4	98.2

	Poorest	Poorer	Middle	Richer	Richest
Ethiopia, urban					
Household size, mean	4.0	3.3	3.5	3.7	4.4
Dependency ratio, mean	0.35	0.29	0.29	0.28	0.28
Head's age, mean	38.3	37.6	38.8	41.3	45.7
Female head, %	38.2	40.9	34.2	36.5	30.5
Literate, %	82.6	87.7	95.6	97.5	99.9
Malawi, urban					
Household size, mean	3.72	4.06	4.74	5.04	5.17
Dependency ratio, mean	0.37	0.34	0.36	0.36	0.29
Head's age, mean	35.4	38.9	40.6	41.4	44.5
Female head, %	29.1	26.0	19.1	19.2	14.8
Literate, %	94.0	95.4	99.9	100.0	100.0
Nigeria, urban					
Household size, mean	4.3	4.8	4.8	4.8	5.1
Dependency ratio, mean	0.46	0.39	0.36	0.38	0.34
Head's age, mean	51.6	49.4	46.8	47.7	49.6
Female head, %	35.6	27.7	18.2	15.6	10.9
Literate, %	82.3	95.0	99.1	99.7	99.4

Source: Constructed using prepandemic data from Living Standards Measurement Study - Integrated Surveys on Agriculture surveys conducted by the World Bank.

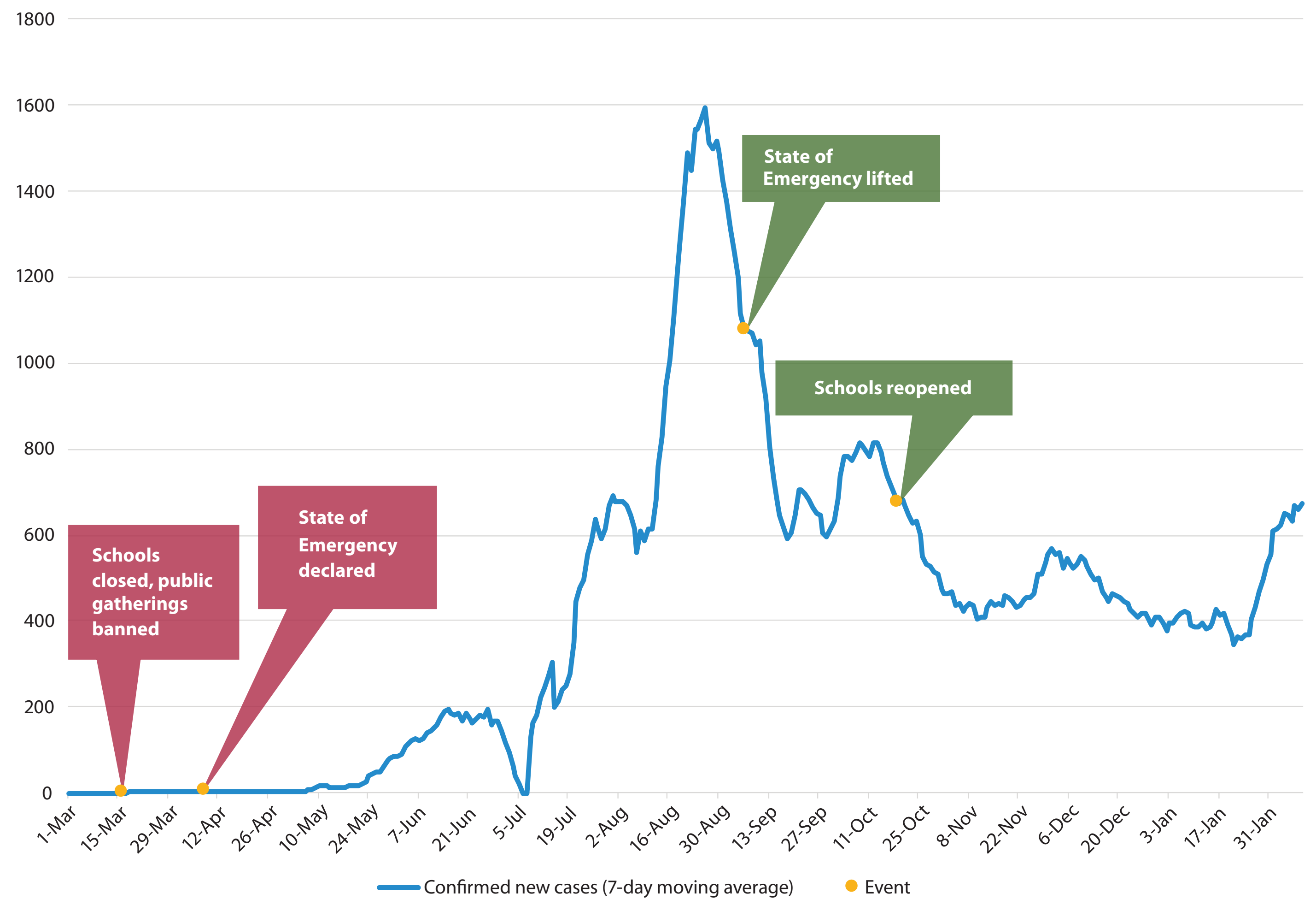
Note: The household was considered literate if at least one member was reported to be able to read and write in any language. The dependency ratio was defined as the number of dependents (those ages less than 15 and more than 65 years) divided by the total household size.

countries in the region, in order to protect the most economically vulnerable segments of the population, Ethiopia never went into a full lockdown that severely restricted movement, imposed curfews, or fully closed all borders (France-24 2020). The state of emergency was lifted on September 6, 2020. This meant largely returning to prepandemic life; transportation restrictions were lifted, bars were allowed to reopen, and face masks were no longer compulsory. Schools were reopened on October 19, 2020.

The main social protection response to COVID-19 in Ethiopia has come through the PSNP, which operates in both urban and rural areas. Launched in 2005 in food-insecure rural areas and in 2017 in selected urban areas, the PSNP is managed by the government of Ethiopia and is mostly funded by a consortium of international organizations and development partners. The PSNP provides monthly cash or food transfers in exchange for labor-intensive public works that build community assets. Eligible households with limited labor capacity receive unconditional cash transfers. Due to the pandemic, the public works requirement was waived and thus all beneficiaries were receiving unconditional transfers. At the beginning of the pandemic, beneficiaries also received three months of payments in advance (Gentilini et al. 2020). It was also announced that both the rural and the urban PSNP would expand to cover additional poor and vulnerable people as well as provide additional support to existing beneficiaries at a high risk of poverty (Gentilini et al. 2020). To this end, two months of additional support were provided to PSNP beneficiaries in most food-insecure rural areas. However, due to external funding constraints, these PSNP expansion plans never materialized in urban areas. In addition to the PSNP, a number of smaller-scale initiatives were launched to support poor and vulnerable households. These included food banks set up by city administrations, community support, and nongovernmental organization programs (Abate et al. 2020).

Ethiopia's PSNP combines geographical and community targeting. The rural PSNP covers the chronically food-insecure rural districts in all but two administrative regions (the program does not currently operate in Benishangul-Gumuz or Gambella). After district selection, communities themselves select the most vulnerable households to be part of the program. The urban PSNP currently operates in 11 major cities, and beneficiaries are selected by communities. In

FIGURE 7.1—TIMELINE OF THE COVID-19 PANDEMIC IN ETHIOPIA

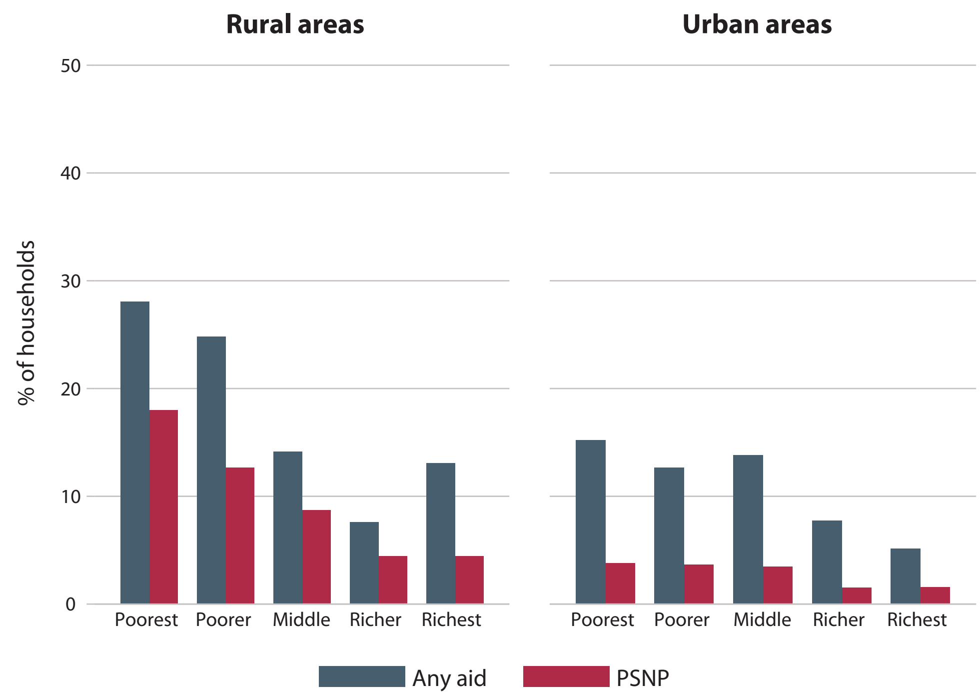


Source: COVID-19 case numbers from Dong, Du, and Gardner (2020).

addition to the PSNP, rural districts can request emergency food assistance. This is common: in unexceptional years, it is estimated that 5 million people, on average, are in need of humanitarian food aid (NDRMC 2018). A series of smaller support mechanisms such as food banks was set up during the pandemic, especially in urban areas.

Figure 7.2 shows the results of the targeting analysis. There was relatively strong progressivity in targeting during the pandemic: poorer households were generally more likely to receive transfers than richer households. This held both for rural and urban areas. In line with analyses done prior to the pandemic (World Bank 2020b), the progressivity was even stronger when analysis was restricted to support from the PSNP only. However, despite this progressivity, many poorer households did not receive any type of support during the pandemic, possibly due to funding constraints.

FIGURE 7.2—TARGETING OF SOCIAL ASSISTANCE DURING THE PANDEMIC IN ETHIOPIA



Source: Constructed using data from World Bank (2020a).

Malawi Case Study

Malawi registered its first case of COVID-19 on April 2, 2020. The disease then spread in two waves (Figure 7.3). The first wave peaked in late July 2020 and subsided toward the end of August. The second wave began in late December 2020, peaked in late January 2021, and was subsiding at the time of writing at the end of February 2021. By February 28, 2021, 31,945 cases were confirmed in the country, although the true number is likely to have been larger considering the limited testing.

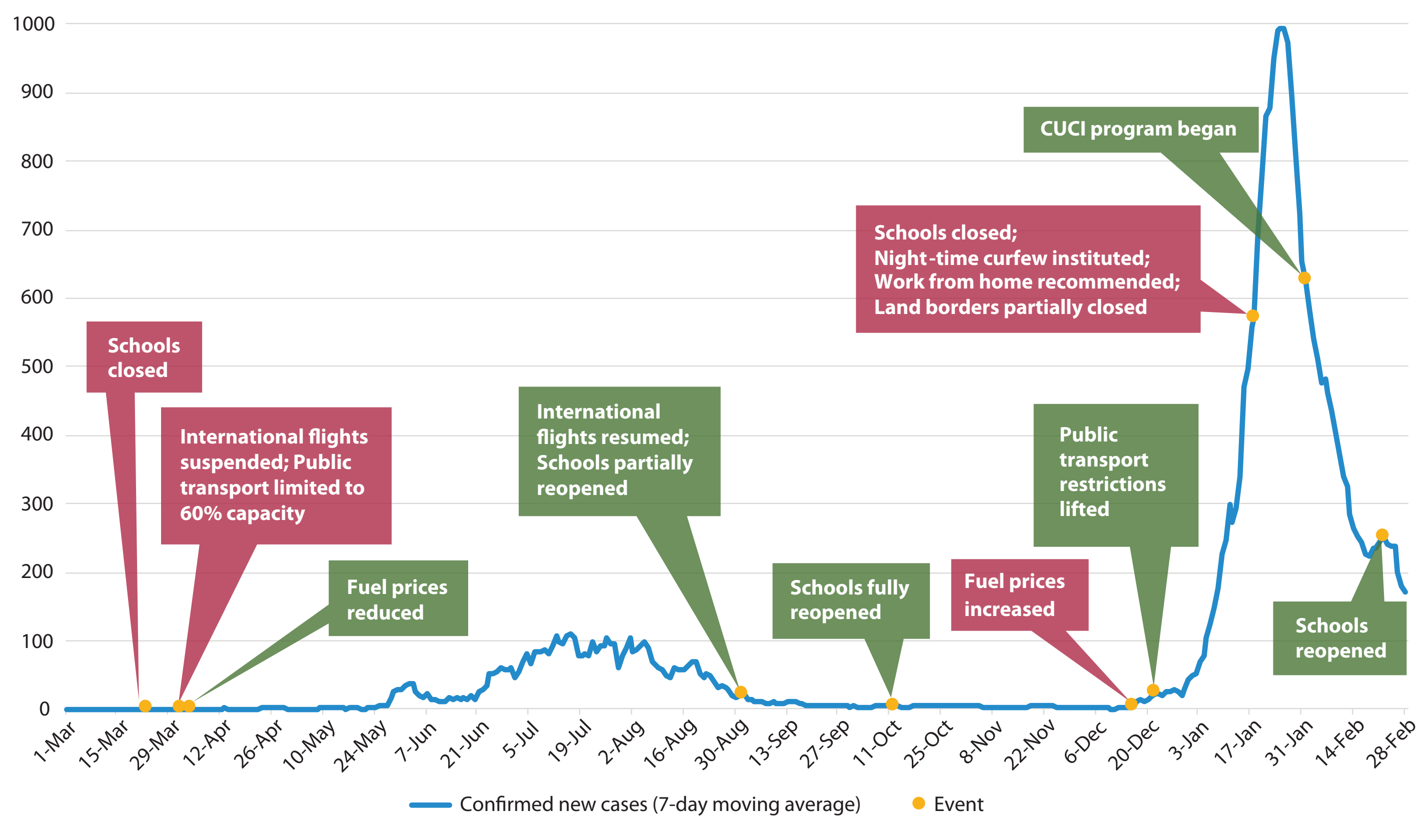
By the time the first case of COVID-19 was confirmed in Malawi, the government had already reacted to the unfolding global pandemic by closing all schools on March 23, 2020, and by suspending scheduled international flights and restricting the maximum number of passengers allowed on road public transport vehicles to 60 percent of capacity on April 1, 2020. Social distancing and wearing face masks in public spaces became mandatory but were not fully enforced or widely practiced until the second wave, in early 2021. Between mid-April and late June 2020, there was considerable uncertainty regarding restrictions on movement and economic activity after a full lockdown announced by the government was stayed and eventually ruled illegal by the judiciary, and thus never implemented. International travel restrictions were lifted on September 1 and instruction in schools was resumed in stages until all schools were fully operating by October 12, 2020. Restrictions on public transport were lifted on December 22, 2020, in response to an increase in retail prices of fuel. However, daily numbers of new COVID-19 cases started rising again by that time, and the restrictions were reintroduced on January 18, 2021, along with a nighttime curfew, a partial closure of land borders, a full closure of schools, and a recommendation to work from home where possible. Schools reopened again on February 22, 2021, but other restrictions remained in place at the time of writing.

The canceled April 2020 lockdown was widely regarded by the public as a political maneuver intended to disrupt Malawi's presidential elections (which were nonetheless held as scheduled on June 23, 2020), and the government's policy responses to counter the negative effects of restrictions on citizens' welfare were often viewed in a similar light (Dulani et al. 2021; Greer et al. 2021). The skepticism may have been justified, as the only major measure that was implemented during the first COVID-19 wave was a reduction in fuel prices on April 4. A vertical expansion of the Social Cash Transfer Programme (SCTP)—the country's flagship social safety net, under which the most vulnerable households in rural areas receive unconditional cash transfers—and an acceleration of SCTP payments, both announced on April 1, 2020, never materialized. A similar scheme targeting the urban poor was announced on April 28, 2020, but received funding only in October 2020 and was not implemented until February 2021.

The government of Malawi provides basic social protection to its most vulnerable citizens through the SCTP. The SCTP targets poor rural households with limited labor capacity using a mixture of proxy means testing and community targeting. In 2019, the program reached 6.4 percent of the Malawian population with monthly payments averaging the equivalent of US$9.40 per household (UNICEF 2020a). At the onset of the pandemic, the government made plans to expand the SCTP horizontally as well as vertically to lessen the impact of restrictive measures on the poorest households, but the plan never materialized. The SCTP also did not react to the pandemic within its existing structure until February 2021, when its first retargeting in six years began.

Instead of building on the existing structure of the rural SCTP, the government announced a parallel cash-transfer program targeting the urban poor. Dubbed the COVID-19 Urban Cash Intervention (CUCI), it did not receive funding until October 2020 and was not

FIGURE 7.3—TIMELINE OF THE COVID-19 PANDEMIC IN MALAWI



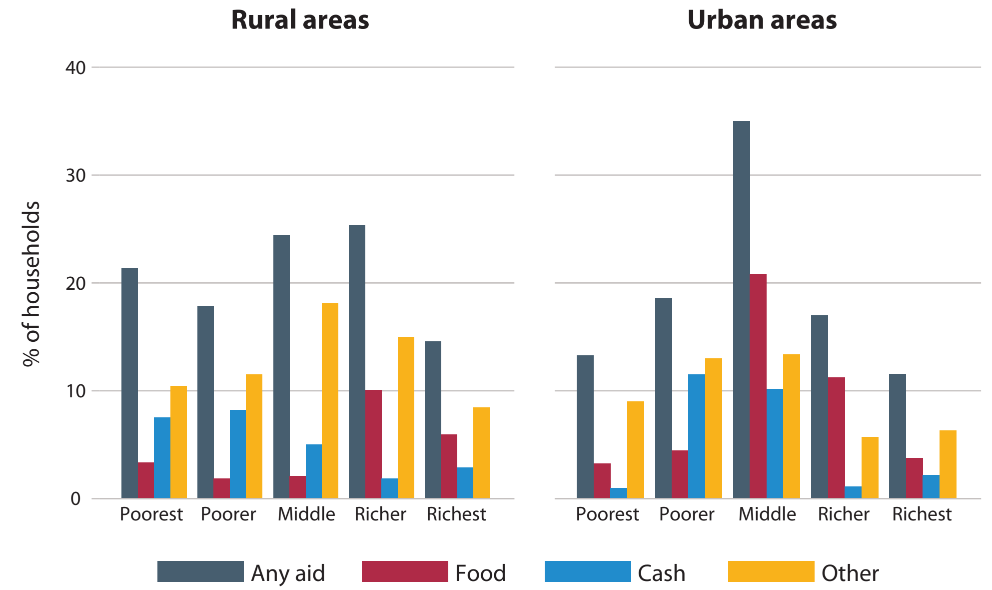
Source: COVID-19 case numbers from Dong, Du, and Gardner (2020).

rolled out until February 2021. In other words, while it might have alleviated some of the economic impact of the measures put in place to counter the second pandemic wave, it could not have helped during the first wave.

With government-run programs reacting to the pandemic at a relatively slow pace, most pandemic-related safety net adjustments seen in 2020 came from smaller, privately run initiatives and informal arrangements. These were numerous and fragmented, so it is no surprise that they were not particularly well targeted in the aggregate, as Figure 7.4 illustrates.

The targeting of social protection programs should, however, become more reflective of the impacts of the pandemic as the CUCI takes full effect and the SCTP gets retargeted in the first half of 2021. Rural households affected by the pandemic may further be helped in the first quarter of 2021 by the Lean Season Food Insecurity Response Programme (LS-FIRP), which delivers direct food or cash transfers to food-insecure households during the lean season. The LS-FIRP is billed as a humanitarian program rather than a social safety net, and it receives ad hoc funding, but it takes place every year and uses a formalized targeting process. The targeting of the LS-FIRP is similar to that used for the SCTP, but it is more flexible in reacting to acute crises like the COVID-19 pandemic because it takes place annually.

FIGURE 7.4—TARGETING OF SOCIAL ASSISTANCE DURING THE PANDEMIC IN MALAWI



Source: Constructed using data from World Bank (2020c).

Nigeria Case Study

Nigeria recorded the first case of COVID-19 on February 28, 2020, and the course of the pandemic there was similar to the course in Malawi, with a first wave peaking in July and a second wave in late January (Figure 7.5). The country had recorded more than 150,000 confirmed cases by February 28, 2021.

The Nigerian government introduced the first pandemic-related restrictive measures on March 26, 2020, when it closed schools, land borders, and—in several states—markets. Full lockdowns were introduced in a number of states a few days later. Despite a still-rising caseload, the government started phasing out daytime lockdowns on May 4 and nighttime curfews on June 2. Domestic flights resumed on July 8 and air borders reopened on September 5. Most schools reopened on October 1. The government introduced new measures in reaction to the second wave of infections on December 21 when it closed bars and restaurants, restricted public transport to 50 percent of vehicle capacity, and recommended working from home when and where possible. At the time of writing, these restrictions remained in place.

In recent years, the government of Nigeria has been in the process of revising its social protection framework. The National Social Investment Programmes were launched in 2016 encompassing a suite of initiatives, including a conditional cash transfer program, to support poor and vulnerable populations (World Bank 2019). The Nigerian government responded relatively quickly to the pandemic by introducing a temporary four-month expansion of its cash transfer scheme, from 2.6 million to 3.6 million households, on

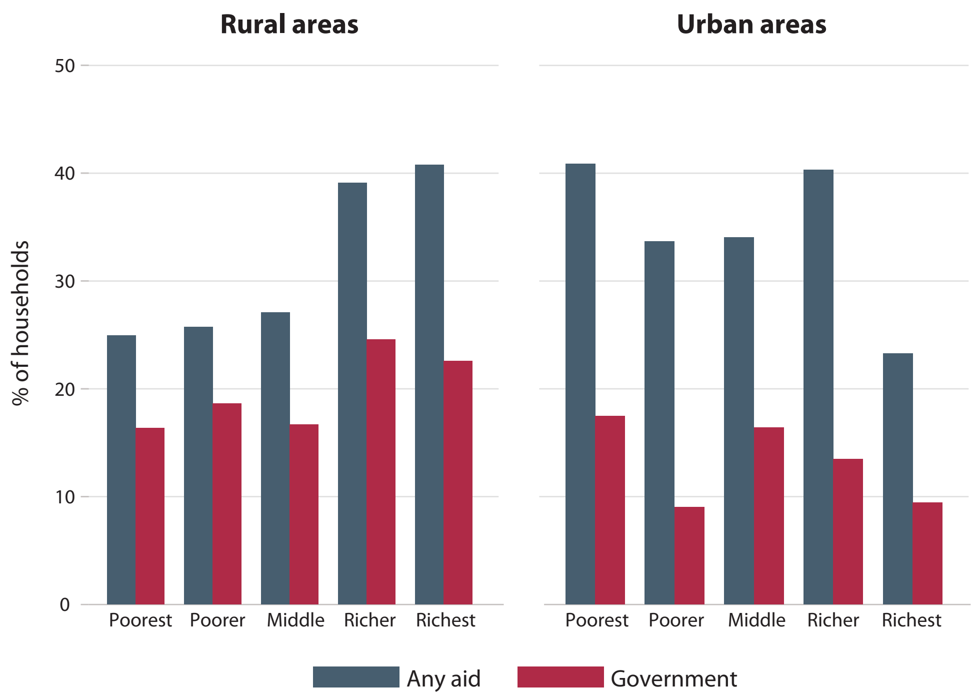
April 1, 2020. On the same day, a three-month program of direct food transfers to vulnerable households was announced in the states under lockdown. Furthermore, a program delivering meals to homes was introduced in several states on May 14 as a substitute for school feeding programs.

Nigeria has several state- and federal-level social protection programs that target poor and vulnerable people (World Bank 2019). In addition, informal social protection arrangements are also prevalent. Similarly to Ethiopia and Malawi, we assess the targeting of any type of aid and of aid from all government levels (federal, state, or local) to account for this complexity.

FIGURE 7.5—TIMELINE OF THE COVID-19 PANDEMIC IN NIGERIA

Source: COVID-19 case numbers from Dong, Du, and Gardner (2020).

FIGURE 7.6—TARGETING OF SOCIAL ASSISTANCE DURING THE PANDEMIC IN NIGERIA



Source: Constructed using data from World Bank (2020d).

Figure 7.6 shows the results of the targeting analysis. Judged by prepandemic wealth levels, the targeting of social assistance during the pandemic was highly regressive in rural areas. This result held when we focused only on support provided by the government. Targeting accuracy was slightly better in urban areas in the sense that compared with other households, the richest households were the least likely to receive assistance. While it is encouraging that more than 40 percent of urban households in the poorest wealth category received transfers, the targeting could not be characterized as progressive in urban areas either. These findings are in line with a recent World Bank report that noted that food transfers (which accounted for the largest share of the support during the pandemic) were more likely to go to households that were not poor (World Bank 2020f).

Conclusions

African governments reacted swiftly to the pandemic. A series of measures to limit the spread of the virus was quickly enacted. Most governments also made rapid adjustments to their existing social protection programs and many launched new ones to protect their poor and vulnerable citizens.

Research carried out prior to the pandemic provides strong evidence that social assistance in the form of cash or in-kind transfers is effective in improving food security and protecting assets (Hidrobo et al. 2018). The COVID-19 pandemic constitutes a new type of shock, simultaneously affecting health systems, livelihoods, and food systems. This raises the question of whether the old social protection models can still work in the face of a pandemic. While the emerging evidence reviewed in this chapter suggests that the answer to this question is yes, the evidence base remains too thin for us to draw definite conclusions.

One of the key conditions for effective social protection programming is that the assistance be targeted at the right people. As our case studies demonstrate, targeting accuracy during the first year of the pandemic was highly variable. Using prepandemic durable asset levels as the targeting metric, we find that the targeting of social assistance was progressive in Ethiopia, but not in Malawi or Nigeria. In all countries, a sizable number of the poorest households in both rural and urban areas were not covered by any social assistance program.

Together, these findings indicate that despite swift adjustments to the existing social protection programs and the launch of many new initiatives, many poor Africans did not receive sufficient assistance during the pandemic. Largely, this is due to insufficient coverage in many areas, but in some countries, the available resources also could have been targeted better.

Expanding social protection during the pandemic has proven difficult because the economic impacts of the pandemic have been truly global. Consequently, new funding from high-income countries was reduced, making it difficult for many lower-income countries to expand their existing programs or to launch new initiatives. Before the pandemic, more than 50 percent of social protection funding in Africa came from development partners (Bossuroy and Coudouel 2018), with some of the largest programs, such as the PSNP of Ethiopia, almost completely externally funded. The limited domestic funding of social protection leaves many African countries highly vulnerable during global crises such as pandemics. Therefore, and to ensure the long-term sustainability of these programs, it is paramount to build up effective domestic resource mobilization mechanisms as well as to strengthen domestic tax collection systems (Bruni et al. 2018; Hirvonen et al. 2018; Niño-Zarazúa et al. 2012).

As for improving targeting efficiency, previous work in this area notes that limited administrative capacity and imperfect information makes it difficult to identify the neediest and most vulnerable households (Coady et al. 2004). Therefore, databases of potential recipients need to be set up, as several countries in Asia and Latin America have done. For example, Indonesia maintains a unified targeting system that has been shown to be effective in reducing targeting errors (Tohari et al. 2019). There is also need for more investment in shock-responsive social protection systems that can be quickly scaled up following a shock and scaled down afterward (Roelen et al. 2018).

CHAPTER 8

Rethinking the Role of Social Protection in African Food Systems Post-COVID-19

Omar Benammour, Benjamin Davis, Marco Knowles, Noemi Pace, and Nicholas Sitko

Introduction

Efforts to contain the spread of COVID-19 have further exacerbated long-standing challenges within African food systems and exposed new sources of vulnerability in people's livelihoods. Emerging evidence demonstrates that the impacts of the COVID-19 pandemic across African food systems are heterogeneous. They vary across income groups, occupations, and geographies and are closely tied to the structural features of the food systems (Egger et al. 2021; Josephson, Kilic, and Michler 2020; Kansiime et al. 2021; Belton et al. 2021; Nechifor et al. 2021).

Structurally, African food systems are characterized by a highly uneven distribution of income and resources within and between actors in the system (Jayne et al. 2003; Sitko, Burke, and Jayne 2018); a preponderance of small-scale and informal actors (Reardon 2015; Sitko and Jayne 2014; Jayne, Mather, and Mghenyi 2010); limited access to formal risk management tools, including credit and insurance; and highly diverse and multivalent livelihood portfolios of many food system actors (Barrett, Reardon, and Webb 2001; Reardon et al. 2007; Davis et al. 2010; Davis, Di Giuseppe, and Zezza 2017). These unique features influence both the vulnerabilities of food system actors in the region and the potential distribution and severity of the welfare impacts caused by the pandemic (Liverpool-Tasie, Reardon, and Belton 2021). Although many countries in the region have implemented new or expanded existing social protection programs to mitigate welfare losses due to the pandemic, the majority of them have been of a relatively small scale in terms of additional populations covered, have been short in duration, and have bypassed many food system actors (Beazley, Marzi, and Steller 2021; Gentilini, Almenfi, and Dale 2020; Barba, van Regenmortel, and Ehmke 2020).

In this chapter we apply a food systems lens to examine how governments in Africa south of the Sahara (SSA) have responded to the COVID-19 crisis, focusing specifically on the social protection response, and to explore the emerging empirical evidence on the impacts the crisis is having on food system actors. We show that the social protection response to the COVID-19 crisis was largely insufficient to stem widespread and substantial welfare losses throughout African food systems and rural spaces. The findings highlight the urgent need to strengthen, reconceptualize, and redesign social protection systems in the region to support effective and inclusive postpandemic recovery efforts and to strengthen resilience to future shocks. Ultimately, we seek to provide conceptual guidance on how social protection systems can be leveraged not only to enhance the building back and resilience of African food systems but also to support more socially, economically, and environmentally sustainable food systems transformation in the region.

Livelihood Vulnerabilities of African Food System Actors in the Context of COVID-19

In this section we explore some of the key socioeconomic features of African food systems, how those features may influence the vulnerability of food system actors to welfare losses caused by the pandemic, and what that implies for leveraging social protection to mitigate such losses. Food systems consist of all the diverse actors and relationships involved in the primary production, aggregation, distribution, processing, and consumption of food, as well as in the distribution of inputs and provision of services for its production. For the purposes of this chapter we conceptualize the food system as comprising four principal actors: farm laborers; primary producers; value chain intermediaries (including aggregators, processors, retailers of food and agricultural inputs, and service providers); and consumers. The impacts of COVID-19 on the welfare of these actors are a function of their level of exposure to economic and health challenges created by the virus and associated control measures, and their socioeconomic capacity to withstand such shocks.

The first set of actors we consider is made up of farm laborers. In SSA, farm labor is overwhelmingly informal and seasonal, relying heavily on family members, particularly women (ILO 2018). It includes periodic piecework carried out on local family farms, as well as seasonal and permanent employment on commercial and estate farms. In SSA, agricultural wage laborers are the poorest of the poor and are often landless or functionally landless, with limited access to both development interventions—in particular those that use land size and other asset (for example, livestock ownership) thresholds for targeting—and social protection (Davis, Di Giuseppe, and Zezza 2017). Moreover, high levels of informality among farm laborers limit their ability to access unemployment benefits or social insurance. For agricultural laborers who rely on seasonal migration, mobility restrictions will have profound adverse welfare impacts. Conversely, for those who work near their homes, welfare losses caused by the pandemic may be less severe. However, given their economic vulnerability, even small reductions in income can have substantial effects on the livelihoods of agricultural laborers.

Primary producers make up the second set of actors we consider. Significant heterogeneity exists among farmers in SSA, which manifests in terms of (1) access to, and control over, productive resources, including land and livestock; (2) variations in levels of production and livelihood diversification versus specialization; (3) degrees of input and output market integration; and (4) access to support systems, including public agricultural subsidy programs, social protection, and development interventions and services (such as health, education, financial, and agricultural extension services).

Despite this heterogeneity, the majority of producers are highly resource constrained, operate under rainfed conditions in a context of increasing climate variability, lack access to formal instruments to manage risks, and often orient their production toward meeting subsistence needs rather than toward maximizing profits (Reardon 2015; Frelat et al. 2016; Barrett et al., n.d.; Zezza et al. 2011). Importantly, their livelihoods are often multivalent, with income derived from a range of sources, including farm production, off-farm business and wages, remittances, transfers from formal and/or informal social protection mechanisms, and gifts. Such diversification, while it may limit specialization and profit maximization, is an important source of resilience to idiosyncratic and covariate shocks. However, in the context of COVID-19, which directly affects a wide range of economic activities simultaneously, high levels of diversification may also increase the number of channels through which the pandemic can influence the welfare of food producers. Those include disruptions to markets for food, inputs, and farm and nonfarm labor, as well as the loss of remittances, closures of off-farm enterprises, and reduced access to services. Moreover, limited savings and assets, combined with the self-employed nature of agricultural production, means that many food producers in SSA lack resources to adequately cope with major income shocks and typically lack access to formal risk management tools, such as insurance and social protection. Current data on social protection coverage in Africa by employment category is not available, but estimates show that SSA has the lowest social protection coverage of any region of the world, with the estimated effective coverage at just 18 percent of the total population (ILO 2017). Given that the majority of the region's poor live in rural areas and rely on agricultural production to meet their subsistence needs, we can assume that low overall coverage levels in the population equate to low levels of social protection coverage of primary producers and other food system actors.

Intermediaries within African food systems are diverse and include a wide range of different types of actors that link producers to consumers, including small- and medium-scale agricultural traders, food processors, input and service providers, and food retailers. The intermediary segment of the food system is a critical source of nonfarm employment in rural SSA, accounting for at least 20 percent of all rural employment—second only behind primary production (Liverpool-Tasie, Reardon, and Belton 2021). Several features define intermediary food system actors in SSA. First, they are overwhelmingly small-scale, unregistered, and self-employed (Sitko and Jayne 2014; Reardon 2015). Liverpool-Tasie, Reardon, and Belton (2021) estimate that roughly 85 percent of food system intermediaries in SSA are small- or medium-scale. Second, mobility is another key feature of this segment of the food system. Aggregators and wholesalers in African food systems consolidate a myriad of small-volume transactions coming from geographically dispersed smallholders into marketable lots that are then sold into processing and urban retail markets (Sitko, Burke, and Jayne 2018; Tschirley et al. 2010). Mobility restrictions implemented to contain the spread of COVID-19 are, therefore, highly disruptive to such actors. Moreover, because such actors are often linked to global and regional markets through cross-border trade, bottlenecks at shipping ports and border crossings caused by lockdown measures can directly affect their capacity to make a living. Finally, efforts to contain the spread of COVID-19 have led to closures and other limitations on informal food retail markets, with implications for marketers and the traders and producers that supply them (Liverpool-Tasie, Reardon, and Belton 2021). Taken together, these factors make food system intermediaries both highly vulnerable to COVID-19 lockdown measures and difficult to target and support through formal fiscal and social protection interventions.

Finally, the consumer segment of the food systems in SSA prior to the COVID-19 pandemic was characterized by persistently high levels of food and nutrition insecurity, with particularly high levels in rural regions (FAO et al. 2021). This has important implications in terms of the additional burdens the COVID-19 crisis has created in terms of food and nutrition security. In The State of Food Security and Nutrition in the World 2021, FAO et al. (2021) estimate that the number of food insecure people in Africa increased by 46 million, reaching a total of 282 million people, or roughly one-third of all food insecure people in the world. In rural areas, the adverse impacts of COVID-19 on food consumption likely come through two channels: (1) effects on livelihoods and purchasing power due to reductions in farm and off-farm income, and (2) increases in food prices driven by market restrictions and lack of availability. Conversely, in urban areas closures of informal food retail markets combined with income losses create a double burden in terms of food access by poor consumers who purchase their food in these markets. An additional factor affecting consumers is the relative reliance of a country on food imports. Some countries face structural food deficits and therefore must rely on food imports to make up for production gaps (Jayne, Mather, and Mghenyi 2010). Disruptions in global trade and bottlenecks in shipping ports caused by labor restrictions has led, in some cases, to reductions in food supplies in urban markets and higher national food prices.

Table 8.1 summarizes the pandemic-related vulnerabilities of each of the four food system actors and the effects of the pandemic on them.

TABLE 8.1—SOCIOECONOMIC FEATURES AND COVID-19-RELATED VULNERABILITIES IN AFRICAN FOOD SYSTEMS

Food system node	Structural features of vulnerability	Effect of pandemic
Farm laborers	• High informality • High poverty • Dependent on mobility • Dependent on casual labor	• Loss of employment due to restrictions on mobility • Elevated risk of COVID-19 exposure due to working conditions • Few options to cope with income loss
Producers	• High informality • Limited assets and resources • Pervasive market failures • Lack of access to formal instruments to manage risk • Sensitive to market disruptions for inputs, outputs, and labor • Reliant on multiple income sources that are vulnerable to COVID-19 disruptions	• Loss of access to input and output markets and access to services • Loss of farm labor • Reduction in remittances • Loss of nonfarm income
Intermediaries	• Preponderance of small-scale actors • Highly informal • Reliant on mobility • Markets subject to closure • Few mechanisms to cope with drops in volumes	• Reduced capacity to acquire products due to mobility restrictions • Temporary closure of and other restrictions on informal food retail markets • Disruption in global input and food trade
Consumers	• Already high levels of food insecurity • Existence of a large number of food producers that also rely on markets to access food	• Loss of purchasing power among households already vulnerable to food insecurity • Disruptions in food markets due to retail market closures

Source: Authors' own elaboration.

The Rising Importance of Social Protection in SSA: Understanding the Prepandemic Trends

Social protection comprises a set of policies and programs aimed at preventing, managing, and overcoming situations that adversely affect people's well-being. Such policies and programs are typically categorized as follows:

- Social assistance/social safety nets typically consist of noncontributory measures that provide resources, either cash or in-kind, to individuals or households. These include cash and food transfers, as well as public works programs.
- Social insurance schemes consist of contributory measures intended to mitigate risks associated with unemployment, ill health, disability, work-related injury, and old age, such as health insurance or unemployment insurance.
- Labor market interventions include policies and programs designed to promote employment, increase the efficient operation of labor markets, and protect workers.

The evidence shows that in rural areas of SSA social protection measures not only protect the income and consumption of beneficiaries in the context of shocks, but also may have beneficial impacts on household-level production and investments as well as on economic activity in local economies (Daidone et al. 2019). Those are critical findings in the context of COVID-19, where policymakers must implement interventions to mitigate short-term welfare losses and support future recovery efforts. The productive impacts come through two mutually reinforcing channels. On the one hand, social protection helps relieve liquidity constraints that prevent households from making investments in their farms or nonfarm enterprises. On the other hand, social protection reduces consumption risks associated with making productive investments. As a result, evidence shows that in rural spaces social protection can, for example, foster diversification into commercialized agricultural enterprises (Pace et al. 2021) and investments in agricultural inputs and nonfarm enterprise assets (Handa et al. 2018; Prifti, Daidone, and Davis 2019). The household-level productive impacts also tend to ripple through local rural economies, generating multiplier benefits for nonbeneficiaries, many of whom operate nonfarm businesses tied to intermediary food system activities (Taylor and Filipski 2014).

The last two decades have witnessed a growing prominence of social protection in the global development discourse, particularly in SSA. Globally, social protection is mentioned in three of the 17 Sustainable Development Goals, whereas it was not mentioned at all in the Millennium Development Goals. In Africa, in 2000 not even one country had a social protection policy. By 2019, 35 out of 55 countries had produced a social protection policy or strategy (Devereux 2020). Excluding subsidies, around 1.5 percent of gross domestic product (GDP) in 2018 was invested in social safety nets in SSA, which is lower than in Europe and Central Asia (2.2 percent of GDP), similar to in Latin America (1.5 percent), and higher than percentages in the other regions (World Bank 2018).

In SSA, the average number of new social safety net programs launched each year rose from seven during the 2001–2009 period to 14 in the 2010–2015 period (World Bank 2018. Moreover, since 2015 all countries in SSA implemented at least one social safety net program, including innovative ones associated with digital technologies. Thanks to this progress, today millions of people in SSA have access to regular social assistance that did not exist 20 years ago. Recent years have also seen some, albeit still limited, progress in terms of extension of social security coverage to informal economy workers, including farmworkers, and economic inclusion programs.

Despite the importance of social safety nets in SSA countries' political agendas, even prior to the pandemic financing fell well below needs—with development partners providing more than half of social safety net financing in the region and coverage extending to only a low share of the population (World Bank 2020; Devereux 2020). As of 2016, 71 percent of the population in the poorest income quintile in SSA had no access to any form of social protection program, and many relied on food systems for their livelihoods (World Bank 2018); only 16 percent of African children were covered by some type of social protection program and only 4.2 percent of SSA workers were covered (ILO 2017). In addition to generally low coverage levels, resource limitations have led policymakers and donors to focus social protection support on the most vulnerable population. As a result, many social protection systems in SSA have targeting criteria, registries, and delivery modalities that are specialized to reach the most vulnerable, and lack the flexibility (and means) required to extend their reach beyond those clients when conditions require it—as was the case following the COVID-19 outbreak.

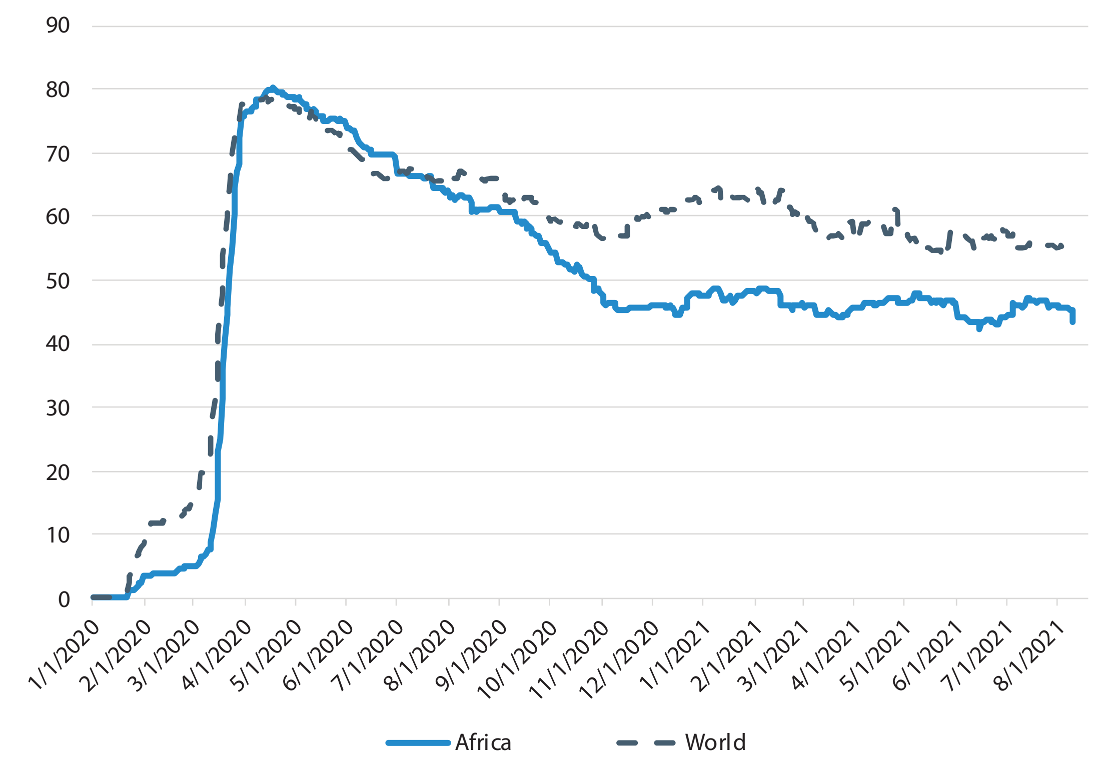
Of course, these figures mask heterogeneity between countries. A limited number of countries, such as Gabon, Mauritius, Seychelles, and South Africa, have large-scale domestically funded noncontributory schemes that provide people with basic income security (ILO 2017). For example, South Africa has managed to reach universal coverage through social assistance and social security schemes (ILO 2017), while the country's child grant program covers more than 60 percent of total households. Ethiopia's Productive Safety Net Program, Africa's second largest social assistance program, reaches 8 million rural people with cash and food assistance and supports the creation of critical public assets. The social safety net programs of Botswana and Namibia cover around 40 percent of the total population (World Bank 2018).

Thus, despite progress in recent decades, many social protection systems in SSA were positioned poorly to respond to an economic and health crisis of the magnitude generated by the pandemic. Moreover, the safety nets that do exist often exclude large segments of the population, among them farmers and the myriad small-scale and informal actors that make up Africa's food systems.

The Response of SSA Governments to COVID 19: Lockdowns and Economic Relief (for Some)

Early on, countries in SSA introduced measures to restrict movement with the intention of containing the spread of COVID-19. As Figure 8.1 shows, such measures were most restrictive in April 2020, soon after the World Health Organization (WHO) characterized COVID-19 as a pandemic, and included restrictions on the movement of people and goods, limits on social gatherings

FIGURE 8.1—TRENDS IN COVID-19 LOCKDOWN STRINGENCY INDEX: AFRICA AND THE WORLD



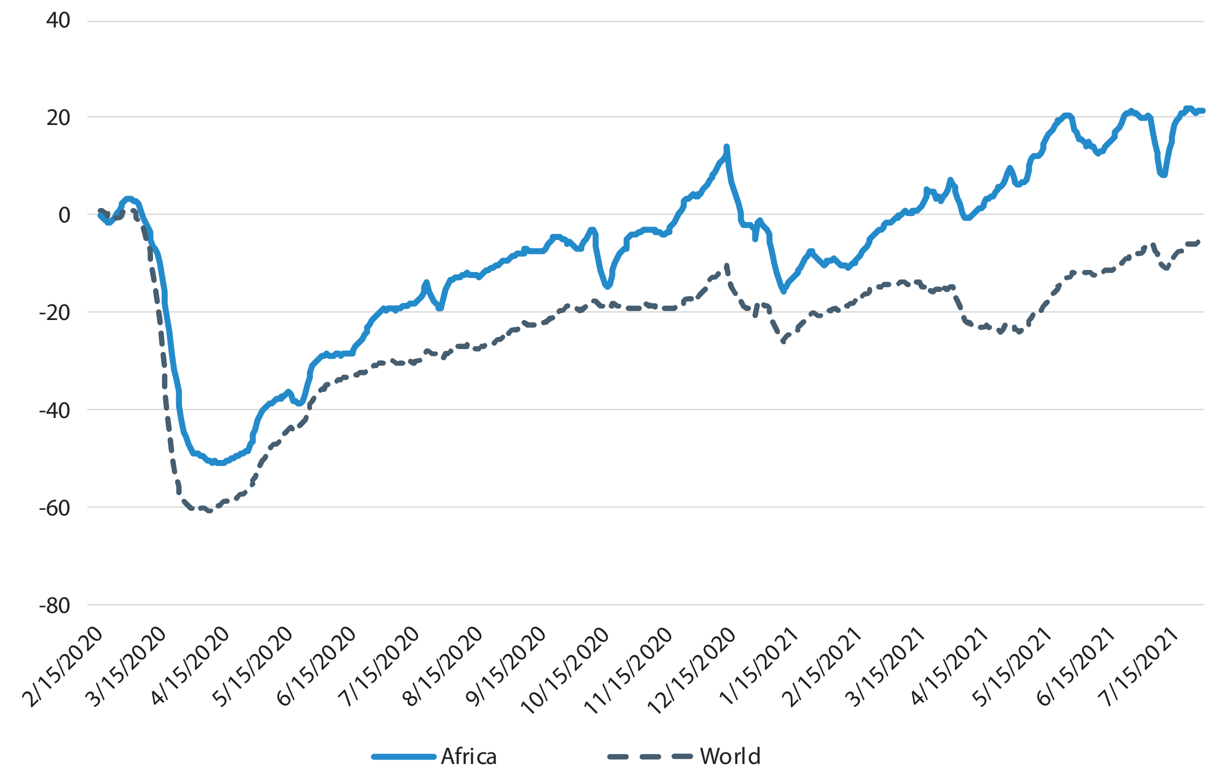
Source: Own elaboration on data by Our World in Data, University of Oxford (https://ourworldindata.org/). Regional averages are computed aggregating national data by using population weights.

(markets, workplaces, eating establishments), and school closures. As Figure 8.2 shows, those restrictions led to significant reductions in the movement of people. Inevitably that reduction in movement limited economic activity, and the effects have rippled through all segments of food systems, from agricultural input availability to food retail outlets. Indeed, even though food products and agricultural inputs were exempted from restrictions on internal and cross-border movements, additional inspections and checkpoints slowed the trade in agricultural products and inputs and increased costs. For example, in Uganda the costs of dairy production increased due to difficulties in accessing inputs, while low demand in domestic markets and bans on dairy imports by Kenya led to a crash in milk prices. Thus farmers experienced the double burden of increased production costs coupled with reduced output prices. In Sierra Leone, small- and medium-scale agribusinesses had made substantial investments to develop export markets for palm oil, ground cassava, and certain fruits and vegetables (FAO, n.d.). Because of supply bottlenecks and the increased transaction costs associated with transport and trade, those firms may lose the nascent export markets as a result of lockdown measures.

SSA governments implemented a range of relief measures in response to the economic hardship COVID 19 containment policies caused. The responses can be divided into three categories (Sotola, Pillay, and Gebreselassie 2021). The first comprises fiscal and financial measures, including tax exemptions on imports, loan guarantee facilities, and suspension of interest payments on government-backed loans. For example, in Sierra Leone, the government provided guarantees on loans to small- and medium-scale enterprises and suspended interest payments. In Niger, the government entered into a partnership with the Professional Association of Banks and Financial Institutions of Niger to establish a line-of-credit support to local enterprises, one-third of which is guaranteed by the state. While not directly targeting food system enterprises, such actions likely benefited some segments of the sector, particularly larger and better-off enterprises (FAO, n.d.; 2020a, 2020b). However, given the degree of informality in the sector, food system actors' access to financial and fiscal interventions is limited, and consequently so is the ability of those interventions to reduce welfare losses in large segments of the food system.

The second type of government response is direct in-kind support targeting primary producers. Recognizing that input supply bottlenecks are hampering food production, governments have both modified existing input subsidy

FIGURE 8.2—PERCENTAGE CHANGE IN THE NUMBER OF VISITORS TO TRANSIT STATIONS (BUS, TRAIN, AIRPORTS) COMPARED WITH PREPANDEMIC LEVELS



Source: Own elaboration on data by Our World in Data, University of Oxford (https://ourworldindata.org/). Regional averages are computed aggregating national data by using population weights.

programs and introduced new ones. In Malawi, for example, the government increased the number of beneficiaries of its input subsidy program fourfold. The governments of Sierra Leone and Liberia supported production by distributing assets and inputs ahead of the planting season (FAO 2020a, 2020c). Such measures can provide critical relief, particularly when private input markets are not functioning; however, they also tend to be high cost, with benefits often concentrated among relatively better-off farmers, and they are not effective or appropriate for nonproducers in the food system (Jayne and Rashid 2013).

The third type of government response is the creation of new social protection programs or the extension of existing ones. In the following section, we explore in detail the social protection response to the pandemic and its implications for food systems in SSA.

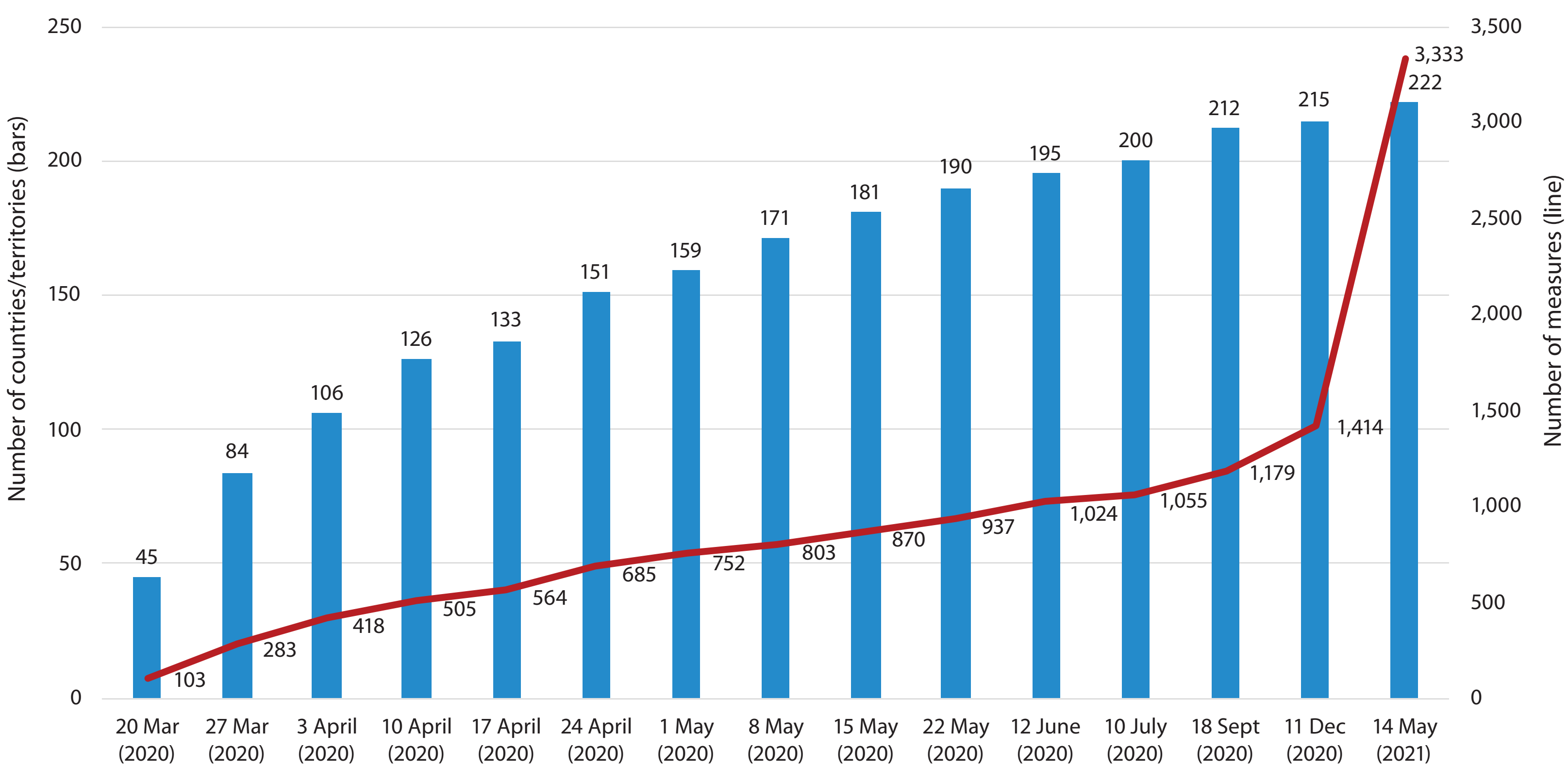
Exploring the Social Protection Response to COVID-19 in SSA

In response to the COVID-19 crisis, countries worldwide, including SSA governments, announced an unprecedented number of social protection measures. However, the SSA governments' social protection response was relatively slower than the rest of the world, and the measures implemented have left many without adequate coverage.

Figure 8.3 shows data on the number of countries introducing social protection measures in response to the pandemic (left Y axis) and the total number of social protection measures proposed (right Y axis) from March 2020 to May 2021. One can see that upon the WHO's characterization of COVID-19 as a pandemic in March 2020, 45 countries around the world announced that they would introduce new social protection programs and/or adapt or expand existing ones in response (Gentilini, Almenfi, and Dale 2020, version 1). The most widely used measures included cash transfers (30 programs), followed by wage subsidies (11), subsidized sick leave (10), and various forms of subsidized social security contributions and unemployment insurance. In most cases, these first responding countries adapted existing social assistance programs, including immediate, anticipatory payments to people through existing cash transfer programs (Colombia and Indonesia), the provision of additional payments (Argentina, Armenia, Australia, Turkey), an increase in benefit levels (China), and an increase in the coverage of existing cash schemes (Brazil) and public works (Uzbekistan). However, in March 2020 no country in Africa implemented a social protection response to the pandemic (Gentilini, Almenfi, and Dale 2020, version 1).

One month later, the number of countries that had introduced or adapted social protection measures in response to COVID-19, or planned to introduce such measures, had increased by three times (151 countries), but the response in SSA was still muted, with only a few countries, including Ethiopia and South Africa, introducing new social protection interventions or expanding existing ones. Despite the late response, between April and December the number of SSA countries introducing at least one social protection intervention increased substantially, and followed a trend similar to the trend observed for the rest of

FIGURE 8.3—TRENDS IN NUMBER OF SOCIAL PROTECTION MEASURES AND NUMBER OF IMPLEMENTING COUNTRIES/TERRITORIES, MARCH 2020–MAY 2021



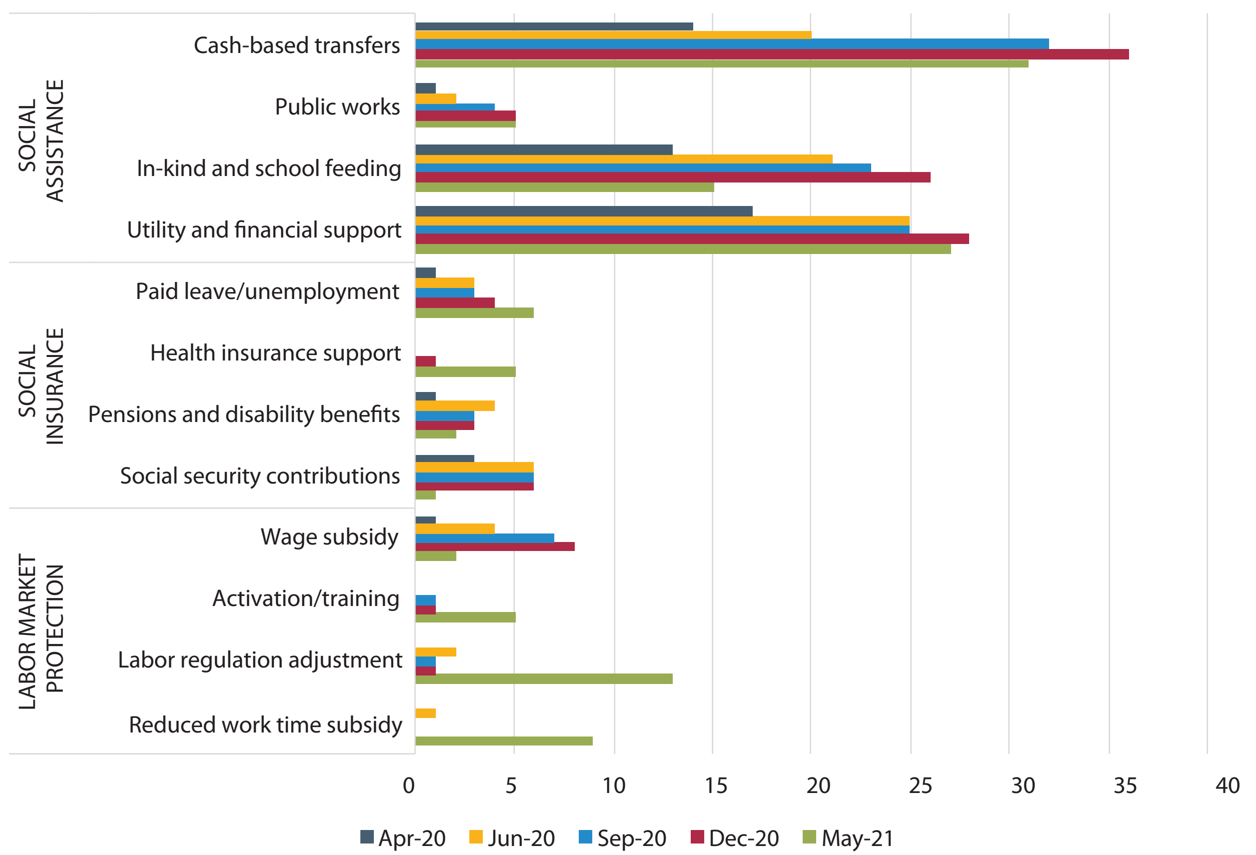
Source: Gentilini, Almenfi, and Dale (2020, version 15).

the world. The delayed social protection response in SSA was due to both budgetary issues, including a lack of resources and challenges mobilizing external support, and a lack of well-developed systems that enable rapid changes in targeting and delivery.

As Figure 8.4 shows, the most prominent form of planned social protection response in SSA was the expansion of existing or creation of new social assistance programs (see the appendix). In particular, between April and December 2020 the number of planned cash-based transfers and in-kind support programs increased substantially in the region. The number of countries with planned cash-based transfer programs increased from 14 in April 2020 to 36 in December (a 250 percent increase). During the same time period, the number of countries that planned to introduce in-kind support or modify existing in-kind/school feeding support rose from 13 to 26 (a 100 percent increase). Conversely, the number of countries with planned social insurance interventions increased only slightly between April and June 2020, and remained stable, and very low, throughout the year. Only six countries planned to introduce policies related to social security contributions and only three countries planned to introduce pension and disability benefits. Labor market protection interventions remained low throughout the year with only eight out of 46 SSA countries providing wage subsidies and just one country introducing labor regulation adjustments (Ethiopia) and one introducing training programs (Botswana) for formal workers. The prioritization of social assistance over labor market and insurance interventions reflects the preponderance of informal workers in SSA, who typically do not benefit from formal labor market and social insurance interventions.

Whereas the trends in the number of countries proposing new social protection interventions (or adapting existing ones) and in the number of social protection programs introduced are indicative of a strong, albeit delayed, response by the SSA governments, these data do not say much about the adequacy of the interventions. For a clearer picture, we must look at data

FIGURE 8.4—NUMBER OF SSA COUNTRIES WITH PLANNED SOCIAL PROTECTION INTERVENTIONS IN RESPONSE TO COVID-19

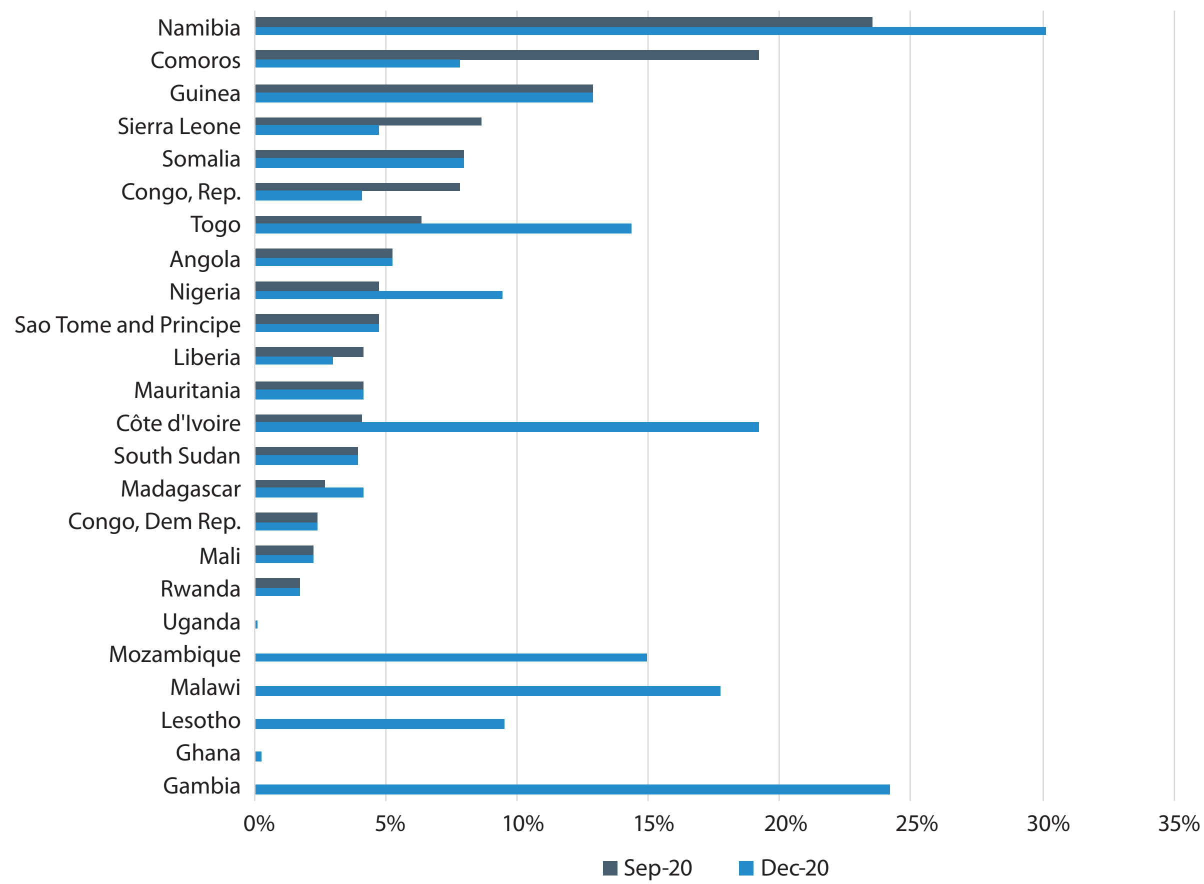


Source: Gentilini et al. (2020, versions 6, 11, 13, 14, 15). Own elaboration of data.

on the coverage and duration of coverage of social protection. Figure 8.5 presents data on the planned number of beneficiaries of cash-based transfers in SSA countries in September and December 2020 (where data are available) as a share of the population. It shows that intended coverage in most countries in SSA is low, exceeding 20 percent of the population in only a few cases. In the majority of cases, the intended number of beneficiaries of cash transfers constitutes less than 5 percent of the population.

Data collected through the World Bank's High-Frequency Phone Survey (HFPS) project substantiates the concern about the lack of overall social protection coverage.[1] HFPS data for Ethiopia, Nigeria, Kenya, Malawi, and Uganda (Figure 8.6) show that social protection coverage since the beginning of the pandemic has been low in all of those countries and lower than generally announced by the governments, and it remains low even five months after the pandemic outbreak (wave 4 for Ethiopia and Nigeria). In general, the data show an initial surge in social protection coverage early in the pandemic (wave 1) and a tapering off in subsequent waves. Differences between rural and urban areas are also apparent, but with no systematic patterns over time or between countries. This likely

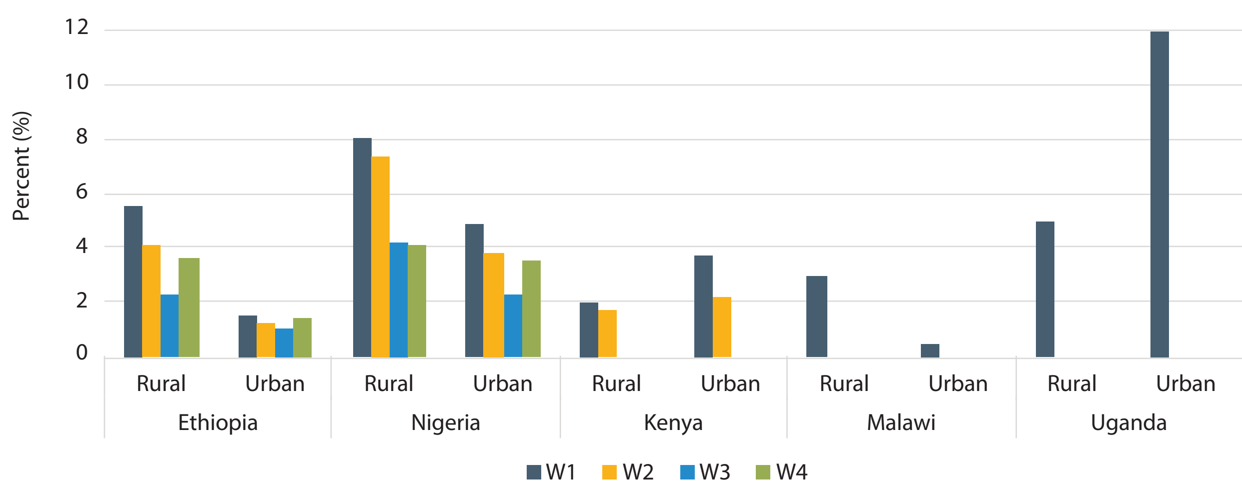
FIGURE 8.5—COVERAGE OF CASH-BASED TRANSFERS IN SSA IN RESPONSE TO COVID-19



Source: Own calculation based on Gentilini, Almenfi, and Dale (2020, versions 11 and 14).

1 In May 2020, the World Bank began implementing phone surveys aimed at collecting data from a nationally representative sample of households that were part of the World Bank Living Standards Measurement Study—Integrated Surveys on Agriculture (LSMS–ISA) initiative prior to the COVID-19 pandemic. The anonymized survey data and documentation are accessible through the World Bank Microdata Library and are comparable across countries (https://microdata.worldbank.org/index.php/catalog/hfps). Whereas phone surveys have proved to be a useful data collection tool during the pandemic, they do have some limitations that are important to mention. First, individuals without access to a phone or with limited network coverage, who normally belong to the poorest and most remote social categories, are underrepresented in the sample. Second, the surveys are affected by high levels of nonresponse and attrition. Third, a trade-off had to be made between the breadth and depth of the questions asked and the length of the calls. Fourth, all questions are asked to a single respondent per household, and therefore individual-level answers might be biased by respondent selection. Finally, in countries where the HFPS panel is a sample from existing prepandemic national surveys, the designated respondent is the household head, and therefore data on employment might differ from those measured by conventional labor force surveys due to characteristics related to being the head of household, such as gender and age. To correct for such biases, household-level weights have been applied to the data in the dashboard.

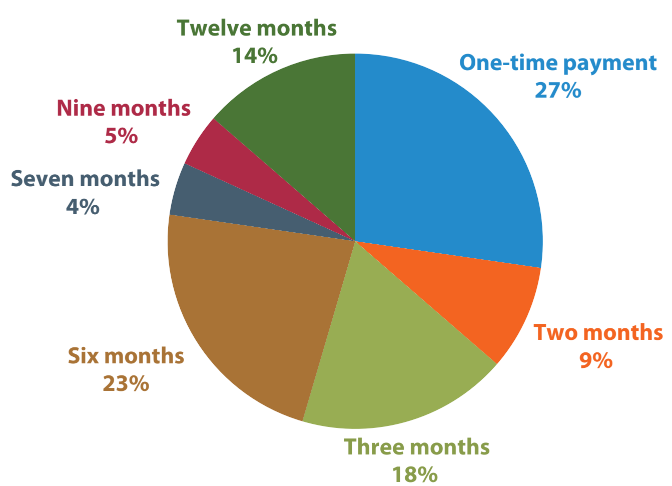
FIGURE 8.6—PERCENTAGE OF HOUSEHOLDS RECEIVING ANY FORM OF GOVERNMENT ASSISTANCE SINCE THE START OF THE PANDEMIC



Source: COVID-19 High-Frequency Phone Survey data, www.worldbank.org/en/programs/lsms/brief/lsms-launches-high-frequency-phone-surveys-on-covid-19.

Note: W1, W2,W3, and W4 refer to the panel survey waves.

FIGURE 8.7—DURATION OF CASH-BASED TRANSFERS IN SSA IN RESPONSE TO COVID-19



Source: Own calculation based on Gentilini, Almenfi, and Dale (2020, version 14) and Barba, van Regenmortel, and Ehmke (2020).

reflects a preponderance of short-term interventions targeting specific regions or subpopulations, as opposed to more systematic and long-term approaches (Barba, van Regenmortel, and Ehmke 2020).

Indeed, when looking at the duration of time beneficiaries receive COVID-19-related cash transfers, data show that most programs in SSA are designed to be very short-lived. As we see in Figure 8.7, 54 percent of the cash transfer programs in SSA were planned and financed to last three months or less, with only 23 percent expected to last six months and 14 percent for 12 months. Indeed, 27 percent of the cash transfers introduced in response to COVID-19 consisted of one-off payments.

Taken together, the SSA countries' social protection response to COVID-19 can be characterized as relatively slow and focused appropriately on social assistance programs. However, the interventions have had fairly limited coverage and generally are of short duration. This suggests that many people in Africa, including the large share of the population that depend on food systems for their livelihood, were not sufficiently protected from major welfare losses caused by lockdown measures.

Exploring the Evidence on the Impacts of COVID-19 on Food System Actors

The limited social protection response in SSA combined with the high level of vulnerability faced by food system actors suggests that the pandemic is likely to have substantial and long-lasting adverse impacts for food system–dependent people (Egger et al. 2021; Josephson, Kilic, and Michler 2020; Kansiime et al. 2021; Belton et al. 2021; Nechifor et al. 2021). In this section, we review evidence from a wide range of studies to understand how household incomes, agricultural production, nonfarm income opportunities, and food security have been affected by the crisis. Where feasible, we present evidence on specific food system actors, but in many cases this sort of disaggregation is infeasible. We, therefore, also provide information that is specific to rural areas where we can infer that these data are likely closely tied to food system–related activities, including production, agricultural labor, and intermediation (for example, Liverpool-Tasie, Reardon, and Belton 2021).

Impacts on Household Income

Multiple data sources from multiple countries in SSA confirm that rural regions have not been spared the adverse effects of the pandemic. Despite lockdown restrictions being most visible and prominent in urban areas (Liverpool-Tasie, Reardon, and Belton 2021), rural people's livelihoods have been upended. In Malawi, Nigeria, Ethiopia, and Uganda, for example, Josephson, Kilic, and Michler (2020) estimate that 77 percent of the population experienced income loss due to the COVID-19 pandemic, with no statistical differences between households in urban and rural areas. This is consistent with findings from Egger et al. (2021) who find that 69 percent of rural households in Kenya and 56 percent of rural households in Sierra Leone lost income due to the pandemic. Rapid phone survey data from Zambia, Ghana, and Senegal are equally consistent, with 51, 81, and 90 percent of rural respondents, respectively, indicating that the pandemic had contributed to a loss of income.

These income shocks are manifesting through multiple livelihood channels including through agricultural income, nonfarm business and wages, and remittances. We explore the evidence on each of these below.

Impacts on Agricultural Income

Reduced competition in output markets, loss of traditional retail market outlets, constraints to accessing agricultural labor, and disruptions in input supplies all contribute to reductions in agricultural incomes (Egger et al. 2021; Belton et al. 2021; Josephson, Kilic, and Michler 2020). Thus, reductions in agricultural incomes not only reflect challenges for food producers, they are emblematic of disruptions to the livelihoods of multiple actors in the food system. In Ethiopia, Senegal, Malawi, Nigeria, and Uganda, households reporting agricultural income losses due to COVID-19 range from 40 percent in Ethiopia to 73 percent in Malawi (Josephson, Kilic, and Michler 2020; Kansiime et al. 2021; IPAR 2020; ISF Advisors 2020). Similarly, in Zimbabwe 58 percent of respondents indicated that farming activities had been negatively affected by COVID-19 (Carreras, Saha, and Thompson 2020).

In Senegal, livestock producers have been particularly hard-hit, with 93 percent of livestock-rearing households reporting declining income from livestock, while in Nigeria 65 percent of households reliant on the aquaculture sector reported a decline in purchasing of inputs for production and 69 percent of households reported a decline in output market participation (Belton et al. 2021; IPAR 2020). Livestock and aquaculture are both high-value and perishable, making them particularly sensitive to drops in consumer purchasing power and disruptions in trade networks associated with COVID-19 lockdowns.

In the context of limited coverage and inadequate social protection, rural households are forced to rely on costly coping measures to maintain consumption as incomes drop, which can have long-lasting adverse effects. As shown by Josephson, Kilic, and Michler (2020), rural households have been more likely to liquidate assets in order to cope with income losses, while in urban areas households are more likely to reduce food consumption and rely on informal support from friends and neighbors. This has worrying implications for the future economic prospects of rural households in the region.

Impacts on Nonfarm Businesses and Wages

The rural nonfarm economy, which is made up in large measure by intermediary food system actors, has been particularly hard-hit by the combination of mobility restrictions and loss of consumer purchasing power due to the pandemic. In rural Malawi, Nigeria, Ethiopia, and Uganda, income loss in the nonfarm sector has been substantial, with 80 percent or more of respondents who earned nonfarm income prior to the COVID-19 pandemic reporting income losses (Josephson, Kilic, and Michler 2020). In Senegal, 95 percent of rural respondents indicated that they have lost income from nonfarm sources (IPAR 2020). Similar results are found in rural western Kenya, where income losses from nonfarm businesses accounted for the largest share of income loss due to COVID-19 restrictions, followed by reductions in formal wages, crop income, and income from informal casual labor (Janssens et al. 2021).

Wage earners in rural areas, which include farm laborers as well as those employed in nonfarm businesses, have also seen a drop in income due to COVID-19. These range from 40 percent of wage earners in Ethiopia to 62 percent of respondents in Uganda (Josephson et al. 2020). Wage losses come from both reductions in wage rates and increased unemployment. In Kenya and Uganda, 21 percent and 16 percent of rural respondents, respectively, indicate that employers have cut their wages as a result of COVID-19 (Kansiime et al. 2021). These adverse impacts are disproportionately concentrated among the poor in the informal economy. They show that people whose monthly incomes range from US$500 [2] to $2,000 and those making more than $2,000 were 18 percent and 35 percent, respectively, less likely to report a loss of income relative to those making less than $500 per month (Kansiime et al. 2021). In Nigeria, the percentage of individuals employed in fish value chains dropped from 52 percent of men prior to the pandemic to 11 percent and from 22 percent of women to 3 percent following the pandemic (Belton et al. 2021).

Mobility restrictions, health concerns, and other factors also contribute to significant challenges in terms of both the availability of work in African food systems and the ability of firms to hire workers. In Ethiopia, Ghana, Zimbabwe, and Nigeria, only between 17 and 33 percent of rural respondents to a rapid survey of food system actors said they could access nonfarm work since the pandemic (Carreras, Saha, and Thompson 2020). At the same time, 66 percent or less of food system employers in these same countries indicated they could hire needed labor (Carreras, Saha, and Thompson 2020). In contrast, in Tanzania, where the government only recently began adopting COVID-19 containment policies, 80 percent of respondents indicated they could find nonfarm work and 79 percent of firms indicated they could hire needed labor (Carreras, Saha, and Thompson 2020).

Remittances

Remittances make up a substantial share of total income for many rural households. In Kenya, for example, gifts and remittances constituted 22 percent of total average income prior to the pandemic (Janssens et al. 2021). Global lockdown measures have undermined the livelihoods of many migrants, with consequences in terms of quantities of remittances they can send home. Survey data from Malawi, Nigeria, Ethiopia, Senegal, and Uganda all show that in rural areas this loss in income is widespread, where between 57 and 92 percent of households report a reduction in income from remittances (Josephson, Kilic, and Michler 2020; IPAR 2020).

Food Security

As the preceding discussion suggests, the COVID-19 pandemic is rippling through rural spaces and undermining livelihoods tied to food systems along multiple dimensions. As an immediate consequence, food insecurity is on the rise. This is linked to both a loss of food markets and a loss of purchasing power.

Because of mobility restrictions, closed markets, and food shortages, access to food markets has been severely constrained by lockdown measures, with adverse impacts on consumers, food retailers, and their suppliers. In national survey data from Burkina Faso, Ghana, Kenya, Rwanda, and Sierra Leone, between 30 and 67 percent of respondents report a loss of food market access since the pandemic (Egger et al. 2021). The disappearance of markets is contributing to a rise in food prices. UN-Habitat and WFP (2020), for example, report food price increases of 8 to 10 percent in eastern Africa between April 2019 and April 2020. Fresh produce such as vegetables, meat, and fish recorded the highest increases, driven mainly by shortages related to disruptions in the supply chain (UN-Habitat and WFP 2020). This is substantiated by data from northern Kenya, which shows that between 61 and 97 percent of respondents, depending on the county, reported increases in food prices since the pandemic (Omosa and Njiru 2020).

Kansiime et al. (2021) estimate that in Uganda and Kenya the prevalence of moderate to severe food insecurity increased by 30 to 37 percent, respectively. They also find that during the pandemic there was a 20 percent increase in the number of respondents in Kenya that indicated that they worried about accessing sufficient food, were unable to eat healthy and nutritious food, ate reduced portions of food, and consumed limited food varieties.

As Husain et al. (2020) argue, the combination of widespread working poverty, high levels of informality, and low social protection coverage before the pandemic exacerbates the negative welfare impacts of lockdowns. Indeed, emerging evidence from Ethiopia suggests that adequate social protection can offset the food insecurity impacts of the pandemic. Abay et al. (2021) find that the Productive Safety Net Program (PSNP), Ethiopia's flagship social protection program that is primarily focused on providing cash for work in rural areas, mitigated the adverse impacts of the pandemic on food and nutrition security. They found that following the pandemic, average rural household food insecurity increased by 11.7 percentage points and the size of the food gap increased by 0.47 months. Participation in the PSNP offsets nearly all of this adverse impact. They show that the likelihood of becoming food insecure increased by only

2 All references to dollars are to US dollars.

2.4 percentage points for PSNP households and the duration of the food gap increased by only 0.13 month. This impact was greatest for poorer households and those living in remote areas. Moreover, PSNP participants were less likely to reduce expenditures on health and education by 7.7 percentage points and less likely to reduce expenditures on agricultural inputs by 13 percentage points. This finding highlights the importance of leveraging social protection in rural areas and among food system actors to address the myriad welfare and food security challenges brought on by the pandemic.

Conclusions

The multiple and overlapping channels through which the COVID-19 pandemic has undermined the livelihoods and welfare of food system actors in SSA suggest the need for a more flexible and multidimensional policy response. Fiscal and financial measures, although important in some cases, can address only the needs of bankable enterprises, which in the context of African food systems make up a small share of the population. Similarly, while input subsidy responses can help reduce the costs of production for those that can access such programs, they do nothing to mitigate losses of income coming from off the farm, including business income, wages, and remittances.

Social assistance interventions can help fill this gap in the context of African food systems by providing a more flexible, and relatively low-cost, mechanism to reach people operating in the informal sector, including the myriad small-scale informal actors that constitute African food systems (Tiwari et al. 2016). As initial evidence from Ethiopia suggests, sustained participation in social protection programs over time is offsetting much of the adverse food insecurity effects of the pandemic and reducing reliance on detrimental coping strategies (Abay et al. 2021). Social protection can also help people—particularly those with few savings or resources to cope with sustained income losses—comply with lockdown measures without jeopardizing their food security and welfare (Ravallion 2020). The prioritization of social assistance by African governments in their COVID-19 response packages is, therefore, commendable.

Moreover, social protection programs have a vital role to play in supporting the recovery of rural livelihoods and economies following the pandemic. The large and growing evidence on the productive impacts that such programs can have in terms of agricultural and nonfarm investments (Daidone et al. 2019; Handa et al. 2018; Prifti, Daidone, and Davis 2020; Pace et al. 2021; Sitko, Scognamillo, and Malevolti 2021) coupled with the substantial growth multipliers such systems can foster within local rural economies (Taylor and Filipski 2014) suggests that social protection must be considered a key element of building back rural economies.

However, as this chapter shows, the scope, scale, and speed with which governments in SSA responded to the pandemic through social protection instruments was limited. Governments and policymakers must urgently address the obstacles that have impeded an adequate social protection response to the crisis in order to support the COVID-19 recovery effort and to enable better responses to future crises. The evidence in this chapter suggests that by addressing four key areas, governments and policymakers can make social protection programs more responsive to shocks and can contribute to the recovery and economic development of African food systems.

First, governments must expand coverage of social protection to reach a larger share of vulnerable rural populations as well as productive populations within the food system who are often excluded from social protection in SSA. This requires changing the targeting criteria for noncontributory social assistance programs and increasing budgetary allocations to support the change. Moreover, opportunities exist to broaden the gamut of social protection instruments in SSA to also include labor market interventions that can reach informal laborers, such as agricultural workers and employees in intermediary food system enterprises.

Second, we need to reconceptualize the role of social protection in SSA. In particular, governments and policymakers should regard social assistance as more than simply a safety net and humanitarian tool for the most vulnerable. When social assistance is predictable and well targeted it can support households to engage in new economic activities and to capitalize on opportunities created by the continued economic dynamism in many parts of SSA (Daidone et al. 2019; FAO 2017; Kangasniemi, Knowles, and Karfakis 2020). At a policy level, this entails better integrating social protection programs into development frameworks and fostering greater coordination and coherence between social protection interventions and public- and private-sector development investments and activities. COVID-19 recovery efforts offer a unique opportunity to put this into practice.

Third, to expand coverage and better respond to crises, there is urgent need to invest in strengthening social protection systems. This includes, among other things, expanding and integrating registries across sectors and industries involved in the food system (for example, social protection, farmers, fisheries, traders), adopting less demanding modalities for identifying beneficiaries (for example, simplifying eligibility criteria, switching to demand-based approaches for identifying beneficiaries), digitalizing payments, and providing a legal framework for social protection. Countries that were able to rapidly provide people with increased social protection coverage in response to the crisis are those that had better developed a gamut of programs through which to respond to different population groups and had more-developed systems (Barca 2020; Beazley, Marzi, and Steller 2021). In much of SSA, these platforms do not exist or are underdeveloped, which hampers policymakers' capacity to respond quickly to crises.

Finally, the ability to strengthen social protection systems critically relies on the availability of adequate financing. Taking into account the impacts of the pandemic, the International Labour Organisation (2020) estimated that countries in SSA will have to invest an additional 8.2 percent of GDP—that is, US$137 billion—to close the financing gap for social protection in 2020 alone. Filling that gap is immensely challenging and will likely require a multipronged approach. An important starting point is to work with international financing institutions (IFIs) to create budgetary space, perhaps through deficit spending, to invest in social protection programs. Indeed, IFIs have encouraged high-income countries to expand fiscal spending on social protection but have not done the same with lower-income countries (Georgieva 2020; IMF 2020). In addition, governments may increase progressive tax revenues and corporate social security contributions. At the same time, governments should invest in ensuring greater tax compliance, reducing leakages, and reducing illicit financial flows. While tax revenue has a critical role to play in increasing fiscal space, it is important that this does not place additional burden on the poorest. The international community also has a role to play. Richer countries should stick by the commitments made to overseas development assistance. Ideas have also been proposed for global financing mechanisms such as the global solidarity taxes, the creation of a global fund for social protection, or the International Monetary Fund's call for temporary "COVID-19 recovery contributions raised on high incomes or wealth to help meet the extraordinary financing needs following the pandemic" (Klemm et al. 2021; UN 2021).

While the pandemic has had devastating impacts on the economies and lives of millions of people in SSA, there is a silver lining. It has placed social protection at the center of government responses and the policy debate at national and global levels (Gentilini, Almenfi, and Dale 2020; *Economist* 2021). This creates a unique moment to mobilize political support for social protection in SSA and to begin to leverage social protection programs to support a more inclusive development pathway from the aftermath of COVID-19 for African food systems and the rural economies and livelihoods they support.

Appendix

TABLE A8.1—PLANNED SOCIAL PROTECTION IX NTERVENTIONS

Country	Planned social protection interventions
Ethiopia	On April 3, 2020 the prime minister's office announced a COVID-19 Multi-Sectoral Preparedness and Response Plan: (1) US$635[1] million (0.6 percent of GDP) for emergency food distribution to 15 million individuals (14 percent of the total population) vulnerable to food insecurity and not currently covered by the rural and urban Productive Safety Net Programs (PSNPs); (2) $430 million (0.4 percent of GDP) for health sector response under a worst-case scenario of community spread, primarily in urban areas; (3) $282 million (0.3 percent of GDP) for provision of emergency shelter and nonfood items; (4) the remainder ($293 million, 0.3 percent of GDP) allocated to agricultural sector support, nutrition, the protection of vulnerable groups, additional education outlays, logistics, refugee support, and site management support. The government plans to temporarily expand the urban PSNP in early fiscal year (FY) 2020–2021 to cover 500,000 new beneficiaries for three months. A broader set of measures is under discussion with the donor community but has not been formalized. The urban PSNP is expected to expand to 16 additional cities in FY 2020–2021, in collaboration with the World Bank.
Ghana	The government has so far committed a total of 11.2 billion cedis (¢) to face the pandemic and its social and economic consequences. The bulk of these funds (¢10.6 billion) is being used under the Coronavirus Alleviation Programme to support selected industries, support small- and medium-sized enterprises (SMEs), finance guarantees and first-loss instruments, and build or upgrade 100 district and regional hospitals. To compensate for larger spending related to the COVID-19 crisis, the government plans to cut spending in goods and services, transfers, and capital investment. In September 2020, Ghana launched a ¢11 million COVID-19 Relief Fund, a cash transfer program to COVID-19-affected daily wage earners. Seventy-five thousand people (0.25 percent of the total population) would benefit from the relief fund.
Kenya	The government, as part of the FY 2019–2020 budget (ending June 30, 2020), initially earmarked 40 billion shillings (KSh) (0.4 percent of GDP) for COVID-19-related expenditures, including health sector; social protection (cash transfers and food relief); and funds for expediting payments of existing obligations to maintain cash flow for businesses during the crisis. The FY 2020–2021 budget includes a KSh56.6 million (0.5 percent of GDP) economic stimulus package that includes a new youth employment scheme, provision of credit guarantees, fast-tracking payment of value-added tax refunds and other government obligations, increased funding for cash transfers, and several other initiatives.
Malawi	The government's response plan includes US$20 million (0.25 percent of GDP) in spending on health care and targeted social assistance programs; this includes hiring 2,000 additional health care workers. In addition, tax waivers are being granted on imports of essential goods to manage and contain the pandemic. An Emergency Cash Transfer Program of about $50 million (0.5 percent of GDP), mostly financed by development partners, is being implemented during May–November.
Nigeria	The government adopted a revised budget for 2020 in response to the COVID-19 shock. A 500 billion naira (₦) (0.3 percent of GDP) COVID-19 intervention fund is included to channel resources to additional health-related current and capital spending and public works programs to support the incomes of the vulnerable. The coverage of the conditional cash transfer program has been broadened and an allocation of ₦150 billion to support state and local governments' spending needs has been made available through the budget. Import duty waivers for pharmaceutical firms were introduced. Regulated fuel prices have been reduced, and an automatic fuel price formula introduced to ensure fuel subsidies are eliminated. Electricity tariff was increased. The social register was increased by 1 million households to 3.6 million to help cushion the effect of the lockdown.
Uganda	In FY 2019–2020, two supplementary budgets increased the spending envelope for critical sectors and vulnerable groups by about US$270 million (0.7 percent of GDP), of which around $110 million (0.3 percent of GDP) is estimated to have been executed. In FY 2020–2021, a supplementary budget increased the COVID-19-related spending by around $310 million (0.8 percent of GDP), partly driven by the delayed execution of some measures originally planned for FY 2019–2020. This includes providing additional funding to the health sector, food to the vulnerable in the urban areas, and social insurance (by continuing the Social Assistance Grants for Empowerment Scheme); introducing a tax exemption on items destined for medical use; and expanding labor-intensive public works programs in the roads and water and environment sectors.
Zambia	The government has waived tax penalties and fees on outstanding tax liabilities resulting from COVID 19. In July, Zambia launched an emergency COVID-19 social cash transfer scheme to help vulnerable communities affected by the pandemic. Kampamba Mulenga, minister of community development, said the emergency social cash transfer will help mitigate the impact of the pandemic in vulnerable homes of the elderly, women, and their children. The beneficiaries will be given money as well as food hampers for a period of six months.
Zimbabwe	In 2020, the government launched the Stimulus Package for COVID-19 aimed at (1) providing liquidity support to agriculture, mining, tourism, SMEs, and the arts; (2) expanding social safety nets and food grants; (3) setting up a health sector support fund; and (4) scaling up investments in social and economic infrastructure in Cyclone Idai–affected communities. It also supported the food security–related program, which included wheat farming and maize procurement, and the Pfumvudza Program, which supports vulnerable households with farming inputs. To cushion the vulnerable members of society, the government provided COVID-19 cash transfers.

Source: International Monetary Fund Policy Tracker, www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

1 All references to dollars are to US dollars.

CHAPTER 9

Remote Sensing and Machine Learning for Food Crop Production Data in Africa Post-COVID-19

Racine Ly, Khadim Dia, and Mariam A. Diallo

Introduction

The world is experiencing an unprecedented health crisis during the spread of COVID-19 (SARS-CoV-2, or Severe Acute Respiratory Syndrome Coronavirus 2). While the pandemic appears to be less severe on the African continent than in other geographic regions[1] (Global Change Data Lab 2021), its economic impact is significantly more pronounced. COVID-19 is upending livelihoods, damaging business and government balance sheets, and threatening to reverse development gains and growth prospects for years to come in Africa south of the Sahara (IFC 2020). The World Bank forecasts that Africa south of the Sahara will go into recession in 2020 and that COVID-19 will cost the region between $37 billion and $79 billion in output losses in 2020 alone. The informal sector, a significant source of income and employment, will be the hardest hit.

In the agricultural sector, COVID-19 threatened to lead to a severe food security crisis in the region in 2020, with disruptions in the food supply chain and expected contractions of 2.6 to 7 percent in agricultural production (Zeufack et al. 2020). Travel bans, border closures, and the late reception and use of agricultural inputs such as imported seeds, fertilizers, and pesticides could lead to poor performance in food crop production. Another layer of disruption introduced by the mobility restriction measures is the scarcity of agricultural workers, mainly seasonal workers. Lockdown measures and border closures limit seasonal workers' ability to get to farms in time for planting and harvesting activities (Ayanlade and Radeny 2020; ILO 2020). Moreover, delivery of most of the imported agricultural inputs relies on air travel, which has been impacted heavily by the pandemic (Vilardell and Baenas 2020). Such transportation disruptions can also negatively affect the food crop production system.

It is challenging to fully understand the relationships between the COVID-19 containment measures taken by countries and their impacts on food crop production. Comprehending these relationships would require studies on the impacts of the containment measures on farmers' and seasonal workers' mobilities and the prompt reception of seeds, fertilizers, and pesticides for cropping activities. The kinds of datasets that would allow these studies are not yet available to the best of our knowledge. However, it is risky to wait to take action until food crop production statistics are available at the end of the agricultural season. Instead, it would be better to have an estimate of the most likely food crop production levels before the harvesting period to allow for better planning and early policy actions. For that goal, data are most needed.

Access to reliable and timely data in the agricultural sector has been problematic in Africa for a long time. Even in regular times, there are difficulties in accessing agricultural statistics. The issue is even more pronounced in crisis times, such as the current pandemic, when, paradoxically, the data are most needed. Uninformed decision-making is the most significant consequence of the lack of data and analytics. Making decisions based on anecdotal facts creates inefficiencies in problem-solving. Much of the assumed knowledge about agriculture in Africa may no longer be valid, given Africa's rapid economic transformation, fast urbanization, demographic and climatic changes, and, more importantly, the scarcity of quality data (Christiaensen and Demery 2018). In a rapidly changing world, the facts that drive research and policy focus quickly become outdated. COVID-19 highlighted the need to improve African food systems' resilience. Access to timely, spatially disaggregated, and accurate agricultural statistics can play a significant role in achieving that goal. That is the main focus of this chapter.

This chapter assesses food crop production levels in 2020—before the harvesting period—in all African regions and for staples such as maize, cassava, rice, and wheat. Production levels are predicted using the combination of remote sensing data retrieved from satellite images and a machine learning artificial neural networks (ANNs) technique. The remote-sensing products are used as input variables in the Africa Crop Production (AfCP) model developed by AKADEMIYA2063. The input variables are the normalized difference vegetation index (NDVI), the daytime land surface temperature (LST-day), rainfall data, and agricultural lands' evapotranspiration (ET). The model's outputs are pixel-level maps of agricultural production forecasts for major crops in all African countries. The product and input time-series data are made publicly available on a web-based platform, the Africa Agriculture Watch, to facilitate access to such information for policymakers and other stakeholders.

The chapter is organized as follows: Section 2 provides the underlying conceptual framework that explains the basis for the use of remote sensing products (RSPs) and machine learning for resilient food systems. Section 3 introduces all variables that have been considered for the predictive model, the methodology used to select the crops for each region, and a methodological

1 As of April 19, 2021

description of the machine learning predictive modeling framework. Section 4 presents the predicted food crop production for each region and crop and discusses potential factors related to COVID-19 that might have caused a decline in food crop production in some African countries. Section 5 outlines the limitations of the model and the direction of future research. Finally, Section 6 proposes recommendations to strengthen African food system resilience through an improved data environment and analytics using emerging technologies.

The Basis for the Use of RSPs and Machine Learning for Resilient Food Systems

A resilient food system is determined by its capacity to withstand and recover from disruptions and to ensure a sufficient food supply for communities. Another aspect of food system resilience is the availability of evidence-based technical assistance to help policymakers and decision-makers more effectively prepare for and respond to shocks. Technological advancements can help with that goal. Remotely sensed data via satellite images are now democratized and show a sufficiently high spatial resolution to include a large proportion of agricultural lands across the continent, and machine learning techniques offer a way to build robust predictive models relieved from rule-based approaches. This section provides a conceptual framework for understanding the building blocks of our approach to using RSPs and predictive modeling through machine learning techniques for better-informed policymaking in a time of crisis such as the COVID-19 pandemic.

The Basis for the Use of RSPs for Decision-Making in Agriculture

Real-time (or near real-time) data gathering and analysis is crucial to providing a clear picture of any crisis dynamic and monitoring the effects of simultaneous shocks. The availability of accurate and frequently updated data that reflect the status on the ground requires significant coordination and collaboration, and robust data systems.

In the African context, the use of remote sensing in the agricultural sector is hindered by a lack of reliable ground-truth data. The cost of generating ground-truth data is usually prohibitive, primarily due to the size of the continent. Moreover—and most importantly—the African food production system is characterized by scattered, small-size farms with significant crop spatial heterogeneity. For instance, most African farmers are smallholders with farm sizes of fewer than 2 hectares on which several crops are grown simultaneously. Such a complex cropping system does not facilitate ground truthing for machine learning applications. The diversity of agroecological zones adds another layer of complexity, as does the frequent cloud cover. These challenges often do not allow satellites' optical sensors to collect ground spectral signatures for an extended period of time in some countries.

The levels of data quality, frequency, and disaggregation do not allow a thorough analysis of cropping activities, early anomaly detection, and forecasting for African food production systems. Through Earth observation, RSPs show promise in significantly reducing the underlying gaps in data quality, size, disaggregation, and frequency. RSPs are used in two main ways in agricultural policymaking. First, they are used to provide disaggregated views of agricultural lands and their corresponding biogeophysical parameters. Second, they are used to monitor the effects of agricultural policies on the ground.

RSPs use the spectral signature of earth's features to monitor agricultural lands. Vegetation indexes, such as the NDVI derived from satellite images, provide an assessment of the health of crops by using measurements of the rate of leaves' infrared reflection as a proxy for their visible light absorption rate (light absorption is needed for photosynthesis). RSPs measure several other biogeophysical parameters related to food crop production, such as ET (Running et al. 2021) and LST-day (Wan et al. 2015), and provide data for indexes like the enhanced vegetation index (EVI) (Didan 2015). In general, the combination of measurements of specific spectral layers allows a determination of the agricultural land's biogeophysical status at a community level (see Figures 9A.1, 9A.2, and 9A.3 in the appendix for NDVI, LST-day, and rainfall anomalies for 2020).

Using RSPs to monitor changes on the ground due to agricultural policy has been successful in other parts of the world. Harnessing moderate resolution imaging spectroradiometer (MODIS) NDVI time-series signals, Lein (2012) showed how a tax-free agricultural ordinance in 2006 impacted the adoption of multiple cropping practices in China. Arvor and colleagues (2011) derived indexes from satellite images to study the relationship between agricultural dynamics in Amazonia and the region's existing public policies during the period from 2000 to 2007.

Moreover, satellites revisit the same area many times a year—typically, every five days for Sentinel-2[2] and daily for MODIS[3] —allowing practitioners to monitor land-use and land-cover changes (Li et al. 2020), identify crop taxonomy (Kpienbaareh et al. 2021) and cropping activities (Rezaei et al. 2020), and assess surface water availability (Pekel et al. 2016). Another added value of using RSPs to improve agricultural statistics is the capacity to provide disaggregated information at a pixel level and disentangle the data from conventional administrative entity-based maps. Several weeks (or months) would be necessary to cover the same area with field agents, and still, the results would be less accurate. This capacity to provide community-level detail on maps could allow for targeted responses where they are needed the most. However, RSPs alone cannot provide estimates of potential future agricultural production and yield—that requires a predictive modeling framework.

The Basis for the Use of Machine Learning for Decision-Making

General-purpose technologies have triggered a wide range of innovations globally. The fast pace of technological advances has reduced the cost of technology products and services, encouraged wide adoption, and significantly increased data generation over the last three decades. Combined with advances in computer modeling, these advances have opened up a new "technium" (that is, the accumulation of inventions that humans have created, and which society depends on as much as nature) of data-driven technologies and machine learning techniques.

Machine learning is a set of techniques particularly suitable for making predictions under certain circumstances. These techniques have the capacity to mimic key characteristics attributed to human intelligence, such as vision, speech, and problem-solving. Several papers have shown how machine learning models outperform humans in accuracy in some tasks (Buetti-Dinh et al. 2019; Mnih et al. 2013; Silver et al. 2016). This performance has been possible due to the combination of significant increases in data availability, improvements in computational power, and advancements in algorithmic techniques in the last three decades. The most commonly used supervised-learning technique uses examples and experience to teach how humans make predictions. The old approach of transferring human knowledge to machines through sequential steps is being replaced with an approach of providing machines with data—the same data humans have access to and use to learn. Since a machine does not have to learn other tasks (as a human does), its resources are fundamentally oriented toward learning the relationship between the input data and the corresponding outcomes. The result is a faster learning process and better accuracy in a specific task.

As in previous technological revolutions, the most significant impact would be expected in sectors that are not traditional users of these technologies, such as agriculture. Machine learning techniques can support efforts to forecast agricultural productions and yields (Ly and Dia 2020; Kaneko et al. 2019), manage natural resources, and reduce uncertainty and risk across the agricultural sector. African farmers are mostly smallholders (Conway, Badiane, and Glatzel 2019) facing significant uncertainties that can lead to poor performance, such as erratic rainfall, lack of knowledge about biogeophysical parameters and soil water content, and inadequate planting periods. The capacity to forecast agricultural production given these uncertainties is pivotal for farmers, planners, and policymakers.

Prediction is at the heart of decision-making; however, predictions are just one component of the process. The other decision-making components are judgment, action, outcome, and three types of data that include input, training, and feedback (Agrawal, Gans, and Goldfarb 2018). When decision-makers have access to the same input and training datasets and the same feedback loop, the two key factors that impact their interventions are judgment and predictions based on context. While judgment is a subjective concept that depends on background and experience, predictions can be objective and follow mathematical formulations; therefore, they can be improved faster and enhance the entire process of designing and implementing informed strategies.

2 Sentinel-2 is an Earth observation mission from the Copernicus Programme that systematically acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters. The mission is currently a constellation with two satellites, Sentinel-2A and Sentinel-2B, operated by the European Space Agency.

3 MODIS is the key sensing instrument aboard the Terra (originally known as EOS AM-1) and Aqua (originally known as EOS PM-1) satellites. Terra MODIS and Aqua MODIS are capturing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths.

Combining RSPs and Machine Learning for Resilient Food Systems

The path from RSPs and machine learning to policymaking is not straightforward, especially in Africa. The requirements for sustainable use of RSPs in policymaking for the agricultural sector (or any sector that requires RSPs) necessitate political will, technical expertise in remote sensing and data analysis, and the institutional strength, including sufficient financial and infrastructural resources, to deal with those tasks. Our rationale for combining RSPs and machine learning to build resilient food systems is as follows: the spatial and temporal resolutions of RSPs allow a disaggregated view of agricultural lands, with several indicators that assess crop growing conditions at a community level. As inputs into the machine learning predictive modeling framework, RSPs are expected to contribute to the development of reasonably accurate predictions about food crop production before the harvesting period. This helps build a more resilient food system by improving knowledge about potential agricultural production at the community level.

Public availability of consolidated, ready-to-use biogeophysical RSPs and food crop production forecast maps would reduce the technical, infrastructural, and institutional barriers that have the potential to prevent African countries from using RSPs and machine learning for resilient food systems. Table 9.1 shows the underlying techniques and concepts that must be harnessed to provide near real-time biogeophysical data and food crop production maps at the community level for all African countries. The corresponding outputs, outcomes, and constraints involved in decision-making in food production systems are illustrated.

TABLE 9.1—TECHNIQUES, OUTPUTS, AND OUTCOMES TO HARNESS RSPS AND MACHINE LEARNING FOR DECISION- AND POLICYMAKING FOR FOOD CROP PRODUCTION

Technique and Concept	Output	Outcome and Constraints Lifted
The use of RSPs and machine learning to assess policies impacts on food crop production systems.	Use the time-series data provided on the web-based tool to assess if the policy goals are reached or not, and take corrective actions.	
Decision-making and policy making based on forecasts and biogeophysical parameters time series.	Use the food crop production disaggregated forecast map at the community level to plan and strategize based on the scenario provided by the model.	All the information based on RSPs and their most likely future outcomes are made available to decision-makers to provide impactful policies.
The use of web-based tools to make datasets and maps publicly available.	Make the food crop production forecast maps and time-series data used as inputs available in a web-based tool.	Remote sensing products and food crop production forecasts at the community level are made publicly available, lifting the data access constraint.
Forecasts based on the combination of RSPs and ML and third-party data.	Use the combination of input variables data and ML method to learn the data patterns and use the data structure learned for future predictions.	The technical field-level expertise needed for a machine learning predictive model is not a constraint anymore.
Remote sensing products from satellite images and machine learning techniques.	Make available preprocessed input maps such as NDVI, LST, rainfall, ET, production maps as labels, and crop masks and choose ML technique.	The lack of technical skills related to data processing methods for satellite image is not a constraint anymore for analysts, decision-makers and policymakers.

Source: Authors.

Note: ET = evapotranspiration; LST = land surface temperature; ML = machine learning; NDVI = normalized difference vegetation index; RSPs = remote sensing products.

Remotely Sensed Data, Crop Selection, and Predictive Modeling Framework

Food crop production estimations based on remote sensing can be built through two main approaches: (1) using remotely sensed data as inputs into agro-meteorological or plant-physiological models, and (2) building a direct mathematical relationship between remotely sensed data and crop production (Huang and Han 2014). The first approach is based on mechanistic descriptions of crop growth, development, and production simulated through mathematical functions. Methods like this have shown satisfactory results but cannot exploit datasets to their full extent due to constraints related to the way crop growth phenomena are described with mathematical functions. The second approach usually relies on derived indicators from remotely sensed data and their correlation with crop growth and yield. In the analysis in this chapter, we follow the second approach to predict food crop production values based on inputs derived from RSPs. In this section, we describe the data used, the selection of crops considered, and the construction of the predictive modeling framework, AfCP.

Biogeophysical Remotely Sensed Data for Food Crop Production Forecasts

One of the most known and used parameters to characterize vegetation cover is the NDVI, derived from near-infrared and red bands from multispectral sensors. The NDVI indicator is extensively used to characterize vegetation cover due to its close relationship with several vegetation parameters such as leaf area index, the fraction of absorbed photosynthetically active radiation, and green biomass. Many studies have been conducted to predict crop yield from NDVI signals (see Liu et al. 2019; Rembold et al. 2013; Rasmussen 1992, 1997). However, there are limitations to using only NDVI as a proxy for crop yield estimation due to its dependencies on the crop, soil, and leaf types. Indeed, even though NDVI is a good proxy for aboveground biomass production, the relationship between biomass and yield varies in time and space (Leroux et al. 2016). Our approach emphasizes the use of several RSPs, and thus ensures the use of even more information about crop status than the use of only NDVI.

Several studies conducted in the 1970s have shown that final crop yield can be related to thermal indexes (Idso, Jackson, and Reginato 1977; Smith et al. 1985). Because of this, an LST-day layer has been used as a proxy for crop water stress in our methodology. Water availability is also a key component for crop growth and yield; therefore, it is essential when building a crop production model to take it into account. However, in most African countries, agricultural lands are rainfed (Stockholm International Water Institute 2018), so rainfall data has been derived from the climate hazards group infrared precipitation with station data RSPs.

Soil water content and its dynamic in the ground under agricultural lands is an important parameter to address. The underground water is conveyed toward the atmosphere through two main channels: evaporation and transpiration. The former corresponds to the transformation of liquid water into a gaseous state and its release into the atmosphere. For the evaporation process to occur, soil moisture, vapor pressure gradient, and 600 calories of heat energy for every 1 gram of water are required. The transpiration mechanism consists of underground water transportation from the soil to a plant's roots, then from the roots to the leaves through the vascular plant tissues, and ultimately, from plant tissues to evaporation into the atmosphere. As explained by Bhatt and Hossain (2019), transpiration is the most desired mechanism since water transportation through the plant's internal structure also carries nutrients from the soil to the plant and prevents the plant's tissue from overheating. However, measuring the two processes' contributions to the amount of water in the atmosphere is difficult; therefore, their combined effects are usually measured with the ET index from RSPs. We use the total ET of crop locations as a proxy for measuring the crops' rate of transpiration, which, by its effectiveness, will inform us of the crops' health.

Our production-estimation methodology allows us to predict production for one crop in the region of interest before the harvesting period and at the community level. Raster-type maps for historical production quantities for 42 crops and at a global scale are publicly available from the spatial production allocation model (SPAM) database (IFPRI 2016, 2019, 2020). They have been generated by an allocation model with a grid cell size of 10 kilometers. These maps are used for two purposes: (1) using the pixel production values as response variables to our model and (2) creating crop masks to target areas where a specific crop is believed to be grown. Table 9.2 summarizes the list of RSPs taken as inputs and

TABLE 9.2—INPUT PARAMETERS FOR THE FOOD CROP PRODUCTION MODEL WITH THEIR SPATIAL AND TEMPORAL CHARACTERISTICS

Input Parameters	Dataset ID	Spatial Resolution (km)	Temporal Resolution (days)	Temporal Extent (period)
NDVI	MOD13A2	1.00	16	2000–NOW
LST-day	MOD11A2	1.00	8	2000–NOW
Rainfall	Africa_monthly	5.55	30	1981–DEC 2020
ET	MOD16A2	0.50	8	2000–NOW
Production	P	10.00	—	2000, 2005, 2010, 2017

Source: Authors.

TABLE 9.3—SELECTED LIST OF FOOD CROPS BY AFRICAN REGION

African Regions (# of Countries)	Food Crops	# of Countries where Crop Is in the Top 5
Eastern Africa (14)	Maize	8
	Cassava	8
	Sugarcane	9
Central Africa (7)	Cassava	5
Southern Africa (5)	Maize	3
Northern Africa (5)	Wheat	4
Western Africa (16)	Cassava	8
	Rice	9
	Maize	7

Source: Authors.

response variables for our food crop production model and their spatial and temporal characteristics.

Crop Selection for the Food Crop Production Model

African farmers are mostly smallholders who grow food for consumption and income. Because of chronic infrastructural and financial issues and difficulties in accessing agricultural inputs and markets, a relatively low-intensity shock could significantly impact their food security status. Therefore, having knowledge of potential future agricultural production before the harvesting period is essential for planning purposes. Crops should be targeted according to their relative importance for a country's most vulnerable communities, especially during a major crisis such as the COVID-19 pandemic.

In this chapter, the criteria that determined the importance of a food crop were a combination of its production quantities and the food self-sufficiency of a country. Two rankings were performed to identify a country's top 5 important food crops: the first was a ranking of the 10 most-produced food crops, and the second was a ranking of food crop self-sufficiency. The analysis relied on agricultural variables that were publicly available on international databases. Production and domestic supply data for 2014–2018 (the most recently available years) were available from the Food and Agriculture Organization (FAO 2021).

For each country, a preliminary list was developed of the 10 most-produced agricultural commodities in terms of quantities. Subsequently, the sufficiency aspect was included through the self-sufficiency ratio, defined by the share of food crop consumption to food crop production at the domestic level. The ratio evaluated whether a country produced enough food crops to cover its own needs for each of the 10 most-produced food crops. An agricultural commodity was considered essential for a country if the consumption was greater than the production. The list of the 5 primary produced and consumed commodities for each country by region are reported in Tables 9A.1, 9A.2, 9A.3, 9A.4, and 9A.5 in the appendix.

The most predominant in the top five food crops among countries were selected for the regional level. Table 9.3 presents the selected list of crops for each region. In eastern Africa, maize, cassava, and sugarcane were selected as the major food crops. Indeed, 8 of 14 countries, based on our ranking, had maize and cassava as their top priority products in terms of production and consumption. Sugarcane was also essential for 9 of 14 eastern African countries. In western Africa, three crops were selected: cassava, rice, and maize. Cassava, maize, and wheat were identified as essential in central Africa, southern Africa, and northern Africa, respectively. Due to data representativeness considerations, only maize was considered for eastern Africa.

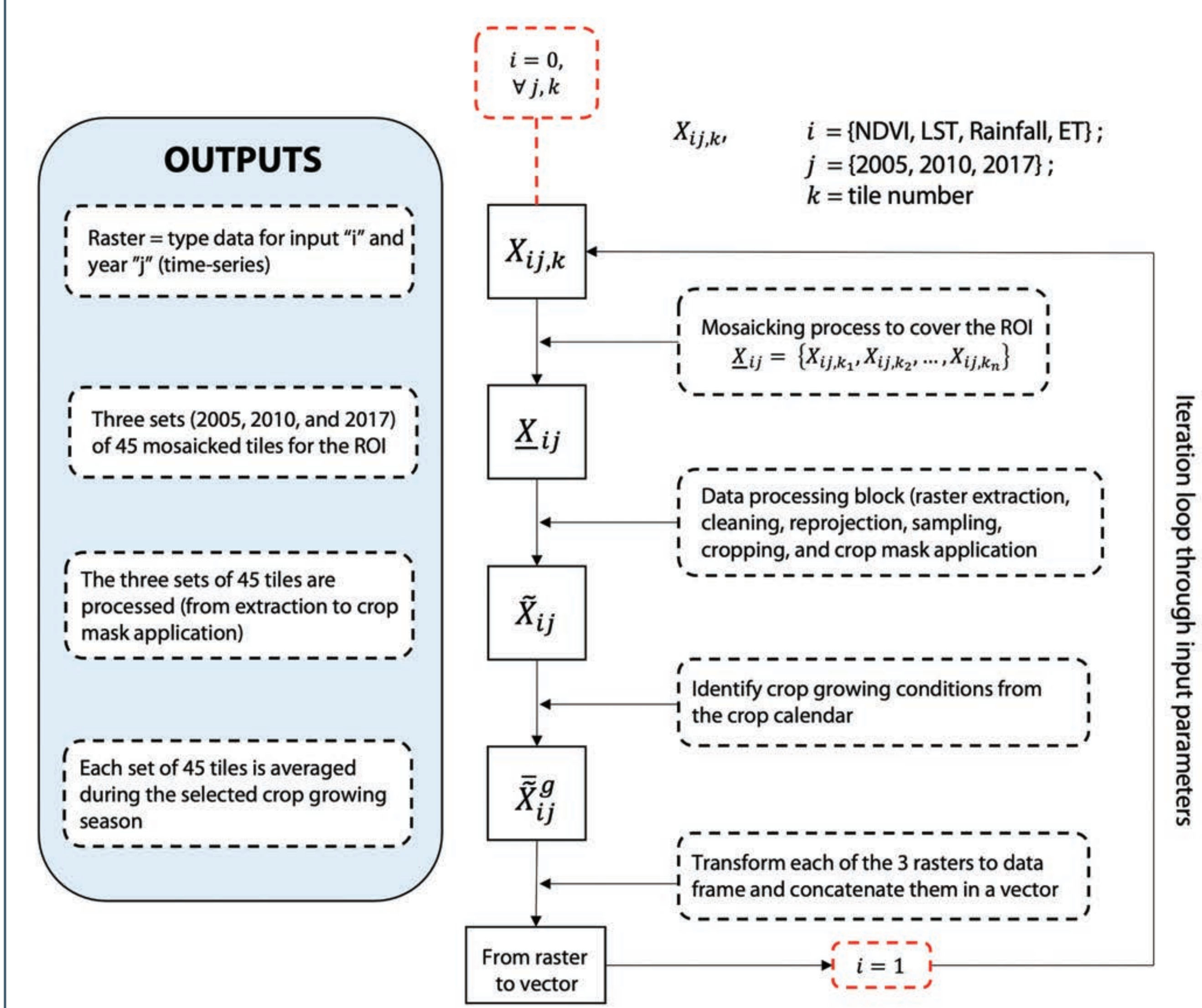
Predictive Modeling Framework

Data Preprocessing and Input Variable Prediction

Data preprocessing procedures were carried out to build the final dataset. The appendix describes the preprocessing steps, which were data access; mosaicking; raster extraction and cleaning; reprojection, pixel resampling, and cropping; crop mask application; and dataframe construction. At the onset of a crop growing season, input variables are not promptly available on the MODIS data portal due to a delay between data gathering, processing, and online publishing processes. Since our model depends on those variables, we used their historical values to predict potential future trends, most specifically during the crop growing season. For this, a random forest (RF) model was used. RF is a supervised learning model that commonly is used for regression problems. It is also known as the bootstrap aggregator due to its two-step procedure to learn patterns within the dataset: (1) feature and raw sampling with replacement and (2) aggregation with majority-vote rule.

For the RF model used to forecast input variable values during the growing season, the Python open-source sklearn

FIGURE 9.1—AN OVERVIEW OF THE AFCP MODEL DATA PROCESSING AND COMPUTATIONS



Source: Authors.

RF regressor was used. One decision tree (DT) layer was created with 2,000 blocks.

The Africa Food Crop Production Model Computational Aspects

The supervised learning ANNs method was used to build the AfCP model. The inputs were the first four biogeophysical parameters listed in Table 9.2, and the corresponding outputs were the production values (Figure 9.1). A preprocessing data stage dealt with building the proper format and splitting the data into training, validation, and testing sets. The learning process was carried out by building the relationship between inputs and response variables with the training dataset that corresponded to 80 percent of the initial dataset. The validation data (10 percent of the dataset) were used to fine-tune the model. Finally, the testing data (the remaining 10 percent of the dataset) allowed assessment of the model accuracy. The model accuracy was assessed by comparing the model predictions on the test set with the corresponding actual values. This choice was motivated by the unavailability of ground-truth data at the same pixel level. An overall arithmetic average of out-of-sample root-mean-squared error (RMSE) of 0.044 was obtained for all African countries (see Table 9A.6 in the appendix for a detailed overview of the model RMSE across countries and crops). In addition, the aggregated prediction data were compared with public databases such as FAOSTAT (FAO 2021) or food crop production as the sanity check for the AfCP model predictions.

Forecasts were made before the harvesting period (in 2020) for each of the targeted crops (Table 9.3). The FAO crop calendar (FAO n.d.) was used to identify sowing, growing, and harvesting periods. For the eastern African region, cassava and sugarcane were not considered in this study due to data availability issues. For each country [4] and crop, the food crop production modeling work starts at the onset of crop greenness, which is considered the beginning of the growing season. Most of the biogeophysical parameters were not available at that time; therefore, their historical values were used in an RF regressor to estimate their future values in the growing season. The future values were then used as inputs in the food crop production model (see Section 3.3.1).

Food Crop Production Forecasts During the Pandemic

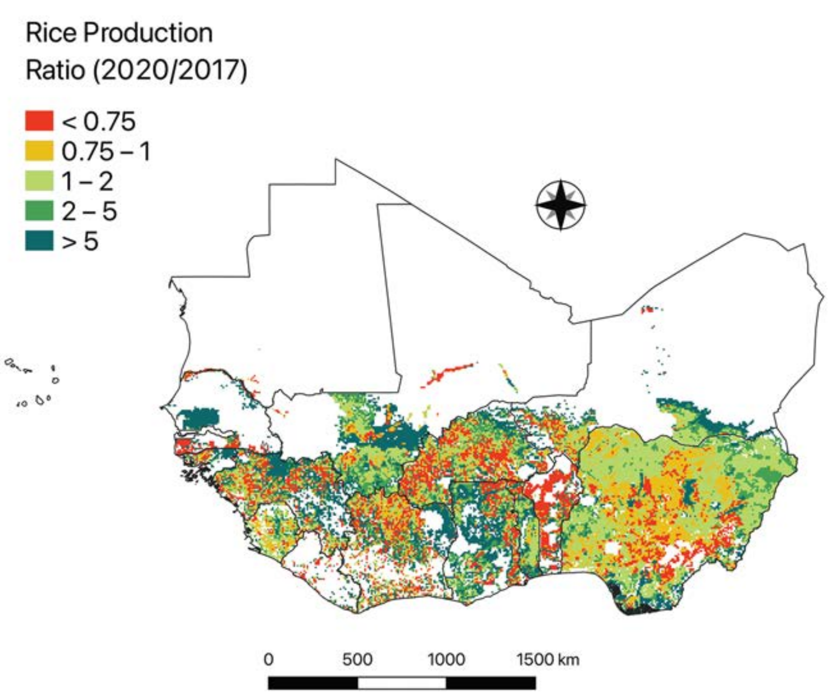
The food crop production model was applied to all African countries and selected crops. Figures 9.2, 9.3, and 9.4 show the 2020 maps' predicted production as a share of the 2017 production for rice, maize, and cassava, respectively, for the western African countries. Figures 9.5 and 9.6 show the maize production ratio for eastern and southern Africa, respectively. Figures 9.7 and 9.8 show wheat and cassava production ratios for northern and central African countries. Figures 9A.4 and 9A.5 in the appendix show the AfCP model's outputs for western (rice, maize, cassava), eastern (maize), northern (wheat), southern (maize), and central (cassava) African regions, respectively.

At the regional level, the production quantities for most of the selected crops in each African region are expected to decline in 2020 as compared to 2017. Only the production quantities for cassava in the western (Figure 9.4) and central (Figure 9.8) African regions are expected to increase, compared with 2017, by 4.2 percent and 28.4 percent, respectively. The sharpest decline in production quantities for the three selected crops in the western African region is expected for rice, with a decrease close to 12 percent, while maize production is expected to decline by close to 5 percent. The decline in maize production is expected to be around 1.5 percent and 18.6 percent for the eastern and southern African regions. Wheat production shows a decline of close to 10 percent in the northern African region in 2020 compared with 2017.

According to the FAO, the six central African countries' aggregated cassava production was around 47 million metric tons in 2017 (FAO 2021). The most significant contributor was the Democratic Republic of the Congo (66.6 percent), followed by Angola (17.9 percent) and Cameroon (10.2 percent). Our model suggests a total cassava production of close to 60 million metric tons for the same countries in 2020, which corresponds to an increase of 28 percent compared to 2017. However, in 2020, the distribution of total production across individual countries is expected to remain the same for Angola, while

4 Food crop production forecasts were performed for each African country. Then national maps were merged together to obtain regional maps. Such a strategy is justified by the need to avoid the so-called "ecological fallacy," which in this case means making predictions for a country based on an aggregated dataset at a continental level. The consequence of that would be country input data impacting the output data for another country.

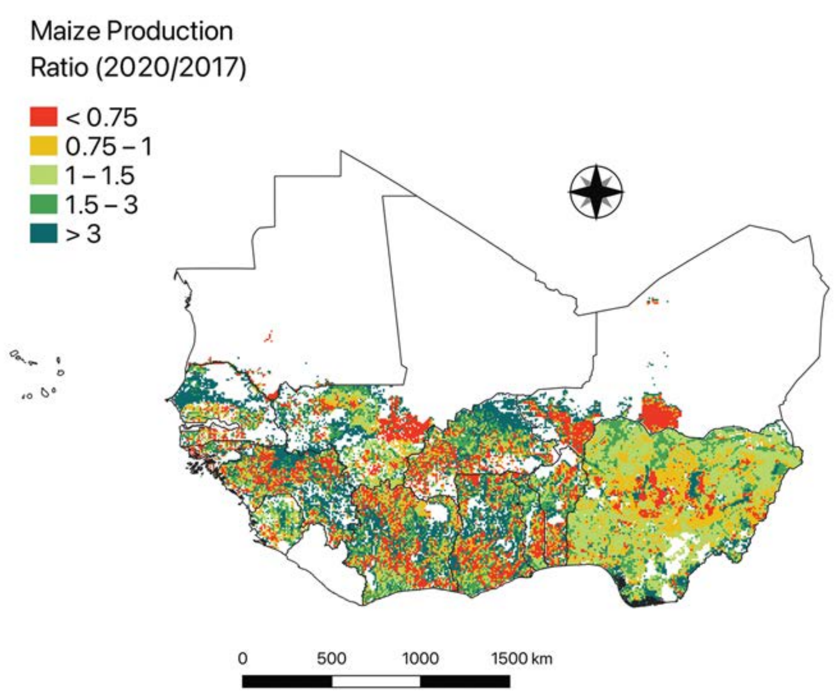
FIGURE 9.2—THE 2020 PREDICTED RICE PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR WESTERN AFRICA



Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

FIGURE 9.3—THE 2020 PREDICTED MAIZE PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR WESTERN AFRICA



Source: Authors.

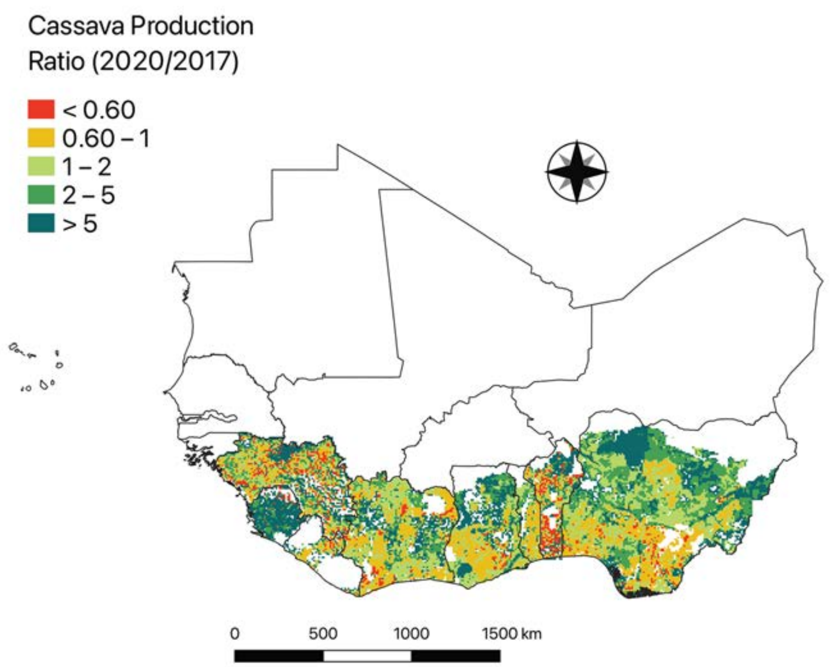
Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

Cameroon's shares are expected to decrease by roughly half (5.6 percent). The Democratic Republic of the Congo has a share increase of nearly 10 percent.

In northern Africa, the ratios between predicted wheat production levels for the 2020 season and actual levels in 2017 show a slight decrease in 2020. On average, the map (Figure 9.7) suggests better wheat production for the 2017 season compared with 2020 for Libya, Tunisia, Morocco, and Algeria. Compared with 2017 production levels, projected wheat production in 2020 in Sudan and Egypt shows an increase of 3.5 percent and 2.8 percent, respectively, while other countries show a decline.

The aggregated maize production predicted from our model for eastern countries is around 28 million metric tons in 2020. Each country's contribution to the global production is as follows: Ethiopia (27.7 percent), Tanzania (20.2 percent), Kenya (12.2 percent), Zambia (10.9 percent), Uganda (10.7 percent), Malawi (9.1 percent), Mozambique (5 percent), Zimbabwe (2.5 percent), Rwanda (1.1 percent), and Madagascar (0.8 percent). In 2017, the production was estimated at around 28.5 million metric tons for the same countries (IFPRI 2020). There is a slight decrease of 1.6 percent in 2020 production estimates compared with 2017. However, some countries, such as Ethiopia, Zimbabwe, Uganda, and Zambia, show a slight increase in their production of

FIGURE 9.4—THE 2020 PREDICTED CASSAVA PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR WESTERN AFRICA



Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

0.8 percent, 13.2 percent, 4.6 percent, and 3.8 percent, respectively, compared with 2017.

Figure 9.6 shows ratios between predicted maize production levels for the 2020 season and actual levels in 2017 in southern Africa. The map suggests disparities in maize production for the 2020 season compared with 2017. Maize production is expected to decline by 30 percent in South Africa, 20 percent in Lesotho, 4.9 percent in Eswatini, and 0.7 percent in Namibia from 2017 to 2020.

While the biogeophysical parameters might not allow the establishment of a causal effect between the agricultural production variabilities and COVID-19, the gap between FAO agricultural production data and the AfCP model

TABLE 9.4—TOTAL PRODUCTION IN 2017 AND 2020, AND THE RATE OF CHANGE FOR EACH CROP AND AFRICAN REGION

Region	Crop	2017 Production (MT)	2020 Predicted Production (MT)	Rate of change (%)
Western Africa	Rice	17,803,495.8	15,640,125.8	−12.15
	Maize	21,666,866.9	20,599,545.5	−4.92
	Cassava	90,151,658.8	93,948,433.2	+4.21
Eastern Africa	Maize	28,539,928.7	28,095,011.8	−1.55
Northern Africa	Wheat	18,392,407.2	16,610,688.1	−9.68
Southern Africa	Maize	420,814.5	342,688.3	−18.56
Central Africa	Cassava	47,209,110.0	60,598,537.0	+28.36

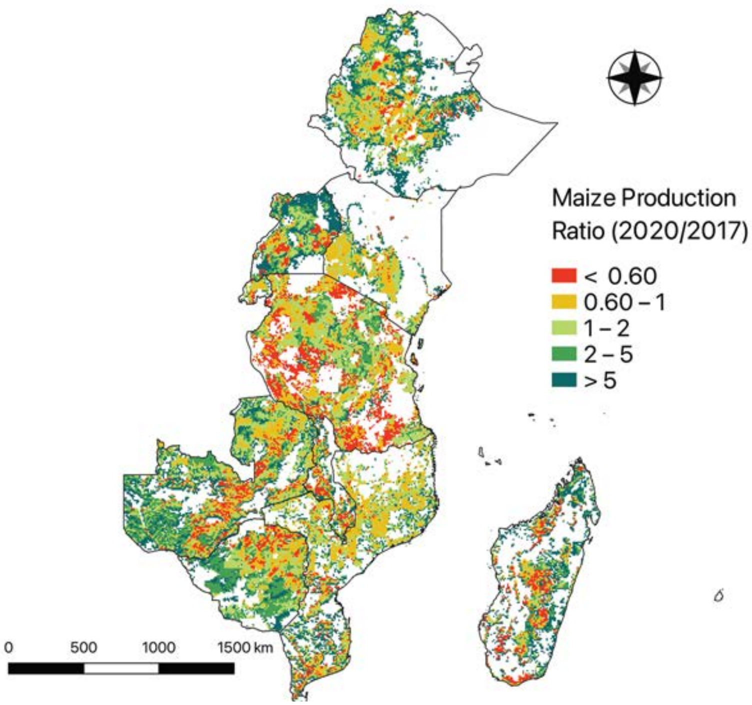
Source: For 2017 production, FAOSTAT; for 2020 production, authors.

Note: MT = metric tons.

predictions can provide information about the potential impacts of government restriction measures.

Indeed, COVID-19 was declared a pandemic on March 11, 2020, and lockdown measures followed shortly afterward. The onset of the pandemic in Africa coincided with the seed marketing period for maize in West Africa and with the end of cassava seed marketing for the same region (de Boef et al. 2021). Seed scarcity is a consequence of mobility restriction measures, and it significantly affects food crop production and pushes farmers to rely more on the informal seed market, leading to less potential for high yields. From the same study, 79 percent of panelists from Myanmar, Nigeria, Ethiopia, and Uganda reported facing significant difficulty in obtaining sufficient volumes of quality early generation seeds of desired varieties. Moreover, according to a forecast from the national seed committees of member states of the Economic Community of West African States and the Permanent Interstate Committee for Drought Control in the Sahel, there will be a shortfall of certified seeds for maize and millet in the 2020 cropping season (CORAF 2020). Fewer than 10,000 metric tons of certified sorghum and millet seeds were produced in 2020 compared with a demand of about 100,000 metric tons, representing only about 10 percent availability. As for maize, about 70,000 metric tons are available, though the need is close to 200,000 metric tons (CORAF 2020). The lack

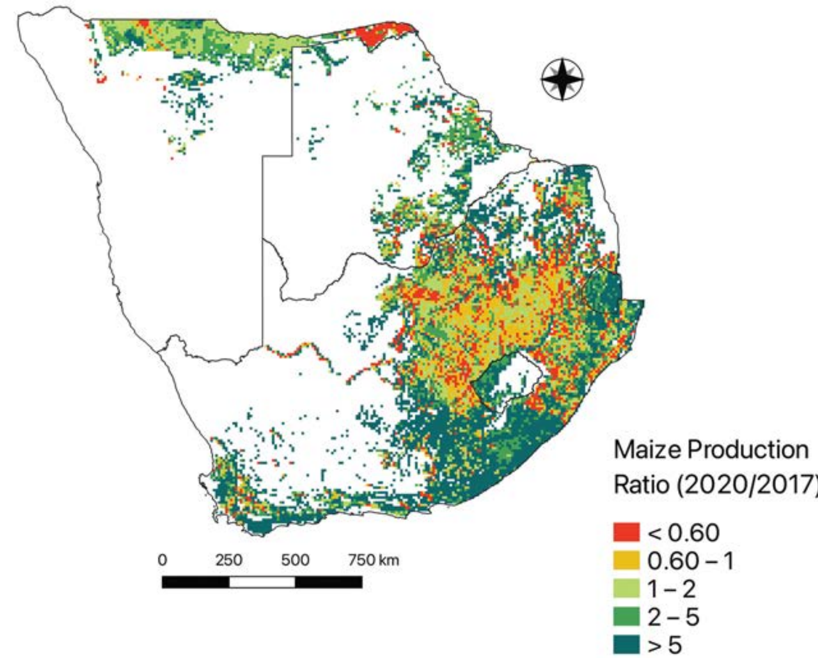
FIGURE 9.5—THE 2020 PREDICTED MAIZE PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR EASTERN AFRICA



Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

FIGURE 9.6—THE 2020 PREDICTED MAIZE PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR SOUTHERN AFRICA



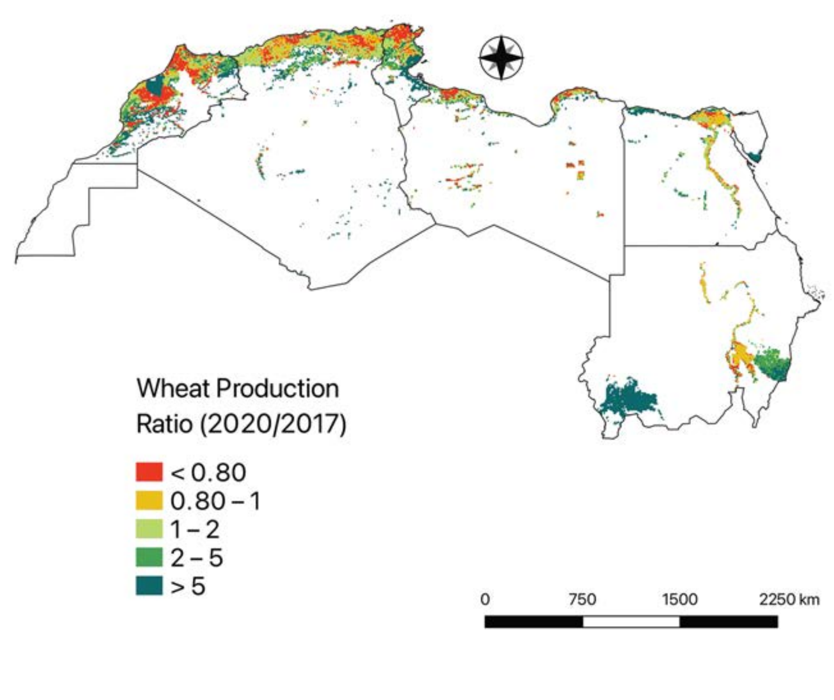
Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

of timely reception and use of seeds due to mobility restriction measures can explain the food crop production decrease at the regional level. However, each country has its own COVID-19 policy for agricultural inputs and a different strategy to secure seeds for its national farmers. This could also explain why some countries in the same region show an increase in the production of a specific crop, while others show a decrease. However, only a comparative analysis between countries' policies could help confirm this assertion. The seed scarcity also coincides with an increase in transaction costs that hinder farmers' access to affordable and certified seeds.

The mobility restriction measures implemented to reduce the spread of COVID-19 have also affected labor mobility, especially for a labor-intensive sector such as agriculture. The sector employs 70 percent (World Bank 2013) of the total workforce in the region south of the Sahara. The planting period corresponds to the peak of labor demand; therefore, any disruption in labor supply will potentially have a negative impact on food crop production. Moreover, most countries implemented border closures during the planting period of maize and rice, with the consequence of potentially delaying the harvesting period. There is a high probability that mobility restriction measures and labor scarcity will significantly impact the production of major staple crops in the region.

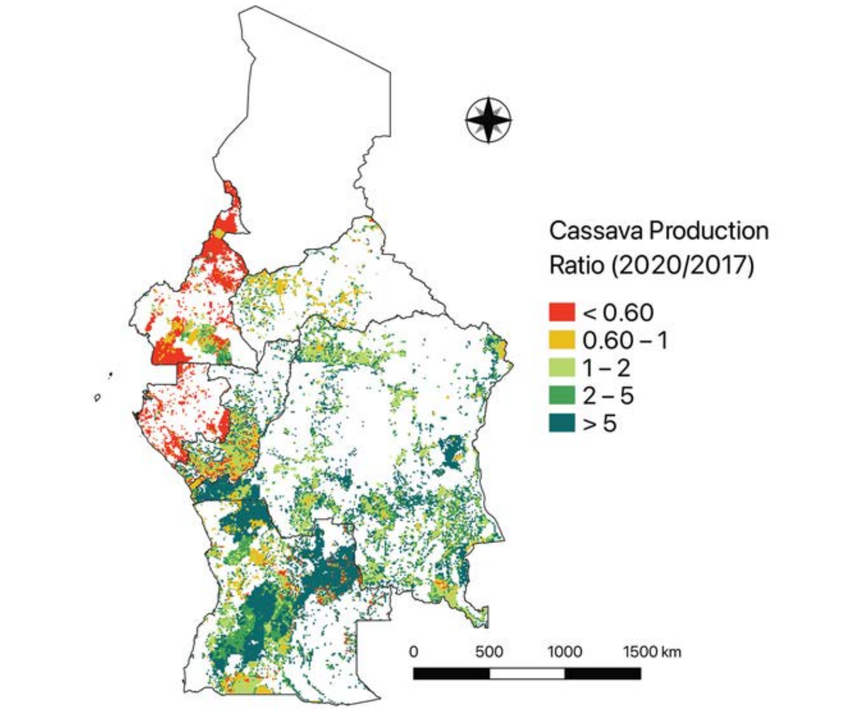
FIGURE 9.7—THE 2020 PREDICTED WHEAT PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR NORTHERN AFRICA



Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

FIGURE 9.8—THE 2020 PREDICTED CASSAVA PRODUCTION AS A SHARE OF THE 2017 PRODUCTION FOR CENTRAL AFRICA



Source: Authors.

Note: If the ratio is above unity, the 2020 predicted production is expected to be larger than the 2017 production. A ratio smaller than unity means an expected decrease in production in 2020 compared to 2017.

As Figures 9.2–8 show, while many areas are expected to experience declines in 2020 production compared with 2017 levels, production is predicted to be higher in other areas. In addition to the impacts of COVID-19, many other factors affect crop production in complex ways: climate and weather variability in particular drive much of the variability in crop production.

In addition to the potential to monitor crops' growing conditions through biogeophysical parameters, the combination of RSPs and machine learning provides several other benefits. The RSPs allow us to bring disaggregation to the community level while the machine learning techniques help us predict food crop production before the harvesting period. These two outcomes are valuable assets to strengthening food production systems in Africa through improved agricultural statistics and analytics. However, the path from RSPs and machine learning to policymaking in the agriculture sector requires several steps.

The AfCP Model Limitations and Future Direction of Research

Nonbiogeophysical Input Parameters

The rationale for building the AfCP model was to provide data and forecasts about agricultural production to help navigate the uncertainties of COVID-19 in the African agricultural sector. We also encountered the need to further disaggregate the data due to the localized impacts of such a crisis (or any crisis), which sometimes are either not perceived or are weakly perceived at the national level. In such a process, the choice of biogeophysical data for the AfCP was made for three main reasons: (1) they provide disaggregated data by nature, (2) they have sufficiently long time-series data for machine learning-type predictive modeling, and (3) they have direct effects on food crop production. However, we acknowledge that other nonbiogeophysical parameters can also have a significant impact on food production, such as population density (as a proxy for labor) and food security status. Such aspects will be included in a future version of the AfCP model.

Spatial Resolution

Another limitation of the AfCP is its spatial resolution, which is 10 kilometers. Such a low resolution is explained by the crop masks that were derived from SPAM production rasters. Because they were the lowest resolution maps among the input and response variables, the choice was made to aggregate the highest resolution rasters' pixels to 10 kilometers rather than resampling the crop masks at a higher resolution, which would bring significant homogenization to the dataset and lower the learning capacity of the AfCP. While the 10-kilometer pixel values are representative of the area covered, they are much larger than typical African farm sizes of fewer than 2 hectares.

An improvement to the AfCP would be the use of higher spatial-resolution rasters, which would allow the further disaggregation of the predictions and increase the overall accuracy of the model. Such an improvement is ongoing, currently with a crop mask derived by the recently released cropland map at 10 meters spatial resolution from the Environmental Systems Research Institute, based on data from Sentinel-2. However, the current degree of spatial resolution already allows us to predict production at a more disaggregated level than the usual administrative divisions in Africa and, therefore, to generate evidence to inform specific policies at the community level.

Ground Truthing

Another limitation of the AfCP is that it was not calibrated with ground-truth data. The data that would allow for that are not available at the same spatial resolution. Therefore, the accuracy assessment was performed on the test set. There is a need to improve the model accuracy with countries' data even though a comparison between predicted and actual values from public datasets, such as the FAOSTAT portal, yielded good results at subnational and national levels. AKADEMIYA2063 is working toward building the partnerships that would allow ground truthing.

Conclusion

As suggested by the impacts of COVID-19, a robust African agricultural statistics system is much needed to create informed and targeted responses and policies. Building a culture of gathering accurate and timely data about features related to food crop production would not only facilitate the production of better policies and monitoring and evaluation mechanisms, it would also be critical to increasing countries' levels of preparedness for any potential future crisis in the sector. Data gathering could help improve preparedness by identifying the crisis early enough to mitigate its impacts or by allowing decision-makers and policymakers to better manage it. This chapter explains how emerging technologies such as RSPs and machine learning can be harnessed to provide valuable information for decision-making processes in the agricultural sector. The AfCP model has been in development from the onset of the COVID-19 crisis. Although the pandemic has been the pretext for the predictive modeling work, this sort of model architecture could be used or adapted outside of the COVID-19 context. However, it is worth noting that any adaptation will require carefully choosing the explanatory variables and ensuring their availability at the pixel level. The path from a raw satellite image to an informative map is not straightforward; several areas of expertise need to operate at different levels.

Capacity building for emerging technologies such as remote sensing and machine learning should be institutionalized. African governments must create special units in which emerging technologies can be harnessed to inform policies. Moreover, incentivizing initiatives in the private sector to do the same would also benefit African countries. However, attracting students into the fields of emerging technologies requires both sectors to create solid public-private partnerships and support for entrepreneurship in science, technology, engineering, and mathematics to create jobs and ensure the availability of a critical mass of experts.

Across African countries, data related to food crop production in the agricultural sector are collected at the season onset and after the harvesting period. The data are mainly collected at the household level, including household information, crop type, production quantities, land size, availability and use of agricultural inputs, post-harvest loss, and trade information. This methodology has proven sufficient for an extended period. However, given technological improvements and their use in more efficient data-gathering processes, there is a need to take full advantage of the current data-gathering technologies, such as unmanned aerial vehicles for spectral signature data gathering and monitoring purposes or tablets with predefined surveys combined with cloud infrastructure for storage and computations.

Metadata are as essential as primary data in obtaining the benefits of recent analytics tools and predictive modeling through machine learning. Metadata help to contextualize the primary datasets and add more explanatory variables into the predictive model for more robustness. The use of cloud technology, telecommunications, and tablets with embedded optimized forms could facilitate gathering such third-party information. The cloud would help to store the data and perform further analysis; the Internet connection could help gather GPS coordinates and inform about the locations where the data were gathered (not only at the household level but at the farm itself, allowing the analysis of biogeophysical parameters from RSPs). For this to occur, at least three enabling technologies are required: (1) the improvement of Internet connections in rural areas where most farms are located, (2) the inclusion of metadata information gathering into agricultural surveys, and (3) the renewal of data-gathering tools to migrate data from papers and laptops to tablets that are more suitable for such a task. Such an approach of using emerging and well-established technologies to support better-quality data gathering in the agricultural sector will progressively require fewer resources, because the use of remote sensing will reduce the need to update some data from the ground.

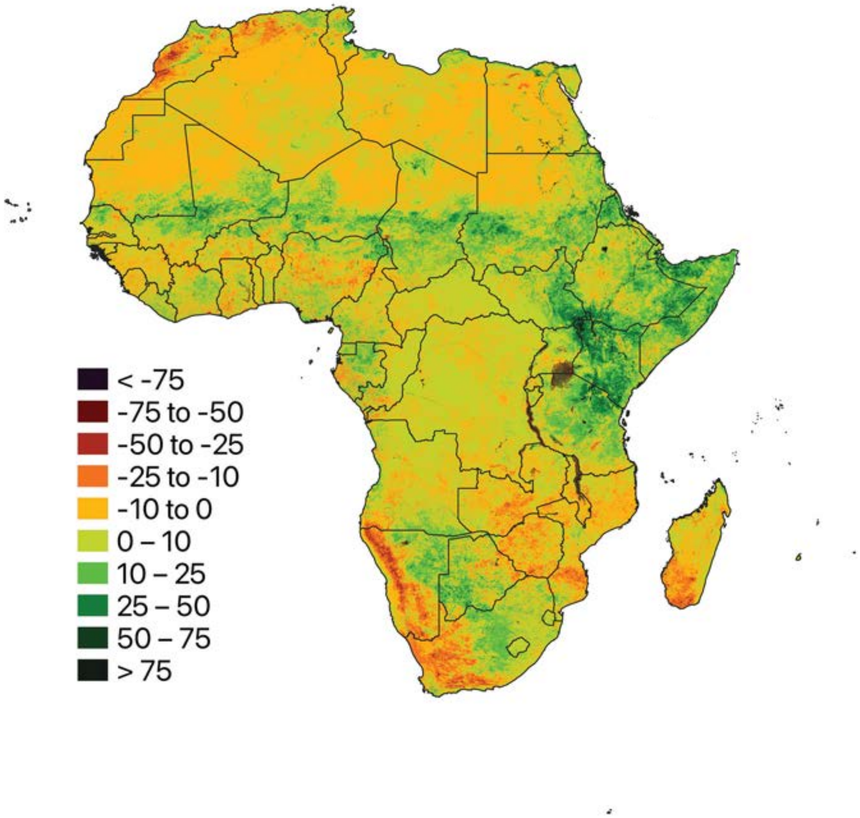
Information asymmetry between researchers and policymakers is a long-standing problem in Africa, especially in the agricultural sector. Moreover, the fast pace of turnover in offices makes the consolidation of technical knowledge within an institution difficult. For instance, an individual at a national statistics bureau could be trained to work with remote sensing products and machine learning techniques within a year. The following year, that individual could have moved to another ministry, another entity of the same ministry, or another institution. From a general point of view, the training is not lost. However, the corresponding technical capacity moves from one entity to another with the risk that is not used where most needed.

The complex African cropping system makes it difficult to collect accurate and timely data in a sustainable way. Data scarcity does not allow the type of detailed analysis that decision-making requires in a time of uncertainty. Even when the data quality and disaggregation requirements are met, however, the way the knowledge is produced seems to be inaccessible to policymakers, especially when emerging technologies are used and are far from reach. One way of closing this gap is to use data visualization expertise to transform data and knowledge from a raw stage to an informational stage. Such expertise is not yet well developed across African countries and needs to be built.

The results of this chapter not only support the use of emerging technologies such as RSPs and machine learning techniques to improve agricultural statistics, but also show how they could be leveraged to increase African countries' preparedness to shocks after COVID-19. The pandemic has shown how much timely and accurate data are needed for early action and intervention in the agricultural sector and beyond. Recent technologies must be considered in every part of the data environment—from collection to analysis.

Appendix

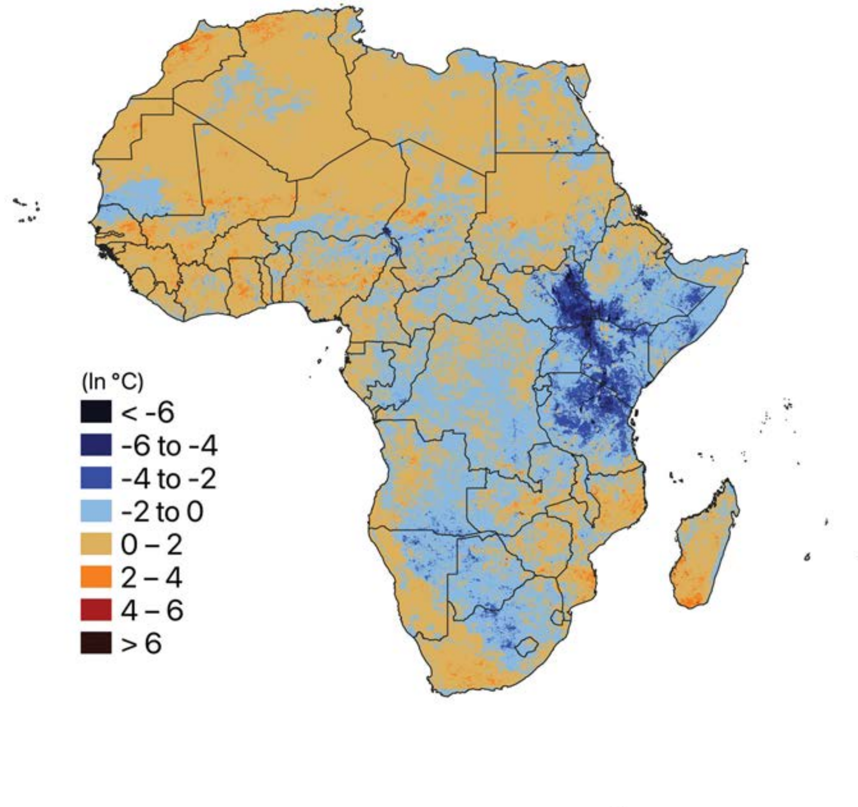
FIGURE 9A.1—NDVI ANOMALY IN AFRICA FOR THE YEAR 2020



Source: Data processing and map from authors.

Note: The values provided are relative to the twenty years (2000–2019) average for each pixel.

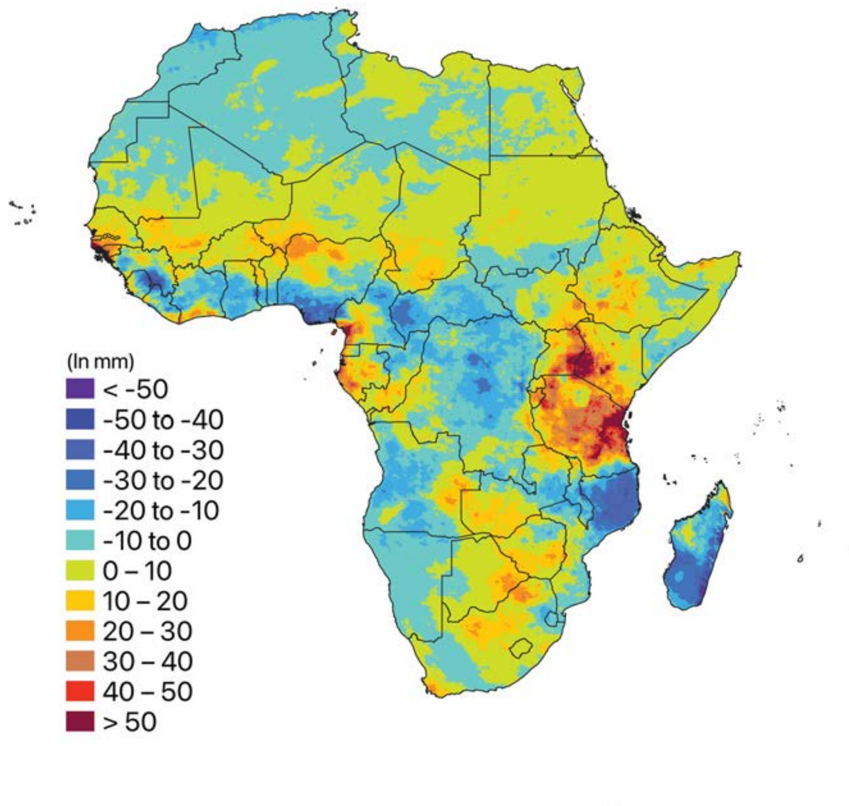
FIGURE 9A.2—DAYTIME LST ANOMALY IN AFRICA FOR THE YEAR 2020



Source: Data processing and map from authors.

Note: The values provided are the absolute difference between the 2020 pixel values and their historical average (2000–2019).

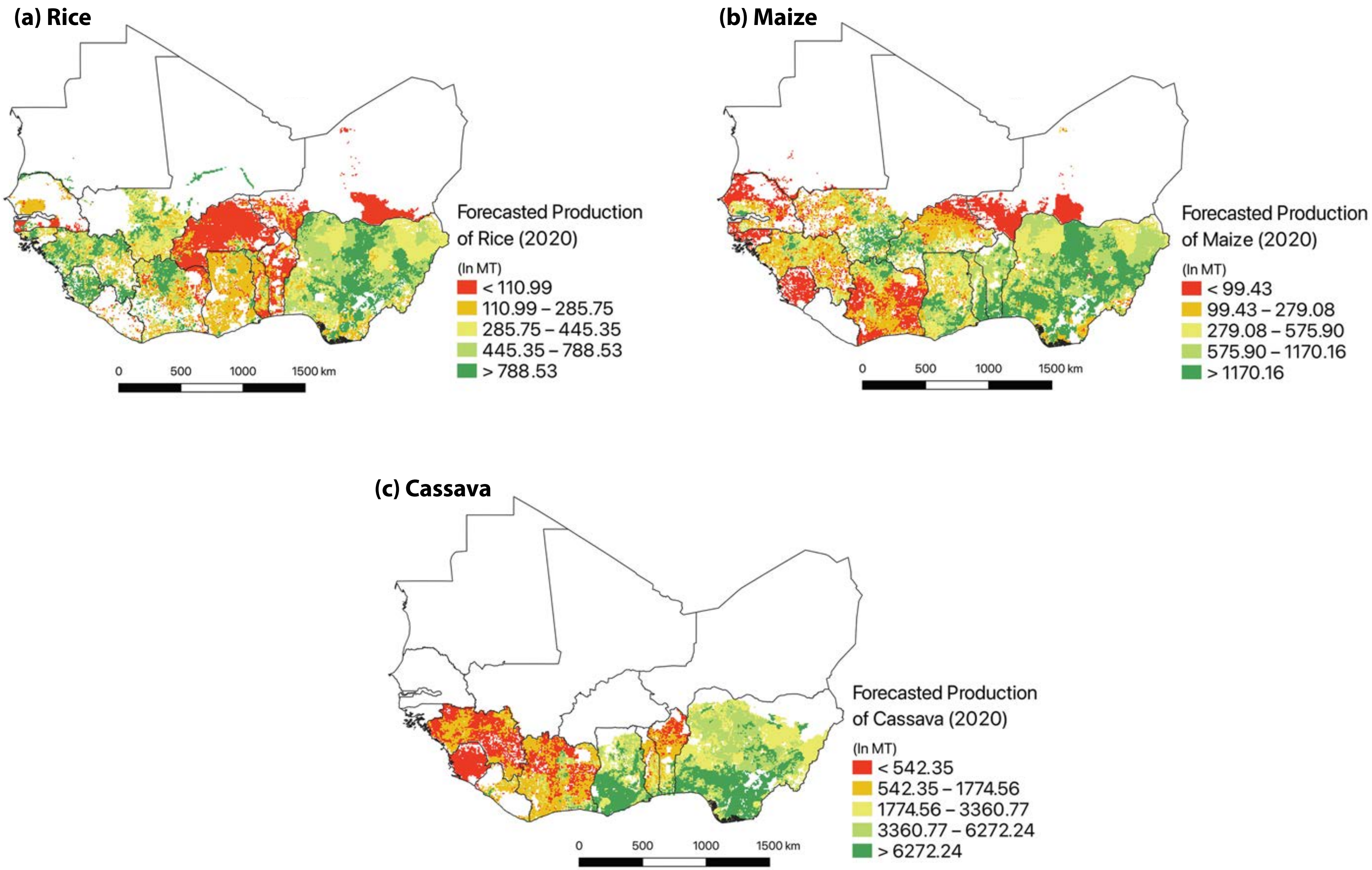
FIGURE 9A.3—RAINFALL ANOMALY IN AFRICA FOR THE YEAR 2020



Source: Data processing and map from authors.

Note: The values provided are the absolute difference between the 2020 pixel values and their historical average (2000–2019).

FIGURE 9A.4—THE 2020 PREDICTED (A) RICE, (B) MAIZE, AND (C) CASSAVA PRODUCTION IN WESTERN AFRICAN COUNTRIES

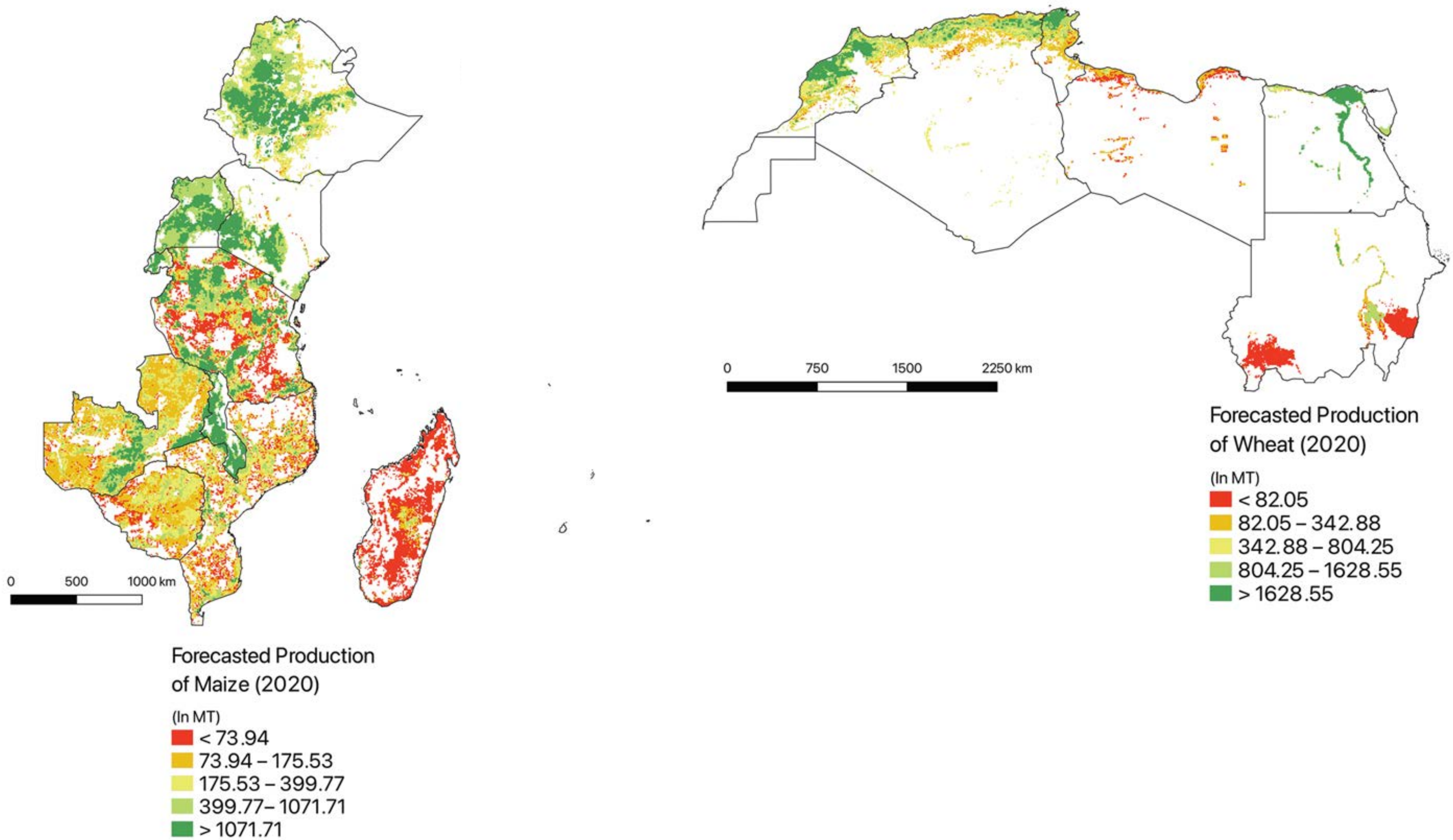


Source: Data, methodology, and maps from authors.

FIGURE 9A.5— THE 2020 PREDICTED (A) MAIZE PRODUCTION IN EASTERN AFRICAN COUNTRIES, (B) WHEAT PRODUCTION IN NORTHERN AFRICAN COUNTRIES, (C) MAIZE PRODUCTION IN SOUTHERN AFRICAN COUNTRIES, AND (D) CASSAVA PRODUCTION IN CENTRAL AFRICAN COUNTRIES *(continued on next page)*

(a) Maize—eastern African countries

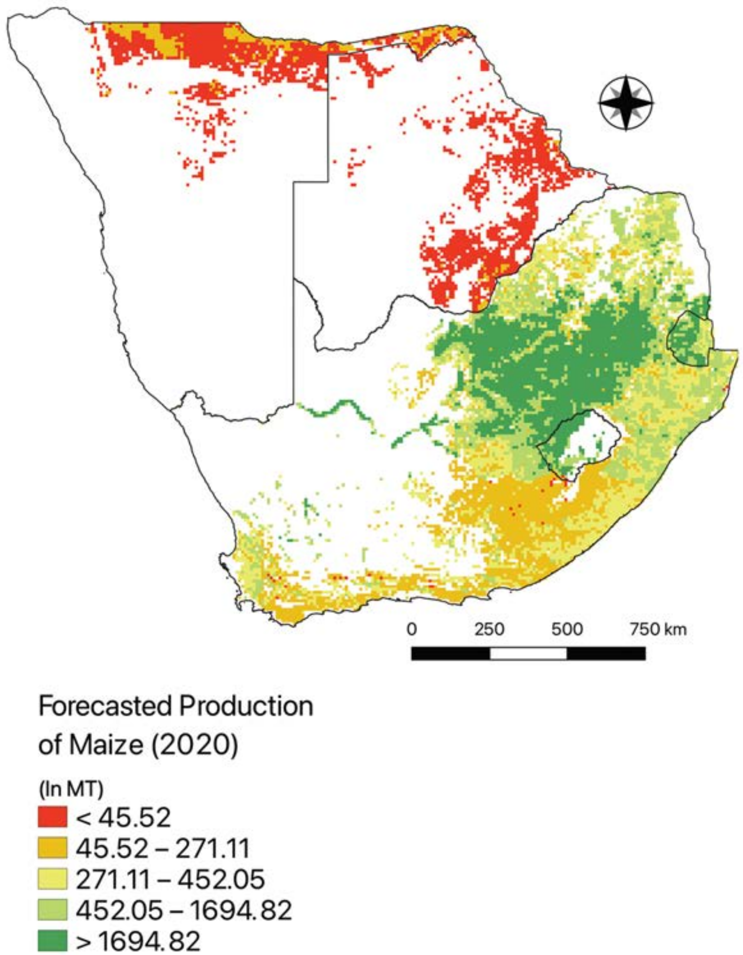
(b) Wheat—northern African countries



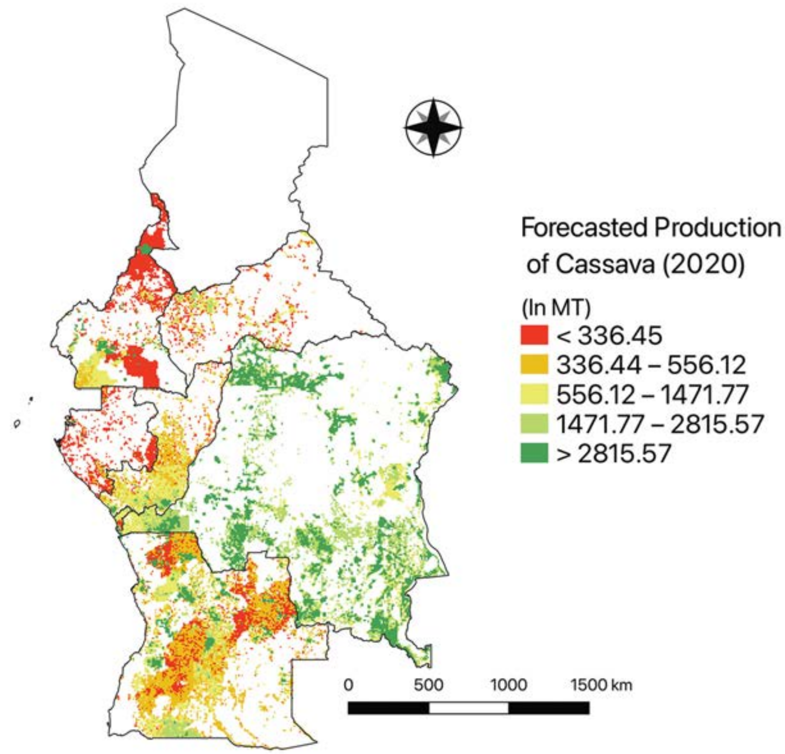
Source: Data, methodology, and maps from authors.

FIGURE 9A.5— THE 2020 PREDICTED (A) MAIZE PRODUCTION IN EASTERN AFRICAN COUNTRIES, (B) WHEAT PRODUCTION IN NORTHERN AFRICAN COUNTRIES, (C) MAIZE PRODUCTION IN SOUTHERN AFRICAN COUNTRIES, AND (D) CASSAVA PRODUCTION IN CENTRAL AFRICAN COUNTRIES *(continued from previous page)*

(c) Maize—southern African countries



(d) Cassava—central African countries



Source: Data, methodology, and maps from authors.

TABLE 9A.1—MOST SIGNIFICANT COMMODITIES BY COUNTRY IN WESTERN AFRICA REGION BASED ON OUR SELECTION CRITERIA

Country	Commodity 1	Commodity 2	Commodity 3	Commodity 4	Commodity 5
Benin	Cassava and products	Yams	Maize and products	Beverages, fermented	Palm kernels
Burkina Faso	Beverages, fermented	Sorghum and products	Maize and products	Millet and products	Pulses, other, and products
Cabo Verde	Sugarcane	Pelagic fish	Tomatoes and products	Vegetables, other	Milk, excluding butter
Côte d'Ivoire	Yams	Cassava and products	Rice and products	Palm kernels	Sugarcane
Gambia	Groundnuts (shelled equivalent)	Millet and products	Milk, excluding butter	Rice and products	Beverages, fermented
Ghana	Cassava and products	Yams	Plantains	Palm kernels	Maize and products
Guinea	Rice and products	Cassava and products	Palm kernels	Maize and products	Groundnuts (shelled equivalent)
Guinea-Bissau	Rice and products	Nuts and products	Roots, other	Palm kernels	Plantains
Liberia	Cassava and products	Rice and products	Sugarcane	Palm kernels	Bananas
Mali	Maize and products	Rice and products	Millet and products	Vegetables, other	Milk, excluding butter
Mauritania	Pelagic fish	Milk, excluding butter	Rice and products	Demersal fish	Sorghum and products
Niger	Millet and products	Pulses, other, and products	Sorghum and products	Vegetables, other	Milk, excluding butter
Nigeria	Cassava and products	Yams	Vegetables, other	Maize and products	Palm kernels
Senegal	Sugarcane	Groundnuts (shelled equivalent)	Rice and products	Millet and products	Vegetables, other
Sierra Leone	Cassava and products	Rice and products	Vegetables, other	Palm kernels	Milk, excluding butter
Togo	Cassava and products	Maize and products	Yams	Sorghum and products	Beans

TABLE 9A.2—MOST SIGNIFICANT COMMODITIES BY COUNTRY IN NORTHERN AFRICA REGION BASED ON OUR SELECTION CRITERIA

Country	Commodity 1	Commodity 2	Commodity 3	Commodity 4	Commodity 5
Algeria	Vegetables, other	Potatoes and products	Milk, excluding butter	Wheat and products	Onions
Egypt	Sugarcane	Sugar beet	Wheat and products	Vegetables, other	Maize and products
Morocco	Wheat and products	Sugar beet	Vegetables, other	Milk, excluding butter	Barley and products
Sudan	Sugarcane	Sorghum and products	Milk, excluding butter	Groundnuts (shelled equivalent)	Onions
Tunisia	Vegetables, other	Milk, excluding butter	Tomatoes and products	Wheat and products	Olives (including preserved)

TABLE 9A.3—MOST SIGNIFICANT COMMODITIES BY COUNTRY IN SOUTHERN AFRICA REGION BASED ON OUR SELECTION CRITERIA

Country	Commodity 1	Commodity 2	Commodity 3	Commodity 4	Commodity 5
Botswana	Milk, excluding butter	Beer	Roots, other	Vegetables, other	Bovine meat
Eswatini	Sugarcane	Sugar (raw equivalent)	Alcohol, non-food	Maize and products	Roots, other
Lesotho	Milk, excluding butter	Potatoes and products	Maize and products	Beer	Vegetables, other
Namibia	Roots, other	Pelagic fish	Beer	Demersal fish	Milk, excluding butter
South Africa	Sugarcane	Maize and products	Milk, excluding butter	Beer	Potatoes and products

TABLE 9A.4—MOST SIGNIFICANT COMMODITIES BY COUNTRY IN CENTRAL AFRICA REGION BASED ON OUR SELECTION CRITERIA

Country	Commodity 1	Commodity 2	Commodity 3	Commodity 4	Commodity 5
Angola	Cassava and products	Bananas	Maize and products	Sweet potatoes	Beer
Cameroon	Cassava and products	Plantains	Maize and products	Palm kernels	Roots, other
Central African Republic	Cassava and products	Yams	Groundnuts (shelled equivalent)	Roots, other	Sugarcane
Chad	Sorghum and products	Groundnuts (shelled equivalent)	Millet and products	Milk, excluding butter	Cereals, other
Congo	Cassava and products	Sugarcane	Beer	Vegetables, other	Palm kernels
Gabon	Plantains	Cassava and products	Sugarcane	Yams	Beer
Sao Tome and Principe	Plantains	Coconuts, including copra	Palm kernels	Roots, other	Pelagic fish

TABLE 9A.5—MOST SIGNIFICANT COMMODITIES BY COUNTRY IN EASTERN AFRICA REGION BASED ON OUR SELECTION CRITERIA

Country	Commodity 1	Commodity 2	Commodity 3	Commodity 4	Commodity 5
Djibouti	Vegetables, other	Milk, excluding butter	Bovine meat	Mutton and goat meat	Fruits, other
Ethiopia	Maize and products	Roots, other	Cereals, other	Sorghum and products	Wheat and products
Kenya	Sugarcane	Milk, excluding butter	Maize and products	Vegetables, other	Potatoes and products
Madagascar	Rice and products	Sugarcane	Cassava and products	Sweet potatoes	Fruits, other
Malawi	Cassava and products	Sweet potatoes	Maize and products	Sugarcane	Fruits, other
Mauritius	Sugarcane	Sugar (raw equivalent)	Vegetables, other	Poultry meat	Beer
Mozambique	Cassava and products	Sugarcane	Maize and products	Milk, excluding butter	Bananas
Comoros	Pelagic fish	Marine fish, other	Demersal fish	Crustaceans	
Rwanda	Bananas	Sweet potatoes	Cassava and products	Potatoes and products	Plantains
Seychelles	Pelagic fish	Demersal fish	Marine fish, other	Fish, body oil	Aquatic animals, other
Uganda	Sugarcane	Plantains	Cassava and products	Maize and products	Beverages, fermented
United Republic of Tanzania	Maize and products	Cassava and products	Sweet potatoes	Bananas	Sugarcane
Zambia	Sugarcane	Maize and products	Cassava and products	Sugar (raw equivalent)	Milk, excluding butter
Zimbabwe	Sugarcane	Maize and products	Sugar (raw equivalent)	Milk, excluding butter	Cassava and products

Appendix continued

TABLE 9A.6—THE AFCP MODEL TRAINING AND ACCURACY ASSESSMENT ACROSS COUNTRIES AND CROPS

Country	Crop	Minimum loss values	Mean loss values	Maximum loss values	RMSE on test set	RMSE on training set
Benin	Maize	0.00169249	0.00433745	0.02844726	0.03255314	0.03179684
Guinea	Maize	0.00242923	0.00383869	0.01885259	0.05860499	0.04483125
Ghana	Maize	0.00249482	0.00436432	0.02395666	0.03866078	0.04119789
Mauritania	Maize	0.00278496	0.00909949	0.04923604	0.03857696	0.03871264
Mali	Maize	0.00198173	0.00337625	0.01827932	0.04331407	0.04117554
Nigeria	Maize	0.00194973	0.00268457	0.01124211	0.03901889	0.04015009
Burkina Faso	Maize	0.00158174	0.00369686	0.02626520	0.03382954	0.03097056
Senegal	Maize	0.00106127	0.00281368	0.02088470	0.03361750	0.03085434
Guinea Bissau	Maize	0.00578081	0.01599571	0.08813826	0.04639926	0.05752965
Togo	Maize	0.00991938	0.02016226	0.09204900	0.10000162	0.08829238
Niger	Maize	0.00074933	0.00233211	0.01700366	0.03924410	0.02696511
Sierra Leone	Maize	0.00649442	0.01353270	0.06295945	0.05847860	0.07298443
Côte d’Ivoire	Maize	0.00105507	0.00227436	0.01596227	0.02108761	0.02094848
Benin	Cassava	0.00072762	0.00371670	0.03267188	0.01755675	0.01948215
Guinea	Cassava	0.00503696	0.00712383	0.02860466	0.06488639	0.06247591
Ghana	Cassava	0.00243144	0.00445531	0.02557120	0.04077162	0.04509468
Liberia	Cassava	0.00256122	0.00774713	0.04726972	0.03403242	0.03722366
Nigeria	Cassava	0.00185424	0.00277686	0.01209194	0.03993116	0.03968683
Togo	Cassava	0.00822577	0.01443074	0.06153987	0.07971147	0.07548504
Sierra Leone	Cassava	0.00185986	0.00511210	0.03064491	0.04245204	0.03845616
Côte d’Ivoire	Cassava	0.00112116	0.00263257	0.03064491	0.03194575	0.03279232
Benin	Rice	0.00071910	0.00496773	0.03950279	0.02117554	0.01622959
Guinea	Rice	0.00191753	0.00384247	0.02495658	0.04171192	0.04041576
Ghana	Rice	0.00088692	0.00214671	0.01569058	0.03193582	0.02447154
Liberia	Rice	0.00742250	0.02365423	0.10664631	0.06688038	0.05961841
Mauritania	Rice	0.01710714	0.04113854	0.09801760	0.04796407	0.07102053
Mali	Rice	0.00110347	0.00215285	0.01203484	0.03269070	0.02598336
Nigeria	Rice	0.00103784	0.00164344	0.00872079	0.03894496	0.03651457
Burkina Faso	Rice	0.00071322	0.00207747	0.01740650	0.03520919	0.02500710

Country	Crop	Minimum loss values	Mean loss values	Maximum loss values	RMSE on test set	RMSE on training set
Senegal	Rice	0.00146573	0.00401248	0.02403932	0.01891044	0.02720833
Guinea Bissau	Rice	0.01117795	0.02698722	0.12662517	0.08494826	0.08147735
Togo	Rice	0.00422155	0.00930080	0.05174400	0.04264234	0.05302349
Niger	Rice	0.00174473	0.00363644	0.01995699	0.03820201	0.03816552
Sierra Leone	Rice	0.00671424	0.01431605	0.07641059	0.07168690	0.07429794
Côte d'Ivoire	Rice	0.00259529	0.00527748	0.03147672	0.04233520	0.04016610
Libya	Wheat	0.00273258	0.00718171	0.04165258	0.04484544	0.04225213
Sudan	Wheat	0.00075528	0.00205568	0.01354778	0.03051089	0.02256988
Tunisia	Wheat	0.00919501	0.01323656	0.04416724	0.09916451	0.08879559
Morocco	Wheat	0.00685901	0.00816831	0.01921000	0.08206151	0.07935333
Egypt	Wheat	0.01897007	0.02592046	0.06760812	0.11164873	0.11744088
Algeria	Wheat	0.00295956	0.00403027	0.01379454	0.05042471	0.05085805
Kenya	Maize	0.00416994	0.00630878	0.02369906	0.05508986	0.05735548
Malawi	Maize	0.00751643	0.01245092	0.05270030	0.07838780	0.07839491
Zimbabwe	Maize	0.00495353	0.00621669	0.01702104	0.05888519	0.06400499
Mozambique	Maize	0.00064125	0.00131989	0.00947815	0.02158957	0.02111065
Ethiopia	Maize	0.00164969	0.00228679	0.00935273	0.03716214	0.03755907
Uganda	Maize	0.00255234	0.00430324	0.02320788	0.03919638	0.04631671
Tanzania	Maize	0.00142267	0.00214565	0.01043562	0.03307371	0.03440688
Zambia	Maize	0.00123491	0.00189236	0.00931647	0.03063931	0.03092630
Madagascar	Maize	0.00025017	0.00086813	0.00857775	0.01171361	0.01382347
Rwanda	Maize	0.00581005	0.01465933	0.06490663	0.05962805	0.05457481
Botswana	Maize	0.00195286	0.00471188	0.02337214	0.04084127	0.03649043
Eswatini	Maize	0.01283505	0.02411070	0.08909293	0.07191201	0.08209138
Namibia	Maize	0.00106955	0.00322694	0.02578572	0.02222601	0.02848192
Lesotho	Maize	0.01070529	0.02000675	0.06323701	0.07826008	0.09075452
South Africa	Maize	0.00158438	0.00195824	0.00549064	0.03786032	0.03599981
DRC	Cassava	0.00049400	0.00093600	0.00673400	0.01760200	0.01908400
Gabon	Cassava	0.00049300	0.00280600	0.02357000	0.00589000	0.00887100
Congo	Cassava	0.00136100	0.00328400	0.02398900	0.03479600	0.03287000
Central Africa	Cassava	0.00135600	0.00298900	0.01983500	0.02625900	0.02808400
Angola	Cassava	0.00031500	0.00072200	0.00545000	0.01251800	0.01243500
Cameroon	Cassava	0.00084300	0.00193800	0.01437900	0.02412500	0.03040200

Note: The root mean squared error (RMSE) on the test set was used for the model accuracy assessment.

Description of Preprocessing Steps

Data Preprocessing

The overarching goal of the data preprocessing procedure was to build the final dataset, which will be used to train the algorithm to learn the relationship between the input features such as the NDVI, LST-day, rainfall, and ET, with the targeted crop production values. This was performed by using available historical data from 2005, 2010, and 2017. The latter selected years are constraints dictated by the data available on the SPAM data portal. The entire process described below was completed with Spyder-Python 3.7.0 provided in the open-source individual Anaconda distribution.

Data Access

The first step of the preprocessing stage is accessing the relevant remote sensing products. For the input data such as NDVI, LST-day, and ET (which are MODIS data), the open-source Python pymodis package was used. The datasets come with a hierarchical data format, which consists of several scientific dataset (SDS) layers. However, for raster-type maps such as rainfall and production, TIF images were downloaded.

The Mosaicking Process

The methodology developed in this chapter embeds a mosaicking process that puts together different tiles from the same sensing date to cover a specific region of interest. Such a process is specific to satellite images due to their trajectory around Earth. The MODIS global sinusoidal tile grid is composed of 595 tiles, 460 of which are not filled. Tiles are 10 by 10 degrees at the equator with the following naming system: H_xx V_xx, where H_xx refers to the horizontal identification (ID), and V_xx, the vertical ID for any tile. The reference H_00 V_00 corresponds to the upper-left corner, and the lower-right corner is H_35 V_17. For our area of interest (the African continent), a dictionary of countries and their corresponding tiles was built for automation purposes. The open-source Python Geospatial Data Abstraction Library (GDAL) package was used for countries that require merging several tiles for complete geographical coverage.

Raster Extraction and Cleaning Process

This step aims to extract only the needed SDS layers from remote sensing products and to drop unreliable pixels. For NDVI, SDS layers 1 (NDVI data) and 12 (Pixel reliability) were used to extract NDVI layers and keep pixels that are labeled as good data (label 0) or marginal data (label 1). The exact process applies to the LST-day data where SDS layers 1 (LST data) and 2 (quality assurance data) were used. The process involves reading each raster of interest as a Python array with its corresponding index from the initial raster. Each data point that is not flagged as good or marginal data from the quality assurance layer is dropped. Then, a new raster is created using the open-source Python Rasterio package with the remaining data points.

Reprojection, Pixel Resampling, and Cropping

At this stage, the methodology dealt with three primary operations: reprojection, pixel resampling, and cropping. MODIS products that were selected for the predictive model were sinusoidal projected. For further computations with country administrative borders, both shapefiles and remote sensing products are required to have the same projection system. The GDAL package was also used to transform each raster projection system from sinusoidal to the 1984 world geodetic system (WGS84).

In addition, pixel size needs to be the same between RSPs and crop masks for further computations. The SPAM spatial resolution was chosen as a reference for other rasters. Therefore, an average resampling procedure using the GDAL package was used to aggregate smaller pixels from NDVI, LST-day, rainfall, and ET data to match the SPAM maps' pixel size. Finally, level 0 shapefile (national level) was applied to isolate the area of interest from the resulting map.

Crop Mask Application

Production maps retrieved from the SPAM portal were used to further isolate explanatory variables at areas where a specific crop is grown. A crop mask was built by allocating a value of one to each pixel with a production value greater than or equal to one and zero elsewhere. Therefore, by performing the arithmetic product of this mask with all the maps that were generated above, the result was new NDVI, LST-day, rainfall, and ET rasters at pixels where the selected crop is grown. However, for the 2020 dataset, we used the 2017 generated mask.

From Raster to Dataframe

Explanatory and response variables are required to build a supervised agricultural production model. In our case, each line (equivalent to a specific pixel) of the final dataset on which the model was built upon is a scenario. Therefore, the temporal resolution between inputs and outputs must match. However, production values are available at an annual basis, which means pixel values for input variables have to be annual, and for that, mean values were computed for each input feature during the crops' growing season only. For one crop, the final outputs would be 18 mean (or annual) rasters that are cropped to the region of interest and correspond to the 3 rasters (2005, 2010, and 2017) times 6 variables (5 as inputs and one as output). Each country would have the same number of scenarios as its number of pixels; most countries have tens of thousands of scenarios.

CHAPTER 10

Measuring Progress Toward the Malabo Declaration Goals in the Midst of COVID-19: A Measurement Approach for a Health Systems-Sensitive Resilience Score

Mark A. Constas, Max Wohlgemuth, and John M. Ulimwengu

Introduction

As an outgrowth of the Comprehensive Africa Agriculture Development Programme (CAADP), the *Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods* (AUC 2014) established both a clear strategic direction and a well-articulated set of agriculture-focused strategic priorities for Africa. Beyond the two overarching commitments to supporting the CAADP process and enhancing investments, the Malabo Declaration drew attention to the goals of achieving zero hunger, halving poverty, boosting intra-African trade in agricultural commodities and services, enhancing the resilience of livelihoods and production systems to climate variability and other shocks, and building mutual accountability to actions and results. With climate change pressures, much of the work on resilience, in connection with the Malabo Declaration and other initiatives, is justifiably based in weather-related shocks. The protracted and pervasive effects of a global pandemic have, however, altered the range of risks to which resilience may be viewed as a strategic response. The present chapter is therefore motivated by the need to explore how indicators related to the shocks and stresses caused by COVID-19 may be incorporated into the CAADP measurement process.

Against the backdrop of COVID-19, the present chapter considers how indicators related to reporting on country-level progress toward the resilience component of the Malabo Declaration goals may be augmented. In this chapter, we introduce both the limited capacity of health systems across Africa and the potential effects of macroeconomic conditions associated with a global health shock as new and important inputs. More specifically, we propose the inclusion of a basic health systems capacity index and an economic country-level resilience capacities score. From an empirical perspective, the motivation for the chapter may be stated as a question: How might reporting on the progress made toward the Malabo Declaration better reflect the effects of a global health shock such as COVID-19? As a first approximation of an answer to this question, we provide a brief empirical demonstration of an approach that examines high-level resilience capacities to global health shocks. Our overall objective is to draw attention to the potential value of including a limited number of health systems and macrolevel indicators as part of reporting on progress made toward the resilience aspect of the Malabo Declaration commitments.

The empirical task was to develop and apply a resilience capacity score for global health shocks (RCS^{GHS}). Recognizing the challenges associated with the suggestion of introducing greater demands on the CAADP measurement process, the intent of this chapter is to describe a compact approach for RCS^{GHS}, one that provides insights about the impacts of a shock such as COVID-19 but does so in a manner that requires limited data inputs and a small number of analytical steps. Thus, the methods used to compose the indicators were not derived from modelling procedures based in a set of analytical techniques that require a strong foundation of assumptions. The approach, which is purposively simple and easily replicated, generates results that are descriptive. With this background, the goal is to simply introduce and report on a limited set of supplementary indicators to consider as a complement to the Africa Agricultural Transformation Scorecard (AATS), which reports on progress toward Malabo Declaration targets, and in connection with future analyses of progress made toward the Malabo Declaration goals where large-scale health shocks may play a role. The way in which some of these indexes may be applied to more fully developed analytical models is the topic of another chapter in the 2021 Annual Trends and Outlook Report. In Chapter 11 of this volume, d'Errico, Jumbe, and Constas combine elements of the RCS^{GHS} with a well-established Resilience Measurement Index and Analysis (RIMA) [1] to generate a form of resilience analysis that is sensitive to health shocks.

The present chapter is organized into three sections followed by a conclusion. The first section provides a brief overview of the resilience component of the CAADP results framework. This section also builds the case for using a special set of indicators to support the effort to track progress being made toward the Malabo Declaration, during and in the aftermath of COVID-19. To introduce the methodology, the second section of the chapter describes the measurement approach and outlines the empirical objective of including composite health systems indicators and a limited set of high-level macroeconomic indicators. The intent of this part of the chapter is to offer an empirically based strategy to measure COVID-19-related factors that might affect progress toward the Malabo Declaration goals. On an operational level, the second section also describes the

1 Technical details that describe how RIMA is developed, implemented, and interpreted are available from FAO (2016).

selection of indicators and the procedures that were used to analyze the data. Section three presents the results of the measurement approach. The chapter concludes by discussing some of the limitations of the proposed approach and explores the additional work needed to develop and incorporate indicators related to the impacts of a global health shock such as COVID-19.

The Need for Indicators Related to COVID-19 and the CAADP Results Framework

Shocks that affect welfare are generally described as either idiosyncratic or covariate. While the notion of idiosyncratic shocks draws attention to shocks that affect individual households, covariate shocks are concerned with disturbances that affect a larger number of households within and across geographic zones and population groups. Shocks that affect multiple regions across disparate regions of the world are categorized as global shocks. A global shock, as defined by the Organization for Economic Cooperation and Development, is a "major rapid-onset event with severely disruptive consequences covering at least two continents" (OECD 2011, 3). The series of events stemming from undue risk exposure associated with mortgage-backed securities produced a series of global shocks that affected every country in the world, across multiple sectors. Arguably, the effects of COVID-19 as a global shock are more severe than the global financial crisis of 2009. This is particularly true when one considers the immediate mortality risks associated with COVID-19.

The inadequate health care prevalent in developing countries highlights a systemic vulnerability to epidemics and diseases. Preexisting health burdens—such as tuberculosis and other respiratory diseases, HIVAIDS, and widespread diarrheal disease—enable increased disease transmission. Weak governance and the lack of strong institutions hinder the formulation of policies and programs that are now needed. Furthermore, with a high proportion of livestock-related livelihoods found in developing countries, the presence of endemic and episodic zoonotic diseases introduces a special, often overlooked, set of risks.

While the immediate and most conspicuous effects of COVID-19 are health related, the scale and duration of COVID-19 has had a negative impact on almost all aspects of well-being. A joint report issue by the African Union Commission (AUC), the United Nations Development Programme (UNDP), and the Africa Centres for Disease Control (CDC) noted how COVID-19 affected "everything from gender equality to governance to peace" (UNDP 2021, 6). The effects of COVID-19 on food security are highlighted in a policy brief from the United Nations, where it was noted that that the funding needs for food security would increase from approximately US$2 billion to nearly $7 billion as a consequence of COVID-19 (2020a). Illustrating the pervasive effects of COVID-19, the comprehensive response plan issued by the United Nations (2020b) listed 31 organizations whose cooperation would be required for a coherent and effective strategy. As expected, the World Health Organization is the lead agency for the COVID-19 response; however, the breadth and level of participation among other UN organizations is unprecedented. The International Food Policy Research Institute (IFPRI) estimated that an additional 140 million people in developing countries would fall into poverty as the result of COVID-19 (Debucquet, Martin, and Vos 2020).

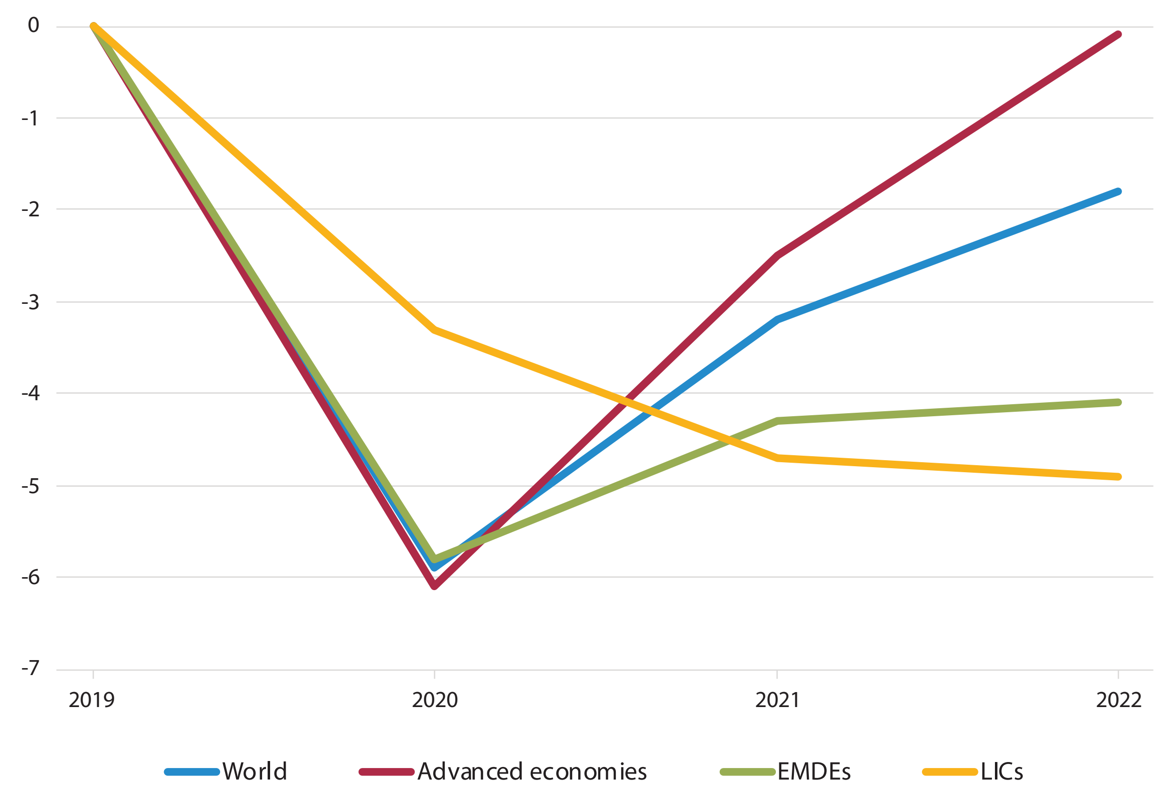
It is now clear that all countries across the globe have been, and will continue to be, negatively affected by COVID-19. Developing countries, however, are particularly vulnerable. The United Nations Department of Economic and Social Affairs noted the potentially "devastating consequences" that COVID-19 may have on least-developed countries (UNDESA 2020). Initial evidence from the United Nations Conference on Trade and Development (UNCTAD) has indicated that declines in foreign direct investment had already begun to emerge toward the end of the first quarter of 2020 (UNCTAD 2020). Similarly, early findings from the Word Trade Organization (WTO) suggest that trade volumes will drop precipitously over the course of 2020, with those effects continuing well into 2021 (WTO 2020). Reductions and reallocations of official development assistance and humanitarian aid as a function of COVID-19 have also been explored (Brown 2021). A study published in The Lancet, for example, reported that progress made toward battling HIV, tuberculosis, and malaria is threatened by altered patterns of health service delivery (Hogan et al. 2020). Problems commonly found in development settings that existed before COVID-19, such as extreme poverty and chronic food insecurity, will not only continue but will likely require more intensive levels of engagement.

For most of 2020, the buffering effects of aid and the early trends on lower disease rates suggested that low-income countries (LICs) might not be the most severely affected by the pandemic. However, the relative damage from COVID-19 is, of course, much worse when one considers the preexisting lower levels of food security and higher levels of poverty found in developing countries. Economic forecasts provided by the World Bank (2021a) compared pre- and post-pandemic outputs of LICs with advanced economies and emerging market and developing economies (EMDEs), leading to projections of both short-term and long-term effects of COVID-19 on outputs. As shown in Figure 10.1, EMDEs and advanced economies have begun to rebound from the initial effects of COVID-19 (World Bank 2021a).

From a resilience perspective, what is perhaps most notable in Figure 10.1 is the varied recovery trajectories among advanced economies, EMDEs, and LICs. While the initial loss was not as severe in LICs, the lack of return to pre-shock levels suggests a lack of resilience.

The effects of COVID-19 on food security and food systems have been raised in the literature (Béné 2020; Devereaux, Béné, and Hoddinott 2020). For example, Deveraux, Béné, and Hoddinott (2020) examined the impacts that COVID-19 has had on food security according to three different frameworks—the four pillars of food security, the food systems framework as conceptualized by the High Level of Panel of Experts on Food Security and Nutrition, and Sen's entitlement approach (FAO 1996; HLPE 2017; Sen 1999). In each case, damage was noted to one or more dimensions of food security. Exploring the breadth of impacts associated with the pandemic, the Food and Agriculture Organization (FAO) published a set of policy briefs that described the negative effects of COVID-19 on food supply chains, trade and markets, smallholder farmers, and safe and sustainable food systems. [2] In each case, FAO reported that the effects of COVID-19 had been, and would continue to be, severe and protracted.

FIGURE 10.1—DEVIATION OF OUTPUT FROM PRE-PANDEMIC PROJECTIONS



Source: World Bank (2021a).

On the economic side, the two impacts of the pandemic that have been perhaps most widely cited are trade and supply chain disruptions. In a global shock, such as COVID-19, countries whose economies are based on trade are likely to be more vulnerable to the effects of trade disruptions. UNCTAD (2020) reported that global merchandise trade values and trade volumes decreased precipitously in response to COVID-19. While trade has begun to

2 A complete list of FAO policy briefs can be found at http://www.fao.org/2019-ncov/resources/policy-briefs/en/.

show signs of recovery in the year after the onset of COVID-19, trade data suggest that indications of global recovery are driven by activity in East Asia and the Pacific (UNCTAD 2021). Trade data from Africa show patterns that are less encouraging, with imports indicating marginal recovery while exports remained in decline. The WTO (2020) reported that trade declines associated with COVID-19 in the second quarter of 2020 were the largest recorded in history. As an integral operational component of trade, the negative effects of COVID-19 on supply chains and global value chains have been well documented (UNCTAD 2020).

To generate data on the Malabo Declaration, the CAADP Results Framework (RF) "is earmarked as the tool that will be used in tracking, monitoring and reporting on the progress in meeting the Malabo commitments" (AUC and NEPAD 2015, 3). The CAADP RF is structured around three levels: Level 1 includes agriculture's contribution to economic growth and inclusive development; Level 2 is agricultural transformation and sustained economic and inclusive agricultural growth; and Level 3 is strengthening systemic capacity to deliver results. Drawing on an array of national, regional, and cross-national data sets, a set of indicators for each level is used to track progress across the three CAADP levels.

Indicators within each level of CAADP RF are organized according to results areas that specify priority indicators. Signaling the commitment to resilience under the Malabo Declaration, Goal VI expresses the aim of "Enhancing Resilience of Livelihoods and Production Systems to Climate Variability and Other Related Risks" (AUC 2014, 5). The inclusion of resilience as one of the seven goals of the Malabo Declaration reflected the realities of the shock-prone contexts in which countries in the African Union must function. Most commonly, references made to shocks and stressors are linked to disturbances caused by climate change and weather-related shocks, social unrest and conflict, the constraints of inadequate infrastructure, and economic volatility in its various forms. The Technical Guidelines for the Biennial Review of the Malabo Declaration Goals and Targets (AUC 2017) provide a detailed description of how the measurement targets of Goal VI are to be operationalized. Reflecting the content of Goal VI, the guidelines define the subtheme, measurement objective, and performance indicators for resilience. Performance indicator 6.1i measured the "percentage of farm, pastoral, and fisher households that are resilient to climate change and weather-related shocks" and indicator 6.1ii measured the "share of agriculture land sustainable land management practices" (AUC 2017, 3). The 2019 CAADP Biennial Review report showed that only 11 countries (Burundi, Cabo Verde, Ghana, Ethiopia, Mali, Mauritania, Morocco, Rwanda, Seychelles, Tunisia, and Uganda) out of 55 were on track for enhanced climate and livelihood resilience, compared to 7 in 2017.

Historically, the continent of Africa has long worked to address a range of health risks such as HIV/AIDS, malaria, and diarrheal diseases. These diseases and others represent serious threats to development (GBD 2019 Diseases and Injuries Collaborators 2020). When the Malabo Declaration was drafted, there was no compelling reason to consider the potential impacts of a global pandemic. Although the effects of Ebola (2014–2016) were tragic, they were largely concentrated in the three countries of Guinea, Liberia, and Sierra Leone. Statistics from the CDC reported that Liberia was worst affected, having the highest number of probable cases (10,678) and deaths (4,810) (CDC 2019). The localized nature of the Ebola outbreak and the relatively quick containment did not seem to influence the CAADP RF toward considering the consequences of a global pandemic. When the CAADP RF was developed, the prospect and consequences of a global pandemic were not central to the planning process. Where health is discussed in the CAADP RF, such discussion is focused on food safety. It is apparent that the deep but narrow impact of Ebola did not influence the way in which the African Union would conceptualize and implement measurement plans for its policy initiatives. It is therefore not surprising that the CAADP results framework did not include health systems or indicators associated with the effects of global health shocks.

Measurement Approach: Resilience Capacities Score for Global Health Shocks

The empirical objective is to better understand how progress made toward the Malabo Declaration might be interpreted in the context of COVID-19. This requires an additional set of indicators comprised of sub-indexes that serve as components of an overall index of resilience in the face of global health shocks. As a simple formulaic expression, the measurement approach for a resilience capacities score in the face of a global health shock may be represented as follows:

$RCS^{GHS} = f\,(HSC, ECRC)$,

Where: RCS^{GHS} = Country-level resilience capacity to a global health shock,
HSC = Health systems capacities, and
ECRC = Country-level resilience capacities.

Indicators for HSC are drawn from readily available data sources provided by the World Health Organization's Global Health Observatory (GHO) and Our World in Data platform. Indicators for ECRC are drawn from the World Bank and Fund for Peace. Further details on the specific indicators drawn from these sources are described below.

While the arrangement of variables in the above expression suggests a causal relationship, the development of RCS^{GHS} represents initial work toward a more modest empirical ambition. As noted at the outset, the goal is to demonstrate how a limited set of proposed resilience capacities specific to COVID-19 may be incorporated into reporting progress on the Malabo Declaration. To connect RCS^{GHS} to the CAADP RF, the results of RCS^{GHS} are combined with the resilience indicator from the Africa Agriculture Transformation Scorecard (AATS) focused on investment in resilience to climate shocks (Indicator 6.2; the details of this combination are discussed later). The integration of the AATS resilience indicator with the RCS^{GHS} is used to construct a simple metric that captures both the resilience capacity to global health shocks and resilience capacity to climate shocks.

Health Systems Capacity: Health Infrastructure and Vaccination Rates[3]

Drawing on data from the GHO, the HSC is structured around three indicators that are likely to be associated with a country's resilience capacities in the face of a global health shock. The ability of a country to respond to a global health shock is based on the health systems' capacity to respond to a public health challenge. Two basic inputs to public health capacity may be measured by the hospital infrastructure that is required to house patients and by the availability of medical professionals who can administer care. Following this logic, the first indicator of hospital bed density (HBD) score is a simple measure of the number of hospital beds per population of 10,000 people. The second indicator, the medical professionals density (MPD) score, combines data from GHO's physician density index and the nurse and midwives density index to generate a single indicator. The MDP reflects the availability of medical professionals for every 10,000 people in a country.[4] The third indicator, which draws on vaccination rate (VR) data from Our World in Data, conveys the percentage of vaccinations for the total population of a country. To construct a composite HSC, country-level data for the HBD, MPD, and VR were divided into quartiles. The score for each of three HSC components could range from 1 to 4, with the lowest quartile as Q1=1 and the highest quartile as Q4=4, and so forth. Summing quartile scores across HBD, MPD, and VR, the total for all three components could range from 3 to 12. The 3 to 12 range was converted to a 1 to 10 scale by converting a total of 3 as the lowest possible score to a 1 and total score of 12 as the highest possible score to 10.

Economic and Country Resilience Capacity: Economic Indicators and Country Fragility

As noted above, two consistently cited impacts of COVID-19 are the effects on trade and the effects on supply chains. Indicators related to these two impacts are supplemented by an indicator of a country's overall condition that may affect its ability to function effectively. As described below, we used the inverse of a measure of country-level fragility for this part of the general resilience capacities score.

Trade

The World Bank defines trade as "the sum of exports and imports of goods and services measured as a share of gross domestic product" (World Bank 2021b). Trade as a percentage of gross product (TGDP) is used as a crude indicator of the role played by trade in each economy. These data were obtained from the World Bank (2021b). Following the same strategy that was used to construct the HSC,

3 All data for the HSC were drawn from the GHO during the month of July 2021.

4 The GHO reports physician density in terms of physicians per 1,000 people. The same ratio is used for nurses and midwifery data. The figures were multiplied by 10 to make the comparable to the hospital bed density data.

data on TGDP were divided into quartiles. For TDGP, the results for quartiles were inverted so that the lower quartile (lower TGDP) was accorded a higher score. Thus, the first quartile was given a score of 4 and the fourth quartile was given a score of 1.

Supply Chains

As a way to assess supply chains, the World Bank's Logistic Performance Index (LPI) provides a composite score based on a multidimensional measurement framework comprised of six performance components: efficiency of customs and border clearance, quality of trade and transport infrastructure, ease of arranging competitively priced shipments, competence and quality of logistics services, ability to track and trace consignments, and timeliness—the frequency of shipments reaching consignees on time (Arvis et al. 2014). Each component is scored on a scale from 1 to 5, and the composite score is also a range from 1 to 5. Weights are derived from a principal component analysis that generated relatively equal weights, ranging from .40 to .42.

Country Condition

The inclusion of an indicator on "country condition" acknowledges the effect that a country's functional qualities and operational integrity may have on progress toward the Malabo Declaration goals. Weak governance, lack of strong institutions, and political instability hinder the ability to formulate policies and programs that are needed to respond to covariate shocks associated with pandemics, climate change, or other disturbances. A reasonable composite indicator of a country's overall stability may be obtained from the 2020 Fund for Peace's (FFP) Fragile States Index (FSI). The FSI is comprised of a set of multidimensional constructs based on cohesion indicators, economic indicators, political indicators, and social indicators (FFP 2017). The higher the FSI score, the greater the fragility of the country for a given reporting period. With the intent to measure resilience capacity, we first organized the distribution of FSI scores into quartiles. Those countries in the lowest quartiles (Q1) were coded as 4 and those in Q4 were coded 1, with Q2 and Q3 coded as 3 and 2 respectively.

Results

To illustrate the condition of health systems in Africa, the first part of the analysis explores the findings associated with three components of the HSC: hospital bed density index, the medical professionals index, and the vaccine rate index. The second and main part of the analysis, which presents results of the RCS^{GHS}, focuses on a sample of 36 African countries south of the Sahara for which all indicators required for HSC and ECRC could be gathered. In addition to excluding countries with incomplete data for the RCS^{GHS}, we also excluded two countries that had unusual profiles because of their economic makeup and one region because of data deficits.[5] Table 10.1.shows the list of 35 countries included in the sample.

TABLE 10.1—LIST OF SAMPLE COUNTRIES BY REGION

Central	Eastern	Southern	Western
1. Cameroon	7. Djibouti	15. Angola	24. Benin
2. Central African Republic	8. Ethiopia	16. Botswana	25. Burkina Faso
3. Chad	9. Kenya	17. Eswatini	26. Côte d'Ivoire
4. Democratic Republic of Congo	10. Madagascar	18. Lesotho	27. Gambia
5. Equatorial Guinea	11. Rwanda	19. Mozambique	28. Ghana
6. Gabon	12. Somalia	20. Namibia	29. Guinea
	13. Sudan	21. South Africa	30. Guinea-Bissau
	14. Uganda	22. Zambia	31. Liberia
		23. Zimbabwe	32. Mali
			33. Niger
			34. Nigeria
			35. Senegal
			36. Sierra Leone

Source: Authors.

5 Countries excluded by region for incomplete data were as follows: central Africa (Burundi, The Republic of Congo, São Tomé and Príncipe), eastern Africa (Comoros, Eritrea, South Sudan, Tanzania), western (Cabo Verde, Togo), and southern Africa (Malawi). These countries were excluded because of data gaps in one or more of the indicators required for the score. Because of data issues that affected regional representation, a decision was also made to not include countries from northern Africa in the analysis. Mauritius and the Seychelles were excluded because their economies are heavily reliant on tourism.

Findings on the HSC

To create a reference point for the data on Africa, we first show HBD, MPD, and VRs for G7 countries: Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (USA). Figure 10.2 shows the combined results for MPD and HBD per 10,000 for the G7 countries.

For HBD, Figure 10.2 displays a range of 24.6 for the UK to 129.9 for Japan, with an average HBD of 54.1 across all G7 countries. For MPD, the results range from a low of 99.1 for Italy to a high of 182.6 for the United States. The unweighted average MPD for G7 countries is 147.3.

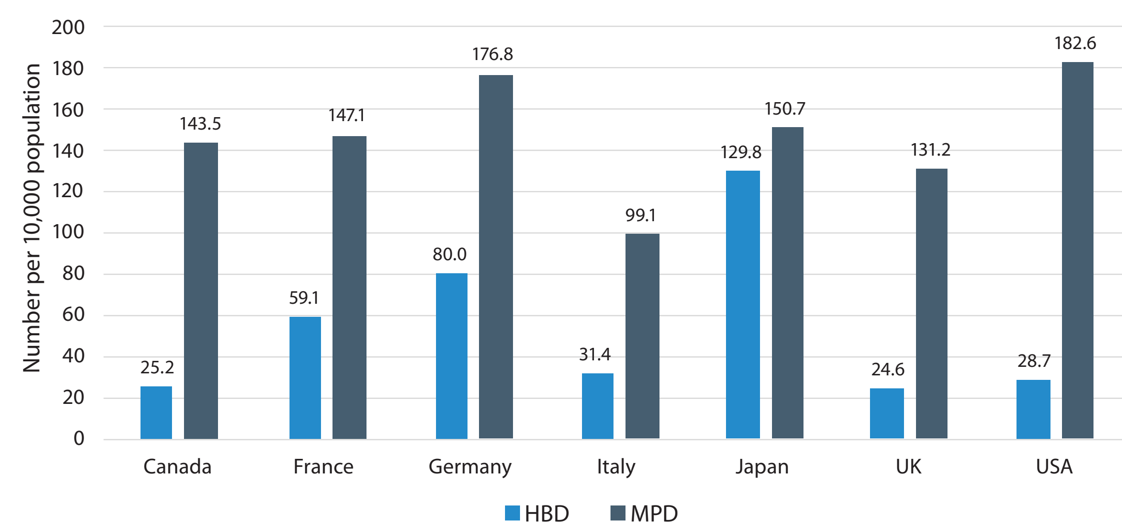
When comparing between G7 countries and Africa on basic infrastructure in the form of hospital beds and medical personnel, a clear contrast becomes apparent. Disparities are observed between African regions, as shown in the results for HBD and MPD in Figure 10.3.

Using regional averages, the HBD ranges from a low of 5.46 for western Africa to a high of 19.83 in central Africa. The approximate average HBD for Africa across regions (unweighted) is 11.50. The HBD for the G7 countries is almost five times the level for Africa. The contrast between G7 countries and Africa is more pronounced when comparing data on MPD. The results of the MPD for Africa range from a low of 8.69 for western Africa to a high of 24.54 for southern Africa. The average MPD for Africa is 12.96. The average MPD for G7 countries is approximately 11 times higher.

Data on vaccination rates for COVID-19 are commonly reported in terms of numbers of persons who have been partially or fully vaccinated.[6] Figure 10.4 shows the vaccination rates for G7 countries.

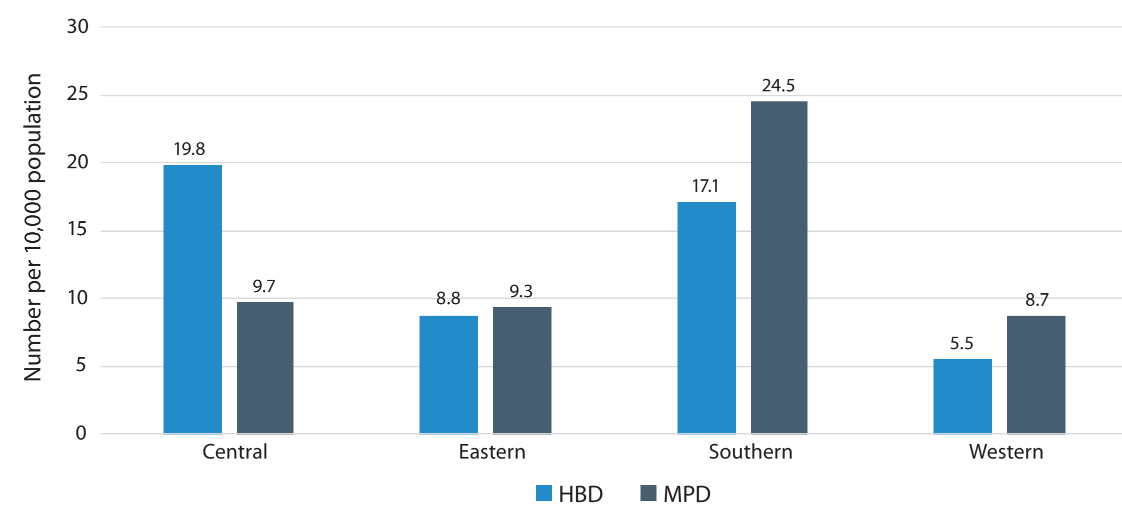
6 Data on vaccination rates was pulled from Our World in Data on July 19, 2021.

FIGURE 10.2—HOSPITAL BED DENSITY AND MEDICAL PROFESSIONALS DENSITY FOR G7 COUNTRIES



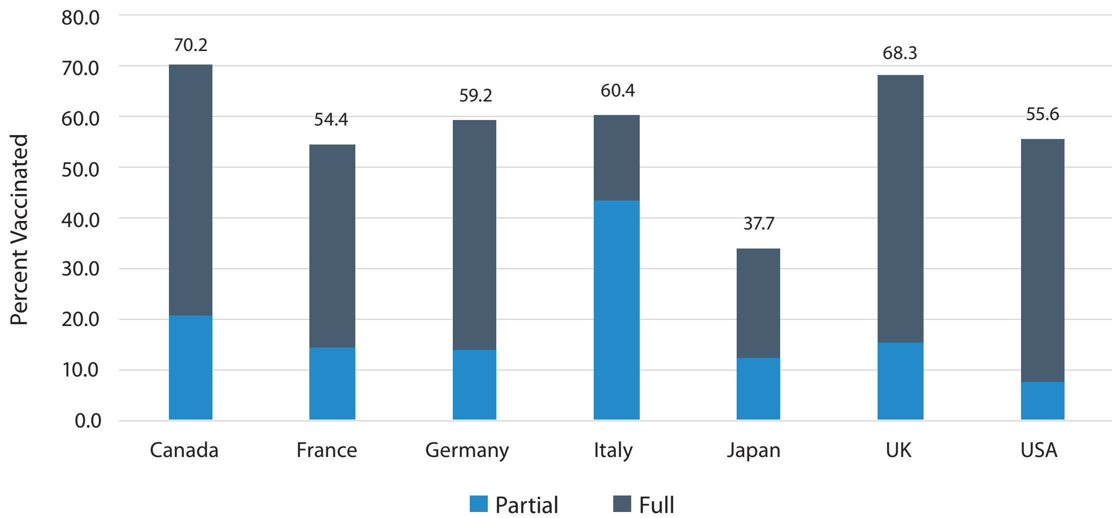
Source: Authors.

FIGURE 10.3—HOSPITAL BED DENSITY AND MEDICAL PROFESSIONALS DENSITY FOR AFRICAN REGIONS SOUTH OF THE SAHARA



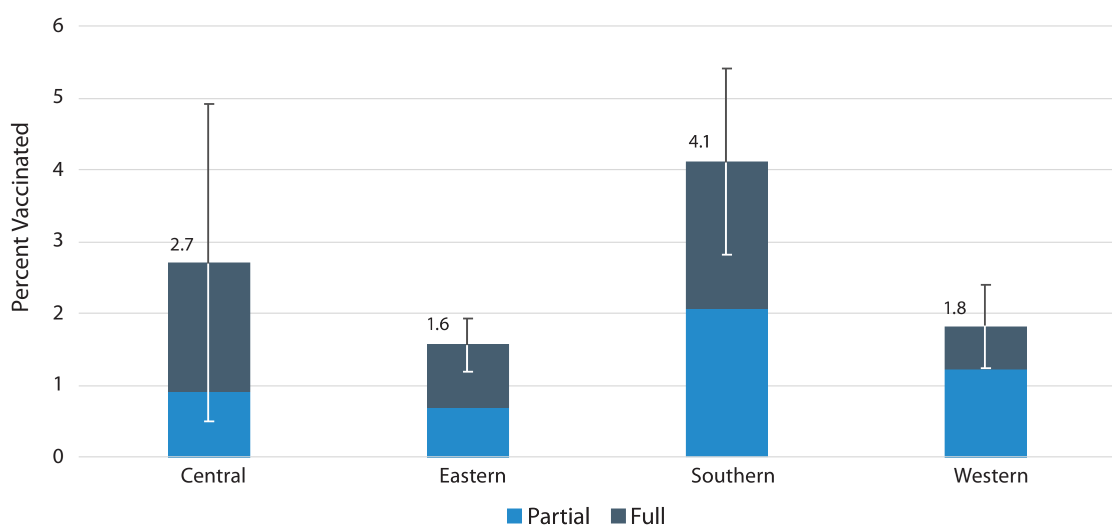
Source: Authors.

FIGURE 10.4—VACCINATION RATES FOR G7 COUNTRIES



Source: Authors.

FIGURE 10.5—VACCINATION RATES FOR AFRICAN REGIONS SOUTH OF THE SAHARA



Source: Authors.

Focusing on the total percent vaccinated (partially or fully), the vaccination rate for G7 countries ranges from a low of 37.7 percent for Japan to a high of 70.2 percent for Canada. The average unweighted vaccination rate for all G7 countries is approximately 58 percent.

The average vaccination rate for countries sampled across Africa is 2.5 percent. As illustrated in Figure 10.5, the vaccination rates show the greatest contrast with the G7 countries. G7 countries have an average vaccination rate that is more than 20 times higher than the average for countries in Africa.

Findings on the RCS^{GHS}

The analysis of RCS^{GHS} followed a simple two-stage process. In the first stage, data from the quartile conversions for each component of the HSC and the ECRC were summed and the average score for a given country was treated as the RCS^{GHS} for that country. In the second stage, a more fine-grained analysis was carried out. Each country's data for the HSC and the ECRC were arranged on a distribution to determine if it was below (ranked low) or above (ranked high) the mean score for HSC and for ECRC. Countries that ranked high on both the HSC and the ECRC were regarded as likely to be most resilient to a global health shock. Countries that ranked low on both the HSC and the ECRC were regarded as likely to be least resilient. Countries that had a combination of high and low rankings were categorized as having mixed capacity. As part of the second stage of analysis, the average score for each country was placed in a two-dimensional plot (ECRC by HSC). The objective here was to illustrate a given country's position relative to others.

Results from the first stage of analysis show RCS^{GHS} scores for a sample of 36 African countries south of the Sahara (Figure 10.6). The mean of 5.50 for the distribution of the RCS^{GHS} is used as a plausible threshold to distinguish between more resilient countries and less resilient countries.

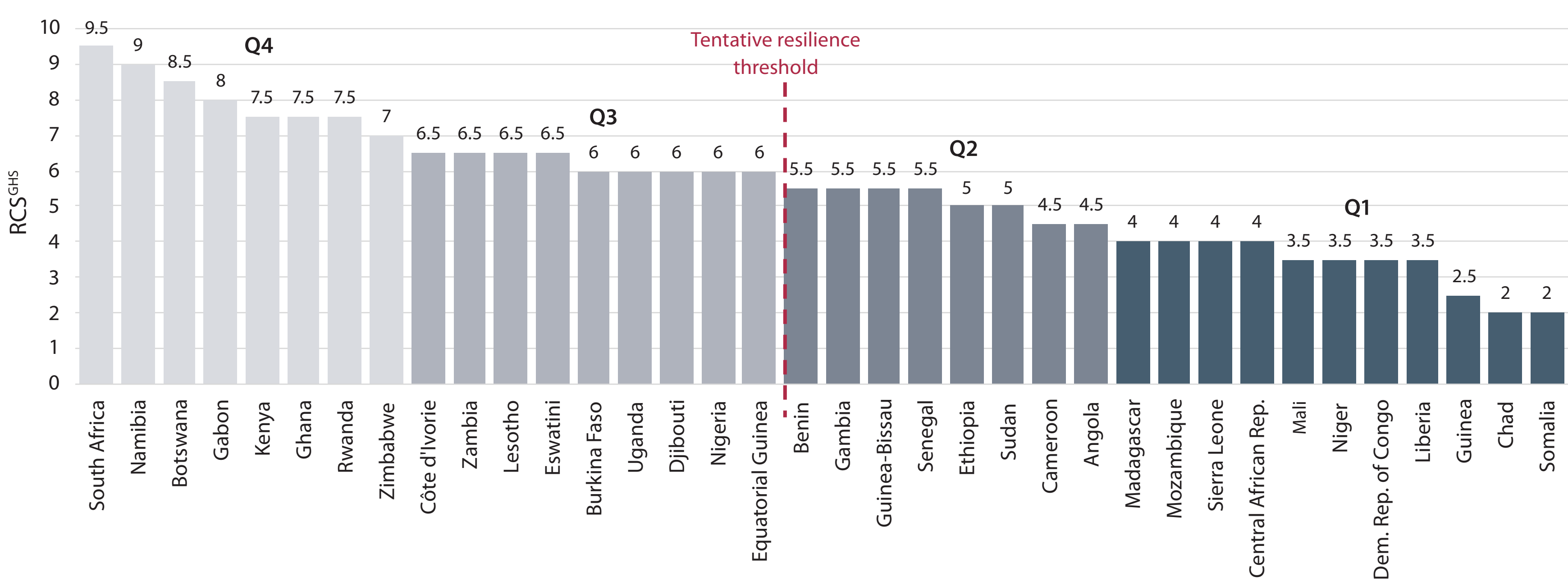
In the second stage of analysis, the coding based on individual components of HSC and ECRC was used to better understand how the two components of the RCS^{GHS} could be used to rank different regions and countries. Those cases that were categorized as mixed remain ambiguous until they are subject to empirical test. Those countries categorized as *most resilient* or *least resilient*, however, can be seen as contrasting cases of resilience capacity. Figure 10.7 presents the findings on most and least resilient countries, with regions arranged in descending order according to most resilient.

The results displayed in Figure 10.7 suggest that southern Africa is, on average, likely to be the most resilient to global health shocks. Eastern Africa follows close behind, with a score that is about 7 percent lower on "most resilient." Southern Africa also has a lower proportion of countries categorized as least resilient. Scoring lowest in the "most resilient" category and highest in "least resilient," central Africa is likely to be the least resilient region of Africa. Western Africa ranks third in terms of proportion of countries categorized as most resilient but has the second highest proportion of countries ranked as least resilient.

Table 10.2 provides a summary of how countries were categorized in terms of their likelihood to be resilient based on the findings from the two inputs of the RCS^{GHS}.

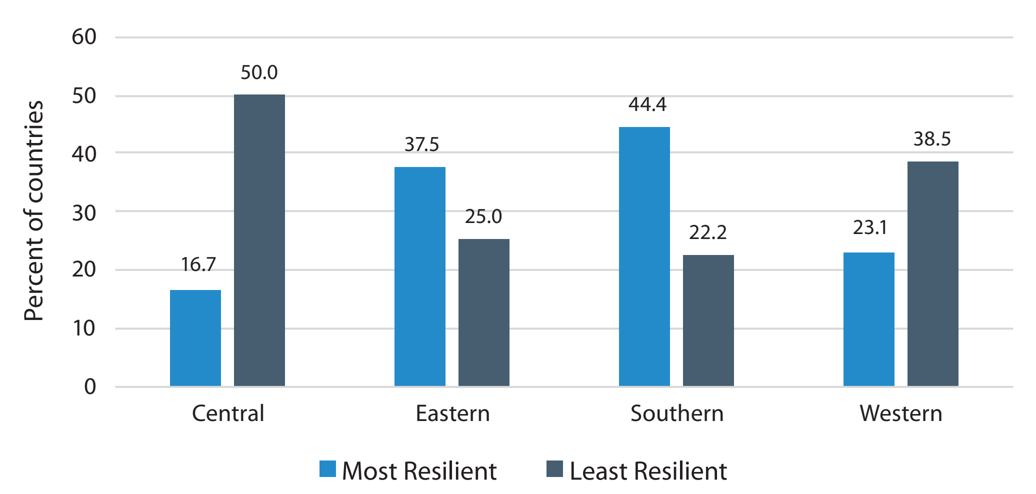
Results for most regions sampled are relatively symmetrical when comparing the most resilient versus least resilient categories. For western Africa, three countries are categorized as most resilient and five categorized as least resilient. Eastern Africa has three countries in the most resilient category

FIGURE 10.6—RESILIENCE CAPACITIES SCORE FOR GLOBAL HEALTH SHOCKS



Source: Authors.

FIGURE 10.7—REGIONAL DISTRIBUTION OF MOST AND LEAST RESILIENT COUNTRIES IN AFRICA SOUTH OF THE SAHARA



Source: Authors.
Note: Columns for each region do not sum to 100 because mixed capacity categories were excluded.

TABLE 10.2—COUNTRY-LEVEL RESILIENCE CODING BASED ON RCS^{GHS} COMPONENTS

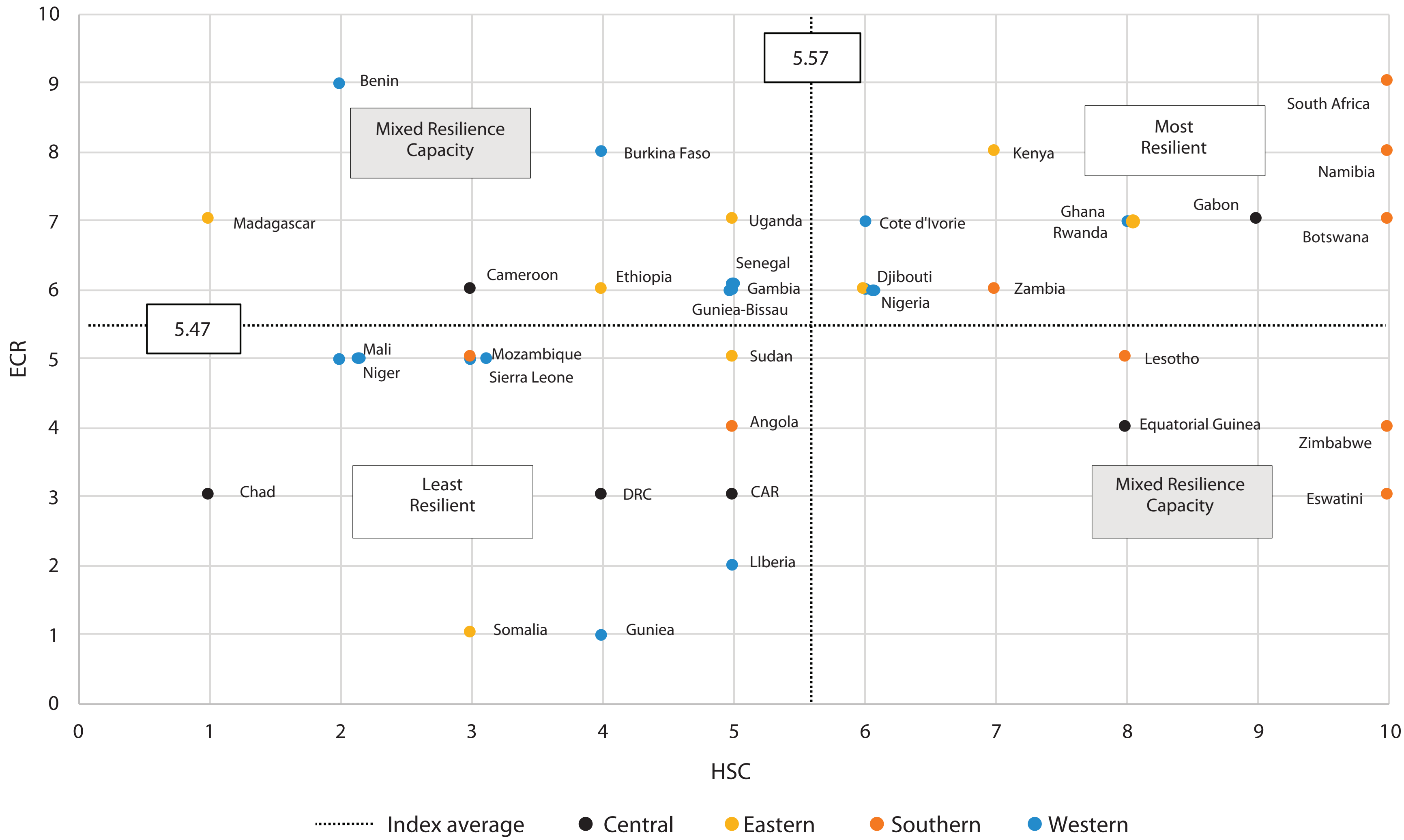
Economic and Country Resilience Index (ECRC)	Health Systems Capacity (HSC)	
	Above the mean	Below the mean
Above the mean	**Most Resilient** (N=11) **Western** • Côte d'Ivoire • Ghana • Nigeria **Central** • Gabon **Eastern** • Djibouti • Kenya • Rwanda **Southern Africa** • Botswana • Namibia • South Africa • Zambia	**Mixed** (N=9) **Western** • Benin • Burkina Faso • Gambia • Guinea-Bissau • Senegal **Central** • Cameroon **Eastern** • Ethiopia • Madagascar • Uganda **Southern Africa** • –
Below the mean	**Mixed** (N=4) **Western** • – **Central** • Equatorial Guinea **Eastern** • – **Southern Africa** • Eswatini • Lesotho • Zimbabwe	**Least Resilient** (N=12) **Western** • Liberia • Guinea • Mali • Niger • Sierra Leone **Central** • Central African. Rep. • Chad • Dem. Rep. of Congo **Eastern** • Somalia • Sudan **Southern Africa** • Angola • Mozambique

Source: Authors.

and two in the least resilient category. Southern Africa has three countries in the most resilient category and two countries in the least resilient category. The findings for central Africa are more lopsided, with one country found in the most resilient category and three countries in the least resilient category. To illustrate a given country's position relative to others, the average score for each country was placed in a two-dimensional plot (ECRC by HSC). Figure 10.8 displays these results.

Similar to the categorization used to organize Table 10.2, the results shown in Figure 10.8 are organized according to most resilient, least resilient, and the two categories of mixed resilience capacity. Unlike Table 10.2, Figure 10.8 presents the findings in a way that illustrates spatial differences among countries. In this way, Figure 10.8 offers a more focused way to examine the resilience capacity of a given country relative to other countries. South Africa emerges as the country with the highest composite resilience score, just above Namibia and Botswana.

FIGURE 10.8—INTERSECTION OF ECONOMIC AND COUNTRY RESILIENCE CAPACITY AND HEALTH SYSTEMS CAPACITY



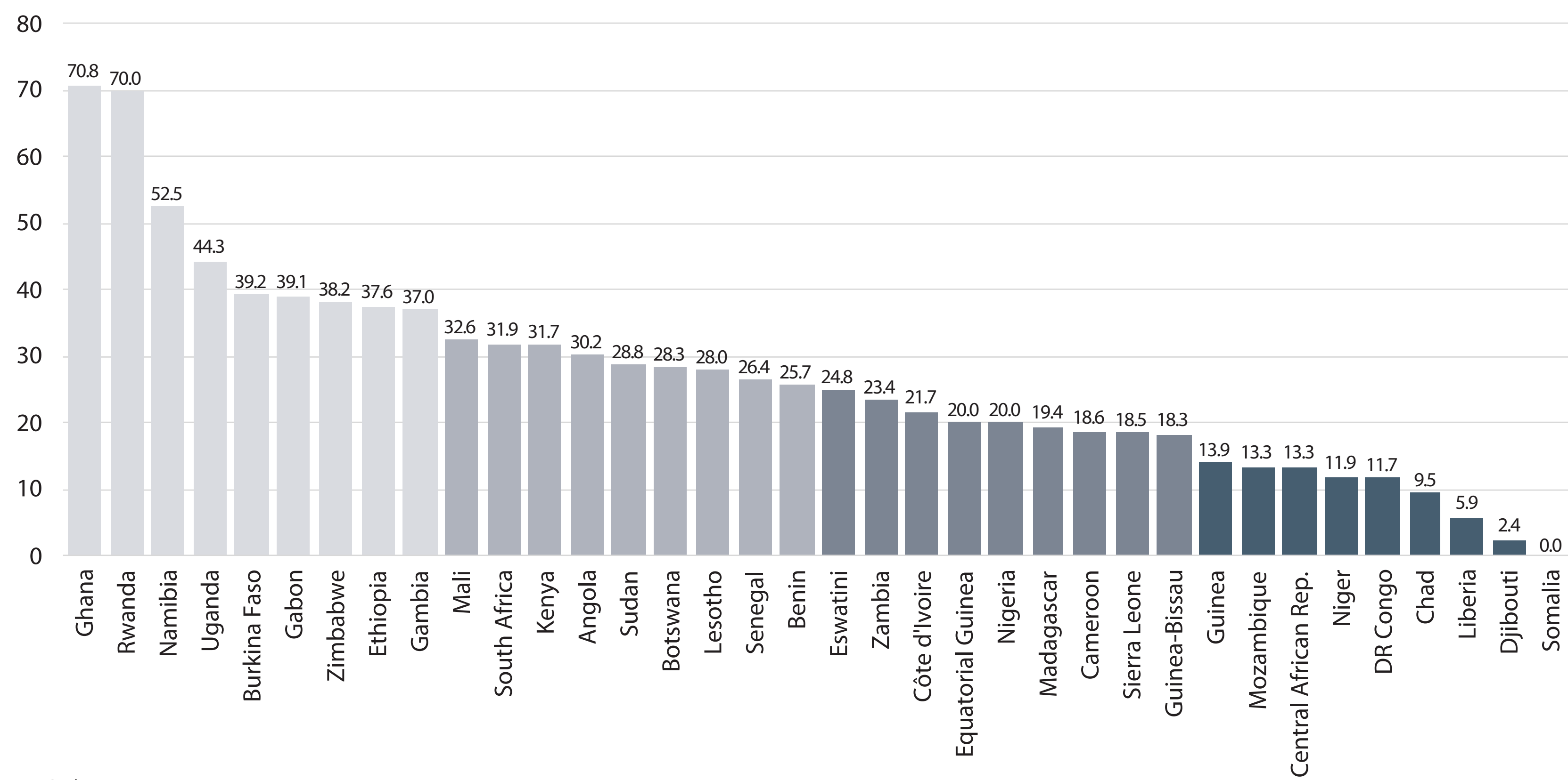
Source: Authors.

Toward an Integrated Resilience Metric for the Malabo Declaration

While the metrics on health systems capacities, economic and country resilience capacities, and macroeconomic factors are important elements of country-level resilience dynamics, the RCS^{GHS} does not consider climate change as a source of shocks to which resilience is a strategic response. With this in mind, we sought to join the RCS^{GHS} with the resilience-focused metric from the Malabo Declaration. The 2019 Africa Agriculture Transformation Scorecard (AATS) reported the most recent progress that each country has made toward the implementation of the Malabo Declaration.[7] Undertaken by the AUC, the AATS provides both an overall ranking of country performance and individual indicators associated with the seven above-referenced Malabo Declaration commitments. Goal VI is focused on "enhancing resilience of livelihoods and production systems

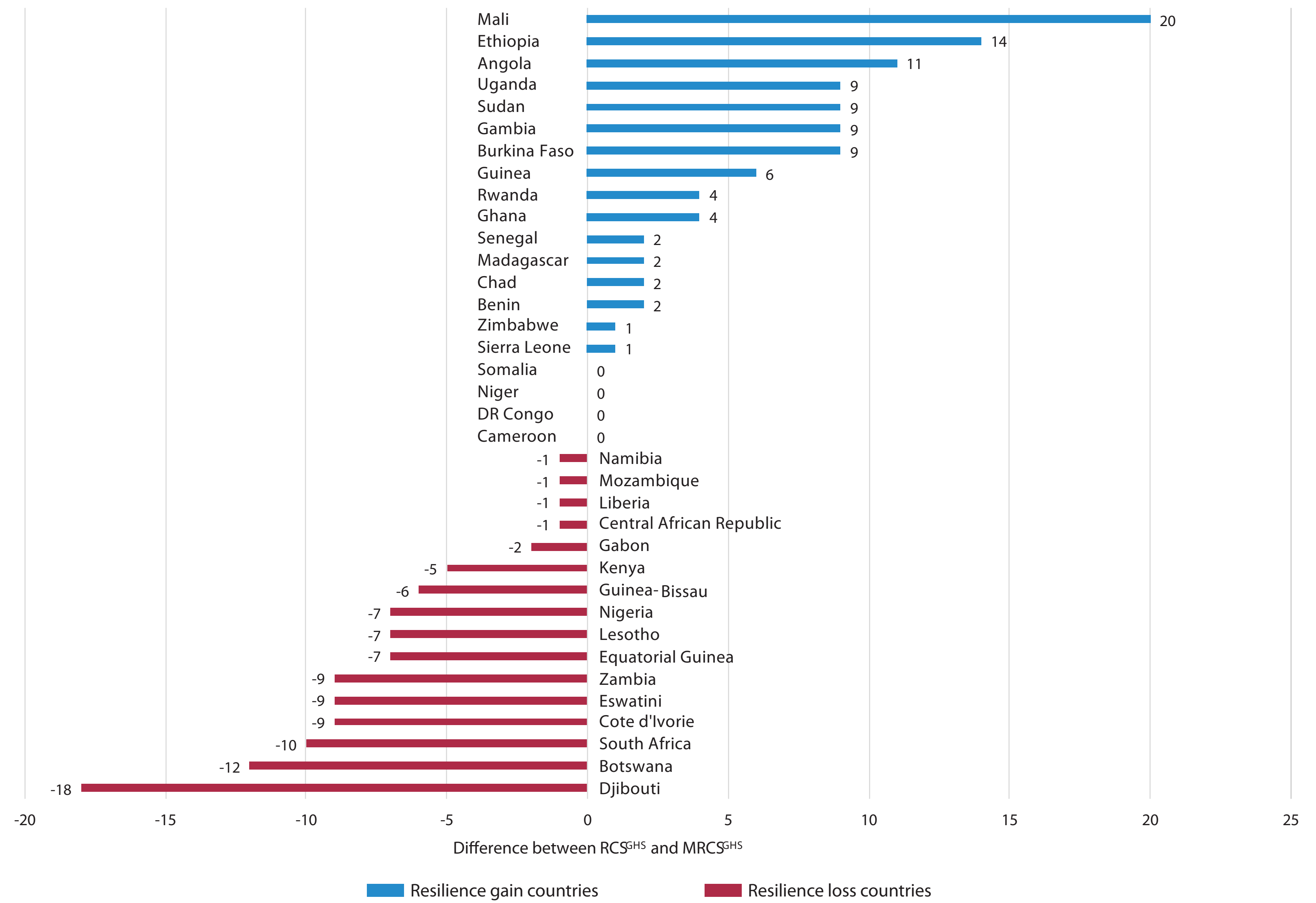
7 For a more complete discussion of the AATS see Benin, Ulimwengu, and Tefera (2018).

FIGURE 10.9—MALABO REFERENCED RESILIENCE CAPACITIES SCORE TO GLOBAL HEALTH SHOCKS ($MRCS^{GHS}$)



Source: Authors.

FIGURE 10.10—RESILIENCE CONVERGENCE SCORE: RANK-ORDER DIFFERENCE BETWEEN RCS^{GHS} AND $MRCS^{GHS}$



Source: Authors.

to climate variability and other related risks" (AUC 2019, 4). A corresponding indicator (indicator 6.2) used for the 2019 Biennial Review provided a measure of commitment to resilience by assessing the investment levels that a given country made toward climate change by searching for the "existence of government budget-lines to respond to spending needs on resilience building initiatives" (AUC 2017, 5). Indicator 6.2 is measured by three associated budgetary components: (1) disaster preparedness policy and strategy, (2) early warning and response systems and social safety nets, and (3) "number (proportion) of households covered by [weather-based] index insurance" (AUC 2017, 46).

To demonstrate how findings from the RCS^{GHS} may be integrated with the resilience component of the AATS, we follow two steps. In the first step, a simple multiplicative score was used to represent the combination of the results of the RCS^{GHS} with the multidimensional AATS resilience indicator. This score, which we refer to as the Malabo Referenced Resilience Capacities Score for Global Health Shocks ($MRCS^{GHS}$), integrates the health systems and macro-level resilience capacities of the RCS^{GHS} with the budgetary commitments to climate-focused resilience building. Organized into quartiles, the results of the $MRCS^{GHS}$ are shown in Figure 10.9. Countries in the fourth quartile had the nine highest scores resulting from their combined performance on the AATS resilience components and the RCS^{GHS}. What is interesting to note here is that the top scoring countries for $MRCS^{GHS}$ represent a markedly different set of countries compared to those countries that were top performers in the $MRCS^{GHS}$. Slightly less than half of the countries in the fourth quartile of RCS^{GHS} (Ghana, Gabon, Rwanda, and Namibia) appear as top-ranking countries for the $MRCS^{GHS}$.

In the second step of the analysis, $MRCS^{GHS}$ was subtracted from RCS^{GHS} to illustrate the changes in ordinal ranking. As shown in Figure 10.10, this simple scaling produces a range of values that reflects gains (positive value) and losses (negative values) associated with a version of resilience capacity sensitive to both global health shocks and climate change. Countries with a positive value are labelled "resilience gain" and those with a negative value are labelled "resilience loss."

Other than Somalia, Niger, Democratic Republic of Congo, and Cameroon—which are the only countries that had no change in rank order position (36th, 31st, 32nd, and 25th, respectively)—countries are widely distributed in their change from RCS^{GHS} to $MRCS^{GHS}$. Changing 18 and 20 places respectively, Djibouti decreased considerably in its resilience capacity score while Mali increased considerably. Although the scores shown in Figure 10.9 could have resulted from a variety of combinations of scores from the RCS^{GHS} and $MRCS^{GHS}$, the array of positive and negative values may be viewed as a kind of resilience convergence score where the higher the score, the higher the convergence between RCS^{GHS} and $MRCS^{GHS}$. It is worth noting that the three countries (Rwanda, Mali, and Ghana) with overall Malabo commitment scores higher than the benchmark displayed positive resilience convergence scores.

Conclusion

The present chapter was motivated by the need to provide basic empirical evidence of some of the factors that may explain varied levels of resilience across Africa[8] in a world where a global health shock such as COVID-19 needs to be considered. There is no question that the most worrisome effects of COVID-19 are health related. It is also clear, however, that COVID-19 has created serious disruptions in supply chains that support the basic functioning of economies. The fact that COVID-19 occupies so much attention and dominates news cycles does not diminish other threats to meeting welfare targets for development, such as those specified in the Malabo Declaration. Most notable among threats that cannot be discounted are those emanating from climate change. For this reason, the measurement model presented here demonstrates how a limited number of indicators related to health system capacities and the macroeconomic effects of a global health shock can be combined to provide useful information to measure progress on the Malabo commitments. This was accomplished by integrating the findings from the RCS^{GHS} with a multidimensional climate-change focused resilience indicator from the AATS. The findings presented here, which categorize countries in terms of resilience capacity, suggest a distribution of resilience capacities to global health across the 36 countries included in the study sample.

The combination of health system indicators and selected macrolevel indicators provide insights about a country's ability to respond to global health shocks. In this way, the measurement approach presented here may

8 While Africa is referenced in several sections of the chapter, the analysis did not include northern Africa. As noted in the introduction, this was a function of data availability.

be viewed as a kind of early warning systems for global health shocks. The early identification of countries with the lowest capacity to respond to global health shocks may help formulate policies and direct investments to avert humanitarian disasters. Conversely, understanding the ability of countries with higher resilience capacities to respond to COVID-19 may provide models that can be replicated in other countries in the continent. It is also important to understand how the resilience capacity in response to COVID-19 interacts with resilience capacities in response to other threats, such as climate change. This is a topic for future research.

The protracted nature of the global pandemic highlights the importance of including indicators that are sensitive to global health shocks as part of the Malabo Declaration's monitoring and evaluation system. In Africa, the impacts of COVID-19 further exacerbate a situation of ongoing shocks, such as desert locust outbreaks, fall armyworm infestations, droughts, conflicts, and insecurity. With respect to food security, disruptions to input markets and reduced labor mobility may result in the delay of planting and harvesting activities, and movement restrictions could cause reduced transactions among food traders, processers, and distributors. The rising incidence of shocks occurring simultaneously because of climate change and other dynamics presents a more complex landscape of risks that threaten development. The simultaneity and propagation of shocks over time also present a new set of challenges for measurement. The development of measurement protocols and analytic tools that are sensitive to interactions should be a priority. Although the findings presented here are based on static measures (without a panel structure), the enduring and lagged effects of shocks and the temporal features of recovery highlight the need for measurement protocols that give careful consideration of time.

With significant dependence on world trade cycles, limited health system capacity, and far more limited access to the internet, African countries are expected to be heavily affected by the direct and indirect global impacts of COVID-19. Given the high proportion of people across Africa who are dependent on agriculture for their livelihoods (Schlenker and Lobell 2010), climate and health shocks must be considered. The model offered here would be strengthened by including metrics that assess the effects of climate shocks that regularly undermine agriculture and threaten the welfare of those who depend on agriculture for their livelihoods. The same is true of any model that aims to measure the resilience of agriculture-based economies in a comprehensive manner.

In closing, we would like to emphasize that we regard our work as an initial, exploratory effort. Clearly, much more research needs to be carried out to develop metrics for health systems resilience capacities and to settle on the macrolevel factors important for measuring resilience capacities in the face of global health shocks. We hope the basic empirical findings offered in this chapter will provide impetus for a focused program of research that examines how the impacts of global health shocks may be incorporated into reporting on the Malabo Declaration goals. It is expected that achieving the Malabo Declaration commitments will pave the way for Africa to achieve the Sustainable Development Goals. However, such progress will require persistent investment in both the commitments themselves and countries' capacities to correctly measure and report on those commitments. In the face of COVID-19, investment strategies and measurement approaches need to be reconceptualized. To this end, the results presented in this chapter are intended as one of many empirical demonstrations on which future work on resilience measurements sensitive to global heath shocks may be based.

CHAPTER 11

The Measurement of Resilience Capacities Through the Integration of Macrolevel and Microlevel Indicators

Marco d’Errico, Ellestina Jumbe, and Mark A. Constas

Resilience measurement can now be viewed as an established body of research with 15 years of empirical evidence. Across this body of work, measurement studies have typically sought to identify key elements that render some households more resilient than others. There is now ample literature that includes robust and solid methods (Cissé and Barrett 2018; d'Errico, Romano, and Pietrelli 2018; Knippenberg, Jensen, and Constas 2019; Smith and Frankenberger 2018), reviews of methodologies (Barrett et al. 2021), solid evidence on the impact of resilience-enhancing interventions (d'Errico et al. 2020), and evidence on the role of macro and covariate shocks (such as conflict) on resilience capacity (Brück, d'Errico, and Pietrelli 2019).

One of the main gaps that exists in the literature is how the traditional microscale resilience perspective can be applied at a macroscale that takes structural parameters into account. The global COVID-19 pandemic highlights the need to consider the structural parameters that reflect, for instance, the health systems capacities and existing health conditions for a given country. Typically, resilience analysis assumes a status quo or stable health system while overlooking important outcomes such as heterogeneous distribution of health service coverage (Bhandari and Alonge 2020). Therefore, one of the motivations of this chapter is the need to explore how estimation may be improved by including indicators of health systems capacity as part of resilience measurement. To do this, we build on an approach used by Gong and colleagues (2020) and Constas, Wohlgemuth, and Ulimwengu (2021) in Chapter 10 of this volume for estimating a Health Systems Capacities Index (HSCI), and we combine this HSCI with a well-tested set of analytical procedures provided by the Resilience Index Measurement and Analysis (RIMA) methodology. As a result, this chapter provides a first attempt to classify countries based on a metric that integrates household resilience and level of efficiency of the national health system.

Consequent to this general gap, another gap in the literature that this paper aims to fill is how (if) a household resilience metric can be integrated with macro indicators to explain food security. Incorporating both micro and macro dynamics of food security into the same analytical framework further contextualizes policies and grants a comprehensive approach. In this context, the second objective of this paper is to model food security against a set of macro indicators and a household resilience capacity construct aggregated at the country level.

This chapter will make use of one of the most widely adopted resilience capacity indexes as well as a set of macro indicators that will be presented in the next pages. The focus of our analysis is Africa, partially because of the mandate of this Annual Trends and Outlook Report and partially because a majority of official assistance in Africa seeks to provide both humanitarian and development interventions.

The data used in this analysis were obtained from multiple sources that will be thoroughly explained in the sections that follow.

Our findings show that the coordinated adoption of a micro, household-level resilience construct and a macrolevel indicator of the status of the health system can provide useful indications vis-á-vis a pandemic like COVID-19. We also show that the combination of micro- and macroscale indicators could prove helpful in improving policy design. Finally, we provide two case studies to show a practical application of our methodology.

Covid-19 and the Food Security Context

Since the onset of the global pandemic in 2019, the attention on resilience has increased. The pandemic caused a crisis that left millions in acute food insecurity and disrupted the global systems that render everyday activities possible. While vaccinations have been ongoing in some countries, the pandemic is constantly worsened by emerging variants. A substantial effort has been made to explore the effects of COVID-19 on different sectors, such as labor, education, health, and the economy more broadly. Recent studies have focused on the pandemic's broader impact, with specific focus on healthcare workers, entrepreneurs, and regional resilience (Bryce et al. 2020; Heath, Sommerfield, and von Ungern-Sternberg 2020; Castro and Zermeno 2020; Gong et al. 2020).

The pandemic has stressed national healthcare systems worldwide. Challenges still exist to manage private and public healthcare and services that are incorporated in a healthy system. The most disadvantaged and poor are often left behind, with low or no support from already overwhelmed national health systems. Apart from affecting the health system, COVID-19 continues to cause disturbances in the worldwide agricultural food market. One outstanding factor, especially for Africa south of the Sahara, is the composition of the informal sector, where a majority of people seem to rely on daily labor to afford everyday food. In addition, the impact of climate change, land grabs, and unfavorable agricultural and economic policies dictated by Western countries threaten to exacerbate food insecurity (Mukiibi 2020). As the pandemic progresses, with new variants emerging, many countries seem to face a trade-off between containing the spread and cushioning the food security crisis. A study in Jordan by Elsahoryi and others (2020) assessed the impact of COVID-19 on household food security, both as the percentage of households that were food insecure and by the level of food insecurity during the quarantine period. The study concluded that less than half of the sample in the study were food secure, while the rest were classified as food insecure. It comes as no surprise that the pandemic affected the supply chain, as the lockdown depressed activity within the food sector in both capital and production. Another study, by Mouloudj, Bouarar, and Fechit (2020), found that COVID-19 severely affected countries in which agriculture represents the largest proportion of the gross domestic product (GDP), including some countries in Africa as well as in Southeast Asia, due to the suspension of agricultural activities such as trade and labor. Countries that depend on food imports from Europe faced another challenge created by the restrictive measures undertaken by some European countries in anticipation of a threat to their own food security. A study by Shupler and colleagues (2021) also confirms the devastating impact of the pandemic on food security in a Kenyan informal settlement. Finally, a study in South Africa by Arndt and others (2020) found that households that were highly dependent on labor income and had a lower educational level were more susceptible to food insecurity as a result of the pandemic.

Most of these studies are, in fact, in alignment that the health shock had some devastating impacts on the global food supply and production rate. Many national and international bodies have shown interest in mitigating this negative impact by introducing various mechanisms to help people in these difficult contexts. The question that seems to be missing from this literature is how countries with good health systems fared relative to their counterparts. Some countries started rolling out COVID-19 vaccines earlier than others, and some countries adopted full lockdown while others adopted partial lockdowns. It is our goal to add to the literature by introducing a health index that gives information on how some countries are capable of handling health risks relative to others, with special emphasis on circumstances that surrounded the responses to the coronavirus pandemic.

Methods

Indicators

There are many ways to measure food security, which are primarily distinguished by their focus on micro- and macrolevels of food security. When referring to the micro level, we normally think in terms of household-level food security, while the macro level considers a country-level indicator of food security. In this chapter, we focus on the latter, bearing in mind that a similar discussion on a micro perspective is necessary. The Food and Agriculture Organization of the United Nations (FAO) normally employs three major indicators of food security: Prevalence of Undernourishment (PoU), Food Insecurity Experience Scale (FIES), and Integrated Food Security Phase Classification (IPC).[1] These three indicators have been designed and created for different purposes and inform different policies and programs. In this paper we will make use of the IPC because of its greater coverage, consistency of results, and wide international acceptance and use.

The IPC is a common global scale for classifying the severity and magnitude of food insecurity and malnutrition, a classification system that is progressively becoming the international standard.[2] The IPC distinguishes between acute food insecurity, chronic food insecurity, and acute malnutrition, since different interventions are needed to address each situation. Furthermore, understanding their coexistence and relationship is invaluable for strategic decision making. The IPC is a platform for presenting the linkages between food insecurity and malnutrition, as well as distinguishing between acute and chronic food insecurity, to support improved integration and coordination of response planning (IPC Global Partners 2019).

Starting with a seminal paper by Pingali, Alinovi, and Sutton (2005), resilience has been adopted as a perspective to support and strengthen food security and food systems. Resilience—and resilience measurement—must be benchmarked to an outcome of interest to be reached (by development interventions) or restored (by humanitarian interventions). A majority of practitioners,

1 It is worth noting that while IPC and PoU are macrolevel indicators of food security, FIES starts at the micro level (based on household data) and can be successively aggregated at the macro level to represent the food security level of an individual country.

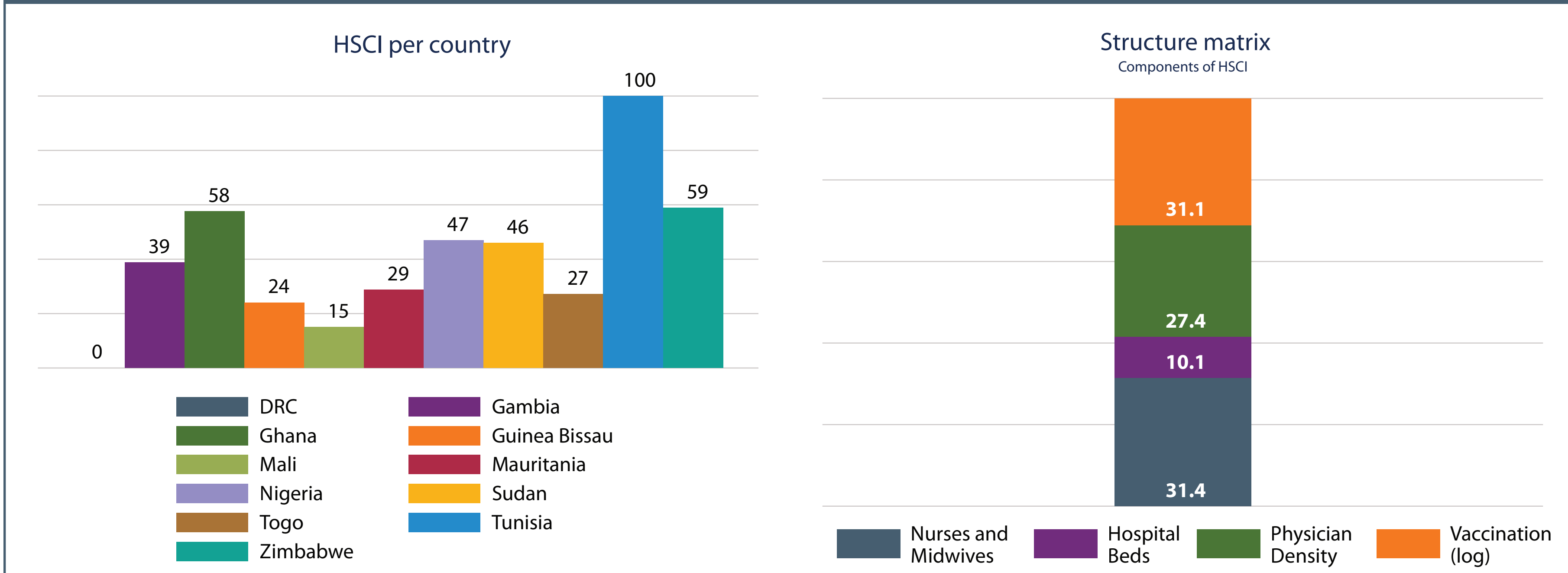
2 See http://www.ipcinfo.org/ipcinfo-website/ipc-overview-and-classification-system/en/.

donors, and international agencies adopt food security as a benchmark of resilience.

After the FAO (2016) presented RIMA, the most recent generation of RIMA applications—by d'Errico and others (2020); d'Errico, Ngesa, and Pietrelli (2021); and Malik and others (2020)—employed factor analysis at the first stage and then estimated the Resilience Capacity Index (RCI) by adopting a structural equation model (SEM) at the second stage (Costello and Osborne 2005; Scott 1966). Researchers used root mean square error of approximation (RMSEA), chi-squared tests, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and standardized root mean square residual (SRMR) estimates to evaluate goodness-of-fit and correlation between residual errors. RIMA is employed to estimate RCI, which is a measure of household resilience capacity that characterizes households resilience against four pillars: access to basic services (ABS), adaptive capacity (AC), assets (AST), and social safety nets (SSN).

RIMA is a well-established and widely used resilience index focusing primarily on household-level variables. This methodology does not, however, include any indicators related to health systems. Methodologies that incorporate health systems data, such as the Health Vulnerability Index (HVI) for disaster risk reduction, do not include household-level data (Chan et al. 2019). HVI is obtained as the result of a two-stage dimension reduction statistical method to determine the weightings of relevant dimensions to the construction of the overall vulnerability index. The proposed final HVI includes nine indicators, including proportion of the population below age 15 and above age 65, under-five mortality ratio, maternal mortality ratio, tuberculosis prevalence, age-standardized raised blood pressure, physician ratio, hospital bed ratio, and coverage of the measles-containing vaccine first dose (MCV1) and the diphtheria, tetanus toxoid, and pertussis (DTP3) vaccine.

FIGURE 11.1—HSCI PER COUNTRY AND STRUCTURE MATRIX



Source: Authors' own analysis. See data source for HSCI calculation in previous section.

To develop a measurement model for resilience capacity that is sensitive to health shocks, we begin with a basic question: what basic infrastructure is required for a country to respond to a health shock of the scale of COVID-19? As a multidimensional concept, the idea of health systems infrastructure comprises health facilities in the form of hospital beds, personnel in the form of physicians and nurses, and the ability to effectively administer vaccines in order to contain a disease. Four different indicators were used to represent the four dimensions of health systems infrastructure of a given country. The final HSCI (Constas, Wohlgemuth, and Ulimwengu 2021) was constructed with the following indicators, with data obtained from two main sources: (a) WHO (2021) and OECD (2021), also supplemented by country data, and (b) Our World in Data (2021):

1. Hospital beds (per 10,000 people)[a]
2. Physicians (per 1,000 people)[a]
3. Nurses and midwives (per 1,000 people)[a]
4. Share of population[3] with at least one dose of COVID-19 vaccine[b]

We constructed the index by employing factor analysis, by considering the variability among observed and correlated variables with the possibility of reflecting variations in other unobserved variables called factors. The factor loadings created by the analysis quantify the extent to which each variable is related to a specified factor. In the end, the resulting HSCI is then a reduction of the observed variables and is rescaled between 0 and 100.

Figure 11.1 shows the constructed HSCI per country (left) and the structure matrix (right). The index shows that Tunisia has the highest health capacity, followed by Zimbabwe and Ghana. The resulting structure matrix indicates that our index is highly correlated by construct due to vaccination rate, physician density, and nurses and midwives. We will proceed to use this index as a variable in our analysis.

Health and Resilience Mapping

The health and resilience (HR) mapping mechanism proposed here serves the purpose of identifying the countries that exhibit the best combination of health systems and resilience capacity levels. The HR map can serve as a synthetic targeting and ranking mechanisms to identify gaps and best practices. The mapping is done by employing k-means cluster analysis, where partitioning of n observations is clustered into k-clusters. The objective function of k-means clustering can be described as

$$J = \sum_{i=1}^{m}\sum_{k=1}^{K} w_{ik} \mid\mid x^i - \mu_k \mid\mid^2,$$

where $w_{ik} = 1$ for data point x^i if it belongs to cluster k, and otherwise, $w_{ik} = 0$. μ_k is the centroid of x^i's cluster.

From Table 11.1, the mapping constitutes four main categories in which countries can be classified according to combination of RCI and HSCI. The ideal combination of high HSCI and high RCI should, in principle, give a country the greatest likelihood of being at low risk. This category represents countries that are optimal in maintaining wellbeing in the face of disturbance such as a health shock on top of the ongoing set of stressors that are faced by a given country. They have the lowest risk of suffering significant losses to their wellbeing. Countries that score low on both RCI and HSCI are categorized as high-risk countries and are likely to be least resilient in the face of a shock. Countries may also present heterogeneous patterns, where they may score high on RCI and low on HSCI or low on RCI and high on HSCI. Based on the assumption that a higher level of one type of resilience capacity may compensate for a lower level of the second type, we view these combinations as representing moderate risk. The logic of this integrated typology is shown in Table 11.1.

For the cluster analysis we employed RCI and its respective pillars (ABS, AC, AST, and SSN), HSCI, Economic Vulnerability Index (EVI), Fragile States Index (FSI),

TABLE 11.1—HR MAPPING DIAGRAM

		HSCI	
		High	**Low**
RCI	**High**	Low-risk capacity	Moderate-risk capacity
	Low	Moderate-risk capacity	High-risk capacity

Source: Authors' own definitions.

3 As of June 21, 2021.

Political Stability and Absence of Violence/Terrorism Index (PVT), and the Human Development Index (HDI). (For definitions of FSI, PTV, and HDI, see Table 11A.1 in the appendix.)

Identification Strategy

We then want to explore the potential explanatory power of the combination of micro-macro covariates to food security. We estimate food security using the following model:

$$\gamma = X\beta,$$

where γ is defined as IPC to measure food insecurity as well as Resilience Capacity Index (RCI) to measure the ability of households to bounce back from a shock or a stressor. X is the design matrix, and β is a vector of parameters of resilience (ABS, AC, AST, and SSN; HSCI; Conflict; and EVI) as well as other control indicators.[4]

The inclusion of these variables uses a simple justification that follows the RIMA methodology. Resilience capacity is affected by households' assets composition and their access to basic services and social safety nets, as well as their adaptive capacity. We include a health indicator, which we expect to designate that countries with relatively stronger health systems are likely to be more resilient and less food insecure. The inclusion of a conflict indicator captures whether there are crises that negatively affect countries' resilience and food security. The conflict variable is a dummy taking one if a region is documented to have had a conflict as reported by the ACLED monitoring datasets. See Data section for further clarification. Lastly, EVI considers other factors that may render countries more or less food secure by underlining how vulnerable their economies are. We also control for other factors that may affect our results.

Data

This section describes the data used for conducting two diverse types of analysis: (1) clustering a set of variables, using all the variables listed in Table 11A.1; and (2) launching regressions to assess how IPC and RCI are affected by a set of independent variables.

Data for IPC come from the IPC Global Partners (2019) classification system, which is an innovative multi-partner initiative for improving analysis and decision making around food security and nutrition. For the countries not mapped under IPC, Cadre Harmonisé (CH) data were used to get the same food security classification as the IPC.[5] The CH is aligned with the IPC, especially within the acute food insecurity component.

Data on RIMA come from an FAO working paper by d'Errico and others (2021). Over the years, FAO conducted resilience analysis using the RIMA methodology in a series of countries. In this study, we are combining some of the most recent datasets. Most surveys are representative of a specific region, and the period they cover extends from 2014 to 2020. We limit our analysis to the countries for which we have data for the entire array of indicators that we are willing to include in our main specification. The countries used in our study are Democratic Republic of the Congo (DRC), Gambia, Ghana, Guinea Bissau, Mali, Mauritania, Nigeria, Sudan, Togo, Tunisia, and Zimbabwe.

The conflict data come from the geo-referenced Armed Conflict Location and Event Dataset (ACLED)[6] that has recorded the date, location, actors, and types of conflict activity covering Africa, the Middle East, and South and Southeast Asia since 1997 (Raleigh and Dowd 2018). ACLED data have previously been employed in evaluating the impact of conflicts on resilience constructs (Brück, d'Errico, and Pietrelli 2019).

The UN Department of Economic and Social Affairs[7] created EVI to identify the least developed countries. EVI is a composition of a country's population size; remoteness; merchandise export concentration; share of agriculture, forestry, and fisheries in gross domestic product; homelessness owing to natural disasters; instability of agricultural production; instability of exports of goods and services; and the share of population living in low-elevation coastal zones.

4 Household size, dummy if household head is female, and household composition.

5 See https://www.food-security.net/en/visualise/.

6 See https://acleddata.com/#/dashboard.

7 See https://www.un.org/development/desa/dpad/least-developed-country-category/evi-indicators-ldc.html.

As discussed in the previous section, a set of control variables was also used in the model identification. These are taken from the RIMA datasets and include household size, dummy if household head is female, and household composition.

Empirical Results

HR Mapping

Results from mapping suggest that countries that are at low risk in terms of resilience and health capacity are Ghana and Tunisia from cluster 1 (See Table 11A.2 in the appendix). This cluster has an average HSCI of 78 and an average RCI of 46. On the other hand, countries that were identified as at high risk in our sample include Mali and Guinea Bissau, with average HSCI of 19 and RCI of 24. The remaining countries were clustered as at moderate risk according to our analysis and possess a potential of growth if the correct context-specific interventions are implemented.

Regression Output

We present four specifications employing IPC and RCI as dependent variables and regressing on a set of independent variables (Table 11.2). We notice that none of the traditional resilience pillars is significant in model (1), while HSCI becomes significant in model (2). The sign of the coefficient is negative, suggesting a positive relationship with food-secure countries. Indeed, as expected, when a country has a higher health capacity, it is most likely to have a lower food insecurity classification. Furthermore, in models (3) and (4), we also notice that countries with higher HSCI have, on average, higher RCI, with SSN and AC being the resilience pillars that are most important. These two main results are not in contradiction and thus provide crude evidence that health systems can render countries better able to manage shocks and stressors. Countries that are affected by conflict, as per our hypothesis, reflect a higher IPC ranking and a reduced resilience capacity. These results are in line with literature giving evidence that conflict has a strong and adverse effect on food security and nutrition. Even though conflict-related food insecurity varies across various types of conflict zones, conflicts share common features that disrupt the food system such as food production and food access. Likewise, EVI suggests that vulnerable countries in general are more prone to food insecurity. For the control variables,

TABLE 11.2—REGRESSION RESULTS FOR NINE COUNTRIES

Variables	(1) IPC	(2) IPC	(3) RCI	(4) RCI
	(Without HSCI)	*(With HSCI)*	*(Without HSCI)*	*(With HSCI)*
ABS	0.000361 (0.00422)	2.40e-05 (0.00421)	0.181 (0.318)	0.252 (0.319)
AST	-0.00333 (0.00487)	-0.00332 (0.00486)	-2.163*** (0.357)	-2.167*** (0.356)
SSN	0.00328 (0.00311)	0.00342 (0.00311)	1.663*** (0.278)	1.636*** (0.276)
AC	-0.00211 (0.00395)	-0.00221 (0.00395)	3.346*** (0.304)	3.366*** (0.302)
HSCI		-0.000323* (0.000190)		0.0680*** (0.0141)
Conflict	0.294*** (0.00670)	0.290*** (0.00565)	-10.65*** (0.518)	-9.909*** (0.557)
EVI	0.0358*** (0.000518)	0.0359*** (0.000512)		
hhsize	-0.0219*** (0.000991)	-0.0222*** (0.000996)	0.105* (0.0547)	0.158*** (0.0559)
femhead	0.102*** (0.0134)	0.0993*** (0.0137)	-0.210 (0.991)	0.301 (0.996)
hhcompo	-8.49e-05 (0.000443)	-4.36e-05 (0.000441)	-0.0312 (0.0355)	-0.0406 (0.0355)
Constant	0.217*** (0.0244)	0.232*** (0.0250)	95.48*** (1.338)	91.85*** (1.561)
Observations	9,100	9,100	9,100	9,100
R-squared	0.500	0.500	0.098	0.100

Source: Authors' own estimation.
Note: Robust standard errors in parentheses. Data on IPC are missing for Sudan and Tunisia.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

our results suggest that households headed by females are less food secure and less resilient than others, as are smaller-sized households.

Case Studies

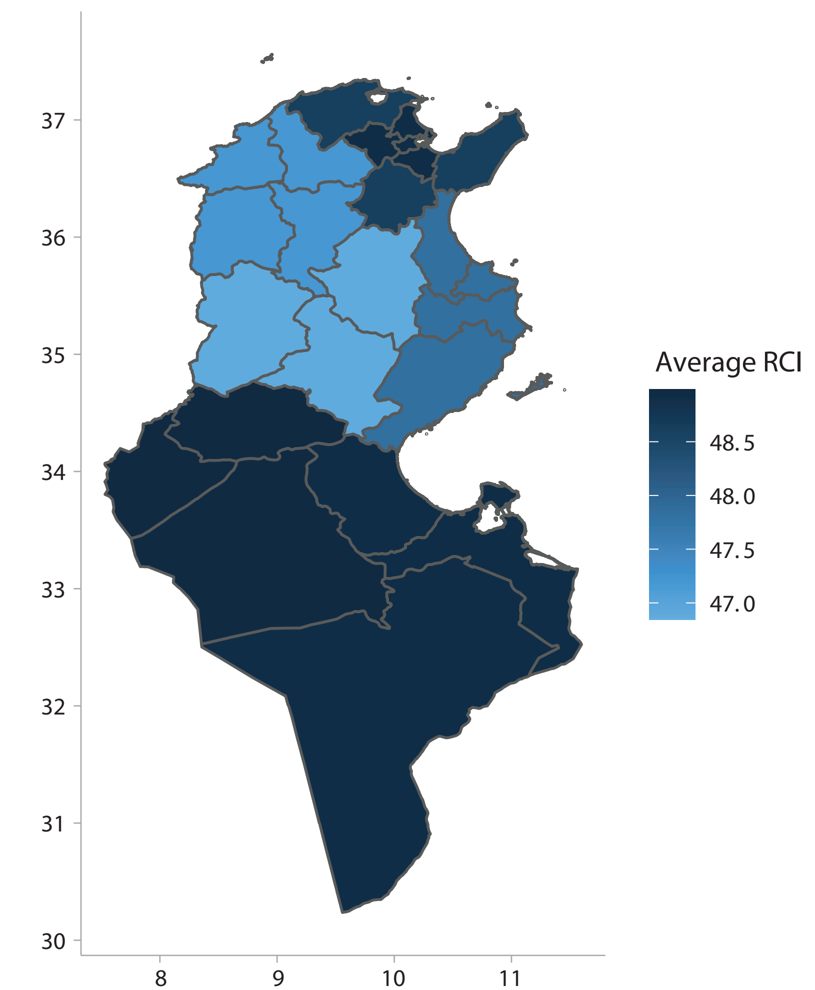
We present two case studies that illustrate the relevance and potential use of our methodologies. As a result of our ranking, Tunisia emerged as the safest and Mali as the most exposed to COVID-19 (Figure 11A.1 in the appendix). This finding is not trivial nor granted, since neither of the countries is the richest or most developed nor the poorest or least developed in the panel that we analyzed. In fact, these countries emerged in our analysis only because of the nature of the adopted methodology, which looks at the interaction between micro- and macroeconomic dimensions.

Case Study 1: TUNISIA

Tunisia diagnosed its first imported case of COVID-19 on March 2, 2020. The country later took a precautionary measure to declare a national general lockdown to contain the spread of COVID-19. By that time, the country had only 300 intensive care beds available for COVID-19 patients out of 20,000 beds located in the various public hospitals across the nation. This represents, on average, 1.1 percent of all the hospital beds (Derouiche-El Kamel and Hentati 2021). This figure includes no beds in regions such as Tataouine, Gafsa, Sidi Bouzid, and 10 other regions in the country. These areas that are recognized as left behind by the country's economic and social development have been identified as "victim regions."

One of the setbacks of the pandemic is that the crisis has exacerbated inequalities in Tunisia, both by income and by opportunity. The government has since taken some countermeasures to mitigate economic impact by providing social protections to the most vulnerable and those with informal employment. Since the country is dependent on agriculture, like most countries in Africa, the effects of climate change coupled with overexploitation of groundwater pose a threat to the nation. Sidi Bouzid governorate, which is at the center of the country, is reporting increasing and rapid food and feed shortages (Dhraief et al. 2019). This area is also characterized by varying income levels and poor and limited infrastructure, accompanied by lower resilience levels (Figure 11.2). Despite this notable setback, the (World Bank 2021) reports Tunisia as one of the countries in Africa that have shown important progress in

FIGURE 11.2—AVERAGE RCI OF REGIONS IN TUNISIA



Source: Authors' own analysis. Data taken from d'Errico et al. 2021.

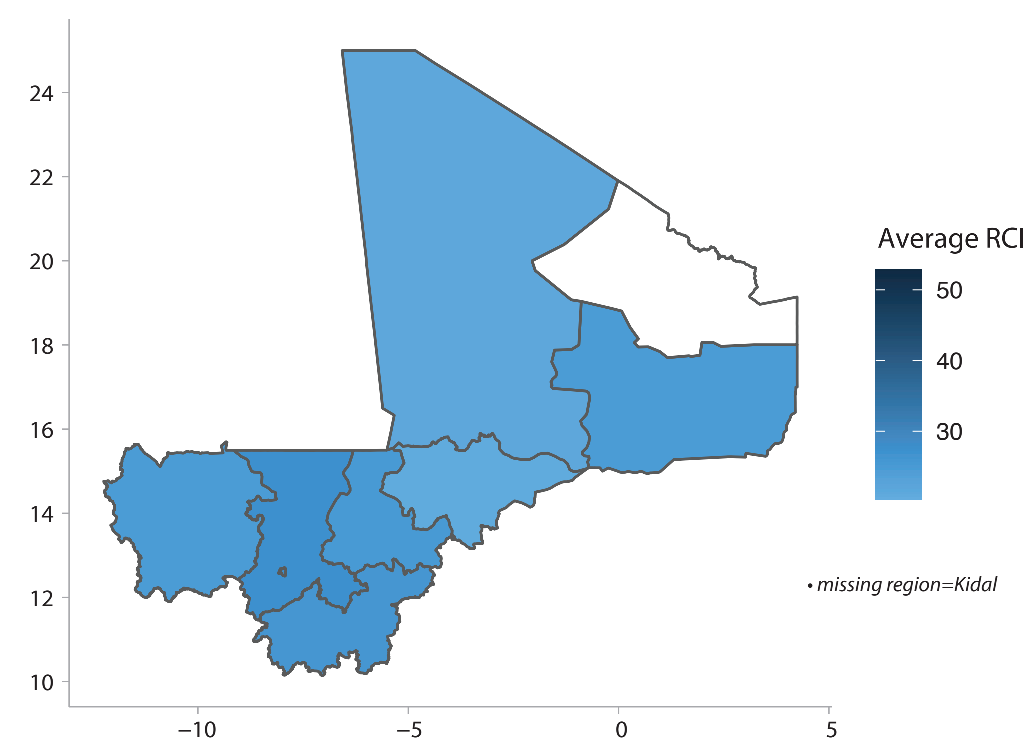
the political transition, however, there is still much to do in terms of Tunisia's economic resilience, which lags in comparison with its neighboring regional peers. In 2020, the GDP growth of the country contracted by 8.8 percent, while unemployment increased to 17.8 percent from its previous level of 15 percent

(World Bank 2021). As a model country in our study, Tunisia emerges with overall high RCI and HSCI in comparison with all the other countries under study, making it low in risk in comparison with the others.

Case Study 2: MALI

The second country under focus is Mali, which has been mired in crisis since 2012. Like most countries in Africa, Mali faced and still faces challenges in its fight against the pandemic, as the onset of a global pandemic in a country perpetually afflicted by conflict was certainly another blow to the economy. The first reported cases of coronavirus in the country were recorded on March 25, 2020. A study by Balde, Boly, and Avenyo (2020) reports that, on average, 25 percent of workers in Mali lost their jobs by the end of April 2020, and this percentage increased to 55 percent when including those that saw a decrease in their earnings. In response to the rising cases, the government worked to mitigate the virus with school closures, public event cancellations, restrictions on gatherings and movement, and border closures, as well as stay-at-home recommendations. At the same time, the government implemented some measures to aid its private sector. At the beginning of the outbreak, the country had only 49 hospital beds available, with personal protective equipment in short supply (Sagaon-Teyssier et al. 2020). In our analysis, not only do we find Mali to be at high risk due to health indicators, but the country also exhibits low RCI across all its regions (around 20) except the capital Bamako, which has an RCI of about 52.9 (See Figure 11.3 and Table 11A.3 in the appendix). This confirms our finding that conflict is in fact detrimental by rendering conflict-affected countries less resilient than others, especially when it relates to a health shock such as COVID-19. In other words, resilience measurement cannot be independent from health indicators in this aspect.

FIGURE 11.3—AVERAGE RCI OF REGIONS IN MALI



Source: Authors' own analysis. Data taken from d'Errico et al. 2021.

Conclusion

Microanalysis of household resilience has been a popular topic in recent times, with researchers adopting different methodologies and different scales—from household to community up to country—to measure resilience. More recently, a strong push toward the measurement of food system resilience has emerged among donors and international agencies. However, there has been no attempt to combine micro- and macrolevel indicators of resilience. Unfortunately, the impact of a global pandemic such as COVID-19 dramatically increased the need to explore how the interconnection of micro and macro mechanisms reacted. We are witnessing a period when resources at the micro level (such as household resilience) and at the macro level (such as a resilient and functioning health system) are facing a violent stressor. Key research questions therefore emerge:

How can we measure or assess whether a country has or does not have the right combination of micro and macro resilience? And more generally, can a resilience analysis that looks at the channels of transmission of the various scales clarify food security issues?

This chapter is a first attempt to integrate a measure of a structural parameter (health system efficiency) with a household-level resilience capacity measure (RIMA). The results show that this method may be used for ranking countries based on a generic micro-macro measure of resilience capacity to face a covariate and global shock such as COVID-19. We find that incorporating health indicators in the traditional resilience measurement approach can better explain why some countries are more resilient than others. The importance of having a resilient health system to feed into food security resilience cannot be denied. This finding has strong policy implications, suggesting which countries have a weaker capacity to react and, consequently, are likely to pay the highest toll in terms of victims. The example of Mali is illuminating; the Sahelian country is not the weakest in food security, nor in human development, nor in GDP. It is difficult to imagine that Mali could be the most exposed to a risk, as compared with other countries such as Sudan or DRC. Nevertheless, our micro-macro analysis showed that what really matters is the combination of resilience capacity with level of efficiency in structural parameters. The fury of COVID-19 has hit countries and people with unprecedented violence; knowing which nation is facing the highest risk is crucial to saving lives.

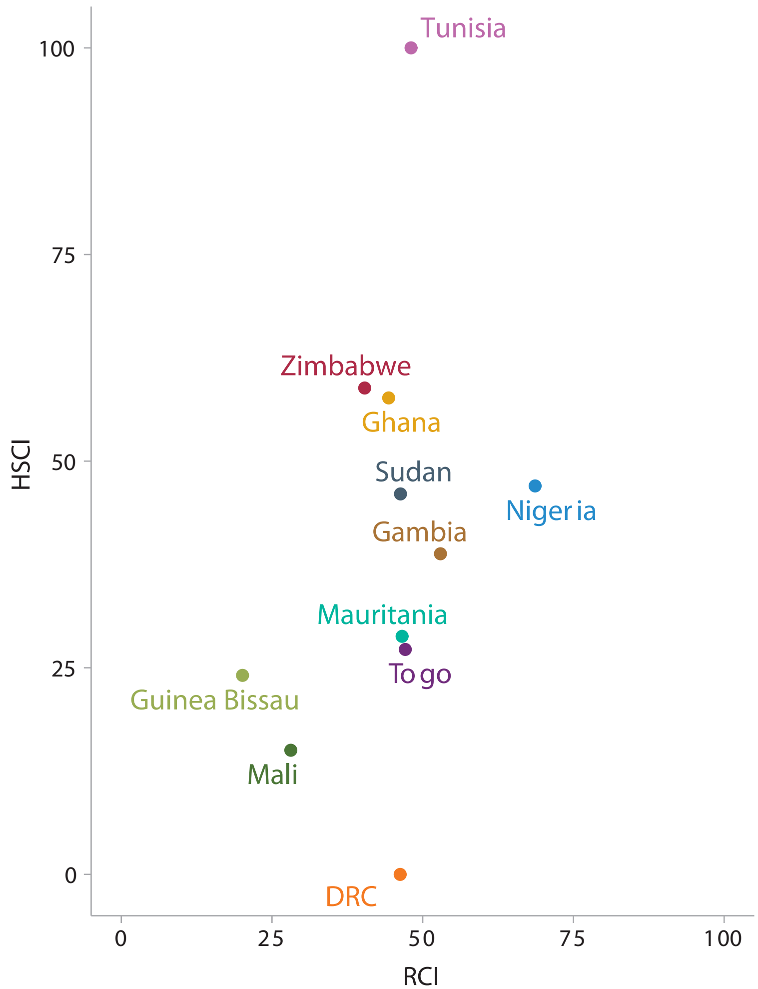
Appendix

TABLE 11A.1—VARIABLES USED FOR CLUSTERING

INDICATOR	DEFINITION	DATA SOURCE	ACCESS
Food security sub-index			
0 to 100 scale	Provides information on countries' exposure to shocks caused by their economic structure. Agriculture, fishing, and forests are particularly subject to natural and economic shocks. Defined as the percentage share of agriculture, fishing, forests, and hunting sectors in the gross value added of a country.	UNSTATS	https://www.un.org/development/desa/dpad/least-developed-country-category/evi-indicators-ldc.html
Political Stability and Absence of Violence/ Terrorism Index (PVT)			
-2.5 (weak) to 2.5 (strong)	Measures perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically motivated violence and terrorism.	Food Systems Dashboard	https://foodsystemsdashboard.org/compareandanalyze
Fragile States Index (FSI)			
0 to 120 scale, where 120 is alert	An annual ranking of 178 countries based on the different pressures they face that impact their levels of fragility. The Index is based on the Fund for Peace's proprietary Conflict Assessment System Tool (CAST) analytical approach.	Fund for Peace	https://fragilestatesindex.org/country-data/
Human Development Index (HDI)			
0 to 1	A statistic composite index of life expectancy, education (mean years of schooling completed and expected years of schooling upon entering the education system), and per capita income indicators, which are used to rank countries into four tiers of human development.	United Nations Development Programlo Index (HDI)	http://hdr.undp.org/en/data
Resilience Capacity Index (RCI)			
0-100, where 100 is strong	An FAO-constructed index that measures household capacity to avoid stresses and shocks from having long-lasting harmful effects. RCI includes the pillars access to basic services (ABS), adaptive capacity (AC), assets (AST), and social safety nets (SSN).	FAO	Data managed by RIMA-TEAM, contact FAO-RIMA@fao.org
Health System Capacity Index (HSCI)			
0-100, where 100 is low risk	As defined by authors in the body of introduction.	WHO and Our World in Data	https://www.who.int/data/collections and https://ourworldindata.org/

Note: All indicators include coverage for all countries.

FIGURE 11A.1—SCATTER PLOT FOR ALL COUNTRIES BY HSCI AND RCI



Source: Authors' own analysis. Data taken from d'Errico et al. 2021.

TABLE 11A.2—CLUSTER ANALYSIS OF COUNTRIES

		HSCI	
		High	**Low**
RCI	**High**	Cluster 1: Ghana Tunisia	Cluster 3: Gambia Mauritania Nigeria Zimbabwe Sudan
	Low	Cluster 2: DRC Togo	Cluster 4: Mali Guinea Bissau

Source: Authors' own analysis. Data taken from sources defined in Table 11A.1.

TABLE 11A.3—CLUSTER MEANS OF COUNTRIES

CLUSTER	COUNTRY	ABS	AST	SSN	AC	EVI	FSI	HDI	HSCI	PVT	RCI
2	DRC	0.265279	-0.31588	0.181713	0.163938	28.76	110	48	0	-2.35	46.24
3	Gambia	-0.10098	-0.02596	-0.07066	-0.07301	51.9	87.1	49.6	38.79	-0.03	52.91
1	Ghana	-0.17072	0.030624	-0.0481	-0.16457	27.12	69.7	61.1	57.65	0.1	44.37
4	Guinea Bissau	-3.1E-05	0.104875	-0.095	-0.1293	40.67	98.1	48	24.05	-0.67	20.1
4	Mali	-0.0434	0.072346	-0.015	-0.04058	49.44	92.9	43.4	15	-1.69	28.09
3	Mauritania	-0.1144	0.077653	-0.0969	-0.01032	45.21	94.9	54.6	28.78	-0.64	46.55
3	Nigeria	0.030554	-0.08803	0.092977	0.081787	36.7	103.5	53.9	46.97	-1.88	68.64
3	Sudan	0.221666	-0.07853	0.171433	0.146328	43.68	110.1	51	46.03	-2.36	46.31
2	Togo	-0.19303	0.100013	-0.11536	-0.11045	25.65	83.9	51.5	27.21	-0.88	47.13
1	Tunisia	-0.06733	0.00974	0.089531	-0.04144	26.88	72.1	74	100	-0.9	48.06
3	Zimbabwe	-0.1569	0.018048	-0.03647	-0.0488	48.79	99.5	57.1	58.85	-0.92	40.38

Source: As defined by authors. See Table 11A.1 for data sources.

CHAPTER 12

Methods of Assessment of the Impact of COVID-19 on Community Dietary Patterns

Mabel Kyei Kwofie, Ebenezer Miezah Kwofie, and Michael Ngadi

Introduction

Food provides the nutrients and energy that are essential for human health. Poor diet is associated with major chronic diseases such as obesity, diabetes, cancer, and respiratory and cardiovascular diseases that persist in both developing and developed nations (Popkin, Adair, and Ng 2012). These diseases contribute to high mortality rates worldwide. A public health challenge is how to reduce exposure to chronic diseases through reinforcement of healthy lifestyles and dietary patterns within populations (Gil et al. 2014). Associations between diet and health outcomes have been observed through longitudinal or retrospective case-control studies, and cross-sectional research studies. Dietary patterns involving healthy food consumption habits among individuals are beneficial in the prevention of diet-related health risks. In dietary patterns studies, it was observed that intake of distinct food combinations is more essential than single nutritive substance or foodstuff consumption (Newby and Tucker 2004). Diet quality assessments that consider overall diet and categorize populations by healthy consumption behavior are crucial tools in monitoring changes within a given population. Broadly, there are two methods—namely, a priori and a posteriori—that have been employed in assessing dietary patterns. The a priori approach assesses consumers' adherence to and application of specific dietary recommendations, whereas the a posteriori approach is data-driven and uses multivariate statistical approaches.

The COVID-19 pandemic has significantly altered the dynamics of nutrition, health, and general dietary patterns for many people around the world. This has accentuated the need to tackle malnutrition in all its forms, including micronutrient deficiencies and obesity. The pandemic has inadvertently highlighted the importance of diet in determining several health outcomes. Although there are minimal data on the impact of early nutritional support in pre-ICU COVID-19 patients, it appears that nutritional status is a significant factor that determines the outcome of COVID-19 infections (Coker et al. 2021). It is known that people who are malnourished have weakened immune systems and may be more susceptible to severe sickness from viruses such as COVID-19 (Global Nutrition Report 2020). The pandemic has disrupted food supply access and hence exposed children to starvation, poor nutrition, and the resulting significant effects on their cognitive development. All of these COVID-19-related hardships come at a time when many families face unemployment and income loss (Coker et al. 2021; World Food Programme and UNICEF 2020). According to the World Food Programme and UNICEF (2020), 368 million children from preschool to secondary school are currently missing school meals, and 148 million (approximately 40 percent) of these children are girls. Global agencies including the World Food Programme have warned that COVID-19 may force an additional 130 million people to the verge of hunger by the end of 2020 (World Food Programme and UNICEF, 2020). In addition, infrastructure flaws in the food supply chain may inadvertently promote the spread and proliferation of the virus (Coker et al. 2021). Therefore, it is crucial to have robust and efficient strategies for monitoring and tracking changes in dietary patterns, particularly during a pandemic.

Dietary surveys are essential policy instruments that can serve several purposes, including identifying hot spots that require interventions, providing better management strategies, and developing improved design of food systems for better availability and accessibility of nutritious foods. This chapter examines the methods of assessment of community dietary patterns and highlights essential elements that may improve measurement to effectively capture the impact of COVID-19.

Dietary Guidelines

Dietary guidelines are typically used to establish public food, nutrition, health, and nutrition educational programs that promote healthy food intake patterns and lifestyles. They give the public advice on nutrition and dietary patterns to help them avoid chronic diseases (WHO 1990). Dietary guidelines must not restrict food intake but must encourage healthy food choices. These guidelines encompass four broad science areas—namely, nutrition, food science, and the agricultural and environmental sciences—as well as educational, social, and behavioral sciences. Since the establishment of food-based dietary guidelines by the Food and Agriculture Organization of the United Nations and the World Health Organization (FAO and WHO 1996), several countries in partnership with international bodies and agencies have adopted their own national nutritional guidelines, often considering each country's ecological and cultural settings, food and nutrients consumption, nutrition outcomes, food supplies, and incidences of diet-related diseases (Herforth et al. 2019). These dietary guidelines can be applied to adjust food consumption patterns and thereby manage populations' health indexes.

Individuals' nutritional status has been a potential protective barrier during the COVID-19 pandemic. Considering that optimal nutrition and dietary nutrient intake have an impact on the immune system, strengthening the immune system is the only long-term approach to survival in the present pandemic circumstances. Dietary guidelines inform people about the foods they should eat to boost their immune system's defenses against viruses like COVID-19.

Dietary Pattern Analysis

Dietary patterns are best in distinguishing the connection between diet and chronic illnesses (Schwerin et al. 1982). They refer to quantities, proportions, varieties, or combinations of different foods and beverages in diets, as well as the frequency with which they are habitually consumed. Improved diet quality and healthier dietary patterns result in better health outcomes (Livingstone and McNaughton 2018). Analysis of dietary patterns normally focuses on the relationship between dietary intake and chronic disease outcomes (Hu 2002). A priori and a posteriori approaches can both be used for dietary pattern analysis. The a priori approach to dietary pattern analysis is created from dietary recommendations or guidelines such as the Diet Quality Index (DQI), Mediterranean Diet Scale (MDS), Healthy Diet Indicator (HDI), and others. The a priori approach describes the extent of consumers' adherence to and usage of set guidelines, whereas the a posteriori approach is data driven and uses multivariate statistical methods (Hu 2002; Panagiotakos 2008; Ramezankhani et al. 2021). The a posteriori approach enables the food intake among population subgroups to be investigated and measured scientifically using statistical tools such as factor and cluster analysis. Several studies have used factor analyses of dietary patterns to reveal population food intake behavior and chronic disease associations (Judd et al. 2015).

Dietary Pattern Analysis—A Posteriori

The a posteriori method of dietary pattern analysis is a data-driven approach that applies mathematics to extract dietary (that is, food consumption) patterns empirically. Food frequency questionnaires, diet records, and 24-hour recalls are commonly used to collect the dietary data. A larger collection of dietary variables is aggregated and reduced to form a smaller set of variables when factor or cluster analysis is used. Each dietary pattern is given a descriptive name based on the most common food groups (Kant 2004).

Factor Analysis

Factor analysis is a technique for reducing the number of dietary variables by identifying factors made up of associated variables (Kant 2004). Principal component analysis (PCA) is a form of exploratory factor analysis that uses matrix algebra to classify the principal components in the data based on a correlation or covariance matrix of the input variables, rather than assuming an underlying model of the factors. The patterns are created using the relationships between the input variables (that is, the foods or food groups) as a starting point. The elements, or factors, that result are linear combinations of the observed variables that explain the data variance. Factor loadings (or scoring coefficients) for each variable are incorporated in the principal components analysis output, which can be interpreted as correlation coefficients (Venkaiah et al. 2011). Food, for example, is divided into groups based on the associations between food products or food groups, and each of the derived factors is assigned a factor score. The best way to represent a person's dietary pattern is to look at his or her factor scores for each derived factor. Confirmatory factor analysis enables the investigator to use previous information about the subject matter by determining both the number of factors and the types of variables that will load in each factor. After that, the researcher constructs the factor model and confirms the factor structure and inputs for every variable.

Cluster Analysis

Cluster analysis creates dietary patterns by grouping people together based on their food consumption variations. Individuals are divided into non-overlapping groups based on their typical dietary intake in this method (Kant 2004). In nutritional epidemiology, clustering approaches divide people into equally exclusive, non-overlapping classes. Individuals can only belong to one cluster, and clusters can then be used in the assessment as categorical (nominal) variables. Many of the methods are vulnerable to outliers, so researchers usually standardize their data before using them in the study. Cluster analysis divides people into classes based on how similar their diets are. The two commonly used cluster analysis approaches are k-means and Ward's method (Newby and Tucker 2004).

Reduced Rank Regression

Reduced rank regression (RRR) is a statistical method for determining dietary patterns (food intake combinations) that explains as much variance among a collection of response variables as possible. Since it incorporates both existing data and exploratory statistics, it is an a posteriori process. To classify response variables, the approach relies on prior information gleaned from established research on nutrient-disease relationships (Vermeulen et al. 2017). These response variables may be nutrients or biomarkers that have been linked to the progression of the health outcome under investigation. Dietary patterns that clarify variance in response variables are detected. Following that, only certain patterns that explain the differences in the response variables are used in subsequent analysis. After this step, each study subject's dietary pattern score is determined for each pattern. These ratings are used in analyses to determine whether any of the dietary patterns are linked to the health outcomes of concern.

Treelet Transform

The treelet transform (TT) is a new method of finding patterns in data from the machine learning discipline. TT is a dimension reduction approach that incorporates features of PCA and cluster analysis to generate a cluster tree that allows a visual examination of how the various variables group. TT reduces multilevel datasets for predictions on a small number of elements that account for the original data's variation. Although very similar to PCA, TT generates sparse components that make it easier to understand (Assi et al. 2016).

Dietary Pattern Analysis—A Priori (Diet Quality Indexes)

Indexes are instruments used to assess and calculate a variety of clinical conditions, patterns, attitudes, and values that are difficult to quantify and accurately measure, such as the severity of a disease, dietary patterns, and health-associated life quality. Specific variables representing index items or components are combined in all indexes. Each indexed dietary item or component represents a different index dimension. These elements are usually scored using random weights and then added together to produce a total score that best reflects people's health, food intake habits, and attitudes. Indexes were generated to address several issues with highly correlated records for evaluation. Table 12.1 summarizes the details of commonly used diet quality indexes. Some selected indexes/indicators are discussed below.

The Diet Quality Index

The diet quality index (DQI) was developed by Patterson, Haines, and Popkin (1994) to provide an effective method for evaluating the risk of dietary patterns on chronic diseases based on dietary guidelines. The index was established by a multidisciplinary committee that reviewed epidemiologic, clinical, and laboratory evidence relating to dietary factors and chronic diseases. Diet and health recommendations were weighted, index scoring cut-offs were created, and scores were averaged across all recommendations. The DQI contained an ad hoc weighting scheme in which three of the diet elements (overall fat, saturated fat, and cholesterol) were used to calculate the first and most important diet and health recommendation on dietary lipids, effectively giving this first diet and health recommendation a weight of three. A person who met the first recommendation target (reduce fat to 30 percent or less of total energy) was expected to meet the second goal for saturated fat. The fourth and fifth index elements distinguished the second diet and health carbohydrate guideline (fruits and vegetables, grains, and legumes). The other three elements (protein, calcium, and sodium intake) were given a lower-priority recommendation (one index calculation each) for food and wellness. The last two guidelines (supplement use and fluoride intake) were not considered relevant enough for chronic disease prevention to be included in the index. A score of 0 was granted to people who met their dietary targets. Those who could not attain a target but consumed poorly earned two points. To score the index from 0 to 100, these points were applied together through eight diet variables on a scale from 0 (excellent diet) to 16 (poor diet). It was deduced that this index ranking of total dietary patterns represented the diet's overall efficiency. DQI may not be representative of total diet quality since many micronutrients are not included in the recorded analyses. It may also not be suitable for people with nutrient concerns.

TABLE 12.1—SELECTED COMMONLY USED DIET QUALITY INDEXES (A PRIORI)

Index Name	Index Characteristics	Score Range	Datasets	Target Area
The Diet Quality Index (Patterson et al. 1994)	8 components	0–100	24-hour recall and two-day food records	United States
The Diet Quality Index Revised (Haines, Siega-Riz, and Popkin 1999)	8 components	0–100	24-hour recall	United States
Healthy Eating Index (Kennedy et al. 1995)	10 components	0–100	24-hour recall and two-day food records	United States
Healthy Diet Indicator (Huijbregts et al. 1997)	9 components	0–100	Food groups and nutrients	Europe
Overall Nutritional Quality Index (Katz et al. 2009)	More than 30 components	1–100	Nutrition, food-groups based FFQ	United States
The Baltic Sea Diet Score (Kanerva et al. 2014)	131 components	Three-point scale (never, scarcely, at least six days)	FFQ	Nordic countries
Canadian Healthy Eating Index (Shatenstein et al. 2005)	Canadian Food Guide	0–100	FFQ and recalls	Canada
Alternate Healthy Eating Index (McCullough et al. 2002)	9 components	0–10	FFQ	United States
Diet Quality Index International (Kim et al. 2003)	17 components (adequacy, variety, moderation and overall [total] balance)	0–100	24-hour recall	Global
The Dietary Variety Score (Drewnowski et al. 1997)	10 components	Five-point scale	Food recall and 24-hour recall	United States
The Healthy Food Index (Osler et al. 2001)	24 components	1–4	FFQ	Denmark
Mediterranean Diet Score (Panagiotakos, Pitsavos, and Stefanadis 2006) (Scali, Richard, and Gerber 2001)	11 components	0–5	Food records	Mediterranean and non-Mediterranean regions
Mediterranean Diet Scale (Trichopoulou et al. 2003)	9 components	0–9	FFQ (150 items)	Greece
The Modified Mediterranean Diet Score (Knoops et al. 2004)	8 components	0–8	Food record and FFQ	Europe (Mediterranean and non- Mediterranean)
Mediterranean Score (Martínez-González et al. 2004)	9 components	0–9	FFQ	Mediterranean and non-Mediterranean regions
A Priori Mediterranean Dietary Pattern (Sánchez-Villegas et al. 2002)	6 components	1–5	Eight quintile, FFQ	Mediterranean and non-Mediterranean regions
The Mediterranean Adequacy Index (Fidanza et al. 2004)	10 components	Two-point scale (good, unhealthy)	Diet history method	Europe
Young Healthy Eating Index (Hurley et al. 2009)	At-risk foods for adolescents	Micronutrients and total energy intake	FFQ	United States
KIDMED Index, (Sahingoz and Sanlier 2011)	16 questions for children	1–8	Questionnaire	Turkey
Variety Index for Children (Cox et al. 1997)	Food Guide Pyramid (four food groups)	0–1	Parent interviews (regarding infants)	United States

Note: FFQ = food frequency questionnaires

The Healthy Eating Index

The Healthy Eating Index (HEI) is a diet quality index established by the United States Department of Agriculture (Kennedy et al. 1995). It was created to examine dietary consumption and wellness promotion activities in the United States. It uses 10 standards to determine the quality of diet, with HEI scores varying from 0 to 100. The dietary recommendations and guidelines for Americans and the Food Guide Pyramid serve as the basis for the HEI requirements (Kennedy et al. 1995; USDA 1995).

The HEI comprises 10 components that are focused on different aspects of a healthy diet. Respondents are given a minimum score of 0 and a maximum score of 10 for each part, for the complete observance of the dietary recommendations. As a result, the overall index ranges from 0 (worst) to 100 (best). Components 1 through 5 determine how closely a person's diet adheres to the USDA Food Guide Pyramid's serving guidelines for five main food groups: grains, vegetables, fruits, milk, and meat. Component 6 is measured as a percentage of total food energy intake. Component 7 is centered on the quantity of total food energy consumption that is saturated fat. Component 8 is based on the amount of cholesterol ingested. Sodium intake is the basis for component 9. Component 10 measures how varied a person's diet is (Kennedy et al. 1995).

The HEI is a measure that helps people to determine the overall quality of their diets, rather than looking only at separate components. The HEI represents the variety of dietary patterns; it is not guided by a single cause, so a high score is not guaranteed by excelling in only one component (Kennedy et al. 1995). Although created for usage with 24-hour recall, the HEI score is a particular algorithm that represents a summary measure of diet quality, incorporating information on the quantity and diversity of foods and recommendations for consumption of specific food components. HEI's drawbacks are that the index is unable to differentiate between whole and processed grains and does not account for dietary fiber.

The Healthy Diet Indicator

The Healthy Diet Indicator (HDI) was developed based on WHO guidelines for chronic disease prevention (Huijbregts et al. 1997). Saturated and polyunsaturated fatty acids; protein; carbohydrates; dietary fiber; fruits; vegetables; pulses, nuts, and seeds; mono- and disaccharides; and cholesterol are the nine foods or nutrient groups that make up the HDI. For each of these classes, a binary variable is produced. These variables were coded as 1 if a person's intake of the foods was within the suggested boundaries of the WHO dietary guidelines and 0 if the intake was below these limits (Peterkin 1990). The balanced diet score (ranging from 0 to 9) was determined by adding all these dichotomous variables together. Overall fat and total carbohydrates were removed to prevent overlap. Since only details about the preexisting sodium content of foods were available, and it was unclear how much salt was added during meal preparation and at the table, salt was not included. The variables for monosaccharides and disaccharides were used instead of free sugars because the free sugars indicator was not equivalent across countries. Also, because high alcohol consumption in some southern European cities dilutes macronutrient intake as compared with other countries, macronutrient intake was measured as a ratio of overall energy intake excluding alcohol. The HDI tends to disregard differences in food or nutrient levels consumed (for example, someone who consumes 11 percent saturated fatty acids as energy is considered the same as someone who consumes 20 percent), and it should have included other nutrients that contribute to the occurrence of chronic diseases, such as sodium. Even so, it is an excellent method for evaluating diet quality and predicting possible adverse health events.

The Mediterranean Diet Scale

The Mediterranean Diet Scale (MDS) was developed to determine the degree of observance of the conventional Mediterranean diet (Trichopoulou et al. 2003). High consumption of typical Mediterranean foods such as cereals, legumes, fruit, vegetables, fish, and wine, as well as the ratio of foods rich in monounsaturated fatty acids to saturated fatty acids, are scored 1, whereas high intake of non-Mediterranean foods such as dairy and meat are scored 0. Thus, the score ranges from 0 to 9, where the higher the score the better the compliance with a traditional Mediterranean diet. For alcohol intake, the scale assigns a value of 1 to either men who consume 10 to 50 grams of wine per day or women who consume between 5 and 25 grams per day. Since monounsaturated lipids are used far more in Greece than polyunsaturated lipids, the proportion of monounsaturated to saturated lipids was applied instead of polyunsaturated to saturated lipids for lipid consumption. Trichopoulou and others (2005) reported a two-point rise in the scale that was correlated with a 33 percent reduction in the risk of coronary heart disease in a large, population-based sample of people from Greece. In addition, the proposed scale was associated with all-cause mortality. The cereal category is considered a positive factor in this score. High cereal intake in the Mediterranean diet has long been thought to be safe, but evidence for this has been limited. The intake of refined cereals is rising around the world, including in Mediterranean countries where cereal use is already high. However, this scale is a useful instrument for assessing the risks of different chronic diseases and determining adherence to a healthy dietary pattern.

Population Food Group Diversity Indicators Often in Use

The COVID-19 lockdown resulted in increased food prices, a decline in household dietary diversification, heightened generalized anxiety disorder symptoms, and altered diet and consumption patterns, according to current research evidence (Matsungo and Chopera 2020). Therefore, it is essential to identify and use indicators that effectively measure household-level impact.

Household Dietary Diversity Score

As part of the Food and Nutrition Technical Assistance (FANTA) II Project, the Household Dietary Diversity Score (HDDS) was released in 2006 as a population-level indicator of household food access. Household dietary diversity, defined as the number of food categories consumed by a household over a specific reference period, is an essential measure of food security for a variety of reasons. Caloric and protein adequacy, percentage of protein from animal sources, and household income are all linked to a more diverse household diet. Based on 24-hour history, the HDDS indicator provides an overview of a household's ability to get food as well as its socioeconomic position. The HDDS indicator is calculated using the following 12 food groups: cereals; root and tubers; vegetables; fruits; meat, poultry, and offal; eggs; fish and seafood; pulses, legumes, and nuts; milk and milk products; oil and fats; sugar and honey; and miscellaneous. A score of 1 (if consumed) or 0 (not consumed) is given to each food group. The total number of food categories consumed by the household determines the household score, which ranges from 0 to 12 (Swindale and Bilinsky 2006).

Although there is no standard cutoff or objective level for determining whether a household's diet is sufficiently varied, FANTA recommends two approaches for using this indicator in performance reporting. One approach is to set a target based on the dietary diversification patterns of wealthier households (the top 33 percent in income), on the assumption that poorer households would increase their dietary diversity as their finances rise. An alternative is to set a target based on the average dietary diversity of the 33 percent of households with the most diversity (Swindale and Bilinsky 2006).

Infant and Young Child Feeding—Minimum Dietary Diversity

The WHO developed the minimum dietary diversity (MDD) score for children ages 6 to 23 months to assess dietary diversity as part of infant and young child feeding (IYCF) practices among children in this age group. The WHO established the MDD as one of eight IYCF indicators to provide simple, valid, and reliable metrics for measuring IYCF practices at the population level. The other seven indicators are early breastfeeding initiation; exclusive breastfeeding under six months; continued breastfeeding at one year; introduction of solid, semisolid, or soft meals; minimum acceptable diet; minimum meal frequency; and intake of iron-rich or iron-fortified foods (WHO 2008). The minimum acceptable diet indicator, which is a composite indicator, incorporates the MDD. The information is acquired through a questionnaire given to the child's caregiver, which is normally included in the IYCF module. Respondents are asked whether their child consumed any food from each of these eight food groups in the preceding 24 hours: breast milk; grains, roots and tubers; legumes and nuts; dairy products; flesh foods; eggs; vitamin A–rich fruits and vegetables; and other fruits and vegetables. The total number of food categories from which a child has eaten is summed to calculate the MDD (WHO 2008).

Minimum Dietary Diversity for Women

Minimum Dietary Diversity for Women (MDD-W) is a population-level indicator of dietary diversity that has been validated for women between the ages of 15 and 49. The MDD-W is a 10-food-group, dichotomous indicator that is widely used to assess dietary variety in women of reproductive age at the population level. The Women's Dietary Diversity Score, a validated continuous indicator based on reported intake of 9 food groups, had been used prior to the MDD-W. After more testing with different datasets, the MDD-W was created with the goal of providing a dichotomous, easily understood indicator rather than a continuous one. Women with minimally appropriate diet variety, according to the MDD-W, have ingested at least 5 of the 10 potential food groups over a 24-hour recall period. When a categorical indicator of individual dietary diversity for women is needed, both the FAO and the United States Agency for International Development (USAID) propose using the MDD-W. If a continuous variable is necessary, these organizations also advocate using the 10-food-group dietary variety indicator. The information is acquired by a questionnaire given to female respondents ages 15 to 49 (FAO and USAID 2016).

Respondents are asked to recollect the food groups from which they ate in the previous 24 hours, using either a list-based method (with questions about intake of each of the 10 food groups in sequence) or an open-recall technique (with questions about intake of each of the 10 food groups in any order). Even though the MDD-W guidelines include both recall methods, the open-recall technique is recommended. The 10 food groups required for the MDD-W are as follows: grains, roots, and tubers; pulses; nuts and seeds; dairy; meat, poultry, and fish; eggs; dark leafy greens and vegetables; vitamin A–rich fruits and vegetables; other vegetables; and other fruits. Enumerators keep count of whether or not the respondent ate foods from each dietary group. The total number of food groups consumed is added together, with each food given an equal weight (FAO and USAID 2016).

Dietary Pattern and Diet Quality Assessment in COVID-19-Related Population Dietary Behavior Studies

Population studies evaluating dietary patterns from a quality perspective have focused on various aspects of diet quality measurements and their corresponding indexes. However, COVID-19 has made it necessary to look beyond the status quo and measure other factors that are essential to augment our understanding of the impacts. In this section, we highlight four elements that may improve dietary pattern measurement and capture the potential impact of COVID-19.

Food Diversity

Eating a balanced diet improves health and reduces risk of preventable chronic diseases such as obesity and associated complications. While some of the current dietary assessments measure food diversity, nutrient-based dietary assessments such as the Nutrient Improvement Score, Nutrient Adequacy Ratio, and Mean Adequacy Ratio may not capture the level of diversity in the diet. Except for the food and behavioral models such as the Preschoolers Diet-Lifestyle Index, Foods E-KINDEX, and the Chinese Children Dietary Index, most dietary pattern assessments were not designed to account for factors such as lifestyle that would reflect the impact of COVID-19, indicating a need for further research efforts (Matsungo and Chopera 2020).

Anxiety

COVID-19-related anxiety issues have been reported globally and have significant effects on what people consume during the pandemic. It is essential to capture anxiety while measuring changes in dietary patterns. Population dietary studies could therefore employ the Generalized Anxiety Disorder scale (GAD-7) to access these changes. This will require measuring anxiety symptoms over a stated period (14–21 days). Matsungo and Chopera (2020) used a four-point Likert scale for a similar measurement. The total GAD-7 score ranged from 0 to 21, with increasing scores indicating more severe functional impairments because of anxiety. Augmenting dietary results with such measurement will provide a more holistic outlook on consumers' dietary patterns during pandemics (Matsungo and Chopera, 2020).

Body Image Perception

COVID-19 has changed how people perceive their body size, since frequent snacking between meals, combined with less activity, has often resulted in body weight gain. Pulvers and colleagues (2004) and Yepes and others (2015) have measured body image perception using a silhouette test. This test allows participants to select matching body sizes that reflect their perceptions of how they look before and after the COVID-19 lockdown (Matsungo and Chopera 2020).

Physical Activity and Lifestyle Changes

There is evidence that COVID-19 has resulted in reduced physical activity and lifestyle changes. Ruiz-Roso and others (2020) observed that walking and moderate physical activity have decreased by more than 50 percent during the lockdown, which could have both mental and physical health implications, considering that insufficient physical activity is seen as a primary risk factor for obesity and cardiovascular disease. There are few dietary assessment tools that measure physical activity levels. It would be important for food- and nutrient-based dietary pattern models to include physical activity and lifestyle changes to account for the impact of COVID-19.

Strategies for Large-Scale Improvements of Populations' Dietary Behaviors

Large-scale behavioral change communication (BCC) techniques have been identified and used as the primary strategy for improving populations' dietary behavior. These strategies may either be education-oriented or community activity–focused, and this section discusses these strategies used in population studies.

Education-Based Large-Scale BCC Strategies

The education-based approach is usually implemented through interpersonal counseling, community-based mass media, community mobilization, or a combination of these techniques (Menon et al. 2016). Education-based BCC strategies are usually delivered through home and local clinic visits, mass media such as radio programs, or community education in the form of community conversations and cooking demonstrations.

As reported by Kim and colleagues (2016), an education-based large-scale BCC strategy was implemented through an Alive & Thrive project aimed to enhance IYCF patterns in four regions in Ethiopia. In the two regions of the study—the Southern Nations, Nationalities, and Peoples Region and Tigray—the effects of the interventions on IYCF practices and anthropometry were evaluated over time. Repeated cross-sectional surveys of households with children ages 0–23.9 months (n = 1,481 and n = 1,494) and children ages 24–59.9 months (n = 1,481 and n = 1,475) were performed at baseline (2010) and end line (2014), using a pre- and post-intervention adequacy assessment design. Regression models were used to quantify the differences in the outcomes over time while accounting for clustering and covariates. Tracing recall of main messages and marketed foods, as well as dose-response tests, were used to determine plausibility. The authors observed changes in the majority of the WHO-recommended IYCF measures. Although the interventions were linked to plausible changes in IYCF practices, there are still significant gaps in Ethiopian children's diets, especially during complementary feeding.

A similar application of the education-based BCC technique employing counseling was reported by Kushwaha and others (2014). The study's main goal was to see how effective peer counseling by mother support groups was at enhancing neighborhood IYCF practices. Between 2006 and 2011, the researchers performed this repeated measure before and after analysis in the Lalitpur district of Uttar Pradesh, India. The following IYCF activities in the group showed substantial improvement: initiation of breastfeeding within one hour of birth, use of prelacteal feeds, rates of exclusive breastfeeding for six months, initiation of complementary feeding, and complementary feeding with continued breastfeeding. Ultimately, peer counseling by mother support groups effected a sustained change in the district's IYCF procedures (Kushwaha et al. 2014).

Community Activity–Based Large-Scale BCC

Besides nutrition education, specific community-based interventions have also been used to improve population dietary and diet-related health behavior. The activities are usually physical activity interventions that enhance community participation. For instance, Xu and colleagues (2017) explored ways to reduce obesity in their research on a community-based nutrition and physical activity intervention for children who are overweight or obese and their caregivers. They emphasized the importance of successful approaches to reduce childhood obesity, and a limited amount of evidence indicates that collaborative community-based services for children and their caregivers could be effective in lowering obesity rates. The study presented the findings of the South County Food, Fitness, and Fun (SCFFF) program, which was established in response to community concerns. Families were referred to the program by their doctors and were able to enroll for free. Daily group diet and physical activity sessions were part of the 16-week intervention. According to the findings, 65 of the 97 children who completed the SCFFF program and provided two-year follow-up data had lower body mass index z-scores two years after the intervention. From baseline to the end of the intervention, these participants reduced their energy, fat, carbohydrate, saturated fat, and sodium intake while increasing core body strength and endurance (Xu et al. 2017).

Conclusion

The literature shows that there are two primary pathways to evaluate population dietary patterns and diet quality: statistics-based multivariate methods (a posteriori) such as cluster or factor analysis, RRR, TT, and PCA; and indexes (a priori) created from dietary guidelines to evaluate diet quality and associated chronic disease risk. Statistical methods are used less frequently because they rely on the existence of previously collected data. The field-based diet quality approach, which is employed in most studies, uses indicators that assess how well the population's diet agrees with an idealized meal. Recent dichotomous, population-level indicators based on food group diversity—including HDDS, IYCF-MDD, and MDD-W—are also becoming widely used. While these models have been successful in measuring population dietary patterns, the impact of COVID-19 has made it necessary to include other factors such as food access, physical activity, dietary diversity, anxiety, and body image perception to account for the impact of COVID-19. Large-scale social and behavioral change communications such as interpersonal counseling, community-based mass media, community mobilization, or a combination of these techniques must be deployed to maintain appropriate dietary patterns in communities.

CHAPTER 13

A Consumer–Food Security Nexus Framework Analysis for Resilient Agrifood Value Chains

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Introduction

There is a global consensus that the current food system, involving the production, processing, transport, and consumption of food, is failing—threatening our food security, nutritional security and health, social justice, and natural resources—and therefore requires an immediate transformation if the global "zero hunger by 2030" agenda is to be achieved (HLPE 2017; HLPE 2020). The United Nations Committee on World Food Security defines "food security" as the state in which "all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their food preferences and dietary needs for an active and healthy life" (FAO 2002, Glossary). Food security is increasingly under threat: a report on global food security crises shows that 108 million people from 48 countries suffered from acute food insecurity in 2016 (FAO 2017). By the end of 2019, the number had increased to 135 million in 55 countries (FSIN 2020). By the end of 2020, the impacts of the COVID-19 pandemic had nearly doubled this number to 265 million people (WFP 2020).

Food insecurity, undernutrition, and overnutrition have been characterized as a triple burden (Pinstrup-Andersen and Watson 2011); this burden is a global challenge that is worsening by the day. The implications are dire and affect millions, including through the incidence of diseases and conditions such as diarrhea, obesity, anemia, cardiovascular disease, growth retardation, and many others (FAO, IFAD, and WFP 2014). Although the triple burden has multiple causes, the diets of consumers play a critical role (Gómez and Ricketts 2013).

Food undergoes a variety of processes before reaching consumers' tables. These processes are known as the value chain and operate in conjunction with agents who work to provide food products (Beretta et al. 2013). The nature of the food value chain influences the availability, accessibility, acceptability, physical and nutritional quality, and utilization of food. Agrifood value chains, within which consumer preferences and needs are embedded, also influence food and nutrition security (Alkire et al. 2014). Disruptions within agrifood chains due to shocks, such as COVID-19, floods, locusts, and others, have a direct impact on food security. Thus, optimizing agrifood value chains is essential to addressing food security issues and consumer needs.

Considering the dynamic environment within which value chains operate, their ability to deal with and overcome unpredictable disruptions (extreme weather, pandemics, etc.) is critical to their performance. An inability to adapt and recover leads to an inability to address the needs and wants of consumers and endangers food security. A value chain analysis (VCA) that does not use a resilience lens cannot reveal the factors that hinder or enhance resilience. Information about these factors can facilitate measures to reduce the costs of disruptions or set up better systems and structures to enable value chains and their actors to adapt to shocks (Carluccio et al. 2020).

The main goal of agrifood value chains is to ensure that a sufficient quantity of nutritious and quality food is made physically and economically accessible to all. The ability to meet this goal despite potential disturbance is embodied by the concept of stability, which is another food security pillar beyond availability, accessibility, acceptability, quality, and utilization (Tendall et al. 2015). Thus, a key step in building resilient food systems is to first understand and assess food value chains through the lens of resilience. This approach requires assessing food value chains with a consumer and food security focus, as well as a with a holistic view comprising social, economic, environmental, and other factors. Such a framework for food value chain analysis can reveal weaknesses in different areas of the value chain and help policymakers better build capacities in the food system to deal with current challenges and future uncertainties (Tendall et al. 2015).

Practically, assessing the value chain through a resilience lens begins with identifying the sources of risks or threats. This identification is necessary to predict and prevent potential shocks and put mitigation strategies into place. The assessment aims to gather information that can be used to help prevent foreseen shocks and to design the strategies necessary to help value chains recover from unforeseen shocks. An understanding of how the value chain can meet consumer preferences and contribute to the achievement of food security is useful for predicting shocks, planning for future mitigation of shocks, and strengthening resilience (Carluccio et al. 2020).

Existing assessment frameworks encompass the social, environmental, and economic aspects of agrifood value chains. However, there has not been any work on a framework with a consumer focus. Current agrifood value chain assessments are usually centered on activities at the production stage, and there is a disconnect with consumers, who are usually the end target of functioning value chains. There are no tools, methods, or frameworks that adequately assess the impact of agrifood value chains from a consumer- and food security–based perspective. This type of tool is crucial during severe disruptions of the supply chain, such as those caused by the COVID-19 pandemic. It is widely recognized that the pandemic placed enormous pressure on food supply chains as a result of social distancing requirements, labor shortages, and widespread lockdowns. In these situations, hardcore economic considerations typically trump the consumer considerations that are crucial for ensuring sustainable production and access to nutritious foods.

In this chapter, we argue for the importance of a consumer focus in agrifood value chain assessments and present a methodological framework for such an assessment. The first section defines a holistic framework for a consumer-centered value chain. Then, a system for the selection of criteria, indicators, and dimensions for performance assessment is outlined. Based on this system, the method of assessment for each dimension and the interrelatedness between dimensions is presented.

Agrifood Value Chains

VCA techniques have been used by businesses for many years to determine strategies to improve competitiveness. This type of analysis has been applied widely in the literature in different fields, including food and agriculture. The majority of agrifood VCAs are focused on identifying product flow and relationships, estimating financial returns, and assessing challenges and opportunities (Dalipagic and Elepu 2014; Kelemework 2015; Tesfaw 2015; Zhang, Ren, and Liu 2012; Kirimi et al. 2011; de Souza and D'Agosto 2013). The primary trend among the studies is an assessment of the value chain from the production perspective, with a focus on improving production quantity, reducing costs, and increasing profits. Hardly any studies have been conducted with the aim of providing more value for consumers while improving economic benefits for value chain actors (Zokaei and Simons 2006).

Agrifood value chain activities are interrelated and interdependent (Flynn and Bailey 2014). Due to these linkages, analysts have proposed that value chains should pursue sustainable development, which is core to fostering consumer satisfaction and contributing to society, the environment, and economic viability (Mitchell, Keane, and Coles 2009). The introduction of a set of different assessment dimensions aims to achieve better alignment between resource allocation, consumer value, and management toward sustainability and profitability. This holistic approach to assessing agrifood value chains will aid value chain actors, policymakers, and other stakeholders in designing and implementing strategies that are effective, applicable, and adapted to the dynamic nature within which the agrifood system functions—thus leading to increased consumer satisfaction, economic viability, and food security.

Recently, environmental and social dimensions have gained importance because of the strong linkages between agrifood industries, society, and the environment (Marsden and Morley 2014), and the failed quest to meet established goals in these areas (McCullough, Pingali, and Stamoulis 2008). A focus on social dimensions has become necessary due the impact of agrifood value chains on the welfare of actors. Thus, issues related to worker safety, gender imbalance in employment, access to inputs and services, labor issues (Ndanga, Quagrainie, and Dennis 2013), and welfare impacts on value chain actors are assessed. Environmental challenges such as land degradation, water scarcity, and climate change resulting from natural resource abuse (Nellemann et al. 2009) have created the need for environmental assessments. These multidimensional assessments focus on ensuring that the agrifood sector is transformed to sustainably feed growing populations (Fritz and Schiefer 2008).

Value chains will not be sustainable without an efficient governance structure and the ability to adapt quickly to changes in the surrounding socioeconomic environment (Bachev 2017). The loss management dimension is important in understanding the factors that contribute to physical, economic, and nutritional losses, especially because these losses have implications for the availability, accessibility, affordability, and nutrient composition of food. A food quality assessment, for instance, is necessary to understand how activities affect the quality attributes preferred by consumers.

Although a focus on sustainability has been proposed, only the primary sustainable development dimensions (economic, social, and environmental) have been integrated into food value chain assessments. The aspect of consumer satisfaction has received little attention, even though the consumer is the ultimate target of the activities undertaken along the value chain. The analysis is not focused on identifying how the activities along the value chain meet consumer needs or influence food security.

The definition of food security centers around the four pillars of availability, access, utilization, and stability (World Summit on Food Security 2009). Food availability focuses on the physical presence of a sufficient quantity of quality food that is made available through domestic production, import, food aid, or stocks (FAO et al. 2019). Food access is the ability to secure food that is adequate to make up a nutritious diet by having access to income and adequate resources (FAO 2008). Food utilization centers on the means by which the body uses the nutrients available in food. This is influenced by diet, eating habits, preparation, and hygiene practices, among others (FAO et al. 2019). Food stability occurs met when all four pillars are met at the same time (FAO 2008) thus focuses on achieving availability, accessibility, and utilization over time. It addresses short- to long-term instabilities caused by economic, climatic, social, or political factors (FAO et al. 2019).

The value chain approach can be used to achieve food security objectives because it helps to identify incentives (or other strategies) to produce and market nutritious foods that meet consumer demands without overlooking production costs. Due to its capacity to reveal underlying constraints in the whole-product production and marketing system, it tends to be a more holistic and sustainable approach to equipping food value chains to better contribute to achieving food security objectives with long-term impacts. This goal is ultimately accomplished by guiding and influencing the activities of value chain actors to meet the needs and preferences of the target market or consumers (Marketlinks n.d.).

VCA approaches operate under the assumption that effective supply chains and cost efficiencies will lead to acceptable consumer satisfaction. This approach is inadequate because the lack of consumer focus will result in production activities that do not respond to shifts in consumer expectations (Thublier, Hanby, and Shi 2010). According to Capper (2013, 157-71), "If a production practice is economically viable and reduces environmental impact yet is unacceptable to the consumer, the system is out of balance." For the consumer, value includes the product's taste, color, size, nutritional content, safety, and convenience of use, among other factors. Therefore, from a subjective point of view, the true value of the product being offered cannot be inferred from assessing value as a benefit-cost ratio. Limited attention has been given to evaluating nonmonetary benefits in a VCA. Making consumers the focus of agrifood value chains is important because food is no longer viewed as something that simply meets a basic need, but also as something that fits into a particular lifestyle and achieves a desired goal (Costa and Jongen 2006). Consumer needs and lifestyles are constantly changing.

Consumers' preferences and needs have not been translated into product features and value chain measures. This makes it difficult to determine how to adequately measure the performance of the value chain in meeting consumer needs and to address these needs. This premise assumes that meeting consumers' needs will lead to consumer satisfaction after consumption. Agrifood sectors need to be upgraded to address newly diversified and expanded consumer demand for high-quality, safe, nutritious, healthy, and convenient foods (Hazell and Wood 2008).

Further, agrifood value chains have not been assessed to determine their effectiveness in positively contributing to the pillars of food security. To expand on the earlier definition, stability represents the ability of the food value chain to continually make nutritionally and culturally appropriate food available in sufficient quantities that are physically and economically accessible to all, even in the midst of a disturbance (Tendall et al. 2015). Resilience is therefore important for food security and directly linked with the functions of food systems (Alinovi, Hemrich, and Russo 2008, 274). Value chain indicators that have direct links with the pillars of food security need to be developed for agrifood value chain assessments. Considering that there has been a consensus about the potential of agrifood value chains to contribute to achieving food security, there should be studies that evaluate the performance of agrifood value chains in doing so (Alkire et al. 2014). Food value chains determine whether food produced is available, accessible, and affordable. They also determine whether the product is acceptable based on consumer preferences, whether consumption and nutritional needs are being met consistently, and whether the system as a whole has the capacity to adequately meet those needs when there is a disturbance.

Food insecurity and malnutrition are caused by challenges on both the demand side (consumer) and the supply side (food value chain). On the demand side, lack of income, employment problems, gender inequality, issues with household food diversity, and low awareness of nutrition are some of the leading causes of food insecurity and malnutrition (Arimond et al. 2010; Black et al. 2013). However, households make food choices based on what is available (including the state, form, desirability, price, and quantity of the products), as well as when, where, and how the food is made available, all of which are impacted by the value chain. Activities along the food supply chain influence what is provided to consumers and, therefore, their food security. Much attention has been paid to understanding and mitigating food insecurity at the household level. While this is important, it is also necessary to transform the agrifood sector (Maestre, Poole, and Henson 2017).

A clear understanding is needed of the conditions within which these value chains operate and how they impact consumer preferences and food security. The ability to develop this understanding will depend on the technique applied to assess food value chains. Assessment tools are structured to assess performance levels, with measurable sub-areas and indicators. Existing tools and indexes take two to five (or more) different dimensions into consideration. Some indexes are more complex than others and include more than 60 broad parameters (Sulewski and Kloczko-Gajewska 2018).

The major dimensions in value chain and sustainability assessments are economic, environmental, and social (Hayati 2017). However, there are no consumer-centered indicators or indicators that are linked to both consumer preferences and the pillars of food security. This chapter presents a methodological approach for the development of consumer-focused indicators to assess the agrifood value chain and its association with food security.

Design and Application of the Consumer-Based VCA Model

Consumer-focused value chains are defined as chains that perform activities in a socioeconomically and environmentally efficient way to meet consumer needs and preferences at all times. The consumer-oriented VCA approach focuses on evaluating the effectiveness of agrifood value chains in meeting consumer preferences, along with achieving food security and meeting nutrition needs. Based on this approach, a conceptual framework was developed as well as a performance index.

The framework helps identify the necessary criteria for agrifood chains to be successful in meeting consumer preferences holistically within a food security context. It reveals the constraining factors and provides policymakers with a more efficient way to design and implement strategies that create an appropriate operational environment for value chains.

Conceptual Model of a Consumer–Food Security Nexus for Agrifood VCA

The model begins by identifying consumer preferences and needs at the household level. It introduces a concept known as household value chain analysis (HVCA), which focuses on consumers and their experiences with a product. An HVCA enables product suppliers to comprehensively understand product users, their relationship with each other, and the use of the product. It identifies the processes that a product goes through from purchase to disposal (the consumption chain) and the product's final users. An HVCA is based on the idea that the product purchased is an input that is transformed into different valued commodities (outputs) within the household to obtain maximum utility. This analysis provides a wide range of information, such as purchase location, delivery, purchase options, price, availability, accessibility, and marketing strategy. It also provides information on household preferences, constraints in the product's utilization, and the quality of the product available to the consumer. It also considers factors that influence preparation, storage, and consumption, and the effect of preparation and storage on the physical and nutritional composition and safety of the product, including constraints and satisfaction with product use.

In the application of an HVCA, product attributes are weighted by observing visible changes or measuring the changes (increases or reductions) in the product's attribute levels as it moves along the consumption chain. For example, if beans become darker in storage, they will be less desirable to consumers who prefer light-colored beans. Information on the importance of product quality attributes can be obtained by asking consumers to rank or rate different levels of product attributes. The ranking or rating of attributes by consumers is useful in determining the level of utility provided by the commodity.

Choice-based models and hedonic price models can be applied to reveal the importance that consumers place on different attributes, trade-offs they are willing to make, and value (willingness to pay a discount or premium for the attribute). The level of satisfaction that consumers have with different attributes as the product goes through different processes can also be solicited. Understanding the different processes (purchase, storage, preparation, consumption) that the product goes through during and after purchase reveals consumer preferences and needs for certain product attributes. The completed HVCA should provide a clear understanding of what is valuable to the consumer. This knowledge will shape the activities performed by value chain actors through process optimization and product development to ensure the sustained demand and consumption of targeted foods.

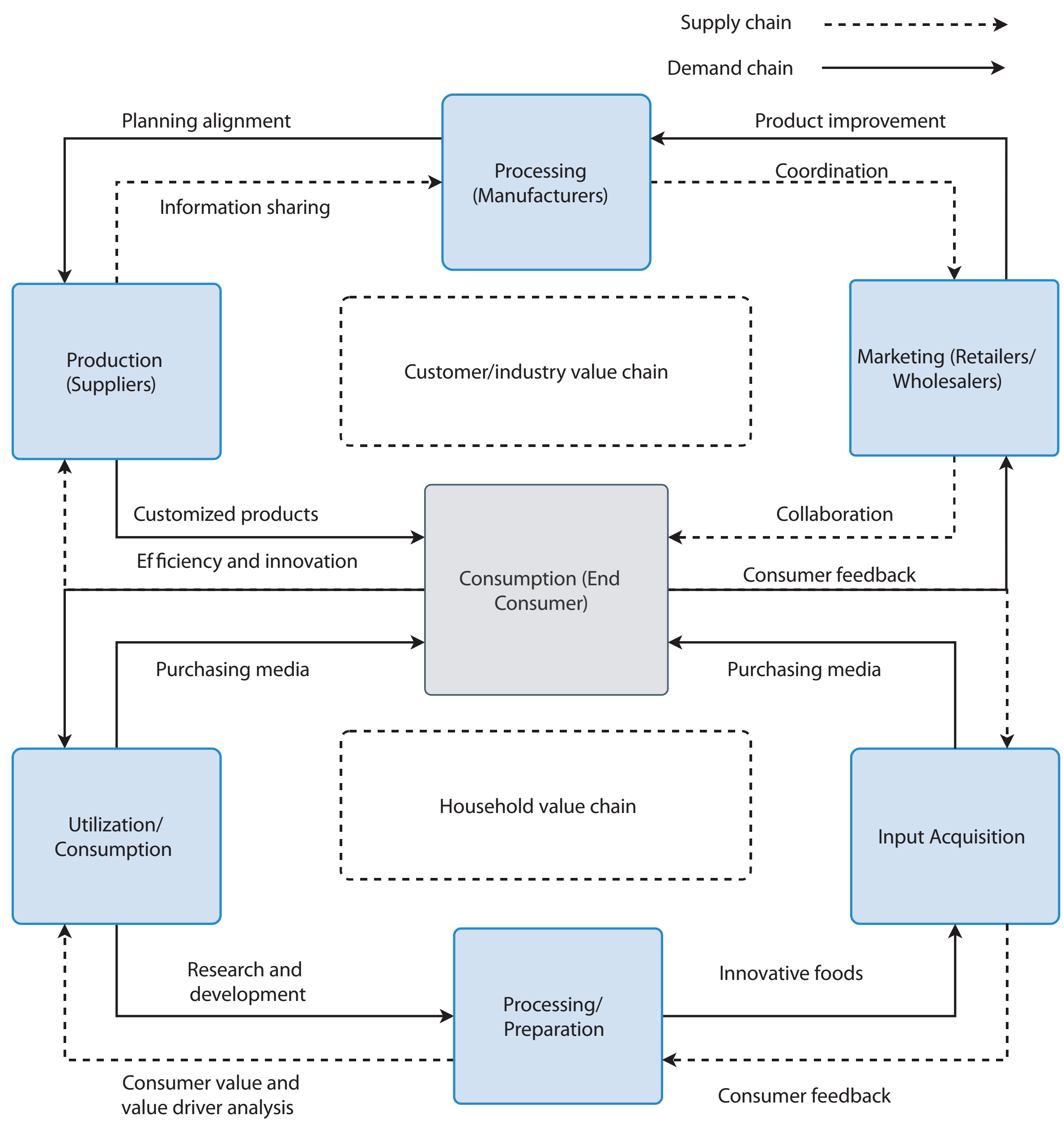
The approach to modeling a consumer–food security nexus for agrifood VCA starts at the consumer/household level, and then the gathered information is used in the food value chain to enable value chain actors to meet identified preferences and needs. The information on consumer preferences and needs is also linked to each food security pillar. Connecting specific consumer preferences to each pillar allows the preferences to serve as sub-indicators of the food security pillars. The sub-indicators are useful for identifying ways to measure and track food security by meeting consumer preferences.

Conceptual Model

Figure 13.1 represents a consumer-based value chain model made up of the product supply and demand chains. The demand chain is the consumption stage, which emphasizes the activities performed by the consumer after the purchase of a product. The demands of the consumers are defined at this stage. These demands are then used as guidelines in evaluating how well the value chain meets consumer preferences and needs. Such information is useful to product supply chain actors such as producers, processors, and marketers. The supply side of the chain focuses on shaping, satisfying, and sustaining consumer demands. Since consumer demands are linked to the food security pillars, satisfying consumer demands will have a positive impact on food security.

Figure 13.2 presents the elements to be considered in a consumer-based VCA. Due to the introduction of food security elements in the analysis, Figure 13.2 also represents a

FIGURE 13.1—CONSUMER-BASED VALUE CHAIN



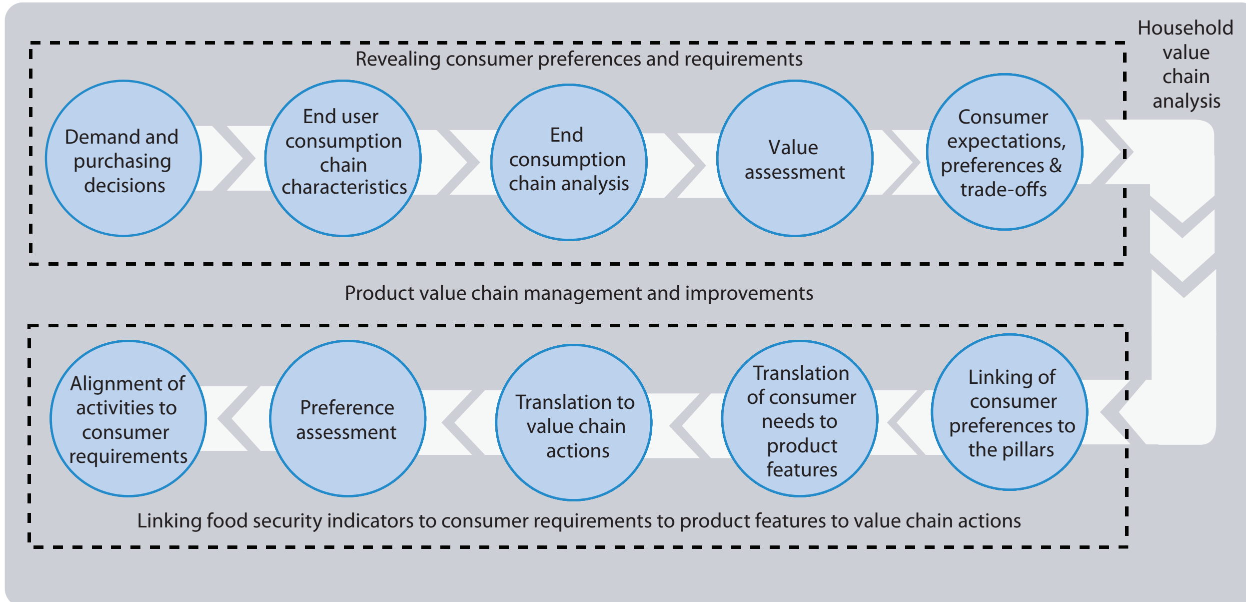
Source: Authors.

consumer–food security nexus for agrifood VCA. The concept centers around the following steps:

1. Effectively capture final consumer requirements, that is, consumer preferences and needs, and categorize their links according to each pillar of food security.
2. Translate preferences and needs, which are sub-indicators of the pillars of food security, into measurable product features and value chain actions. The consumer requirements are linked to the food security pillars (CRFSP), which are then associated with supply chain dimensions (comprised of indicators). This will give value chain actors a clear way to incorporate consumer requirements into their activities.
3. Identify indicators and dimensions at the supply chain level that are output parameters in order to evaluate the chain's performance in meeting consumer requirements and food security pillars.
4. Identify and implement strategies to meet consumer requirements.

The overall concept depicted in Figure 13.2 centers around the determination of consumer requirements, linking consumer requirements to food security pillars; an assessment of the supply chain's performance in meeting consumer requirements and aligning with food security pillars; and the identification and implementation of strategies to close the gaps. The focus is on addressing the following questions: What are consumers' requirements and what values do they desire from a product? How are these requirements and desired values linked to food security pillars? How can profitable operations along the value chain be adjusted to provide the desired value while positively impacting food security?

FIGURE 13.2—FLOW OF CONSUMER-BASED VALUE CHAIN ANALYSIS



Source: Authors.

Application of the Consumer-Based Model

Analysis of the Consumption Chain

Different forms of assessment can be used to analyze the consumption stage of the product value chain, including the following:

1. Determine what consumers require, factors influencing their requirements, and the value expected from the use of a product. This assessment answers questions such as: What do consumers do with the product? How do they use it? Why do they use it that way? What do they prefer?
2. Identify and assess the different activities performed, the resources (time, energy, etc.) used for each process during the utilization of the product, and the factors influencing the different activities performed.

3. Assess how consumers make trade-offs between different products and product attributes. For instance, during a purchase, consumers might have to choose a product based on a group of attributes (taste, size, color, etc.) with different characteristics (tasty/bland, small/large, white/brown, etc.). Considering that their desired attributes may not all be available in one product, consumers would have to make trade-offs between attributes. Supply chains make many trade-offs in determining how to create more value for consumers. Instead of making such decisions based only on industry capacities and timeframes, consumer preference information can enable industries to make sounder and more profitable trade-offs.
4. Identify constraints and satisfaction with the product at different levels of the consumption chain (input acquisition, preparation/procession, and utilization).

Connecting Consumer Preferences with Food Security Pillars

Information gathered from the consumption chain assessment on consumer preferences can then be linked to food security pillars. These preferences make up the measurable indicators which will be linked to the food security pillars. The food security pillars considered in the framework are availability, accessibility, affordability, acceptability, utilization, and stability. These food security pillars and the consumer requirements that can be linked to them are explained below.

1. Availability: The food must be physically available through farm production and easily accessible to traders and processors who purchase for redistribution and value addition. Consumer requirements related to availability include frequency/seasonality, quantity, and variety.
2. Accessibility: The food must be physically accessible to consumers at a relatively low cost in the locations where they reside or perform livelihood activities. Consumer accessibility requirements in relation to time, frequency/seasonality, quantity, variety, distance to market, and the availability of different types of markets can be linked to this pillar.
3. Affordability: Consumers should have the economic capacity to purchase foods. The ability of value chains to provide low-cost foods is dependent on the availability of price incentives (Hawkes et al. 2012) and the undertaking of cost-efficient measures. Consumer price requirements or concerns and their implications for purchase can be linked to this pillar.
4. Acceptability: Food must be acceptable to consumers in meeting their tastes and requirements. These requirements include physical appearance, ease of preparation, compliance with cultural norms, and consumption patterns. Consumers do not want to make trade-offs between requirements when purchasing specific foods, even if those foods happen to be nutritious. Consumer requirements regarding taste, size, freshness, convenience, color, packaging, and cleanliness, among others, can be linked to this pillar.
5. Consumption/utilization: At the point of consumption, food must be safe, nutrient-dense, and in different forms that meet the requirements of diverse groups of consumers ranging from infants to adults. Consumer requirements regarding safety, nutrition, and value-added products, for example, can be linked to this pillar.
6. Stability: This pillar requires that consumers have access to adequate food at all times, including in the event of sudden shocks (FAO 2006). The other five pillars mentioned above all hinge on this one, which reinforces the need to assess the performance of agrifood value chains in meeting food needs in both the short and long term. This performance assessment should consider the capacity of agrifood value chains to prevent or mitigate risk, and withstand and adapt to disturbances over time. Basically, value chains should be resilient enough to withstand and recover from disruptions in ways that ensure there is always a sufficient supply of acceptable and accessible food for all.

Consumer-Based Performance Assessment Index for Agrifood Value Chains

The consumer-based assessment index for agrifood value chains is developed in a four-step process.

Step 1: Translation of CRFSP product features

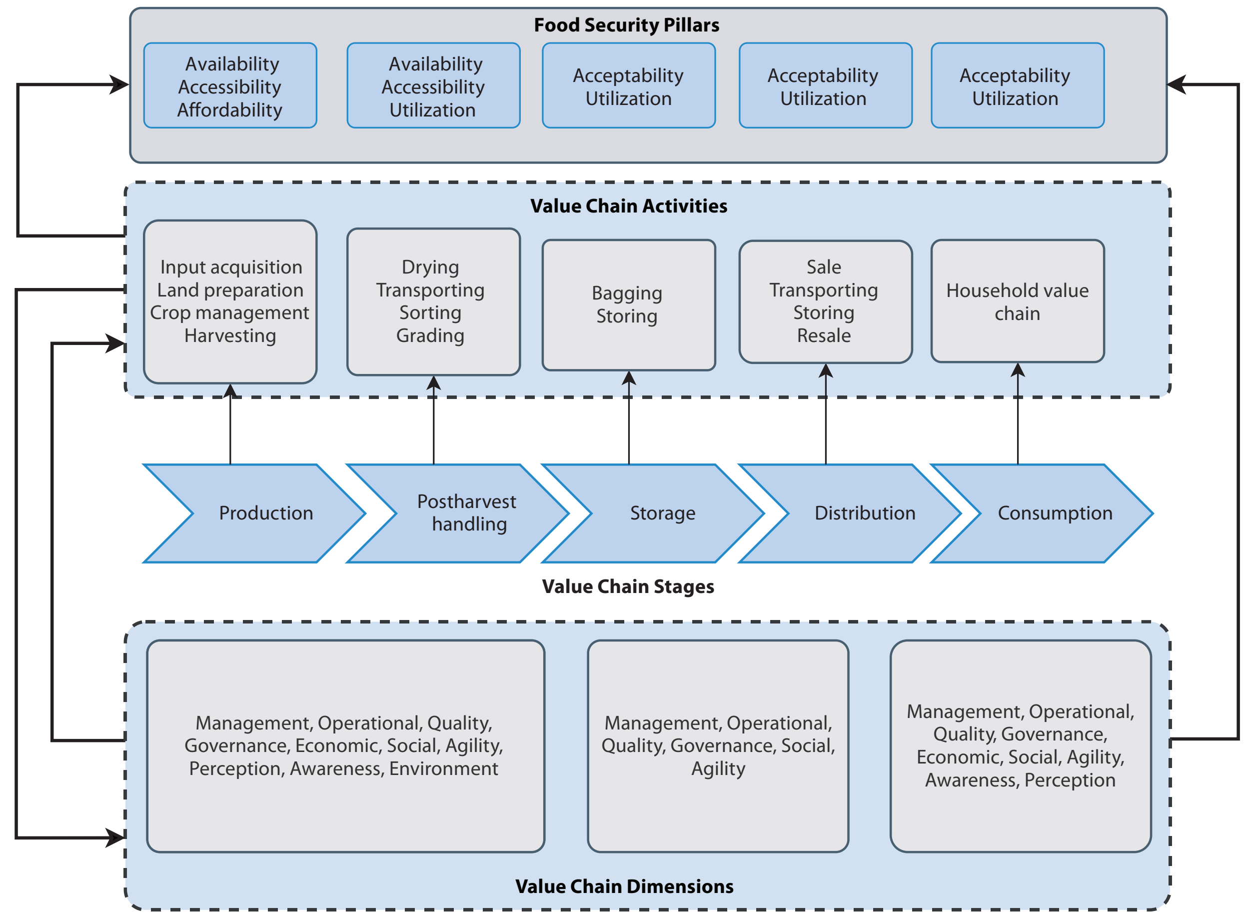
Consumer requirements can be used to define product features that consumers desire in the market. After linking consumer requirements to food security pillars, the requirements are further translated into product features.

Step 2: Translation of CRFSP into value chain actions

It is important for consumer requirements to be translated into measurable value chain actions. Information gathered on consumer requirements can then be translated into product features and processes. For each food security pillar, the authors first assessed what the consumer requires and values when a product is considered. How will this preference then be translated into a product feature? What actions along the value chain need to be taken to provide this feature? Lastly, how will the efficiency of the value chain actions be measured? Translating consumer requirements into value chain actions aims to determine the factors and activities along the value chain that are needed to meet these consumer requirements. The value chain actions are used as indicators to assess the performance of the chain in meeting consumer requirements.

In this step, we develop a performance index based on a system for selecting indicators, criteria, and dimensions with a focus on consumers and food security. For each dimension, there is a corresponding set of value chain indicators that are made up of value chain actions. The dimensions are further linked to food security pillars that have consumer requirements as sub-indicators. The value chain indicators are measurable parameters of the different dimensions. The tool is a multidimensional performance-based index that determines not only how the chain is performing across the different dimensions but how these dimensions influence consumers and food security (Figure 13.3). It considers more than one dimension, value chain stage, and actor (meaning producer and trader, both performing activities at different locations). The food security pillars and value chain dimensions represent areas of possible impact, while the indicators are the practical measures of assessment. Their scores determine the overall performance of the value chain (Shmitt et al. 2016).

FIGURE 13.3—THE INFLUENCE OF VALUE CHAIN ACTIVITIES AND THEIR OPERATIONAL ENVIRONMENT ON FOOD SECURITY PILLARS



Source: Authors.

The framework is significant because it goes beyond recommending production and quality improvements to specify what should be improved and produced. At the end of the assessment, activities that negatively impact consumer value and food security should be eliminated or adjusted, if possible. Furthermore, a future state of the value chain can be generated based on recommendations that could range from short- to long-term interventions.

Step 3: Determination of indicators, criteria, and dimensions

The dimensions are factors to be assessed and linked with measurable indicators. Indicators provide information that can be used as a benchmark in decision-making. Indicators need to be clearly linked to objectives. They should be reliable, appropriate within a particular location and context, easy to identify, and acceptable to a wide range of stakeholders (Meszaros et al. 2015). The indicators should also be practical, that is, measurable and representative of the system under study.

Lebacq and colleagues (2013) recommend the use of a set of indicators instead of a single indicator, a suggestion which the authors included in their own selection of indicators. These indicators should be few in number, consistent, and sufficient to jointly answer the applicable question (Lebacq, Baret, and Stilmant 2013). These factors were taken into consideration in the selection of indicators. The individual indicators were obtained from survey data and aggregated to obtain a composite indicator. Aggregation was achieved through sums and normalization techniques (Finn et al. 2009).

Consumer requirements were selected based on information gathered from consumer studies (DeYoung et al. 2017; Schilima, Mapemba, and Tembo 2016; Mishili et al. 2009; Medard, 2017; Hella et al. 2013; Quaye et al. 2011) and were categorized as sub-indicators within each food security pillar. The indicators selected for this framework can be applied to other food value chains, though these particular ones are slightly tailored to the consumers and value chain of legumes. The value chain indicators were selected with the demand-side indicators in mind to ensure that they are directly linked and have implications for the consumer–food security pillars.

The process of identifying the value chain indicators was based on both a literature review and subjective decisions, as the indicators provided in the literature were not all relevant to assessing the performance of value chains with a consumer and food security focus. Thus, some of the indicators were based on existing studies (Liu et al. 2019; Bachev 2017; Sulewski and Kloczko-Gajewska 2018; Meszaros 2015; Fedorova and Pongracz 2019; Bevilacqua et al. 2019; Matias et al. 2018; Watabaji, Molnar, and Gellynck 2016) and others were created based on a survey (interviews and data gathered from stakeholders along different stages of the product value chain who were able to provide adequate information on activities and challenges along the value chain). Indicators considered in the index also include some that have been proposed by the Food and Agriculture Organization of the United Nations as important in achieving food security, such as public-private partnerships, value addition, and policies to promote agribusiness and food value chains.

Focusing the analysis on the consumer requires the inclusion of other indicators beyond social, environmental, and economic dimensions. A conceptual approach used primarily in the social sciences was adopted to develop the indicators (Kuhndt, von Geibler, and Eckermann 2004). The approach requires breaking down the concept into dimensions, categories, aspects, and then indicators. The indicators selected for each segment were clearly specified with different units of measurement (percentages, ratios, quantities, and averages). Quantitative indicators are easier to measure, but qualitative indicators were also chosen when required.

Step 4: Selection of food value chain assessment dimensions and indicators

Agrifood value chains can be simple or complex. A chain comprises persons, processes, and products. The processes are the activities required to transform materials into outputs (products) by value chain actors equipped to perform those activities. The activities performed, actors' interactions, flow of information, costs, benefits, social incentives, and governing structures, among other factors, influence the performance of the chain (Maestre, Poole, and Henson 2017). Thus, understanding the functioning of the product chain along different dimensions and the subsequent implications for meeting food security outcomes is essential. The dimensions were selected based on different factors and explained below.

Environment dimension

The food value chain needs to be able to conserve natural resources to ensure its continuous use. The contribution of the value chain to resource sustainability or scarcity through its operations must be considered and assessed. Overexploitation impacts the pillars of food security, as the pillars are inputs to agrifood activities. Without them, consumer requirements cannot be fulfilled sustainably.

Quality dimension

Quality attributes vary on a wide range to meet consumers' needs for products that align with their preferences and lifestyles (Trienekens et al. 2012). These attributes influence the acceptability of a product and its consumption. This dimension addresses the effect of value chain activities on physical, nutritional, and safety attributes.

Social dimension

The agrifood value chain needs to perform activities to ensure that the conditions and health of the actors are not negatively impacted. Functional social networks and acceptable working conditions are necessary for agents to perform their activities consistently along the chain (Hampel-Milagrosa 2007, 74). Adequate working conditions lead to lower labor costs and prices and to increased work efficiency. These conditions translate into greater productivity and higher economic performance, which positively impacts food security. This dimension evaluates safety, trust, employment, collaboration, and social networks along the chain.

Economic dimension

The agrifood value chain needs to be productive and profitable to ensure financial stability. Value distribution along the value chain reflects the economic power of the agents. High costs and unequal value distribution can translate into high prices for consumers, which can affect product affordability, acceptability, and utilization.

Management dimension

The management dimension primarily considers two factors: postharvest loss management and knowledge management. A significant level of food losses affects the availability and accessibility of food for consumption (Gustavsson et al. 2011). In turn, affordability is affected when supply is not able to meet demand. Losses can also involve quality, where certain products do not meet consumer requirements, which affects acceptability, and, in cases where losses involve nutrients, consumption and nutrition. Losses are often due to a lack of knowledge of management practices. Thus, this dimension includes evaluation of timely and frequent access to knowledge on activity performance, consumer requirements, loss management, and so on.

Governance dimension

Functional governing structures oversee the efficient coordination and sharing of information, policies, regulations, and public and private interactions. These structures are necessary to ensure maximum efficiency in the performance of activities within the chain. The value chain environment can increase costs, contribute to uncertainty, limit entry into the chain, or discourage consumer-centered activities (Maestre, Poole, and Henson 2017; Camanzi et al. 2018). These factors are considered in this dimension.

Awareness and perception dimension

Given that the actions of agents along the agrifood value chain can be influenced by their perceptions and awareness, it is important to include such variables in assessing performance. The agents' knowledge of consumer requirements and their attitudes, perceptions, and willingness to meet those requirements affect their value chain activities and the food security pillars.

Agility dimension

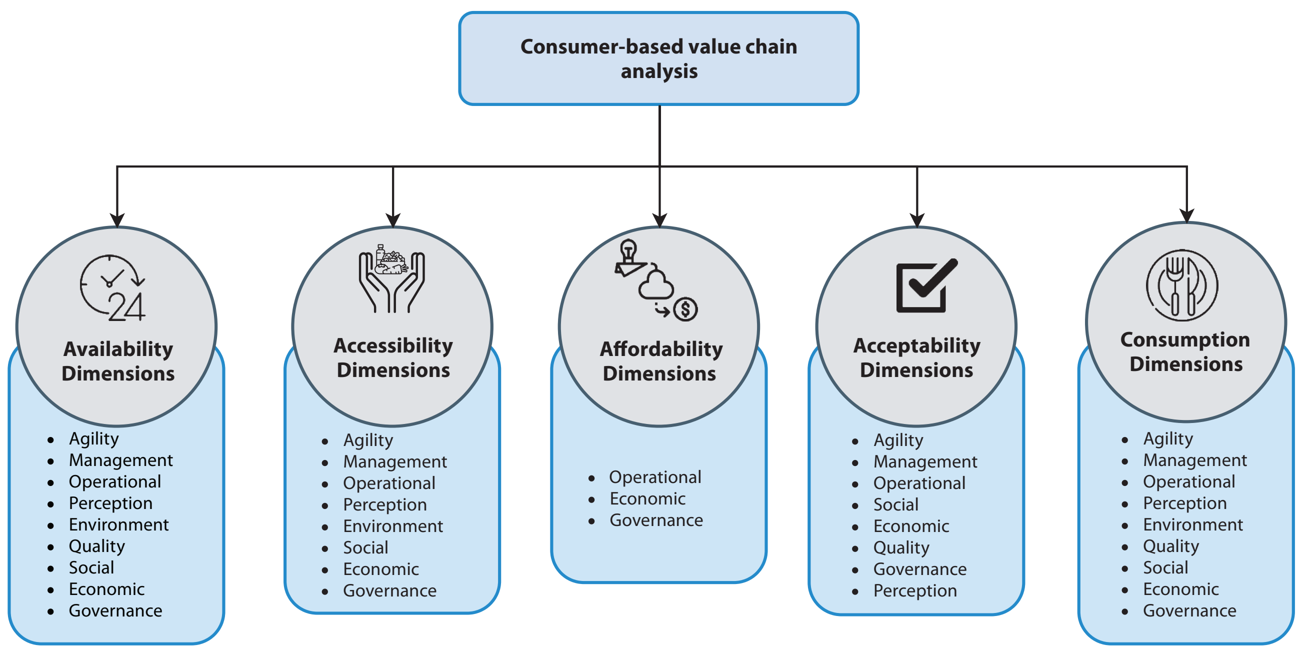
Agrifood chains are embedded within complex social, environmental, political, and economic systems as well as the physical, financial, and human institutions that govern these systems (Mahoney and Pandian 1992), coupled with changing consumer demands. Resilience in the agrifood system is necessary to produce and market nutritious, diverse, quality, and affordable foods amid disturbances; recover from shocks; and adapt to ongoing changes (Biggs, Schlüter, and Schoon 2015). Furthermore, agility is necessary when the element of food security and stability is taken into consideration. Stability requires that all of the other food security pillars be stable throughout the year, which depends on the ability of the chain to adjust adequately to changes.

Operational dimension

Activities performed along the chain from farming to marketing, and the processes involved in each activity, affect product features and consumer requirements. The efficiency with which they are performed affects the food security pillars.

A breakdown of the dimensions constituting each food security pillar (except stability) in the performance index is presented in Figure 13.4.

FIGURE 13.4—DIMENSIONS USED IN THE ASSESSMENT OF FOOD SECURITY PILLARS



Source: Authors.

Methodology

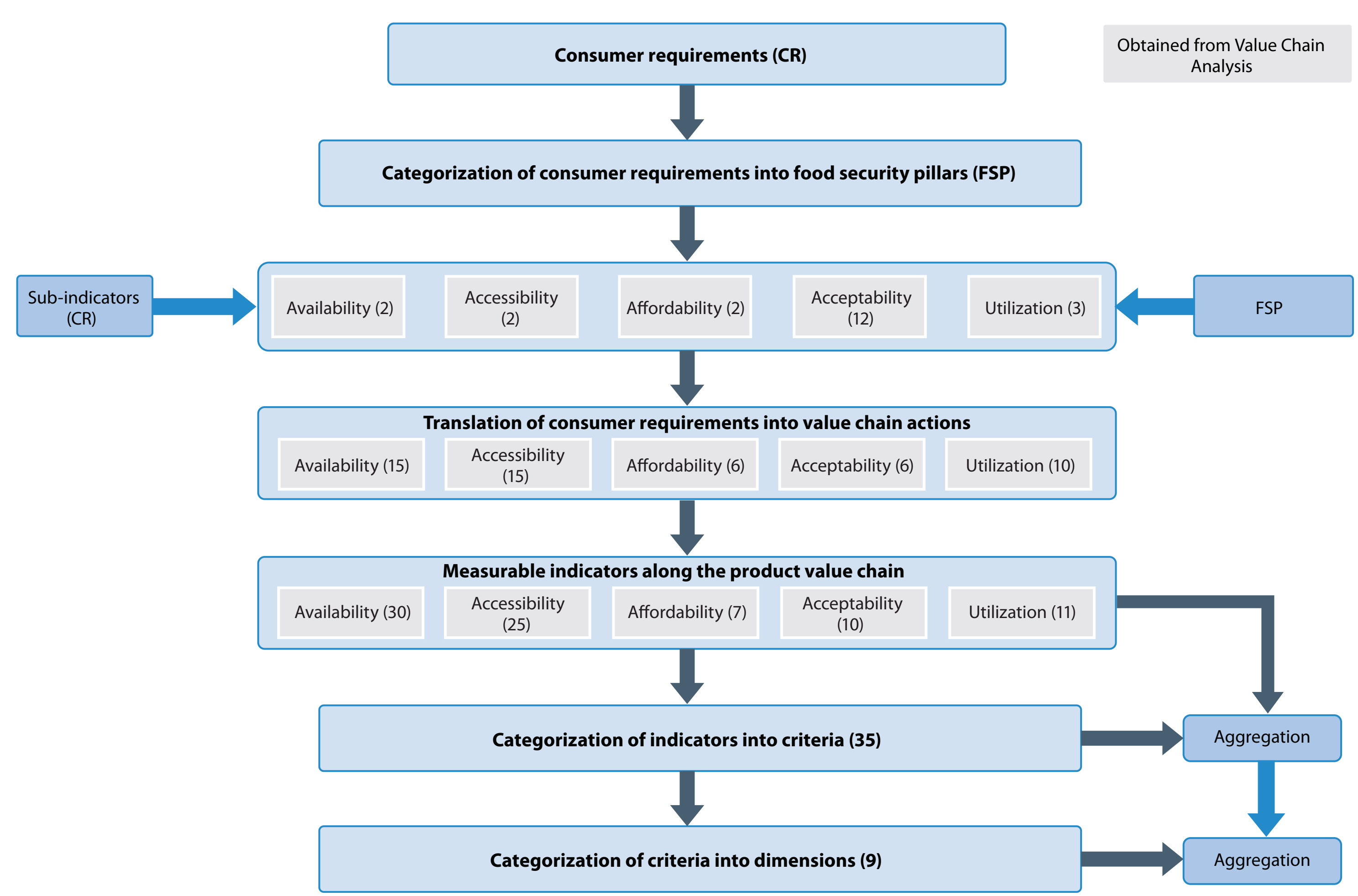
Following the selection of dimensions, criteria, and indicators, data were gathered to measure the indicators. The next step is the normalization of indicators for comparison, followed by aggregation. In the index, there are 9 dimensions, 35 criteria, and 51 indicators. Some studies have combined different dimensions to understand agricultural systems, with a varied number of components ranging from 12 to 41 indicators and up to 60 parameters (Kania and Kapłon 2014; Feledyn-Szewczyk and Kopiński 2015; Bojarszczuk, Księżak, and Feledyn-Szewczyk 2017). The dimensions were assessed through a sum of indicators, using a multiple-weight method and assigning scores through expert assessment.

Indicators that represent the context of a food system and could be measured were selected for the index. The procedure and relations between the dimensions, criteria, and indicators are presented in Figure 13.5. The groupings in the figure are broad categories that encompass different numbers of indicators (2, 15, 30, etc.). The selected indicators, though clearly defined, do not have a uniform measurement unit. The indicators also were not weighted according to their importance; instead, it was assumed that all indicators, categories, and dimensions had equal weight for simplicity of analysis.

In the process of normalization, various methods can be employed to reduce outliers. These methods include rescaling, percentage relations, mathematical transformation, and distance measurements (Salzman 2003). Aggregation can also be performed through addition, factor analysis, means, and the use of weights and rules (Mazziotta and Pareto 2013). The normalization and standardization techniques used were based on Sulewski and Kloczko-Gajewska (2018). A mathematical transformation was employed for normalization, while additions and means were used in aggregation. The output parameters for the indicators were scaled along the 0 to 1 range. Data on different subjects were gathered through varied types of measurement. Continuous variables, such as yield values, were transformed into the 0 to 1 range based on the quantiles (deciles) method; that is, the distribution is segmented into 10 sections. After being sectioned, they are then provided with scores ranging from 0 to 1. This means, for example, that for values falling within the ninth and tenth deciles, a point of 1 is assigned; if they fall within the eighth and ninth deciles, they are given a value of 0.9.

This method helped in assigning points to variables that would have been difficult to value objectively. With this method, the need for expert assessment

FIGURE 13.5—PICTORIAL VIEW OF THE FRAMEWORK



Source: Authors.

at the indicator level is eliminated. The approach by Ostasewicz, Rusnak, and Siedlecka (2011) is applied in estimating the value of individual deciles:

$$Q_k = X_{Qk} + \frac{N_{Qk} - \sum_{i=1}^{k-1} n_i}{n_m} i_{Qk}, \qquad (1)$$

where Q_k is the symbol of the k-th decile; X_{Qk} is the lower limit of a given range; N_{Qk} is the position of a given decile calculated based on $kN/_{10}$; $\sum_{i=1}^{k-1} n_i$ is the number cumulated to the range preceding decile; i_{Qk} is the span of the range in which the right deciles are located; k is the number of the range in which the corresponding decile follows; and N is the collectivity size.

In cases in which ordinal variables were measured through the use of a Likert scale, the distance between the ranks is divided into equal sections. The sections are divided to be within 0 and 1, with equal distances between the ranks. For instance, if a four-level scale is used, the correct answer or the highest score is given a point of 1 and then 0.75 and so on. In cases in which the variable is dichotomous, such as in cases with "yes" or "no" options, the expected response is assigned 1 and the other 0.

After the indicators were normalized, they were aggregated through summation to obtain performance scores for the different dimensions. However, care was taken to ensure that an average was not estimated for parameters that are not comparable. Aggregation was performed by estimating sums and means of the various indicators and criteria as follows:

$$Performance\ of\ Criteria\ (PC) = \sum(Sum\ of\ Indicators, SI)/_{n} \quad (2)$$

$$Performance\ of\ Dimension\ (PD) = \sum(Sum\ of\ Criteria, SC)/_{n} \quad (3)$$

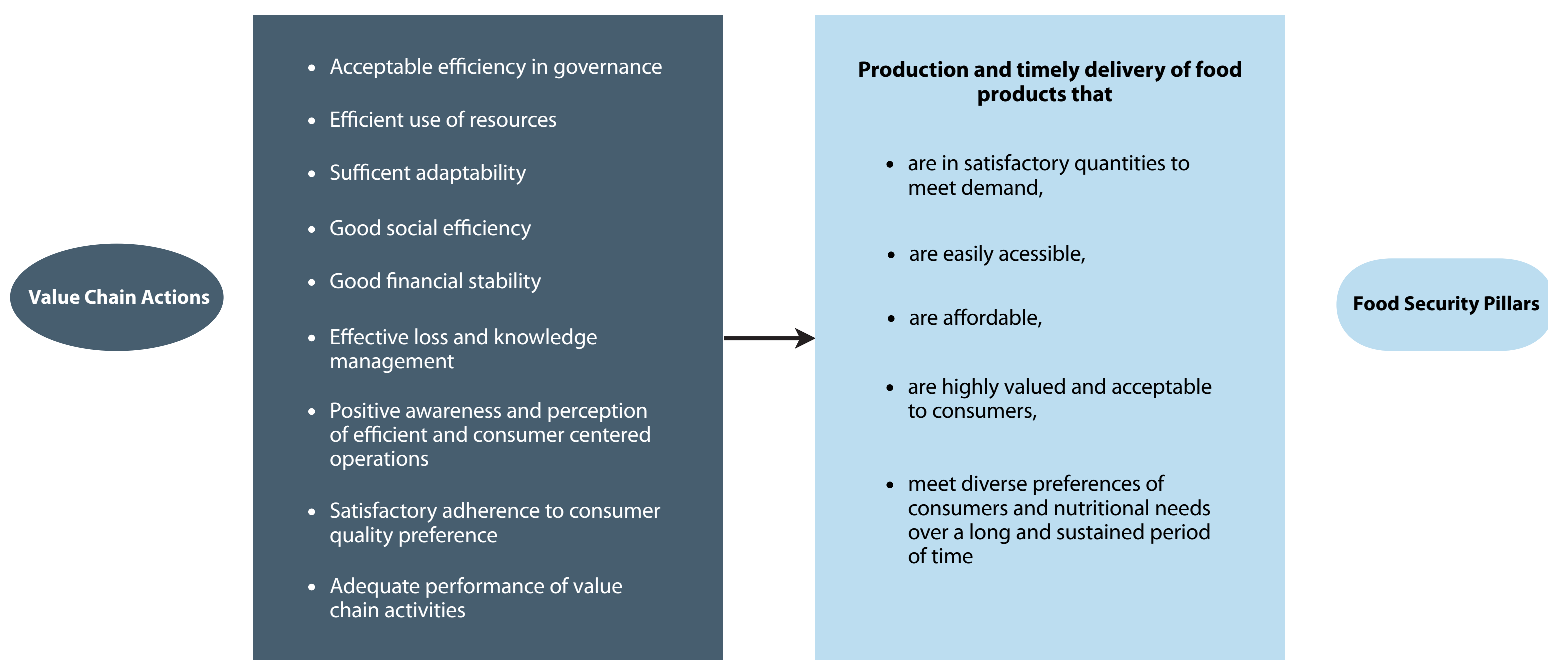
$$Performance\ of\ Food\ Security\ Indicator\ (FSI) = \sum(Sum\ of\ Dimensions, SD)/_{n} \quad (4)$$

where n = number of indicators, criteria, and dimensions.

The dimensions were employed in measuring the major pillars of food security. Thus, the dimension scores corresponding to each food security element were also aggregated to obtain the value chain performance score in meeting each food security element. The performance scores were interpreted as high (0.83–1), good (0.50–0.82), low (0.22–0.49), and poor (0.00–0.20). The performance of the product supply chain in meeting each food security pillar is then assessed based on standards (Figure 13.6). These standards are the levels or states that the dimensions being assessed are supposed to attain.

The quantile method was used to transform the data to ensure that they were all on the same scale, with a minimum score of 0 and a maximum score of 1. The scores for each dimension and food security element were standardized by dividing by the number of indicators that made up each parameter (total possible score to be attained). This ensured that a comparison could be made. In the performance index, performance levels for the dimensions and food security elements were determined based on percentage ranges: the closer the score is to 100 percent, the better it is. However, for certain indicators, such as the amount of fertilizer and pesticides required per hectare, adequate storage length, and temperature, etc., information gathered from the literature served as benchmark in determining whether there was a deviation from the expected result.

FIGURE 13.6—SATISFACTORY STANDARDS FOR THE PRODUCT VALUE CHAIN AND FOOD SECURITY PILLARS



Source: Authors.

For variables such as income, profits, processing times, losses, and yields, value chain actors with higher amounts had higher scores. For variables that required ranking, responses that leaned toward the most positive response or the expected response had higher scores. The performance index was designed to take the entire product value chain into consideration, because understanding and tackling issues affecting food security and nutrition will not be comprehensive if only one stage of the chain is studied.

Test of Correlation

The variables included in the design of an index should be as comprehensive as possible and correlated with the index. This is because poorly correlated variables may be measuring something different than expected (Babbie 1995; Sulewski and Kloczko-Gajewska 2018). Thus, an analysis of the correlation matrix was used to determine the variables to be included in the index, after which poorly correlated variables (those lacking statistical significance) were removed (Sulewski and Kloczko-Gajewska 2018). Spearman's correlation analysis was used to estimate the coefficient between indicator and dimension scores as well as dimension scores and scores for each food security element. This was done to ensure that the indicators used in assessing the performance of the chain on the pillars of food security are correlated to the measurement index. The correlation coefficients ranged between the dimension scores, and the food security scores ranged between 0.23 to 0.87. The variables that did not have any correlation were removed. The correlation analysis results have been presented in the Appendix.

Alignment of Value Chain Activities to Meet Consumer Requirements and Improve Food Security

Following the performance evaluation, strategies should be put in place to align value chain activities to product features based on consumer requirements. At this stage, activities are adjusted to physically bridge the gap between the potential and actual value that the consumer could derive from the product. By doing this, the food value chain draws nearer to closing the gap between current food security achievements and desired goals.

The framework and index were employed in studying the common bean value chain in Zambia as a case example. The common bean value chain in Zambia (specifically, the northern province) is made up of only two main stages or activities, namely production and marketing. Common beans are produced in Zambia mainly by smallholder farmers who cultivate local varieties. Average yields range from 0.3 to 0.5 metric tons per hectare, which are low compared to 2 tons per hectare when high-yielding and resistant varieties are used (Mwansa 2004). The marketing system is uncoordinated and largely informal, with uneven power distribution between traders and producers (Amanor-Boadu and Williams 2004). The industry is characterized by information asymmetry and no price transparency (Mwansa 2004). For poor households, beans are usually the closest substitute to other protein sources such as meat and fish (Beebe 2012). Pele (2007) found that consumers in Zambia allocated a small proportion of their food expenditure to beans, indicating that beans were not significant in the food basket. Bean consumption is low; however, this can be increased if appropriate activities along the value chain are undertaken within the right policy environment (Birachi 2012; Mwansa 2004). Improvement should be directed towards providing adequate quantities of nutritious, safe, acceptable and affordable food to growing populations within a dynamic environment (Marsden and Morley 2014). Applying the value chain concept to achieving this is advantageous because it allows for a systematic evaluation of the different stages and processes in the chain to identify discrepancies.

Conclusion

Agrifood value chains have an essential role to play in contributing to the achievement of food security. Realizing food security is inherently linked with meeting the requirements of consumers, which are based on their preferences. Thus, there is a need for assessment methods that have both a consumer and a food security focus. The importance of resilience for food security (particularly during pandemic situations) and its direct link with the functions of food systems further highlights the need to have a consumer–food security nexus framework for agrifood VCA. The authors present a conceptual framework and a performance index that focuses on the requirements of the consumer and connects them to food security. The framework also introduces a way to link consumer requirements with value chain actions, making it easy to identify improvement opportunities. Characteristics such as convenience, speed, variety, low price, sufficient quantity, and others have been translated into agrifood chain characteristics such as delivery, volume, quality, value addition, and efficiency. This approach has the potential to change the way products are designed, developed, and delivered to consumers while meeting food security challenges.

The selection and measurement of variables is difficult, especially since it is best to use different variables to measure a specific indicator, given that no one particular indicator can be used to adequately explain a dimension. Information from multiple sources was used to deal with this challenge. The limitation of some of the variables selected for the index is that they require laboratory and survey data, which can be costly and time-consuming to obtain.

Overall, the framework contributes to quantifying performance and understanding the food system. It is useful in determining the challenges that limit the capacity of the agrifood chain to meet consumer requirements and impact food security.

Appendix

Spearman's Correlation Analysis

This section presents information on Spearman's correlation between dimensions and food security pillars and the variables (value chain indicators) used in creating them. The dimensions are aggregated value chain indicators that describe a similar value chain function. Correlation analysis was used in the study as a statistical measure of the relationship between the value chain indicators and dimensions, as well as the dimensions and food security pillars. Correlation is a good indication of the strength and direction of the relationship between two variables. All correlations between dimensions and food security pillars were positive and statistically significant from zero.

The consumer-food security nexus framework and performance index were applied to assess the common bean value chain in northern Zambia as a case study. For each food security indicator, a link was made between the indicator and the specific consumers requirement(s) that must be met by value chain actors based on how their activities are performed. A correlation matrix was also employed to ensure that only indicators with a statistically significant correlation with the overall dimension score were included in the index to estimate performance scores for food security pillars. Those that did not have any correlation were removed.

A range of correlation coefficients is reported since different indicators were used in estimating the dimension score but not all could be presented. Only those that were statistically significant were included in the table. The positive linear correlations indicate that as the score of one variable increases, the score of the other also increases. Correlation coefficients above 0.5 indicate strong linear correlations between the scores, while those at 0.3 and lower indicate weak correlations.

Appendix *continued*

1. Availablity

TABLE 13A.1—SPEARMAN'S CORRELATION BETWEEN VARIABLES USED IN ASSESSING THE PERFORMANCE OF THE VALUE CHAIN IN CONTRIBUTING TO FOOD SECURITY PILLARS (FSP) (AVAILABILITY)

Criteria	Indicator	Correlations: Indicator vs. Dimension	Dimension	Correlations: Dimensions vs. Availability	FSP
Production	Production capacity	0.24–0.45	Operational	0.34	Bean availability
	Land productivity	0.23–0.48			
	Production/value chain practices	0.20–0.45			
Technology	Technical capability	0.43v0.58			
Market	Delivery reliability	0.47			
Market	Product quality/Market surplus	0.40	Management	0.27	Bean availability
Loss management	Loss management	0.25			
Knowledge/Communication	Information access	0.22–0.65			
Agro-technique	Agro-techniques	0.99	Environment	0.32	Bean availability
Activity management	Governing activity	0.20–0.76	Governance	0.33	Bean availability
	Relationship	0.60–0.62			
Institutions	Stakeholder involvement	0.23			
Profitability	Production value	0.54	Economic	0.40	Bean availability
Financial capability	Production investments	0.67			
	Income stability	0.67			
Employment	Employment	0.44–0.75	Social	0.35	Bean availability
	Worker efficiency	0.18–0.40			
Safety	Health/Safety	0.26			
Adaptability	Consumer adaptability	0.44–0.47	Agility	0.36	Bean availability
	Environment Adaptability	0.31–0.44			
Attitude and perception	Actor attitude and perception	0.77–0.82	Attitude and Perception	0.33	Bean availability

Note: Only statistically significant variables at p-value of 0.05 are reported. FSI=Food Security Indicator.

2. Accessibility

TABLE 13A.2—SPEARMAN'S CORRELATION BETWEEN VARIABLES USED IN ASSESSING THE PERFORMANCE OF THE VALUE CHAIN IN CONTRIBUTING TO FOOD SECURITY PILLARS (ACCESSIBILITY)

Criteria	Indicator	Correlations: Indicator vs. Dimension	Dimension	Correlations: Dimensions vs. Availability	FSP
Market	Product delivery	0.70	Operational	0.37	Bean accessibility
	Delivery reliability	0.73–0.77			
Market	Product quality	0.60	Management	0.017	Bean accessibility
	Loss management	0.56			
Information access	Market/consumer knowledge	0.62			
Governance of activity	Trust/Relationship	0.43	Governance	0.30	Bean accessibility
	Entry restrictions	0.62			
Profitability	Production value	0.72–0.83	Economic	0.34	Bean accessibility
Financial stability	Sources of funds for investment	0.63			
Employment	Employment	0.49–0.58	Social	0.18	Bean accessibility
	Efficiency of worker	0.33–0.59			
Adaptability	Consumer adaptability	0.40–0.79	Agility	0.33	Bean accessibility
Attitude and perception	Actor attitude and perception	0.99	Attitude	0.50	Bean accessibility

Note: Only statistically significant variables at p-value of 0.05 are reported. FSI=Food Security Indicator.

3. Affordability

TABLE 13A.3—SPEARMAN'S CORRELATION BETWEEN VARIABLES USED IN ASSESSING THE PERFORMANCE OF THE VALUE CHAIN IN CONTRIBUTING TO FOOD SECURITY PILLARS (AFFORDABLITY)

Criteria	Indicator	Correlations: Indicator vs. Dimension	Dimension	Correlations: Dimensions vs. Affordability	FSP
Cost efficiency	Cost efficiency/ Pricing scheme	0.97	Operational	0.87	Bean affordability
Trust	Trust	0.99	Governance	0.23	Bean affordability
Cost	Cost	0.35	Economic	0.30	Bean affordability
Price	Average price	0.57			
	Price fluctuation	0.53			
	Gross margin	0.52			

Note: Only statistically significant variables at p-value of 0.05 are reported. FSI=Food Security Indicator.

4. Acceptability

TABLE 13A.4—SPEARMAN'S CORRELATION BETWEEN VARIABLES USED IN ASSESSING THE PERFORMANCE OF THE VALUE CHAIN IN CONTRIBUTING TO FOOD SECURITY PILLARS (ACCEPTABILITY)

Criteria	Indicator	Correlations: Indicator vs. Dimension	Dimension	Correlations: Dimensions vs. Availability	FSP
Product reliability	Adherence to consumer quality preferences	0.22–0.86			Bean acceptability
Efficiency of system	Quality control	0.70	Operational	0.22	Bean acceptability
	Defect rate	0.87			
Profitability					Bean acceptability
Loss management	Loss management	0.92	Management	0.55	
Knowledge acquisition	Market knowledge	0.40			Bean acceptability
Adaptability	Consumer adaptability	0.99	Agility	0.47	Bean acceptability
Attitude and perception	Actor attitude and perception	0.67–0.81	Attitude and Perception	0.37	Bean acceptability

Note: Only statistically significant variables at p-value of 0.05 are reported. FSI=Food Security Indicator.

5. Utilization and consumption

TABLE 13A.5—SPEARMAN'S CORRELATION BETWEEN VARIABLES USED IN ASSESSING THE PERFORMANCE OF THE VALUE CHAIN IN CONTRIBUTING TO ACHIEVING FOOD SECURITY PILLARS (UTILIZATION AND CONSUMPTION)

Criteria	Indicator	Correlations: Indicator vs. Category	Dimension	Correlations: Dimensions vs. Availability	FSP
Actor attitude and perception	Attitude towards processed products, safety, and nutrition	0.50–0.72	Attitude	0.60	Bean utilization/consumption
Knowledge acquisition	Knowledge of market and value addition	0.99	Management	0.61	Bean utilization/consumption
Safety	Safety	0.64	Quality	0.51	
Product quality	Stored product quality	0.43			Bean utilization/consumption
Efficiency of system	Efficiency to detect and remove infested beans	0.38–0.46	Operational	0.27	Bean utilization/consumption
Product diversity	Level of product diversity	0.80			Bean utilization/consumption
Technology and assets	Technical and financial capacity	0.33			

Note: Only statistically significant variables at p-value of 0.05 are reported. FSI=Food Security Indicator.

CHAPTER 14

Tracking Key CAADP Indicators and Implementation Processes

Wondwosen Tefera, Julia Collins, and Tsitsi Makombe

Introduction

In the 2003 Maputo Declaration on *Agriculture and Food Security*, African heads of state and government resolved to urgently implement the Comprehensive Africa Agriculture Development Programme (CAADP)—a continentwide framework for reducing poverty, food insecurity, and hunger and revitalizing agriculture through increased investments (AU 2003). Early on, the two main CAADP targets were allocating 10 percent of national budgets to the agricultural sector and achieving a 6 percent agricultural growth rate at the national level. In 2014, African leaders reasserted their commitment to CAADP and broadened the agenda by adopting the Malabo Declaration on *Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods*. Through seven broad commitments in the Malabo Declaration, the leaders resolved to uphold CAADP principles and values, increase investment in agriculture, end hunger and halve poverty by 2025, boost intra-African agricultural trade, enhance resilience to climate variability, and strengthen mutual accountability for actions and results by conducting a continental Biennial Review (BR) of progress made in achieving the commitments (AUC 2014).

The Regional Strategic Analysis and Knowledge Support System (ReSAKSS) was established in 2006 to provide data and knowledge products to facilitate CAADP benchmarking, review, dialogue, and mutual learning processes.[1] Starting in 2007 at the behest of the African Union Commission (AUC), ReSAKSS led the development of the first CAADP monitoring and evaluation (M&E) framework for assessing CAADP implementation progress and performance. The CAADP M&E framework identified key indicators for tracking progress in allocating resources and achieving targets; outlined the required data, sources, and methods for estimating the indicators; and laid out a plan for successfully implementing the framework (Benin, Johnson, and Omilola 2010). With the adoption of the 2014 Malabo Declaration, AUC and the African Union Development Agency–New Partnership for Africa's Development (AUDA-NEPAD) developed the CAADP Results Framework (RF) for 2015–2025 to benchmark progress in CAADP implementation including progress toward meeting the seven Malabo commitments (AUC and NPCA 2015).

To help report on the provisions of the Malabo Declaration, the CAADP RF is organized into three levels: (1) outcomes, (2) outputs, and (3) inputs. Level 1 of the CAADP RF includes broader development outcomes and impacts to which agriculture contributes, including wealth creation; food and nutrition security; enhanced economic opportunities, poverty alleviation, and shared prosperity; and resilience and sustainability. Level 2 encompasses the outputs from interventions intended to transform the agricultural sector and achieve inclusive growth, including improved agricultural production and productivity; increased intra-African trade and functional markets; expanded local agro-industry and value chain development, inclusive of women and youth; increased resilience of livelihoods and improved management of risks in agriculture; and improved management of natural resources for sustainable agriculture. Level 3 involves inputs and processes required to strengthen systemic capacity to deliver CAADP results and create an enabling environment in which agricultural transformation can take place: it includes effective and inclusive policy processes; effective and accountable institutions that regularly assess the quality of implementation of policies and commitments; strengthened capacity for evidence-based planning, implementation, and review; improved multisectoral coordination, partnerships, and mutual accountability in sectors related to agriculture; increased public and private investments in agriculture; and increased capacity to generate, analyze, and use data, information, knowledge, and innovations. There are 38 indicators in the CAADP RF: 14 for level 1, 12 for level 2, and 12 for level 3 (Table 14.1). ReSAKSS tracks progress on CAADP indicators in the CAADP RF for 2015–2025 through its flagship Annual Trends and Outlook Report (ATOR) and website (www.resakss.org).

Although the CAADP RF is intended to help track progress in implementing the Malabo Declaration, the CAADP Biennial Review (BR) process initiated in 2015 introduced indicators to monitor the specific commitments in the declaration using the Africa Agriculture Transformation Scorecard (AATS) (Table 14.1). Data on many of the CAADP RF indicators are available for a larger number

1 ReSAKSS is facilitated by AKADEMIYA2063 and works closely with CAADP stakeholders across the continent. The ReSAKSS activities discussed in this chapter were carried out in collaboration with partners such as the African Union Commission, the African Union Development Agency-New Partnership for Africa's Development, regional economic communities, national governments, farmer organizations, members of the African and international research communities, and development partners.

TABLE 14.1—NUMBER OF INDICATORS IN THE CAADP RESULTS FRAMEWORK AND BIENNIAL REVIEW

CAADP Results Framework	**Number of indicators**
Level 1: Agriculture's contribution to growth and development	14
Level 2: Agricultural transformation and inclusive growth	12
Level 3: Systemic capacity to deliver results	12
Total number of indicators	38
CAADP Biennial Review and Africa Agriculture Transformation Scorecard	**Number of indicators**
Theme 1: CAADP processes and values	3
Theme 2: Investment finance in agriculture	6
Theme 3: Ending hunger by 2025	21
Theme 4: Halving poverty by 2025	8
Theme 5: Boosting intra-African trade in agricultural commodities and services	3
Theme 6: Enhancing resilience to climate variability	3
Theme 7: Mutual accountability for results and actions	3
Total number of indicators	47

Source: Authors, based on AUC and NPCA (2015) and AUC (2014).

of countries and for longer time periods. This in turn allows for aggregation across countries and an examination of trends over long time periods and across different country groupings (for example, organized by economic categories, regional economic communities, and stage of CAADP implementation) that are not considered by the BR. While the CAADP BR indicators are broader in coverage, there is considerable overlap between these indicators and those in the CAADP RF. Although ReSAKSS tracks progress in most of the overlapping indicators, some of the indicators in both the CAADP RF and the CAADP BR are not yet included in the ReSAKSS database because data are not yet consistently available or are not available across all countries to allow for cross-country aggregation. These include several indicators on access to finance, private sector investment, postharvest loss, women's empowerment, food safety, and resilience. Discussions on filling data gaps are underway among CAADP technical partners, but increasing data availability in these areas is challenging and will require concerted efforts by countries and their partners to define methodologies and develop and fund data collection efforts.

Objectives of the Chapter

This chapter discusses progress on 27 of the 38 CAADP RF indicators for which cross-country data are available (Table 14.2)—details of the indicators and aggregate statistics are available in the data tables in Annexes 1–3 of this report. Eighteen of the 27 indicators tracked are also CAADP BR indicators. Progress is discussed across different geographic and economic groupings on the continent, comparing trends in the RF indicators during the first five years after the adoption of CAADP (2003 to 2008) with later CAADP subperiods. In keeping with the 2021 ATOR report's thematic focus on the COVID-19 pandemic, which has severely impacted economic activity in Africa, the chapter discusses Africa's performance prior to the pandemic while highlighting its performance in 2020 during the pandemic using available 2020 data or recent studies. The ReSAKSS database has 2020 data for indicators related to GDP, household consumption expenditure, employment, agricultural value added and productivity, and government agricultural expenditure; for indicators for which 2020 data are not available, the chapter reviews projections and emerging findings from other studies.

Starting with the next section, the chapter also discusses the CAADP implementation process itself in terms of country and regional progress in developing evidence-based, Malabo-compliant national agriculture investment plans (NAIPs) and operationalizing CAADP mutual accountability processes to support agricultural sector review and dialogue. The CAADP implementation process is led by the AUC and AUDA-NEPAD in collaboration with partners including national governments, regional economic communities (RECs), development and technical partners, and nonstate actors. The chapter describes general progress in the implementation process while highlighting the contribution of ReSAKSS as a technical partner.

Progress in CAADP Implementation Processes

CAADP implementation under the Malabo Declaration has four components (AUC and NEPAD 2016). Implementation starts with the domestication of the Malabo Declaration commitments and is followed by NAIP appraisal (or formulation). The third component is the implementation of the NAIP with the

TABLE 14.2—CAADP RESULTS FRAMEWORK INDICATORS DISCUSSED
Level 1: Agriculture's contribution to economic growth and inclusive development
1. L1.1.1 GDP per capita (constant 2010 US$)
2. L1.1.2 Household final consumption expenditure per capita (constant 2010 US$)
3. L1.2.1 Prevalence of undernourishment (% of population)
4. L1.2.2a Prevalence of underweight, weight for age (% of children under five years of age)
5. L1.2.2b Prevalence of stunting, height for age (% of children under five years of age)
6. L1.2.2c Prevalence of wasting, weight for height (% of children under five years of age)
7. L1.2.3 Cereal import dependency index
8. L1.3.1 Employment rate
9. L1.3.3 Poverty gap at $1.90 a day (2011 PPP)
10. L1.3.4 Extreme poverty headcount ratio at $1.90 a day (2011 PPP), % of population
Level 2: Agricultural transformation and sustained inclusive agricultural growth
11. L2.1.1 Agriculture value added (million, constant 2010 US$)
12. L2.1.2 Agriculture Production Index (2004–2006 = 100)
13. L2.1.3 Agriculture value added per agricultural worker (constant 2010 US$)
14. L2.1.4 Agriculture value added per hectare of agricultural land (constant 2010 US$)
15. L2.1.5 Yield for the five most important agricultural commodities
16. L2.2.1 Value of intra-African agricultural trade (constant 2010 US$, million)
17. L2.4.2 Existence of food reserves, local purchases for relief programs, early warning systems, and school feeding programs
Level 3: Strengthening systemic capacity to deliver results
18. L3.1.1 Existence of a new NAIP/NAFSIP developed through an inclusive and participatory process
19. L3.2.1 Existence of inclusive institutionalized mechanisms for mutual accountability and peer review
20. L3.3.1 Existence of and quality in the implementation of evidence-informed policies and corresponding human resources
21. L3.4.1 Existence of a functional multisectoral and multistakeholder coordination body
22. L3.4.2 Cumulative number of agriculture-related public-private partnerships that are successfully undertaken
23. L3.4.3 Cumulative value of investments in public-private partnerships
24. L3.5.1 Government agriculture expenditure (GAE) (billion, constant 2010 US$)
25. L3.5.2 GAE (% of total government expenditure)
26. L3.5.3 GAE (% of agriculture value added)
27. L3.6.2 Existence of an operational country SAKSS

Source: Authors, based on AUC and NPCA (2015).

Note: GDP = gross domestic product; NAFSIP = national agriculture and food security investment plan; NAIP = national agriculture investment plan; PPP = purchasing power parity; SAKSS = Strategic Analysis and Knowledge Support System; Highlighted indicators are also BR indicators.

aim of realizing the commitments in the Malabo Declaration. The fourth component refers to mutual accountability whereby the progress of the NAIP implementation is measured through the agriculture joint sector reviews (JSRs). The development and implementation of national or regional agriculture investment plans that are aligned with goals and targets of the Malabo Declaration is central to operationalizing the Declaration. The Malabo NAIP domestication event, led by AUC, AUDA-NEPAD, and RECs, convenes national CAADP constituencies to discuss and agree on a country roadmap to review and revise the NAIP. The roadmap specifies roles, timelines, and coordination modalities needed to generate the NAIP. To date, domestication events have been held in 25 countries (Table L3(a) in Annex 3d). By the end of September 2021, a total of 42 African countries had drafted, reviewed, and/or validated a Malabo-compliant NAIP (Table L3(a)).

Between 2016 and 2020, ReSAKSS, under the leadership of AUC and AUDA-NEPAD and in partnership with local experts, provided analysis to inform the design of country NAIPs in the form of three main deliverables: the Malabo Status Assessment and Profile (SAP), the Malabo Goals and Milestones Report (MGM), and the Policy and Program Opportunities Report (PPO). By the end of September 2020, ReSAKSS had completed SAP reports for 31 countries, MGM reports for 25 countries, and PPO reports covering policy best practices in nine thematic areas (Table L3(a)), including regional trade, value chain development, food security and nutrition, gender, climate-smart agriculture, social protection, agricultural technical vocational education and training (ATVET), and mutual accountability. In addition, country-specific

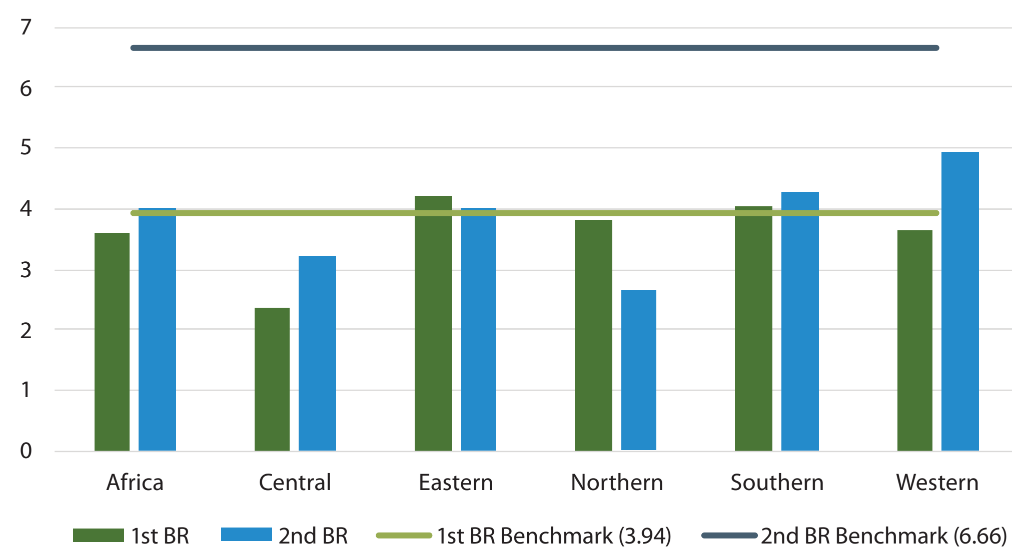
PPO reports were also completed for 8 countries: Angola, Botswana, Eswatini, Gabon, Lesotho, Namibia, Zambia, and Zimbabwe.

The Malabo Declaration commitment on mutual accountability calls for (1) a systematic biennial review using the CAADP RF of the progress made in implementing provisions of the Declaration and (2) enhanced multisectoral efforts and multi-institutional platforms for peer review, mutual learning, and mutual accountability (AUC 2014). Under the CAADP agenda, the principle of mutual accountability has been operationalized at the country and regional levels through agriculture JSRs and at the continental level using the CAADP BR process. JSRs provide an inclusive, evidence-based platform for multiple stakeholders to jointly review progress; hold each other accountable for actions, results, and commitments; and based on gaps identified, agree on future implementation actions. Moreover, because JSRs are the bedrock for inclusive and comprehensive mutual accountability processes, AUC, AUDA-NEPAD, and technical partners such as ReSAKSS have called on and supported countries and RECs to embed their BR process into the country and regional JSR processes. Doing so helps to streamline and institutionalize mutual accountability processes in the countries and RECs. At the request of AUC and AUDA-NEPAD, ReSAKSS has been strengthening agriculture JSRs since 2014 by conducting assessments of JSR or JSR-like processes at the country and regional levels. To date, ReSAKSS has completed JSR assessments in 21 countries and in 2 RECs: the Economic Community of West African States (ECOWAS) in 2015 and the East African Community (EAC) in 2019 (Table L3(a)). The assessments evaluate the institutional and policy landscape as well as the quality of current agricultural review processes, identifying areas that need strengthening in order to help countries and RECs develop JSR processes that are regular, comprehensive, and inclusive. The COVID-19 pandemic has delayed JSRs and JSR assessments in several countries; as JSR activities restart, ReSAKSS will continue to support the enhancement of review processes.

The CAADP BR is a process for promoting mutual accountability by reviewing country performance toward meeting Malabo Declaration commitments by 2025. To date, Africa has successfully held two BRs in 2017 and 2019. The third BR took place in 2021, with the report and scorecard expected to be presented at the AU Summit in early 2022. On average, Africa achieved stronger performance in the inaugural BR in 2017 compared to the second BR in 2019. In particular, 20 countries and 2 regions (eastern Africa and southern Africa) were on track toward achieving the overall Malabo commitments in 2017 compared to just 4 countries (Rwanda, Morocco, Mali, and Ghana) being on track in 2019 (Table L.3(a)). The slowdown in progress in 2019 partly reflected the higher overall benchmark score of 6.66 out of 10 that the continent, sub-regions, and countries needed to achieve to be on track, as compared to the overall score of 3.94 out of 10 in 2017. Many countries also made less progress or even regressed on some of the BR indicators and themes (Benin 2020). Nonetheless, the 2019 BR report shows that 36 out of 49 reporting AU member states improved their overall agricultural transformation scores compared to the 2017 BR.

During both BRs, Africa as a whole was off track in achieving the overall Malabo Declaration commitments by 2025 (Figure 14.1). Despite the continent being on track to meet four out of the seven Malabo commitments in 2017, it

FIGURE 14.1—AFRICA'S PERFORMANCE IN THE 2017 AND 2019 BRS (AVERAGE AGRICULTURAL TRANSFORMATION SCORE)



Source: Authors' compilation based on AUC (2018) and AUC (2020).

was off track to meet a single commitment in 2019. In 2017, the continent was on track to meet the following four commitments: recommitment to the CAADP process (commitment 1), halving poverty through agriculture (commitment 4), tripling intra-African trade in agriculture (commitment 5), and mutual accountability to actions and results (commitment 7).

In 2021, ReSAKSS published an analysis of the 2019 BR in 16 briefs for Angola, Botswana, Burkina Faso, Eswatini, Kenya, Lesotho, Madagascar, Mauritius, Mozambique, Namibia, South Africa, Uganda, Zimbabwe, EAC, ECOWAS, and the Southern African Development Community (SADC). The briefs highlight policy and programmatic adjustments made by countries and RECs in order to meet the Malabo commitments by 2025. Adjustments include pledges to increase the agriculture budget share to at least 10 percent in Lesotho, Mali, and Mozambique; promotion of private sector agricultural investments in Mozambique; and the establishment of new agriculture financing mechanisms in Benin, Burkina Faso, Côte d'Ivoire, Niger, Nigeria, and Togo (Matchaya et al. 2021; Seiwoh et al. 2021; Vilisa et al. 2021).

The third BR process was launched at the country level in April 2021 following continental training workshops in March and early April. Along with other technical partners, ReSAKSS supported the process by contributing to technical improvements and updates to BR guidelines and tools as well as providing training for country and REC focal points. It also made improvements to the digital eBR data entry platform to reduce errors and enhance the platform's functionality. In addition, ReSAKSS supported countries with BR data collection, review, and validation. By early September 2021, a total of 51 countries had submitted their 2021 BR data to their respective RECs (Table L3(a)). Following data submission by the countries, ReSAKSS supported RECs with data reviews and regional validation and supported AUC in analyzing the data and drafting the continental BR report in September 2021. The 2021 BR Report and Africa Agriculture Transformation Scorecard will be reviewed by AUC's Specialized Technical Committee on Agriculture, Rural Development, Water and Environment in late 2021 in preparation for its launch at the AU General Assembly in early 2022.

Progress in CAADP Indicators

This section discusses Africa's performance on 27 of the 38 CAADP RF indicators for which data are available, organized by the three RF levels.[2] Data on the 27 indicators are presented in Annexes 1–3. Progress on the quantitative indicators is presented at the aggregate level in seven different breakdowns: (1) for Africa as a whole; (2) by the AU's five geographic regions (central, eastern, northern, southern, and western); (3) by five economic categories (countries with less favorable agricultural conditions, countries with more favorable agricultural conditions, mineral-rich countries, lower-middle-income countries, and upper-middle-income countries); (4) by the eight RECs (Community of Sahel-Saharan States [CEN-SAD], Common Market for Eastern and Southern Africa [COMESA], EAC, Economic Community of Central African States [ECCAS], ECOWAS, Intergovernmental Authority on Development [IGAD], SADC, and Arab Maghreb Union [UMA]); (5) by the period during which countries signed the CAADP compact (CC0, CC1, CC2, and CC3);[3] (6) by the level or stage of CAADP implementation reached by the end of 2015 (CL0, CL1, CL2, CL3, and CL4);[4] and (7) by the distribution of countries in formulating first- and second-generation NAIPs (N00, N10, and N11).[5] Annex 4 lists countries in the various geographic, economic, and REC categories; Annex 5 lists the countries in the different groupings for CAADP compact signing or level of implementation reached; and Annex 6 lists countries by NAIP formulation category. Progress is also reported over different subperiods, with achievement in the early CAADP subperiod of 2003–2008 compared with achievements in later

2 Several of these indicators are also part of the CAADP BR and AATS.

3 CC0 = group of countries that have not yet signed a CAADP compact; CC1 = group of countries that signed the compact in 2007–2009; CC2 = group of countries that signed the compact in 2010–2012; CC3 = group of countries that signed the compact in 2013–2015.

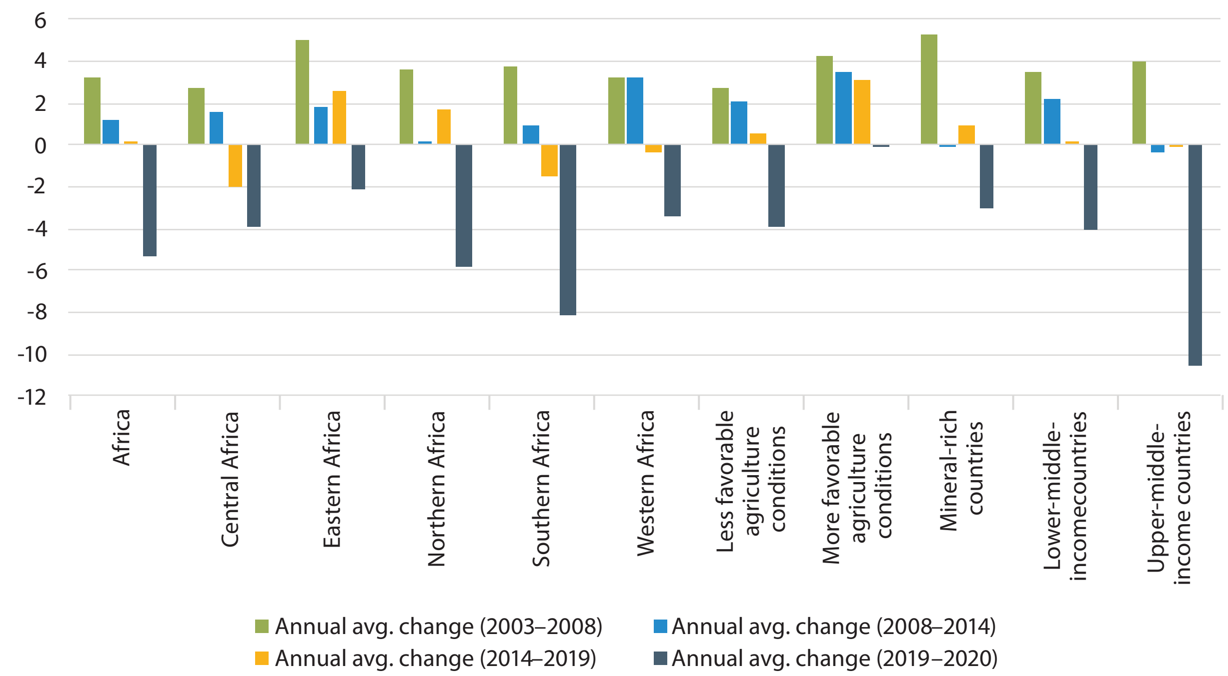
4 CL0 = group of countries that have not started the CAADP process or have not yet signed a compact; CL1 = group of countries that have signed a CAADP compact; CL2 = group of countries that have signed a compact and formulated an NAIP; CL3 = group of countries that have signed a compact, formulated an NAIP, and secured one external funding source; CL4 = group of countries that have signed a compact, formulated an NAIP, and secured more than one external funding source. Obtaining funding for NAIPs is a key step in CAADP implementation, and countries that have secured external funding sources are expected to be better able to implement NAIPs and other agricultural investments (Benin 2016).

5 N00 = group of countries that have neither a first-generation NAIP (NAIP1.0) nor a second-generation NAIP (NAIP2.0); N10 = group of countries that have NAIP1.0 but do not have NAIP2.0; N11 = group of countries that have both NAIP1.0 and NAIP2.0.

subperiods of 2008–2014 and 2014–2019, as well as with status in 2020.[6] 2020 is considered separately in order to highlight the effects of the COVID-19 pandemic, which had severe impacts on many of the CAADP RF indicators.

The discussion of trends and changes in CAADP indicators pertains to country categories or groupings as a whole and not individual countries within the categories; for example, it relates to Africa as a whole, central Africa as a group, ECOWAS members as a group, and groups of countries categorized by their stage of CAADP implementation and NAIP formulation experience. Presenting the trends by different groups helps to determine how the implications for strengthening or maintaining desirable outcomes or for reversing undesirable outcomes may differ across the continent, without inference of causality. Unless otherwise stated, all monetary values have been converted into constant 2010 US dollar prices for intertemporal and cross-country or cross-category comparisons.

FIGURE 14.2—GROSS DOMESTIC PRODUCT PER CAPITA (CONSTANT 2010 US DOLLARS), ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2020



Source: ReSAKSS, based on World Bank (2021) and ILO (2021a).

CAADP Results Framework Level 1 Indicators: Agriculture's Contribution to Economic Growth and Inclusive Development

Wealth Creation

The COVID-19 pandemic caused Africa to undergo its first economic recession in approximately 25 years (World Bank 2020). In 2020, Africa's *GDP per capita* contracted by 5.3 percent in real terms from its 2019 level. This decline presents a sharp contrast with the average annual growth rate of 3.3 percent recorded during the early CAADP period, 2003–2008; growth then declined to 1.2 percent and 0.2 percent during the 2008–2014 and 2014–2019 periods, respectively (Table L1.1.1 and Figure 14.2). Prior to the pandemic, the growth deceleration observed in recent years was associated with the economic slowdown and lower commodity prices recorded at the global level. The pattern of positive but slowing GDP per capita growth before the COVID-19 crisis is observed among most geographic regions and country groups, with some exceptions; growth had

6 Considering that CAADP was launched in 2003, renewed in 2008, and renewed again 2014 with the Malabo Declaration, the years 2003, 2008, and 2014 represent important milestones. Therefore, the post-CAADP subperiods for reporting on progress use overlapping years to mark these milestones that usually occurred during the middle of the year in June, that is, 2003–2008, 2008–2014, and 2014–2019.

already declined in central, southern, and western Africa during the 2014–2019 period. In 2020, the GDP per capita contraction was the lowest in eastern Africa at 2.1 percent and the highest in southern and northern Africa at 8.2 percent and 5.8 percent, respectively. Countries with more favorable agriculture conditions appeared to be the most resilient group, recording the smallest decline in 2020 of 0.1 percent. The countries that have formulated both a first-generation NAIP1 and a second-generation NAIP2 (N11) and the groups of countries that joined the CAADP process early (CC1 & CC2) or advanced farther along the CAADP implementation process (CL3 & CL4) also showed relatively lower rates of reduction.

During the successive CAADP subperiods, real GDP per capita for Africa as a whole grew from an average level of $1,736 during 2003–2008 to $1,932 and $2,010 during 2008–2014 and 2014–2019, respectively.[7] GDP per capita declined to $1,911.60 in 2020, equivalent to the value recorded a decade prior in 2010 and 2011. Real GDP per capita in 2020 was the highest for the upper-middle-income countries ($6,747.60). UMA ($3,855), the group of countries that have not yet embarked on a NAIP ($3,580.90), northern Africa ($3,460.20), and southern Africa ($3,292.40) also recorded relatively higher GDP per capita in the same year. Countries with less favorable agricultural conditions and countries with more favorable agricultural conditions showed the lowest real GDP per capita levels throughout the entire CAADP period, reaching $635.20 and $737.30 respectively in 2020.

Household expenditure is a major catalyst of countries' economic growth (Chai 2018) and consists of all spending made to meet the daily needs of households. In 2020, *household consumption expenditure per capita* declined for Africa and the various country groupings except for central Africa, northern Africa, COMESA, EAC, ECCAS, and mineral-rich countries. Similar to GDP per capita, a decelerating trend was already in place for most of the subgroupings as well as for Africa as a whole during the 2014–2019 period, but the contraction was notably higher in 2020. For Africa as a whole, growth in household consumption expenditure per capita declined from an annual average of 1.7 percent during 2003–2008 to 1.1 percent during 2008–2014 and 0.4 percent during 2014–2019 (Table L1.1.2). In 2020, household consumption expenditure per capita contracted by 3.56 percent from the 2019 level. For the same period, relatively higher rates of contraction were observed for mineral-rich countries (10.53 percent), upper-middle-income countries (8.75 percent), western Africa (7.25 percent), and southern Africa (6.62 percent).

Food and Nutrition Security

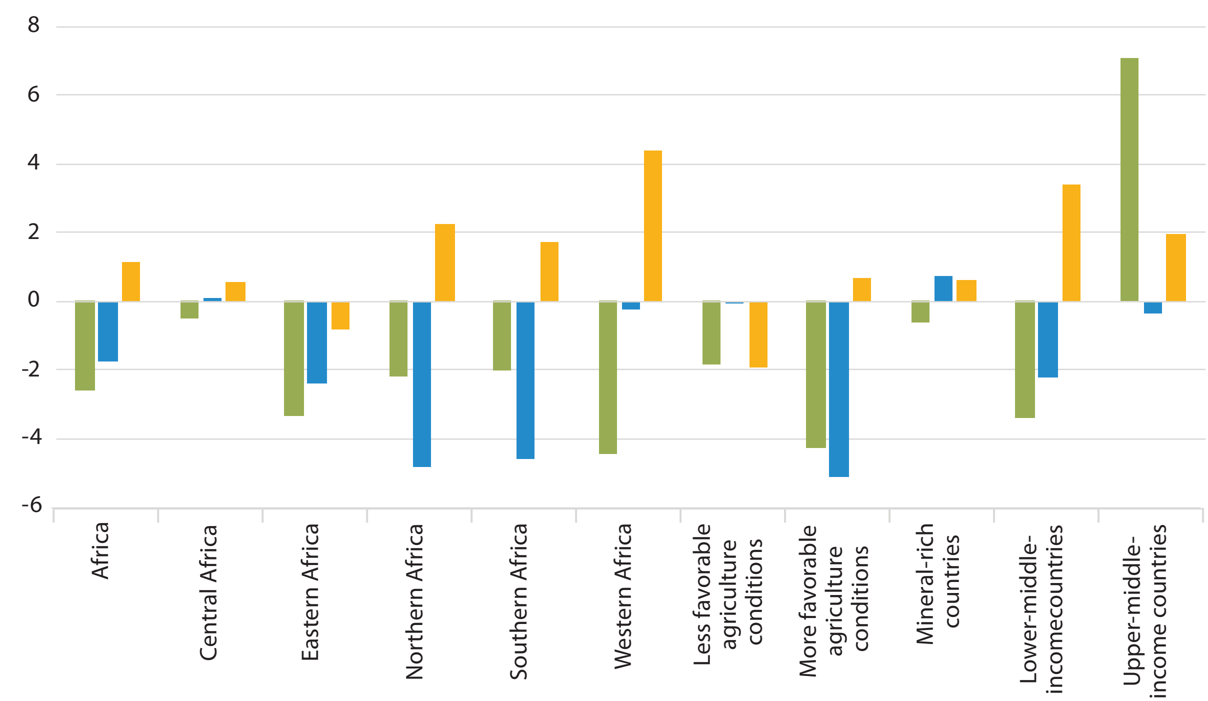
The *prevalence of undernourishment* measures the proportion of the population whose food intake is below the minimum dietary energy requirement. For Africa as a whole, the prevalence had been falling during the initial CAADP subperiods before the trend reversed in recent years and undernourishment began to rise again. As Table L1.2.1 and Figure 14.3 show, the prevalence of undernourishment declined by an annual average of 2.6 percent during the early CAADP period (2003–2008) and by 1.8 percent during 2008–2014. In the most recent period of 2014–2019, the prevalence of undernourishment increased by an annual average of 1.1 percent. Several factors have influenced this trend of rising undernourishment, including economic instability, conflict, and climate variability (FAO et al. 2021). In level terms, Africa's undernourishment prevalence rose slightly to 18.8 percent in 2019 from an average of 18.3 percent during 2014–2019.

The prevalence of undernourishment is likely to have worsened in 2020 as the COVID-19 pandemic exacerbated the various drivers of undernourishment. According to FAO et al. (2021), the prevalence is projected to reach 21 percent for Africa as a whole in 2020, adding 46.2 million more people to the undernourished category. The same report estimates that the majority of the additional undernourished people are located in western Africa (24.6 million) and eastern Africa (13.8 million); these two regions are also expected to see the largest increases in the prevalence rate, at 5.2 and 2.5 percentage points, respectively. The number of additional undernourished people in the other regions is estimated to be smaller, with 4.2 million for central Africa, 1.9 million for northern Africa, and 1.7 million for southern Africa (FAO et al. 2021).

The pre-pandemic undernourishment growth trends observed at the continental level were similar for most of the country groupings. All country classifications recorded a decline in the prevalence rate during 2003–2008. The decline was maintained during 2008–2014 except in central Africa, which recorded an annual average increase of 0.1 percent. During 2014–2019, all

7 All dollar amounts listed in the chapter are constant 2010 US dollars, unless stated otherwise.

FIGURE 14.3—PREVALENCE OF UNDERNOURISHMENT, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2019



Source: ReSAKSS, based on World Bank (2021) and ILO (2021a).

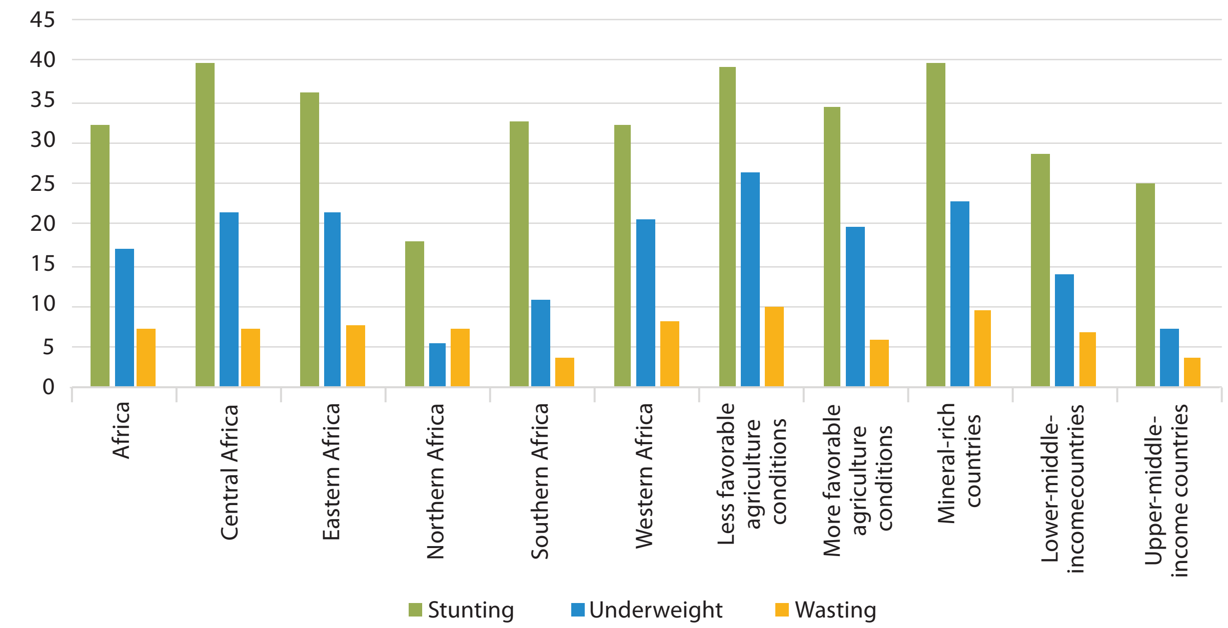
country groups except eastern Africa, countries with less favorable agriculture conditions, IGAD, and the group of countries that are yet to embark on NAIP formulation (N00) recorded increases in the prevalence rate, ranging from 0.6 percent per year (in central Africa) to 4.4 percent per year (in western Africa). Among geographic regions, only eastern Africa reduced its undernourishment level, by an annual average of 0.8 percent. Reviewing trends from the various country groupings shows that the countries that are yet to embark on NAIP formulation (N00) saw a gradual fall in the prevalence rate throughout the entire CAADP period, while for the other categories (N10 and N11), the decline observed in the initial CAADP period was not sustained in more recent years. Lower- and upper-middle-income countries recorded a notable deterioration during 2014–2019 when compared with the other economic categories.

Child growth is recognized worldwide as a crucial indicator in gauging the health and nutritional status of children (Mitsunaga and Yamauchi 2020). The three measures of child malnutrition presented in this section are child underweight, child stunting, and child wasting. For Africa as a whole, the *prevalence of child stunting*, a measure of low height for age in children under the age of five, declined steadily but slowly from an average of 38.4 percent in the 2003–2008 period to 35 percent and 32.1 percent in 2008–2014 and 2014–2019, respectively (Table L1.2.2B; Figure 14.4). Despite the declining trend in the prevalence rate, Africa is the only continent that recorded an increase in the number of children with stunting, from 54.4 million in 2000 to 61.4 million in 2020 (UNICEF et al. 2021). As an indicator of chronic malnutrition, stunting is expected to further increase due to the negative impacts of the COVID-19 pandemic on food security. One study estimates that the number of stunted children in low- and middle-income countries could increase by 2.6 million by 2022 (Osendarp et al. 2021); however, the full impacts of the pandemic on stunting may take years to become apparent, depending on the duration of the pandemic's negative economic effects as well as its impacts on maternal nutrition (UNICEF et al. 2021). Although most of the country classifications recorded declines in stunting during the entire 2003–2019 period, many subgroups still showed high rates of more than 30 percent in the most recent CAADP period of 2014–2019; stunting remained close to 40 percent in central Africa and ECCAS.

The country groupings with lower child stunting rates include northern Africa (17.8 percent) and UMA (14.8 percent).

The *prevalence of child underweight* (low weight for age) in children younger than five years of age showed an improving trend with varying rates during most of the review period (Table L1.2.2A; Figure 14.4). For Africa as a whole, the prevalence declined from an average of 21.3 percent during 2003–2008 to 19.1 percent and 17.2 percent during 2008–2014 and 2014–2019, respectively. In the most recent subperiod 2014–2019, central, eastern, and western Africa showed prevalence rates higher than the Africa average. Northern and southern Africa not only had lower prevalence rates but also recorded the largest annual average reductions at 4.2 percent and 5.1 percent, respectively. Between the most recent (2014–2019) and earliest (2003–2008) CAADP periods, a reduction of five percentage points or more in the prevalence rate was recorded in eastern Africa, countries with more favorable agricultural conditions, IGAD, countries that joined CAADP early (CC1), countries that are most advanced in implementing CAADP (CL4), and countries that formulated both NAIPs (N11).

FIGURE 14.4—PREVALENCE OF STUNTING, UNDERWEIGHT, AND WASTING IN AFRICA (PERCENTAGE OF CHILDREN YOUNGER THAN FIVE), 2014–2019



Source: ReSAKSS, based on World Bank (2021) and ILO (2021a).

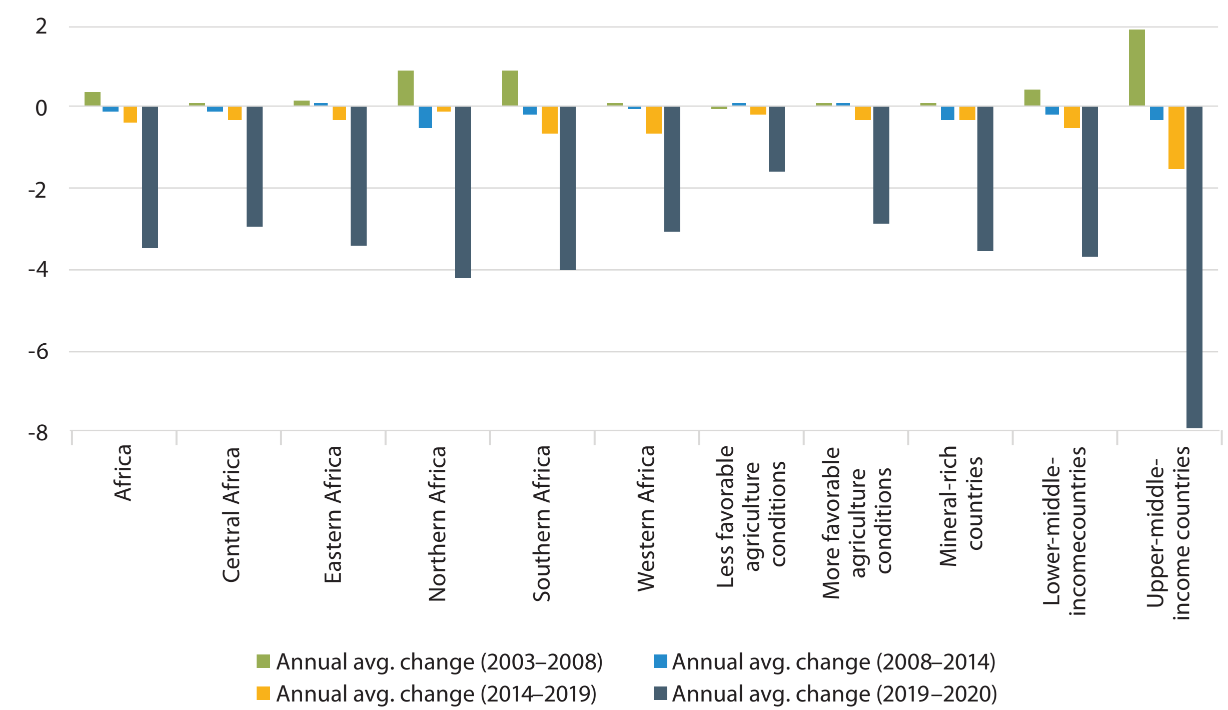
The *prevalence of child wasting* (low weight for height), a measure of acute undernutrition in children younger than five years of age, declined moderately during the review period. For Africa as a whole, wasting prevalence declined from an average of 8.8 percent in the 2003–2008 period to 8 percent in 2008–2014 and 7.2 percent in 2014–2019. Between 2003–2008 and 2014–2019, a number of country groupings managed to improve child wasting from a "high prevalence" level (that is, more than 10 percent) to "moderate prevalence" (less than 10 percent). This includes western Africa, central Africa, countries with less favorable agricultural conditions, mineral-rich countries, CEN-SAD, ECOWAS, and the countries that joined CAADP early (CC1). Similarly, some country groupings managed to join the low wasting category with less than 5 percent prevalence during 2014–2019. These groups include southern Africa, upper-middle-income countries, SADC, and UMA, with a range of 4.5 percent to 3.9 percent. Conversely, northern Africa recorded a steady increase in wasting prevalence throughout the CAADP period, from 6.1 percent during 2003–2008 to 7.3 percent during 2014–2019 (Table L1.2.2C; Figure 14.4). This is the only country group that showed a worsening of child wasting during 2014–2019. According to UNICEF (2021), deteriorating social, economic, and health conditions due to ongoing conflicts over many years have negatively affected the nutritional status of children in northern Africa. In 2020, an estimated 12.1 million children younger than 5 years were wasted in Africa, with most living in western Africa (4.5 million) and eastern Africa (3.5 million), and the smallest number in southern Africa (200,000) (UNICEF et al. 2021). In addition, the COVID-19 pandemic is expected to reverse previous progress and exacerbate the prevalence of wasting in low- and middle-income countries in Africa and elsewhere for several reasons, including severe deterioration in household incomes, interruption of services such as social protection and health, and fluctuations in the availability and affordability of healthy diets (Headey et al. 2020). According to FAO et al. (2021), between 2020 and 2022 the number of wasted children younger than five years of age in low- and middle-income countries will increase by 11.2–16.3 million. This estimate indicates that the impact of the pandemic will persist in coming years and will require concerted action to reverse.

Africa's dependency on cereal imports increased steadily but marginally during the whole CAADP period (Table L1.2.3). The continent's cereal import dependency ratio, or the share of imports in total cereal supply, increased from an average of 25.6 percent in the 2003–2008 period to 26.4 percent in 2008–2014 and to 27.6 percent in 2014–2017. The average for Africa conceals notable differences among the various country groupings. For the most recent subperiod for which data is available (2014–2017), more than half of cereal demand in northern Africa was met through imports, while eastern Africa had the lowest import dependency ratio of less than 15 percent. Countries that were less engaged with CAADP—those that had not yet signed a CAADP Compact (CC0), those that had not begun the CAADP process (CL0), and those that had not yet developed a NAIP (N00)—had the highest cereal import dependency ratios of more than 40 percent. The import dependency ratio increased by an annual average of 2.3 percent for Africa as a whole during the 2014–2017 period. Annual average growth in cereal import dependency was notably higher for upper-middle-income countries, at 16.5 percent, due to a rise in cereal imports starting in 2015.

Employment

Africa's *employment rate*, which is measured as a proportion of the labor force (Table L1.3.1A) and as a proportion of the population 15 years of age and older (Table L1.3.1B), recorded a slight decline since 2008, which accelerated significantly in 2020. For Africa as a whole, the employment rate as a proportion of the labor force marginally declined from 93.5 percent during 2008–2014 to 93.2 percent in 2014–2019. When the population 15 years of age and older is considered, the employment rate declined from 60 percent during 2008–2014

FIGURE 14.5—EMPLOYMENT RATE (PERCENT OF LABOR FORCE, 15–64 YEARS OF AGE), ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2020

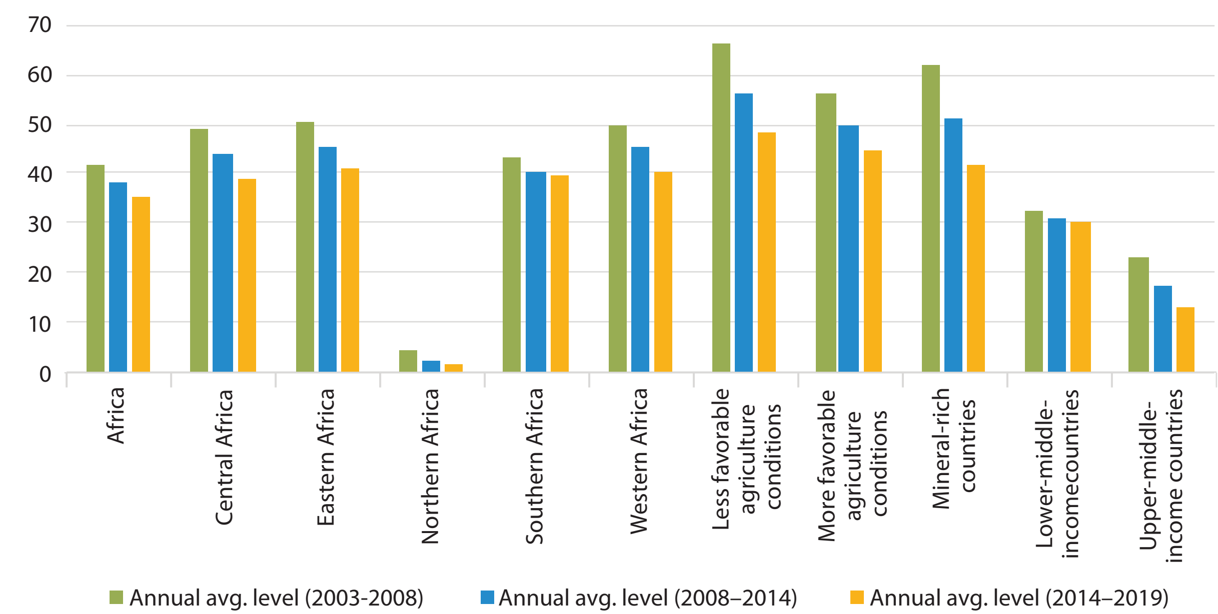


Source: ReSAKSS, based on ILO (2021a).

to 58.8 percent in 2014–2019. With the onset of the COVID-19 pandemic, the reduction in employment in 2020 was notably higher. The decline in the employment rate (measured as a proportion of the labor force) for Africa in 2020 amounts to 3.4 percent, much higher than the 0.04 percent annual average job loss recorded during 2014–2019 (Figure 14.5). In 2020, job losses higher than the average for Africa were recorded in northern and southern Africa, lower- and upper-middle-income countries, and the group of countries that are yet to formulate their NAIP (N00). According to the AU Labour Migration Advisory Committee (2020), about 20 million jobs are estimated to have been lost in Africa in 2020 due to the pandemic. The hardest hit are those employed in the informal sector, the majority of whom are women.

A report by the International Labour Organization (ILO) (2021b) similarly estimates that the crisis has resulted in the loss of 17 million jobs in Africa in 2020 compared to the situation in the absence of the pandemic. Different food system segments have been affected by the pandemic to varying degrees. At a global level, the food service and hospitality industries are expected to have suffered the heaviest employment losses, while agricultural employment is believed to have remained fairly stable (ILO 2021b). Preliminary analysis of enterprise survey data from the Democratic Republic of the Congo suggests that agricultural and agroprocessing firms experienced less severe COVID-19-related employment losses during the second quarter of 2020 than firms in many other sectors, including non-agricultural manufacturing (Collins and Ulimwengu 2021).

FIGURE 14.6—POVERTY HEADCOUNT RATIO AT $1.90 (2011 PPP) PER DAY (PERCENT), 2003–2019



Source: ReSAKSS, based on World Bank (2021) and ILO (2021a).

Poverty

As a measure of extreme poverty, the *poverty headcount ratio* measures the proportion of the population living below the international poverty line ($1.90 per day in 2011 PPP). During the entire review period, the poverty headcount ratio for Africa as a whole consistently declined from an average of 41.7 percent in the 2003–2008 period to 38.1 percent in 2008–2014, and further down to 35.2 percent in 2014–2019 (Table L1.3.4; Figure 14.6). However, the absolute numbers of people living in poverty have increased throughout the CAADP period. The COVID-19 pandemic is expected to further worsen poverty both in Africa and worldwide. The number of people living in extreme poverty globally is projected to increase in 2020 for the first time in more than 20 years (UN 2021). Compared to estimates of poverty in the absence of the pandemic, the number of poor is estimated to have increased by about 97 million in 2020 (Mahler et al. 2021), with Africa south of the Sahara accounting for nearly one-fourth of this projected rise. During the 2014–2019 period, UMA and northern Africa had the lowest poverty headcount ratios at less than 2 percent.

Poverty headcount ratios remain above 30 percent for all other geographic regions and RECs, with the highest rates—above 40 percent—in eastern Africa and EAC. Poverty is especially high in the group of countries which signed a CAADP Compact but did not advance further in the CAADP process (CL1), at 55.5 percent during 2014–2019.

The *extreme poverty gap* serves as a gauge of the severity of poverty by measuring the average shortfall in income from the poverty line. Table L1.3.3 shows that the poverty gap for Africa as a whole declined consistently during the whole CAADP period, dropping from an average of 16.4 percent in the 2003–2008 period to 14.1 percent in 2008–2014 and 12 percent in 2014–2019. The depth of poverty is the least severe in northern Africa and UMA, with poverty gaps of less than 0.4 percent, while the gap is highest in SADC and in the group of countries that signed a CAADP Compact only (CL1), with poverty gaps higher than 19 percent. The pandemic is expected to increase the depth of poverty and further widen the gap between the different income groups. The increase in COVID-19-induced poverty is not surprising given the outlook for wealth and employment status in Africa discussed in earlier sections. That is, the contraction in GDP per capita and job losses can be expected to worsen living standards and increase the proportion of the population living under extreme poverty.

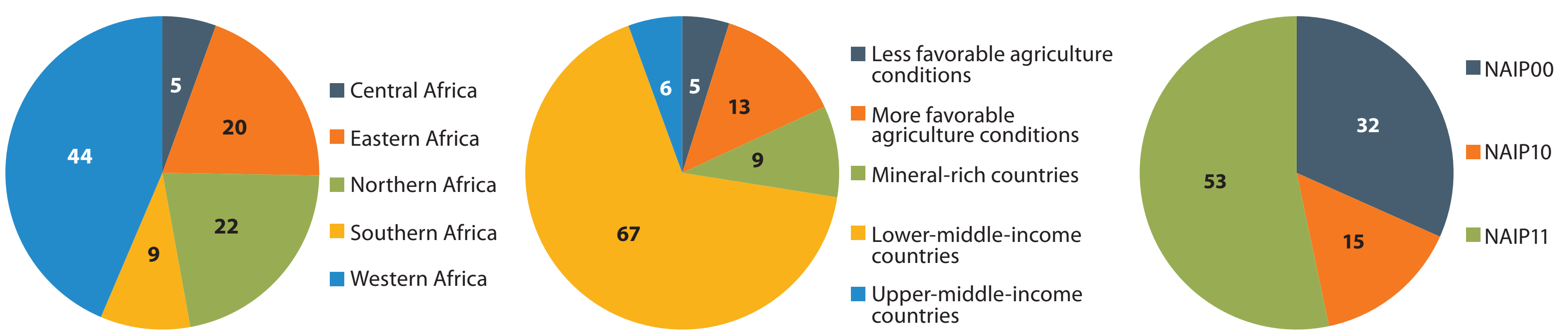
CAADP Results Framework Level 2 Indicators: Agricultural Transformation and Sustained Inclusive Agricultural Growth

Agricultural Production and Productivity

In Africa, the agricultural sector occupies a substantial social and economic position (Goedde, Ooko-Ombaka, and Pais 2019). It is a mainstay of the African economy, employing a significant portion of Africa's population, and as is shown in the section below, it is a source of growing intra-African trade. For Africa as a whole, *agriculture value added* increased from $222.3 billion in 2003 to $384.9 billion in 2020 (Table L2.1.1). During the CAADP period, the highest growth in agriculture value added was recorded during 2008–2014 with an annual average rate of 3.5 percent, which later dropped to 3 percent in 2014–2019. From 2019 to 2020, agriculture value added increased at a slightly slower rate of 2.4 percent. Among the different geographic regions, northern Africa showed the highest agriculture value added growth during 2014–2019 of 4.1 percent, followed by western Africa with 3.4 percent; agriculture value added declined by an annual average of 1.7 percent in southern Africa.

Western Africa accounts for the largest share of Africa's total agriculture value added with a share of 43.6 percent during 2014–2019, followed by northern Africa and eastern Africa with 21.9 percent and 19.7 percent, respectively.

FIGURE 14.7—AGRICULTURE VALUE ADDED, PERCENTAGE SHARE IN AFRICA TOTAL, 2014–2019

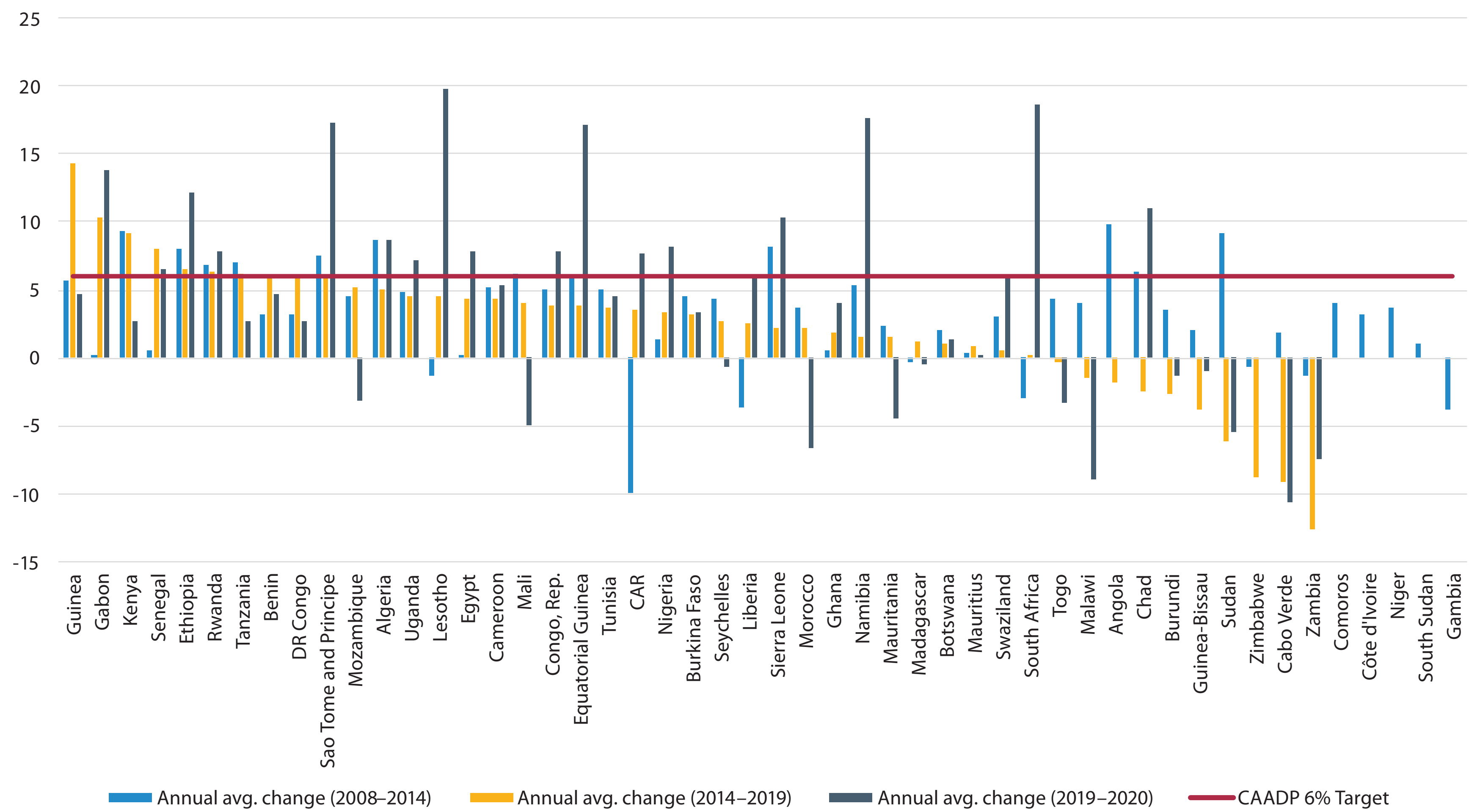


Source: ReSAKSS, based on World Bank (2021).

Central Africa has the smallest share of 5.5 percent. Among the economic categories and the groupings by NAIP progress, lower-middle-income countries and the countries that formulated both NAIP1 and NAIP2 (N11) account for the largest shares of agriculture value added (Figure 14.7).

Performance at the country level shows marked differences. Even though the majority of countries recorded positive agriculture value added growth during most of the CAADP period, only a few countries managed to meet or surpass the 6 percent CAADP growth target (Figure 14.8).

FIGURE 14.8—AGRICULTURE VALUE ADDED ANNUAL AVERAGE GROWTH (PERCENTAGE), 2008–2020

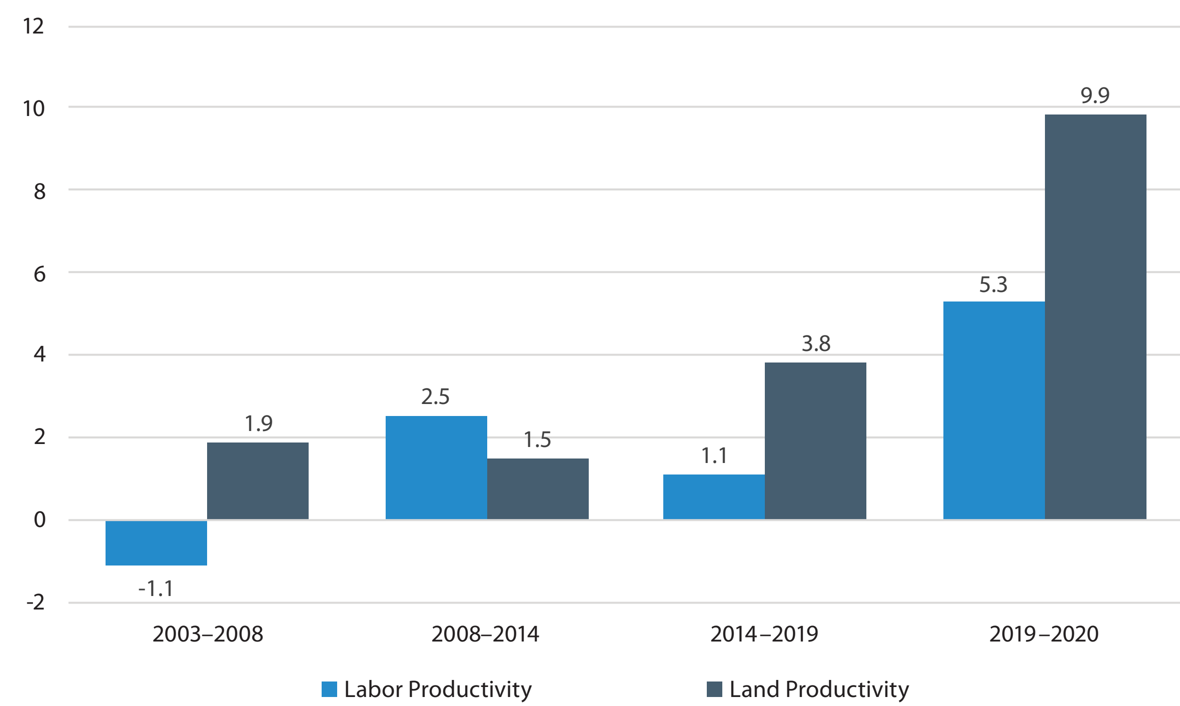


Source: ReSAKSS, based on World Bank (2021) and ILO (2021a).

Note: Countries are listed in order of their average change during the 2014–2019 period. Data are missing for some periods for Angola, Central African Republic (CAR), Comoros, Côte d'Ivoire, Gambia, Niger, South Sudan, and Zimbabwe.

The countries that managed to consistently achieve the CAADP target during 2008–2019 include Kenya, Rwanda, and Tanzania. During the most recent CAADP period of 2014–2019, Guinea and Gabon surpassed the 6 percent growth target by achieving annual average growth rates higher than 10 percent. Other countries that recorded notable growth and met the CAADP target of 6 percent in the same period include Niger, Senegal, Côte d'Ivoire, Benin, Democratic Republic of Congo, and Mozambique. Among country groupings, only EAC met the growth target through the entire 2008–2019 period, and only EAC and countries that signed CAADP compacts during 2010–2012 (CC2 countries) met the target in the most recent period of 2014–2019. The group of countries that signed a compact and formulated a NAIP (CL2 countries) came close to meeting the target, with an average annual growth rate of 5.9 percent (Table L2.1.1). Although few countries and country groups met the target in the most recent period, analysis by Benin (2016) found that advancement in the CAADP process had a positive effect on agriculture value added.

FIGURE 14.9—LABOR AND LAND PRODUCTIVITY IN AFRICA, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2020



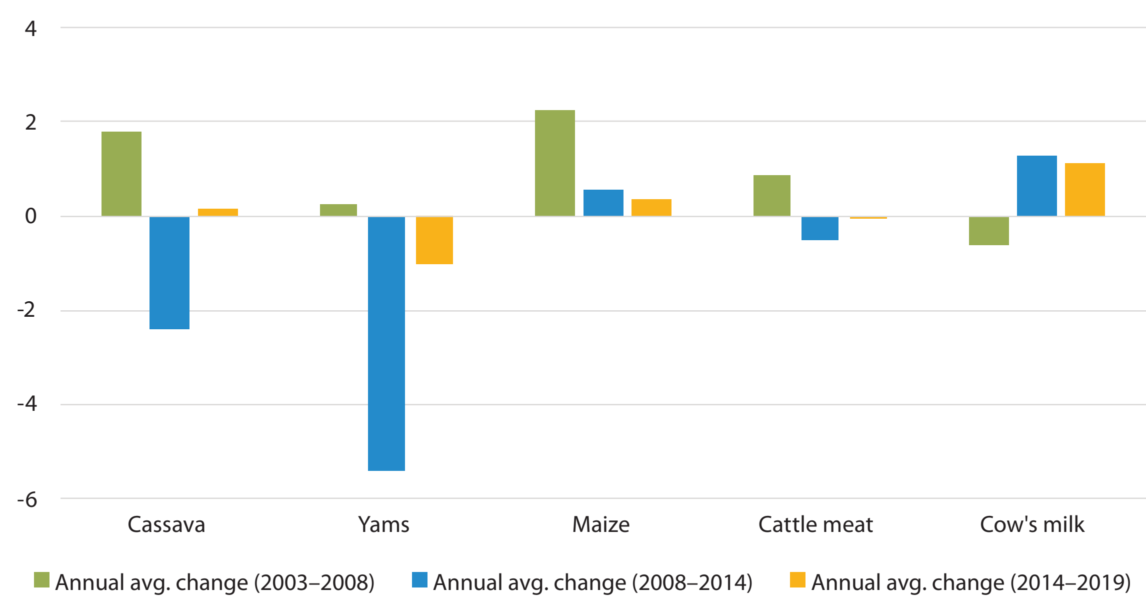
Source: ReSAKSS, based on World Bank (2021) and FAO (2021).

Despite the negative impacts of the COVID-19 pandemic on many economic sectors, agricultural output in Africa south of the Sahara increased in 2020 compared to 2019 (Zeufack et al. 2021). Many countries experienced strong agricultural growth, and nearly 20 countries met the CAADP 6 percent growth target in 2019–2020 (Figure 14.8). While this growth is likely due to many factors, it reflects research findings that the agricultural sector was not as adversely affected by the COVID-19 pandemic as other economic sectors (Bouët, Laborde, and Seck 2021; Amankwah, Gourlay, and Zezza 2021). Surveys in several African countries found that more households entered than exited agriculture in mid-2020, suggesting that households may have turned to agriculture to fill income and food gaps (Amankwah, Gourlay, and Zezza 2021).

The *agriculture production index* (API),[8] a measure of change in agricultural output, consistently increased for Africa as a whole and for the different country groupings throughout the pre-CAADP and post-CAADP periods. This indicates continued agricultural productivity growth in the continent. Table L2.1.2 reveals that API increased from an average of 76.1 points during 2003–2008 to 88.4 and 103.6 points during 2008–2014 and 2014–2019, respectively. The average growth

8 The API is calculated based on agriculture value added. Index values of 100 correspond to the average level of agriculture value added during the 2014–2016 period.

FIGURE 14.10—YIELDS FOR THE FIVE TOP AGRICULTURAL COMMODITIES IN AFRICA, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2019



Source: ReSAKSS, based on FAO (2021).

rate of the API increased over time, indicating accelerating production growth, before slowing slightly in the 2014–2019 period. Trends in the API growth rate were similar among the various subgroupings despite some differences; central Africa consistently had the highest API growth among the geographic regions. During 2014–2019, the API growth rate was highest for countries with less favorable agriculture conditions at 5.3 percent and lowest for upper-middle-income countries at 0.4 percent.

Agricultural productivity growth benefits smallholder farmers in terms of improved incomes, employment, and livelihoods. It also helps consumers by reducing prices and increasing food availability. Therefore, productivity growth plays a critical role in improving food security and contributing to poverty alleviation efforts. *Agricultural labor productivity*, measured by agriculture value added per agricultural worker, declined for Africa as a whole during 2003–2008 at an annual average of 1.1 percent before rebounding to 2.5 percent growth in 2008–2014 (Figure 14.9). However, the growth rate slowed to 1.1 percent during 2014–2019. Between 2008 and 2019, consistently high and increasing labor productivity was recorded in northern Africa, while productivity fluctuated for many of the other country groupings (Table L2.1.3).

Studies show that agricultural growth in Africa south of the Sahara is mainly a result of area expansion and cropping system intensification rather than productivity improvement (OECD/FAO 2016). Despite this general trend, the recent performance shows that agricultural land productivity, measured by agriculture value added per hectare of arable land, recorded notable growth for Africa as a whole, increasing by an annual average of 3.8 percent during 2014–2019 (Figure 14.9). A similar trend is also observed among the different country groupings, indicating the presence of consistent land productivity growth since 2014.

Agricultural productivity growth notably increased during 2020, with land and labor productivity rising by 9.9 percent and 5.3 percent, respectively, between 2019 and 2020 for the continent as a whole. This strong productivity growth is reflected in the positive and robust agricultural value added growth seen in many countries (Figure 14.8).

The gross production value is a monetary measure of production. The average gross production value in 2014–2016 constant prices shows that cassava, yams, maize, cattle meat, and cow's milk are the five major agricultural products for Africa during the CAADP period.[9] Except for cow's milk, growth in yields of these major products has declined from average rates during the 2003–2008 period (Tables L2.1.5A, L2.1.5B, L2.1.5C, L2.1.5D, L2.1.5E; Figure 14.10). For cassava, yams, and cattle meat, negative yield growth, indicating absolute declines in yield, was recorded during 2008–2014; for yams, the negative yield

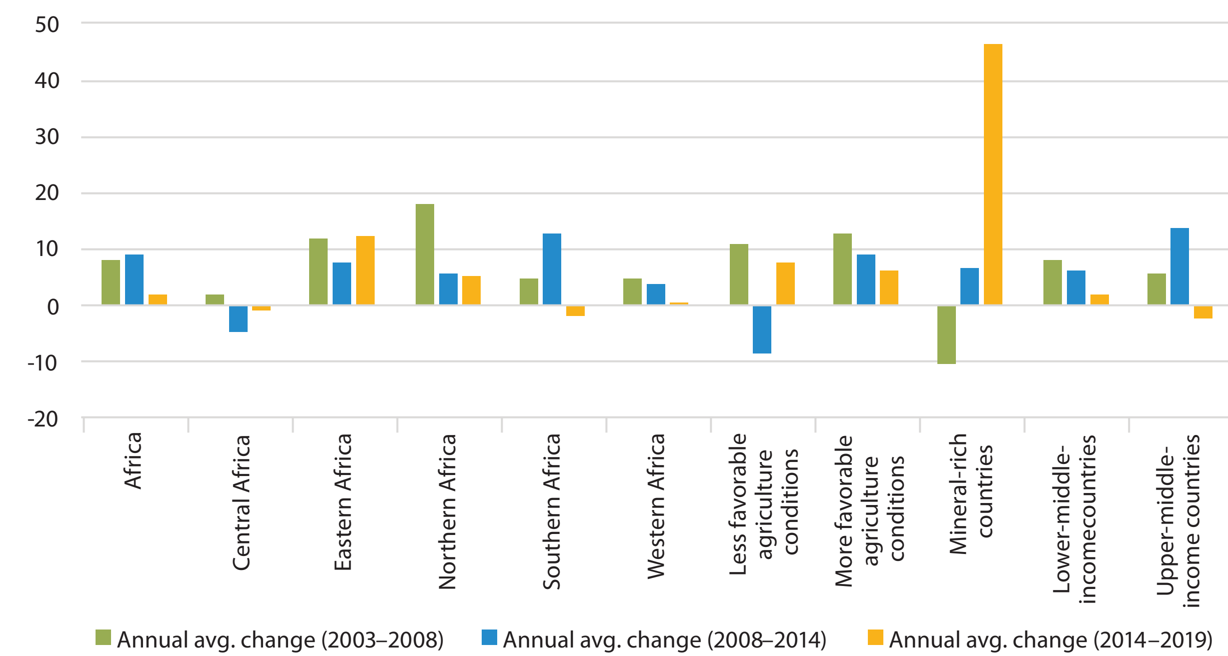
9 Data on gross production values during 2003–2019 are from FAO (2021).

growth persisted throughout 2014–2019 albeit at a slower rate. Even though growth in maize yield remained positive throughout the entire CAADP period, its rate has decelerated since the 2003–2008 period. Figure 14.10 also shows that growth in milk yield remained consistently positive since 2008.

Intra-African Agricultural Trade

Africa's annual food imports reached an average of $80 billion in the 2015–2017 period, having doubled within a decade (FAO and AUC 2021). Africa imports more than 80 percent of its food demand from outside of the continent, with spending amounting to approximately $35 billion (Akiwumi 2020). Increasing intra-African agricultural trade would permit a larger share of Africa's food demand to be met by producers within the continent, providing benefits that include job creation and improved incomes. In this regard, the 2014 Malabo Declaration includes a commitment to triple intra-African trade in agricultural commodities and services by 2025 (AUC 2014). Between 2015 and 2019, intra-African agricultural exports grew by only 10.5 percent.[10] Analysis from the 2021 Africa Agriculture Trade Monitor (AATM) shows that intra-African trade in processed agricultural products is growing faster than trade in raw materials, accounting for nearly half of intra-African agricultural trade by 2019. Efforts to boost regional trade should emphasize the acceleration of trade in processed products (Goundan and Tadesse 2021).

FIGURE 14.11—INTRA-AFRICAN AGRICULTURAL EXPORTS, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2019



Source: ReSAKSS, based on UNCTAD (2021) and World Bank (2021).

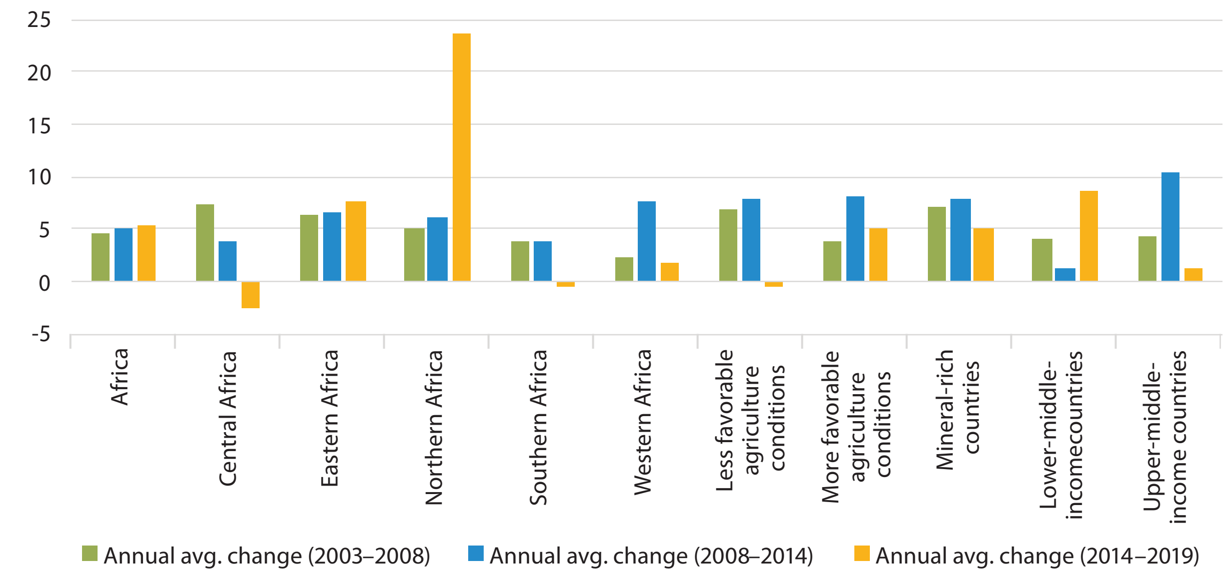
However, the COVID-19 pandemic has severely obstructed intra-African trade. Movement restrictions, border closures, and other measures put in place to mitigate the spread of the disease also had the effect of disrupting food supply chains and impeding the movement of goods both within countries and across borders. Findings by Yade and colleagues in this volume demonstrate the large staple food price swings that occurred in the early months of the pandemic following movement restrictions that disrupted both international trade and domestic transport of goods. Complete data on intra-African trade in 2020 are not yet available, but several studies show large negative impacts on cross-border trade, particularly informal trade, an important income source for many households. For example, data collected at three border posts in Uganda suggest that formal trade declined by 16.4 percent between 2019 and 2020, while informal

10 It should be noted that ReSAKSS data on intra-African trade, which are based on data from the United Nations Conference on Trade and Development (UNCTAD), concern agricultural goods, while the Malabo Declaration intra-African trade commitment refers to trade agricultural services as well as goods. Tracking trade in agricultural services remains a major challenge, and defining methodologies to measure services trade has been identified as a priority by the AUC, AUDA-NEPAD, and technical partners supporting the BR process, including ReSAKSS (Fofana 2021).

trade fell by 77.6 percent (Bouët, Laborde, and Seck 2021). Similarly, informal maize trade measured at select borders in 11 East African countries was 58 percent lower in the second quarter of 2020 than the five-year second quarter average (FSNWG 2020). The pandemic also delayed the launch of trading under the African Continental Free Trade Area (AfCFTA) agreement by six months until January 1, 2021 and caused the postponement of other AfCFTA activities and events (Iroulo 2020). Disruptions in supply chains and trade resulting from the pandemic have highlighted the need for countries to ensure that health-related restrictions do not further impede food trade (FAO 2020).

For Africa as a whole, *intra-African agricultural exports* nearly doubled from an annual average of \$7.9 billion during 2003–2008 to \$15.3 billion in 2014–2019 (Table L2.2.1A). For the continent as a whole, growth in intra-African agricultural exports has decelerated, increasing at an annual average of 9 percent during 2008–2014 but slowing to 2.1 percent in 2014–2019 (Figure 14.11). During 2014–2019, export growth was highest for mineral-rich countries, with annual average increases of more than 40 percent; however, this country group accounts for a very small share of intra-African agricultural trade. Among the geographic regions, eastern Africa experienced the largest increase in intra-African agricultural exports of 12.4 percent during the 2014–2019 period; exports declined slightly in central and southern Africa. For Africa as a whole, the value of *intra-African agricultural imports* increased from an annual average of \$8.2 billion during 2003–2008 to \$15.1 billion in 2014–2019 (Table L2.2.1B). Annual growth in intra-African agricultural imports for the continent as a whole remained around 5 percent on average during the 2003–2008, 2008–2014, and 2014–2019 periods (Figure 14.12). Over the 2014–2019 period, northern Africa saw rapid increases in imports of more than 20 percent per year on average, while imports declined slightly in central and southern Africa. It is important to note that the majority of African countries have already ratified the AfCFTA agreement (Tralac 2021). AfCFTA implementation is expected to expand intra-African trade by lowering barriers to the free movement of goods and services, thus enhancing the benefits of trade in terms of incomes, employment, and food security.

FIGURE 14.12—INTRA-AFRICAN AGRICULTURAL IMPORTS, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2019



Source: ReSAKSS, based on UNCTAD (2021) and World Bank (2021).

Resilience of Livelihoods and Management of Risks

The existence of food reserves, food insecurity response programs, and early warning systems is a key indicator for assessing the resilience of livelihoods and production systems to climate variability as well as for managing risks associated with the agricultural sector. As of September 2020, 42 countries had food reserves, conducted local purchases of food for relief programs, had early warning systems, and were implementing school feeding programs (Table L3(b)). It is important to note that resilience-enhancing investments and interventions extend beyond those retained as indicators in the CAADP Results Framework. The BR process has highlighted the need to clarify what "building the resilience of production systems" encompasses in order to ensure that it includes areas such as irrigation, soil conservation and improved soil fertility, agroforestry, drought-resistant crop varieties, and other technologies and practices that can boost resilience and sustainably increase productive capacity.

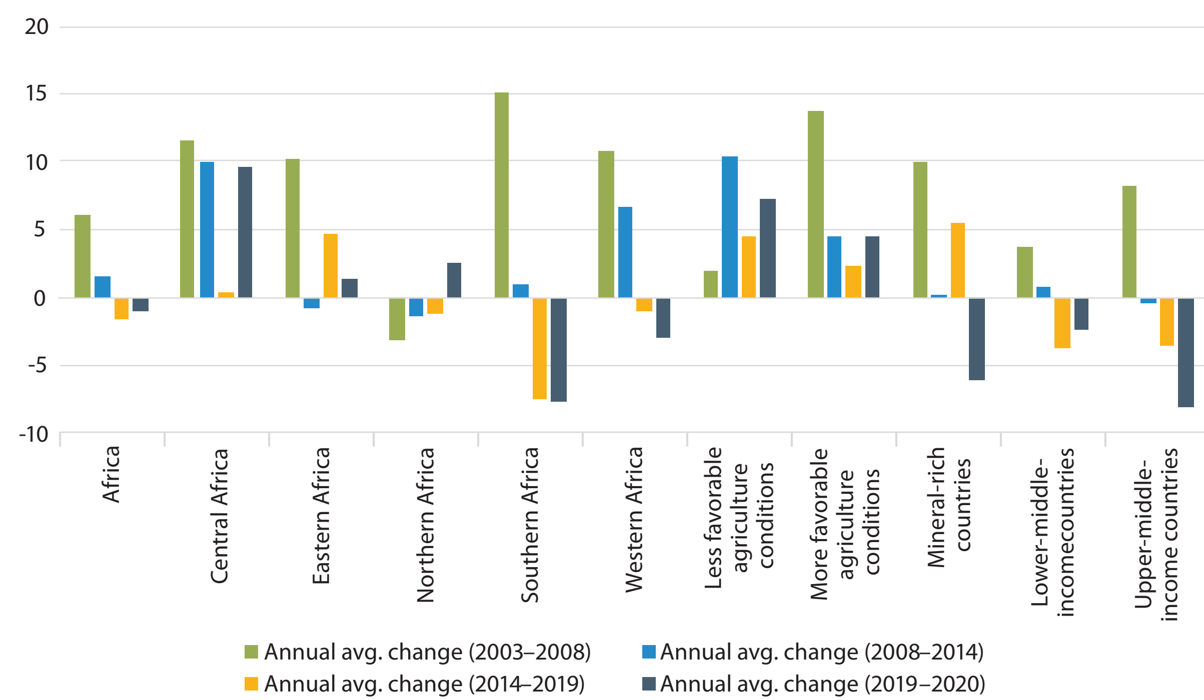
CAADP Results Framework Level 3 Indicators: Strengthening Systemic Capacity to Deliver Results

Capacities for Policy Design and Implementation

Progress in the implementation of actions intended to strengthen systemic capacity for agriculture and food-security policy planning and implementation is presented in Table L3(b). As of September 2021, 42 countries had drafted or formulated new or revised second-generation NAIPs through inclusive and participatory processes; 28 had inclusive institutionalized mechanisms for mutual accountability and peer review (mainly JSRs); 36 were implementing evidence-based policies; 31 had functional multisectoral and multistakeholder coordination bodies—mainly agricultural sector working groups; and 22 had successfully undertaken agriculture-related public-private partnerships to boost specific agricultural value chains.

As highlighted in JSR assessments carried out by ReSAKSS,[11] processes in many countries can be improved in terms of inclusivity and comprehensiveness, but are already strengthening accountability standards, improving coordination, and providing opportunities for a broader group of agricultural sector stakeholders to participate in policy formulation and evaluation (Ulimwengu et al. 2020). In addition, Strategic Analysis and Knowledge Support System (SAKSS) platforms, which help countries meet their specific data, analytical, and capacity needs, have been established in 14 countries. Ensuring the sustainability and performance of SAKSS platforms requires local ownership, engagement with an inclusive group

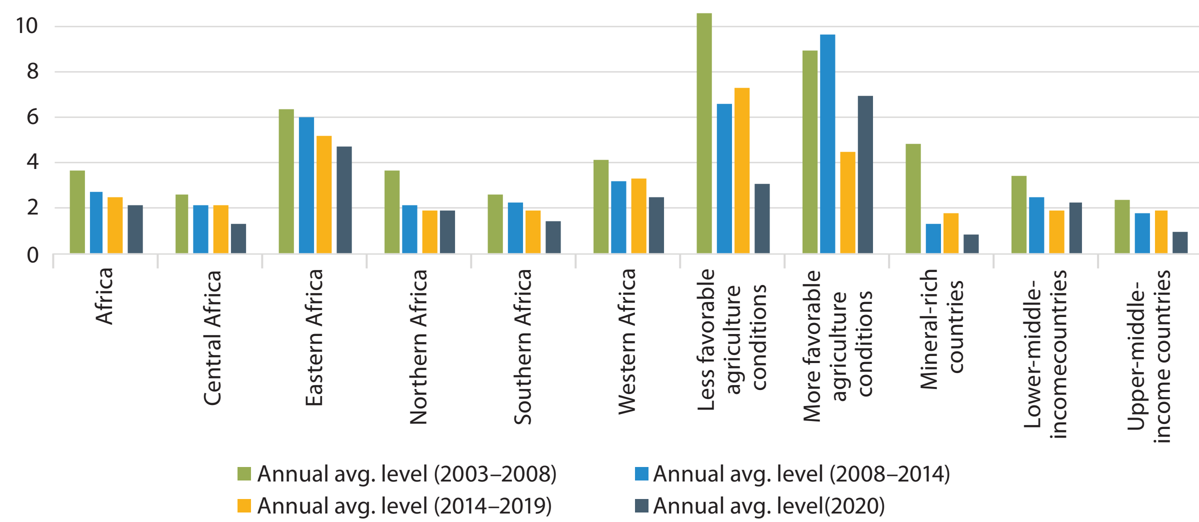
FIGURE 14.13—GOVERNMENT AGRICULTURE EXPENDITURE, ANNUAL AVERAGE PERCENTAGE CHANGE, 2003–2020



Source: ReSAKSS, based on IFPRI (2019), World Bank (2021), and national government sources.

11 JSR assessment reports are available at https://www.resakss.org/publications/aw?key=&type=Agriculture+Joint+Sector+Review+%28JSR%29+Assessment+Report&country=0&topic=0.

FIGURE 14.14—SHARE OF GOVERNMENT AGRICULTURE EXPENDITURE IN TOTAL GOVERNMENT EXPENDITURE (PERCENT), 2003–2020



Source: ReSAKSS, based on IFPRI (2019), World Bank (2021), and national government sources.

of local partners, links with policy agenda-setters, and robust financial support from multiple sources (Johnson and Flaherty 2011).

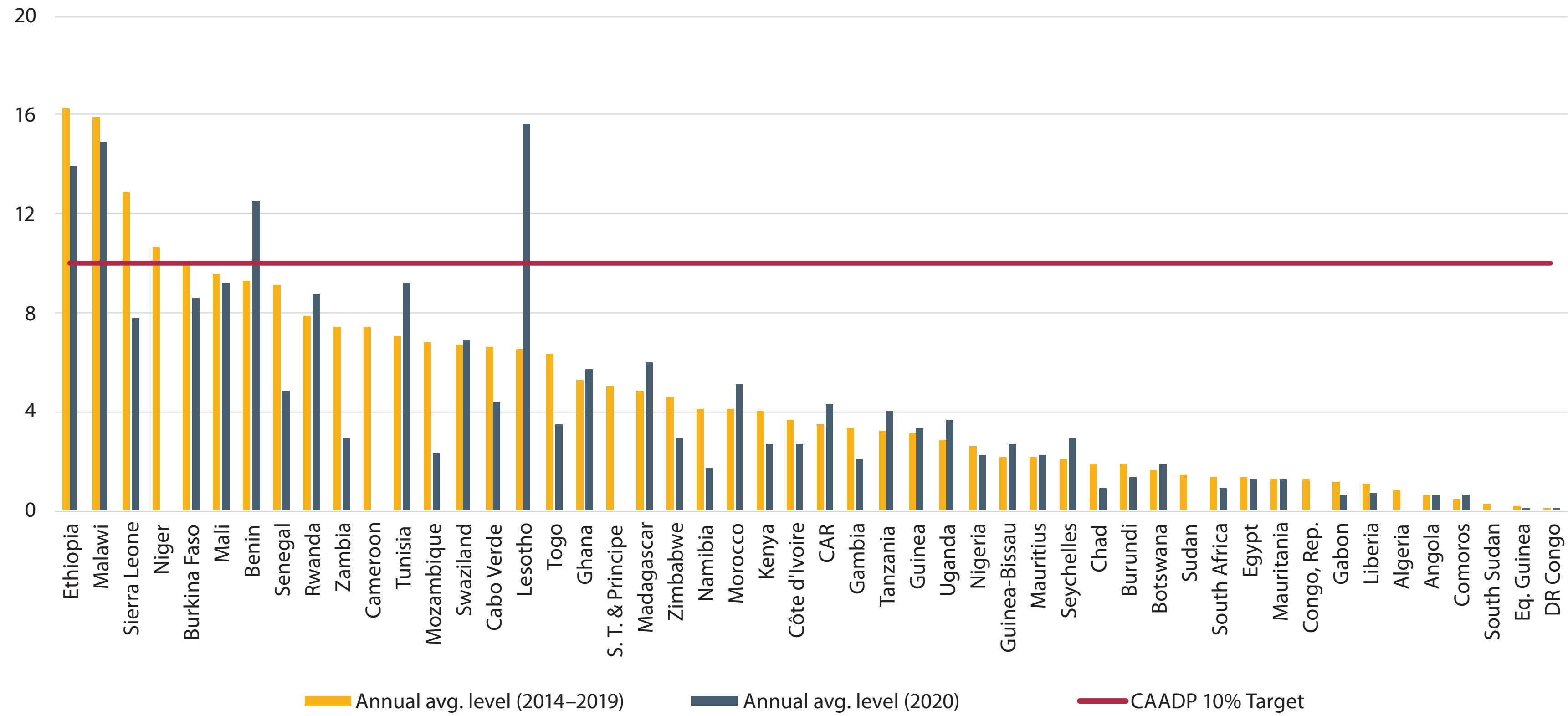
Government Agriculture Expenditure

Government expenditure is one of the key tools that African governments can employ to transform the agricultural sector, reduce hunger and poverty, and promote economic growth. As agriculture is the mainstay of most African economies, increased spending in the sector can accelerate economic growth and transformation on the continent. Yet the growth in Africa's government agriculture expenditure (GAE) has been in decline in recent years. Although GAE experienced strong growth following the launch of CAADP when it rose at an annual average of 6.1 percent from 2003 to 2008 for Africa as a whole, growth has since decelerated—GAE grew at 1.6 percent from 2008 to 2014 but contracted 1.5 percent from 2014 to 2019 and 1 percent from 2019 to 2020 (Figure 14.13 and Table L3.5.1). For Africa as a whole, the declining growth trend continued during the COVID-19 pandemic when GAE marginally fell from an annual average of $16.1 billion in the 2014–2019 period to $15.5 billion in 2020.

In addition to Africa as a whole, the majority of the other country groupings also experienced negative growth in GAE, particularly during 2014–2019 and 2019–2020 (Figure 14.13 and Table L3.5.1). A few country groupings experienced positive growth in GAE during 2014–2019, but only mineral-rich countries and EAC recorded annual average growth rates of at least 5 percent during this period (Figure 14.13). A similar pattern occurred in 2019–2020, when most country groups saw slower or negative growth in GAE. Only three country groups—central Africa, countries with less favorable agriculture conditions, and EAC—recorded annual average growth rates in GAE of at least 5 percent in 2019–2020 (Figure 14.13). While the rate of growth in GAE has slowed, the average level of expenditures has generally increased over time. For example, Africa's GAE increased from an annual average of $13.2 billion during 2003–2008 to $16.1 billion during 2014–2019 and fell slightly to $15.5 billion in 2020.

A key provision of the 2003 Maputo Declaration and 2014 Malabo Declaration is the commitment by African leaders to allocate at least 10 percent of national budgets to the agricultural sector. For Africa as a whole and several country groupings, agriculture expenditure as a share of total government expenditure has not only remained below the 10 percent CAADP target, but it has also been on a declining trend during the post-CAADP period (Table L3.5.2 and Figure 14.14). For Africa as a whole, the annual average share fell from 3.6 percent during 2003–2008 to 2.7 percent in 2008–2014 and down to 2.5 percent in 2014–2019. In 2020, the share dropped further to 2.1 percent. While no country grouping met the CAADP budget share target of 10 percent in 2008–2014, 2014–2019, and 2020, countries with more favorable agriculture

FIGURE 14.15—SHARE OF GOVERNMENT AGRICULTURE EXPENDITURE IN TOTAL GOVERNMENT EXPENDITURE (PERCENT), 2014–2019 AND 2020



Source: ReSAKSS, based on IFPRI (2019), World Bank (2021), and national sources.

Note: 2020 data missing for Algeria, Cameroon, Niger, Sao Tome and Principle, Republic of Congo, South Sudan, and Sudan.

conditions achieved an agriculture expenditure share of at least 5 percent in 2020. Country groupings that achieved at least a 5 percent agriculture expenditure share during 2014–2019 include eastern Africa (5.2 percent), countries with less favorable agriculture conditions (7.2 percent), IGAD (5.9 percent), and the group of countries advanced in implementing CAADP (CL4) (5.5 percent) (Table L3.5.2 and Figure 14.14). The groups of countries that launched the CAADP process early (CC1 and CC2), are most advanced in implementing CAADP (CL4), and those that have completed both first- and second-generation NAIPs (N11) also showed higher agricultural expenditure shares than the groups of countries that joined CAADP later and have not advanced in CAADP implementation.

Although no country grouping met the CAADP 10 percent budget target, several countries met the target during 2014–2019 and even in 2020. Figure 14.15 shows that five countries met or surpassed the 10 percent target in 2014–2019 (Ethiopia, Malawi, Sierra Leone, Niger, and Burkina Faso), while four countries met or surpassed the target in 2020 (Ethiopia, Malawi, Benin, and Lesotho). Three countries—Mali, Benin, and Senegal—came close to meeting the

10 percent target in 2014–2019, while Mali and Tunisia also came close in 2020 with agriculture budget shares of more than 9 percent. While raising the level of expenditure is important, African countries also need to pay close attention to the quality and composition of the expenditure in order to ensure its effectiveness in meeting agricultural transformation objectives (Goyal and Nash 2016; Pernechele et al. 2021). Moreover, in light of the COVID-19 pandemic and the importance of the agricultural sector, governments need to prioritize quality investments in agriculture, which remains a primary source of income and employment in many African countries.

The *share of GAE in agricultural GDP* provides a good measure of the priority a government places on agriculture expenditure relative to the size of its agricultural sector. While GAE as a share of agricultural GDP increased during 2003–2008 following the launch of CAADP for Africa as a whole and most country groupings, it has since declined and remained rather low. For Africa as a whole, the share declined from an average annual level of 5.8 percent during 2003–2008 to 4.6 percent in 2014–2019, before further declining to 4 percent in 2020 (Table L3.5.3). Thus, less and less government agriculture spending has been allocated relative to the size of the agricultural sector. In contrast, the share has remained relatively higher (above 10 percent) in southern Africa and upper-middle-income countries, reflecting, on average, the relatively smaller share of the agricultural sector in the economies of these country groupings (Table L3.5.3).

Conclusion

This chapter discusses Africa's performance on 27 CAADP RF indicators across different geographic and economic groupings, comparing trends during different CAADP subperiods. The chapter assesses Africa's performance prior to the COVID-19 pandemic while also highlighting changes to the indicators during the pandemic in 2020. Prior to the pandemic, during 2014–2019, Africa faced declining GDP per capita growth, a rising prevalence of undernourishment, high proportion of child stunting, increasing number of poor people, and declining share of and growth in GAE. The COVID-19 pandemic has aggravated Africa's performance in these key indicators and further threatened progress toward meeting the commitments of the 2014 Malabo Declaration.

In recent years, before the onset of the COVID-19 pandemic, Africa's economic growth had been decelerating for several reasons, including the economic slowdown and lower commodity prices recorded at the global level. The pandemic worsened these challenges and resulted in an economic recession for the first time in more than two decades. For example, Africa's GDP per capita in 2020 regressed to the amount recorded a decade earlier. Africa's employment rate had been decreasing slightly prior to the pandemic, but employment fell more sharply in 2020, with the pandemic estimated to have cost the continent millions of jobs. Household consumption expenditure per capita also contracted in 2020, reflecting reduced incomes that resulted from the crisis.

For food and nutrition security, similar challenges have also been observed in recent periods. The prevalence of undernourishment increased by an annual average of 1.1 percent during 2014–2019; in 2020, the proportion is estimated to have expanded to 21 percent, with the number of undernourished people in Africa increasing by 46.2 million (FAO et al. 2021). Despite progress in reducing the prevalence of child stunting, underweight, and wasting, levels of child malnutrition remained high prior to the pandemic, and the absolute number of stunted children increased since 2000 (UNICEF et al. 2021). The number of malnourished children likely increased further during 2020 and will potentially continue growing in subsequent years. Several factors contribute to the pandemic's negative impact on nutrition status, including significant reduction in household incomes, interruption of services, and fluctuations in the availability and affordability of healthy diets. These factors will significantly affect Africa's progress toward the Malabo Declaration targets of reducing stunting to 10 percent and underweight to 5 percent by 2025.

Studies show that for the first time in more than two decades, the poverty headcount ratio at $1.90 a day is expected to have expanded globally in 2020. Africa already faced challenges in translating economic growth into poverty reduction prior to the COVID-19 crisis: although the prevalence and depth of poverty declined during the CAADP period up until the onset of the pandemic, the absolute number of poor people was already increasing. Progress toward the Malabo Declaration goal of halving 2015 poverty levels by 2025 has been further threatened by the pandemic.

The agricultural sector plays a pivotal role in Africa in terms of employment, incomes, trade, and food security. Growth in agricultural labor and land productivity—essential for increasing incomes and ensuring adequate food for a growing population—has been positive during most of the CAADP period. Agricultural production and productivity also continued to increase in 2020, in contrast to many other economic sectors. The continent, however, has not been able to achieve the CAADP and Malabo Declaration target of 6 percent annual growth in agriculture value added throughout the CAADP period. Furthermore, for Africa as a whole, GAE as a share of total government expenditure declined from 2.5 percent during 2014–2019 to 2.1 percent in 2020. Only four countries (Ethiopia, Malawi, Benin, and Lesotho) met or surpassed the CAADP and Malabo Declaration budget share target of allocating 10 percent of the national budget to agriculture in 2020. This suggests the need to not only raise the level of agricultural investments but to also prioritize quality investments to ensure the effectiveness of the expenditures.

Given the severe impacts of the COVID-19 pandemic and the existing challenges in sustaining progress toward development goals, investment in programs and initiatives is urgently needed to reduce vulnerabilities exacerbated by the pandemic. These necessary initiatives include improvements to the coverage of social protection programs, which are essential to preserving households' wellbeing during times of crisis (see chapters 7 and 8 in this volume); expansion of irrigation to reduce climate- and weather-related risks; and other investments in resilience and productive capacity. In particular, governments should increase investments in agricultural productivity, including by adequately funding agricultural research and development.

Although intra-African agricultural exports consistently increased during the CAADP period, they grew at a slower rate of 2.1 percent in the more recent 2014–2019 period. The slower growth may not bode well for achieving the 2014 Malabo Declaration goal of tripling intra-African trade in agricultural commodities and services by 2025. Thus, policies to promote cross-border trade are important to ensure consumers' access to food and producers' access to inputs and broader markets. In addition to trade facilitation efforts, these policies should include initiatives to improve the quality and completeness of trade data, including informal trade, in order to allow countries to better monitor the effects of crises on trade and identify means to mitigate negative impacts (Bouët, Tadesse, and Zaki 2021). The launch of trading under the AfCFTA agreement on January 1, 2021 was an important positive development during the COVID-19 period. AfCFTA implementation should be accelerated in order to ensure that its potential benefits—in terms of increased incomes and food security—contribute to Africa's recovery from the effects of the pandemic.

CHAPTER 15

ATOR 2021: Summary and Conclusions

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and Julia Collins

The 2021 Annual Trends and Outlook Report (ATOR) includes three major sections in addition to the chapter tracking progress toward Comprehensive Africa Agriculture Development Programme (CAADP) goals. First, the report assesses the impact of COVID-19 on African economies with a focus on food systems from access to inputs to household consumption. Second, it reviews policy interventions to stop the spread of the pandemic and contain its negative impact on food systems across the continent. Third, the report highlights innovations in measurement needed to better understand the effects of the pandemic and the factors contributing to resilience.

Overall, the 2021 ATOR presents a body of research-based evidence to understand the pandemic's effects and support the design of post-COVID-19 recovery strategies, and it offers insights on how progress toward such recovery has thus far been measured. The accumulation of evidence, combined with guidance on how additional evidence might be gathered, provides a foundation of knowledge and analytical procedures to support efforts to strengthen the resilience of African food systems. Below, we present the summary of findings and methodologies. Following the structure of the ATOR 2021 report, the summary is organized in terms of reported impacts, strategic responses, measurement issues, and progress toward the CAADP goals.

Impacts of COVID-19 on African Countries

Although significant disruption was observed across the continent until mid-2020, overall trade in the agricultural sector remained resilient following the onset of the pandemic. Trade disruption was limited for staple foods compared to other commodities such as beverage, fishery, and non-food products, including cotton, cut flowers, and tobacco (chapter two). The findings in chapter four also indicate that the COVID-19-induced global trade shock generally had moderate impacts on Africa's food systems, although there was notable variation among countries. African countries with well-diversified export bases tended to be more resilient to external shocks. Chapter three's findings on the impact of COVID-19 on staple food prices confirm that location matters. After restrictions were introduced during the pandemic, prices of staple foods increased in deficit areas of western Africa, while prices declined in both surplus and deficit areas of eastern and southern Africa.

Unlike the limited impact on agricultural trade, COVID-19 has significantly influenced hunger and food insecurity across the continent. As reported in chapter two, a total of 46 million additional people in the continent were affected by hunger in 2020, exacerbating already high levels of hunger and food insecurity. In addition, the pandemic led more than half of the continent's population (close to 800 million people) to become either moderately or severely food insecure. Chapter five highlights the correlation between food security and vulnerability. This relationship suggests the need for interventions that target the most vulnerable households in order to enhance their resilience capacity.

Strategic Responses of African Countries to COVID-19

In response to the COVID-19 pandemic, African governments took several policy response measures to contain the spread of the virus and support economic activity. There is a great deal of heterogeneity both in the type of measures followed and the speed with which countries adopted them (Hale et al. 2020). As discussed in chapter 6, sector-specific in-kind transfers were the main policy response, though the intensity and type varied between countries. However, the effectiveness in implementing the policy responses as well as the use of innovative approaches were minimal.

The findings in chapter 7 suggest that already existing social transfer programs can better respond to COVID-19-induced shocks than new ad hoc initiatives. However, the programs need to expand to urban areas to aid the vulnerable poor disproportionately affected by the pandemic. To enhance the sustainability of social protection programs, domestic resource mobilization efforts also need to be strengthened. This is important because external funding to finance social protection programs tends to dematerialize during global crises such as the COVID-19 pandemic. Chapter 8 shows that the actions taken by governments in Africa to contain the pandemic not only exacerbated existing challenges but also exposed new sources of vulnerability. The social protection instruments applied by countries in Africa south of the Sahara in response to COVID-19 were limited in scope, scale, and speed. Moreover, there is a need to recognize the role of social protection interventions beyond that of a safety net and to improve the integration of social protection programs into overall development frameworks.

Measurement Issues

The challenge posed by COVID-19 is enormous—the world has not faced a test of such scale since the Second World War (GCA and AAI 2020). Responding to this challenge will require methodological tools to better understand impacts and identify solutions. Chapters 9–13 of this ATOR address measurement issues to help improve evidence-based policymaking processes. Access to accurate and timely food crop production data is paramount, as it provides information that can better prepare a country to respond to shocks. Nonetheless, for several reasons—including human capital, finances, and other limitations—the sustainable collection of accurate and timely data remains a challenge for most African countries. Thus, there is a need to pursue remote sensing data and machine learning techniques as viable data generation and processing options (chapter 9). Digital data must be scaled in use and effectiveness to fulfill a just transition to more regenerative agricultural practices that advance both food production and timely distribution to meet local and cross-border trade needs, as well as to minimize waste. As we head into the decade of ecosystem restoration, how Africa feeds itself must align with how countries meet their National Determined Contributions to meet Paris Agreement targets and contribute to local adaptation and mitigation strategies.

The pandemic has tested the ability of socioeconomic and health systems to withstand major shocks and adapt accordingly (Ayadi 202o). In consideration of the overarching impact of the global health shock brought on by COVID-19, chapter 10 proposes including a basic health-systems capacity index and an economic country-level resilience capacities index to improve efforts to track the resilience component of the Malabo Declaration goals. The chapter's findings confirm that indicators related to health system capacities and the macroeconomic effects of a global health shock can be combined to provide useful information to measure progress on the Malabo commitments; these results provide initial evidence of how resilience to COVID-19 may be modelled. In chapter 11, the authors argue that integrating micro and macro scales into resilience analysis helps explain why some countries are more resilient than others. The results also identify which countries have a weaker capacity to react and are thus likely to suffer the greatest toll.

As indicated in chapter 12, disruptions to food systems can negatively influence the availability of and access to nutritious food, leading to unhealthy diets and health risks. Adequate measurements of dietary patterns are needed to monitor and manage changes in a population's dietary behavior. Although posteriori and priori methods of dietary pattern analysis have been successful in measuring population-wide dietary patterns, the COVID-19 pandemic has necessitated the inclusion of other factors, such as food access, dietary diversity, physical activity, anxiety, and body image perception, to account for related impacts. Chapter 13 presents a methodological approach to develop consumer- focused indicators for assessing the performance of a value chain and its correlation to food security. Different analytical dimensions are included to ensure that value chains focus on both consumers and food security. The framework captures consumers' preferences, categorizes and links them to the pillars of food security, and translates those preferences into measurable value chain actions.

Progress Toward CAADP Goals

Africa's performance in key CAADP indicators is presented in chapter 14. The findings show that Africa as a whole has made progress toward achieving CAADP goals, although the rate of progress on several indicators, including economic growth, has slowed in recent years. The COVID-19 pandemic has further affected the performance of many indicators. In 2020, Africa recorded an economic recession for the first time in more than two decades and the continent's GDP per capita regressed to the level recorded a decade ago. Millions of jobs have also been lost as a result of the pandemic. The significant reduction in household incomes, interruption of services, and fluctuations in the availability and affordability of healthy diets played a notable role in generating similar negative trends for nutrition. After increasing in recent years, the prevalence of undernourishment further expanded in 2020. Prior to 2020, meaningful progress was made to consistently reduce child malnutrition, although the level remained high. The pandemic, however, is expected to reverse this progress for years to come.

Conclusion

Building greater resilience will require both the deployment of new measurement methodologies and the adoption of more ecologically viable agricultural production practices. Amid accelerating agricultural contributions to greenhouse gas emissions, the continent faces the dilemma of how to feed a population set to double by 2050 while suffering continued degradation of soils and biodiversity loss. The effects of climate change present an additional set of challenges in need of an aggressive response. Combined remote sensing data and machine learning techniques that improve the ex ante estimation of crop production should be further developed to integrate ecological practices that maximize organic soil carbon sequestration and capacity for water retention. Increasing the availability, accuracy, and timeliness of agricultural data would not only help to anticipate and mitigate food crises after shocks, but would also provide valuable information to inform day-to-day policy- and decision-making on sustainable practices that can contribute to multiple sustainable development goals while limiting biodiversity loss.

Analytical methodologies to estimate the resilience of households, communities, and countries to shocks should transcend threats related to climate change. The COVID-19 pandemic has highlighted the need to consider shocks and stressors associated with health emergencies and the lack of health infrastructure. As this volume has underlined, making food systems more resilient will require more complex forms of analysis. To be productive, analyses of food systems should consider the multidimensional nature of the challenges faced across the continent. Such research might, for example, involve more precisely mapping the interdependence of healthy soil systems, exploring innovations in biodiversity management, or examining the roles and needs for capacity building in agricultural workforces. To accumulate evidence, it will be crucial to disaggregate data with respect to age, gender, and land ownership. To develop strategies that are sensitive to spatial variation, the integration of satellite and remote sensing data will be crucial. The 2021 ATOR chapters have demonstrated that paying attention to supply and value chains, logistics, and multi-dimensional resilience must be core features of future research, both for strategic planning and for data management that drives CAADP activities. Work of this kind will require a transdisciplinary, cross-country perspective to better integrate the management of social, natural, and human capital.

With the overall goal of supporting resilient food systems, the ambition of this report is to identify evidence-based strategies that ensure stable food and nutrition security and support economic growth across the continent. The range of shocks and stressors experienced in Africa have long interfered with the continent's ability to achieve this goal. The impact of COVID-19 has introduced another set of pressures that hinder plans to achieve a "prosperous Africa based on inclusive and sustainable economic growth and development" (African Union 2015, 2). Taken as a whole, the evidence and ideas presented in the 2021 ATOR volume provide a useful starting point to plan interventions and specify data strategies. In closing, the editors of this volume offer three recommendations:

1. **Enhance social protection programs.** While African governments almost uniformly scaled up social protection programs in response to the pandemic, evidence suggests that coverage did not extend to large shares of the poor and vulnerable. To enhance the role of social protection in both responding to crises and contributing to longer-term development, governments should improve targeting and coverage by reviewing the design and implementation of programs. Adequately funding social protection programs will require increasing the mobilization of domestic resources. Social protection should be reconceptualized to play an important role in economic development, beyond serving as a safety net in crisis situations.

2. **Ensure the functioning of markets.** Movement restrictions, border closures, and other impediments to domestic and cross-border trade caused sharp changes in staple food prices during the first months of the pandemic. Both price increases and declines contribute to uncertainty and cause harm to different groups of food system actors. Throughout the remainder of the pandemic and when faced with future shocks, governments must design containment policies carefully to ensure that they do not impede the movement of food commodities and the functioning of markets. Trade policies should be coordinated within regions, and impacts of policies should be carefully monitored.

3. **Develop a more comprehensive indicator framework.** The growing demand for evidence-based solutions underscores the need for a well-developed indicator framework, a need that has been amplified by the multidimensional effects of COVID-19. While the CAADP Results Framework provides a blueprint for the kinds of indicators needed to track agricultural growth and monitor welfare, that framework was developed before the unprecedented effects of a global health shock had been experienced. The effects of COVID-19 highlight the need to include indicators related to health systems, vulnerability to health shocks, and

macro-level effects (such as food and commodity prices, supply chains, and trade) in our data systems.

These three recommendations represent only a partial list of actions that might be taken, but we believe that investing in social protection programs, understanding market dynamics, and developing a more comprehensive data strategy are important first steps.

ANNEXES

Core CAADP Monitoring & Evaluation and Supplementary Indicators

Annexes:
Core CAADP Monitoring & Evaluation and Supplementary Indicators

This section presents data and trends across three levels of the CAADP Results Framework as well as supplementary data and trends.[1]

The data are presented at the aggregate level for the entire continent (Africa); the five geographic regions of the African Union (central, eastern, northern, southern, and western); eight Regional Economic Communities (CEN-SAD, COMESA, EAC, ECCAS, ECOWAS, IGAD, SADC, and UMA);[2] five economic categories defined by agricultural production potential, nonagricultural sources of growth, and income level; nine CAADP groups representing either the period during which countries signed a CAADP compact or the level of CAADP implementation reached by countries by the end of 2015; and three levels of progress for countries in formulating national agriculture investment plans (NAIPs). Data for individual countries and regional groupings are available at www.resakss.org.

Technical Notes to Annex Tables

1. To control for year-to-year fluctuations, moving averages are used. Therefore, the values under the column "2003" are averages over the years 2002 to 2004 and the values under the column "2019" are averages over the years 2018 to 2019. Data reported in the column "2020" are an exception, and represent values for the year 2020 alone. This was done to account for the fact that 2020 is an outlier with respect to several of the indicators, with large changes in values compared to previous years.
2. Annual average level and annual average change for 2014–2019 include data from 2014 up to either 2019 or the most recent prior year that is measured and available.
3. Annual average level is the simple average over the years shown, inclusive of the years shown.
4. Annual average change for all indicators is annual average percent change, from the beginning to the end years, shown by fitting an exponential growth function to the data points (that is, "LOGEST" function in Excel).
5. For indicators for which there are only a few measured data points over the years specified in the range (such as poverty, which is measured once every three to five years or so), a straight-line method was used to obtain missing values for the individual years between any two measured data points. Otherwise, estimated annual average change based on the measured values is used to obtain missing values either preceding or following the measured data point. In cases where the

1 Future Annual Trends and Outlook Reports (ATORs) will report on more of the CAADP Results Framework indicators as more data become available.

2 CEN-SAD is the Community of Sahel-Saharan States; COMESA is the Common Market for Eastern and Southern Africa; EAC is the East African Community; ECCAS is the Economic Community of Central African States; ECOWAS is the Economic Community of West African States; IGAD is the Intergovernmental Authority on Development; SADC is the Southern African Development Community; and UMA is the Union du Maghreb Arabe.

missing values could not be interpolated, the data are reported as missing and excluded from the calculations for that time period. Any weights used for these indicators are adjusted to account for the missing data in the series.

6. Values for Africa, the regional aggregations (central, eastern, northern, southern, and western), economic aggregations (less favorable agriculture conditions, more favorable agriculture conditions, mineral-rich countries, lower middle-income countries, and upper middle-income countries), Regional Economic Communities (CEN-SAD, COMESA, EAC, ECCAS, ECOWAS, IGAD, SADC, and UMA), CAADP groups (Compact 2007–2009, Compact 2010–2012, Compact 2013–2015, Compact not yet, Level 0, Level 1, Level 2, Level 3, and Level 4), and NAIP groups (NAIP00, NAIP10, and NAIP11) are calculated by weighted summation. The weights vary by indicator and are based on each country's proportion in the total value of the indicator used for the weighting measured at the respective aggregate level. Each country i's weight in region j (wij) is then multiplied by the country's data point (xi) and then summed for the relevant countries in the region to obtain the regional value (yj) according to: yj = Σi wijxi.

The trend data are organized as follows:

Annex 1
Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development

Annex 2
Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth

Annex 3
Level 3— Strengthening Systemic Capacity to Deliver Results

Annex 4
Distribution of Countries by Geographic Regions, Economic Classification, and Regional Economic Communities

Annex 5
Distribution of Countries by Year of Signing CAADP Compact and Level of CAADP Implementation Reached by End of 2015

Annex 6
Distribution of Countries in Formulating First-Generation Investment Plans (NAIP1.0) and Second-Generation Investment Plans (NAIP2.0) Reached by September of 2021

Annex 7
Supplementary Data Tables

ANNEX 1a: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.1.1

TABLE L1.1.1—GDP PER CAPITA (constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	1,496	1.4	1,604	1,736	3.3	1,932	1.2	2,010	0.2	1,912
Central	755	0.0	789	852	2.7	934	1.5	933	-2.0	863
Eastern	583	1.6	623	695	5.0	838	1.8	958	2.6	992
Northern	2,560	2.5	2,821	3,092	3.6	3,394	0.1	3,519	1.7	3,460
Southern	3,013	1.0	3,166	3,439	3.7	3,763	0.9	3,735	-1.5	3,292
Western	1,137	1.8	1,275	1,384	3.2	1,656	3.2	1,792	-0.4	1,729
Less favorable agriculture conditions	452	1.5	494	537	2.7	599	2.0	645	0.5	635
More favorable agriculture conditions	392	1.8	423	466	4.3	572	3.5	684	3.1	737
Mineral-rich countries	623	0.6	650	723	5.3	847	-0.1	891	0.9	868
Lower-middle-income countries	1,684	2.0	1,852	2,014	3.4	2,346	2.2	2,505	0.1	2,417
Upper-middle-income countries	6,167	1.4	6,630	7,326	4.0	7,764	-0.3	7,576	-0.2	6,748
CEN-SAD	1,423	1.9	1,559	1,702	3.5	1,938	1.3	2,056	0.5	2,023
COMESA	983	1.1	1,019	1,106	3.7	1,230	0.4	1,303	1.6	1,328
EAC	587	1.1	623	687	4.6	825	1.4	923	2.3	971
ECCAS	946	0.9	1,019	1,157	5.4	1,344	1.6	1,330	-2.8	1,188
ECOWAS	1,137	1.8	1,275	1,384	3.2	1,656	3.2	1,792	-0.6	1,729
IGAD	577	1.5	617	694	5.7	853	1.7	976	2.2	1,020
SADC	1,872	0.6	1,938	2,084	3.3	2,253	0.8	2,245	-2.0	2,001
UMA	3,161	2.4	3,515	3,876	3.3	4,131	-0.2	4,207	-0.2	3,855
CAADP Compact 2007-09 (CC1)	891	2.0	1,016	1,120	3.9	1,383	3.6	1,512	-0.3	1,465
CAADP Compact 2010-12 (CC2)	630	0.1	640	682	2.6	776	2.5	891	2.3	923
CAADP Compact 2013-15 (CC3)	1,439	1.8	1,552	1,733	4.9	2,011	1.6	2,035	-1.9	1,818
CAADP Compact not yet (CC0)	3,350	2.0	3,642	3,957	3.2	4,210	0.2	4,393	1.5	4,218
CAADP Level 0 (CL0)	3,350	2.0	3,642	3,957	3.2	4,210	0.2	4,393	0.5	4,218
CAADP Level 1 (CL1)	1,520	1.8	1,638	1,846	5.4	2,162	1.6	2,167	-2.7	1,906
CAADP Level 2 (CL2)	571	-1.1	563	590	1.9	637	1.8	710	1.2	722
CAADP Level 3 (CL3)	555	1.6	595	635	3.0	749	2.5	814	0.6	814
CAADP Level 4 (CL4)	866	1.7	965	1,057	3.6	1,286	3.5	1,436	0.2	1,422
NAIP00 (N00)	2,945	1.8	3,180	3,475	3.7	3,802	0.5	3,844	0.1	3,581
NAIP10 (N10)	697	1.2		814	4.1	943	1.2	1,015	0.8	989
NAIP11 (N11)	867	1.5	743	1,043	3.5	1,259	3.3	1,395	0.4	1,382

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Aggregate value for a group is the sum of real GDP for countries in the group divided by total population of countries in the group.

ANNEX 1b: *Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.1.2*

TABLE L1.1.2—HOUSEHOLD CONSUMPTION EXPENDITURE PER CAPITA (constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	1,065	0.3	1,097	1,129	1.7	1,222	1.1	1,337	0.4	1,285
Central	473	-1.3	465	475	1.2	504	1.3	571	0.4	580
Eastern	668	-1.0	656	690	2.3	675	-1.9	716	2.2	729
Northern	1,567	0.2	1,586	1,621	2.2	1,893	2.9	2,213	2.5	2,345
Southern	2,093	-0.1	2,094	2,189	2.1	2,202	0.0	2,210	-1.4	1,986
Western	735	2.9	862	889	1.4	1,135	5.0	1,365	-0.5	1,228
Less favorable agriculture conditions	383	-0.6	396	401	1.9	444	2.3	494	0.9	498
More favorable agriculture conditions	459	-0.4	463	489	2.6	454	-2.7	461	1.6	497
Mineral-rich countries	518	-0.6	506	547	2.8	635	3.5	738	0.4	644
Lower-middle-income countries	1,098	1.1	1,171	1,199	1.6	1,454	3.8	1,725	0.7	1,685
Upper-middle-income countries	3,666	0.0	3,714	3,908	2.8	4,340	1.7	4,508	-0.1	4,124
CEN-SAD	964	1.4	1,039	1,076	2.1	1,302	4.0	1,532	0.7	1,475
COMESA	923	-0.2	906	933	2.4	924	-1.4	976	1.6	1,011
EAC	577	-1.5	564	582	1.9	596	1.2	652	2.1	695
ECCAS	582	-2.4	545	551	1.2	640	2.7	780	0.1	775
ECOWAS	735	2.9	862	889	1.4	1,135	5.0	1,365	-0.5	1,228
IGAD	797	0.1	800	842	2.1	745	-4.4	758	2.4	781
SADC	1,280	-0.8	1,250	1,297	1.8	1,338	0.6	1,357	-1.3	1,223
UMA	1,697	-1.1	1,671	1,628	0.3	1,754	2.3	2,037	2.1	2,047
CAADP Compact 2007-09 (CC1)	705	3.2	854	884	1.6	1,037	0.9	1,152	-0.5	1,050
CAADP Compact 2010-12 (CC2)	537	-1.0	523	538	1.4	556	1.3	613	1.7	633
CAADP Compact 2013-15 (CC3)	989	-1.3	941	958	1.7	1,104	3.4	1,336	-0.2	1,242
CAADP Compact not yet (CC0)	2,058	0.5	2,111	2,198	2.2	2,425	2.1	2,665	1.3	2,688
CAADP Level 0 (CL0)	2,058	0.5	2,111	2,198	2.2	2,425	2.1	2,665	1.3	2,688
CAADP Level 1 (CL1)	1,046	-1.7	976	994	1.9	1,160	3.7	1,408	-0.4	1,297
CAADP Level 2 (CL2)	457	-0.8	447	457	0.8	464	0.5	513	0.9	487
CAADP Level 3 (CL3)	482	0.9	515	559	3.7	543	0.4	561	-0.2	553
CAADP Level 4 (CL4)	692	1.8	784	805	1.3	941	1.8	1,068	0.2	1,013
NAIP00 (N00)	1,839	0.1	1,851	1,912	2.1	2,130	2.1	2,355	0.8	2,342
NAIP10 (N10)	518	-1.5	501	531	2.3	621	3.0	703	0.4	656
NAIP11 (N11)	712	2.2	808	833	1.5	937	1.3	1,054	0.2	998

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Aggregate value for a group is the sum of real GDP for countries in the group divided by total population of countries in the group.

ANNEX 1c: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.2.1

TABLE L1.2.1—PREVALENCE OF UNDERNOURISHMENT (% of population)

Region	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. level (2014-2019)	2019
Africa	23.4	21.9	-2.6	19.9	-1.8	18.3	1.1	18.8
Central	35.1	34.5	-0.5	33.9	0.1	33.8	0.6	34.4
Eastern	38.3	35.1	-3.3	31.9	-2.4	25.8	-0.8	25.7
Northern	6.6	6.4	-2.2	5.3	-4.9	4.5	2.3	4.8
Southern	24.1	22.7	-2.0	18.8	-4.6	17.8	1.7	18.2
Western	15.2	13.5	-4.5	11.9	-0.2	12.6	4.4	14.0
Less favorable agriculture conditions	89.2	85.5	-1.8	90.4	-0.1	73.6	-2.0	71.6
More favorable agriculture conditions	29.6	26.6	-4.3	19.9	-5.1	16.9	0.7	17.2
Mineral-rich countries	29.5	29.1	-0.7	28.5	0.7	29.3	0.6	29.8
Lower-middle-income countries	15.1	13.8	-3.4	12.2	-2.2	11.8	3.4	12.7
Upper-middle-income countries	2.3	2.6	7.1	3.3	-0.4	3.2	2.0	3.4
CEN-SAD	20.5	19.1	-2.8	18.7	-0.4	17.4	1.5	18.1
COMESA	27.1	25.4	-2.5	23.0	-2.0	20.8	0.9	21.3
EAC	20.7	18.4	-4.8	15.6	-1.9	15.2	2.1	15.7
ECCAS	38.9	37.1	-1.9	32.0	-2.1	30.7	0.7	31.3
ECOWAS	15.2	13.5	-4.5	11.9	-0.2	12.6	4.4	14.0
IGAD	47.3	43.3	-3.3	39.1	-3.2	29.3	-1.4	28.9
SADC	25.1	24.2	-1.3	22.7	-0.9	23.2	1.3	23.7
UMA	7.2	6.8	-2.2	5.4	-6.6	4.2	0.4	4.3
CAADP Compact 2007-09 (CC1)	22.1	19.5	-4.7	15.4	-3.5	13.5	2.8	14.6
CAADP Compact 2010-12 (CC2)	29.2	27.9	-1.7	27.0	-0.4	26.6	0.8	27.0
CAADP Compact 2013-15 (CC3)	26.7	24.3	-3.6	17.9	-5.3	17.5	2.2	18.2
CAADP Compact not yet (CC0)	18.3	18.2	-0.5	20.3	0.2	16.9	-1.2	16.7
CAADP Level 0 (CL0)	18.3	18.2	-0.5	20.3	0.2	16.9	-1.2	16.7
CAADP Level 1 (CL1)	30.4	28.9	-1.6	25.2	-3.7	23.8	1.4	24.4
CAADP Level 2 (CL2)	34.4	33.3	-1.2	32.9	0.9	33.5	0.3	33.8
CAADP Level 3 (CL3)	40.8	36.5	-5.1	24.5	-5.8	23.1	2.3	24.3
CAADP Level 4 (CL4)	21.1	18.8	-4.4	15.3	-3.0	14.0	2.5	14.9
NAIP00 (N00)	23.0	22.3	-1.4	21.8	-1.5	19.2	0.0	19.3
NAIP10 (N10)	23.5	23.0	-0.7	23.3	0.3	23.5	0.5	23.7
NAIP11 (N11)	23.6	21.0	-4.6	16.8	-3.4	15.0	2.5	16.0

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Data are only available from 2000 to 2019.

ANNEX 1d: *Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.2.2A*

TABLE L1.2.2A—PREVALENCE OF UNDERWEIGHT, WEIGHT FOR AGE (% of children under 5)										
Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	23.6	-1.3	22.3	21.3	-1.6	19.1	-2.3	17.2	-2.0	16.3
Central	27.0	-1.0	25.8	25.0	-1.4	23.2	-1.2	21.6	-1.7	20.7
Eastern	30.9	-1.5	28.8	27.7	-1.8	24.6	-2.2	21.7	-2.3	20.7
Northern	8.5	-1.6	8.1	7.0	-4.6	6.1	-1.5	5.4	-4.2	4.9
Southern	18.1	-1.9	16.6	15.1	-3.3	13.1	-2.6	11.0	-5.1	9.8
Western	26.9	-1.6	25.2	24.5	-0.8	22.2	-2.4	20.6	-0.9	19.7
Less favorable agriculture conditions	32.4	-1.5	30.6	29.9	-1.3	27.7	-0.6	26.5	-1.9	26.0
More favorable agriculture conditions	30.2	-1.5	27.8	26.3	-2.2	23.0	-2.4	19.6	-3.5	18.3
Mineral-rich countries	27.3	-0.8	26.2	25.5	-1.3	24.0	-1.1	22.7	-1.3	21.9
Lower-middle-income countries	19.2	-1.3	18.3	17.4	-1.5	15.5	-3.0	13.9	-1.4	13.1
Upper-middle-income countries	9.5	-1.3	9.0	8.8	0.0	8.2	-2.3	7.2	-1.8	7.0
CEN-SAD	22.3	-1.1	21.3	20.9	-0.7	19.1	-2.2	17.7	-0.9	17.1
COMESA	23.6	-1.2	22.2	21.1	-1.9	18.9	-2.0	16.7	-2.5	15.8
EAC	20.4	-1.9	18.8	18.5	-1.2	16.0	-3.2	14.3	-0.9	14.1
ECCAS	27.2	-1.6	25.4	24.2	-2.3	21.9	-1.8	19.7	-2.6	18.6
ECOWAS	26.9	-1.6	25.2	24.5	-0.8	22.2	-2.4	20.6	-0.9	19.7
IGAD	31.1	-1.6	28.7	27.7	-1.8	24.4	-2.4	21.4	-2.4	20.4
SADC	22.5	-1.4	21.1	19.7	-2.5	17.7	-1.9	15.6	-3.2	14.5
UMA	8.2	-0.9	8.1	6.7	-6.3	5.4	-3.1	4.5	-4.7	4.1
CAADP Compact 2007-09 (CC1)	30.6	-1.8	28.1	26.9	-1.6	23.9	-2.6	21.6	-1.7	20.4
CAADP Compact 2010-12 (CC2)	21.4	-1.2	20.2	19.3	-1.4	17.5	-2.0	15.7	-2.3	14.9
CAADP Compact 2013-15 (CC3)	21.4	-1.2	20.2	19.3	-1.4	17.5	-2.0	15.7	-2.3	14.9
CAADP Compact not yet (CC0)	9.6	-1.4	9.3	8.5	-2.3	7.7	-1.9	6.7	-3.0	6.4
CAADP Level 0 (CL0)	9.6	-1.4	9.3	8.5	-2.3	7.7	-1.9	6.7	-3.0	6.4
CAADP Level 1 (CL1)	21.4	-1.1	20.6	19.6	-2.4	18.2	-1.5	16.5	-2.8	15.5
CAADP Level 2 (CL2)	25.3	-0.9	24.2	23.5	-1.5	21.9	-1.2	20.4	-1.7	19.4
CAADP Level 3 (CL3)	24.8	-0.9	23.6	22.5	-1.1	20.6	-1.4	19.0	-2.3	18.3
CAADP Level 4 (CL4)	28.6	-1.9	26.3	25.1	-1.6	22.0	-2.9	19.6	-1.7	18.4
NAIP00 (N00)	15.5	-0.8	15.3	14.3	-2.7	12.9	-2.3	11.2	-3.1	10.5
NAIP10 (N10)	21.9	-0.9	20.8	19.9	-1.5	18.6	-1.2	17.1	-2.1	16.3
NAIP11 (N11)	28.1	-1.7	26.0	25.0	-1.4	22.2	-2.6	20.0	-1.7	19.0

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: For regions or groups, level is weighted average, where weight is country's share in population under 5 years for the region or group.

ANNEX 1e: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.2.2B

TABLE L1.2.2B—PREVALENCE OF STUNTING, HEIGHT FOR AGE (% of children under 5)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	41.5	-1.2	39.6	38.4	-1.1	35.0	-2.1	32.1	-1.2	31.2
Central	45.0	-1.0	43.9	43.2	-0.7	41.2	-0.8	39.5	-0.9	38.7
Eastern	50.3	-1.5	47.1	45.4	-1.7	40.5	-2.3	36.3	-1.4	35.2
Northern	25.2	-3.0	23.0	22.3	2.0	20.4	-3.3	17.8	-3.4	16.6
Southern	45.2	-1.6	42.5	40.3	-1.6	36.7	-2.7	32.4	-2.4	30.7
Western	39.7	-0.9	38.1	37.1	-1.4	33.9	-1.7	32.1	-0.3	31.7
Less favorable agriculture conditions	45.1	-0.5	43.5	43.3	-0.8	40.5	-1.0	39.1	-0.2	39.3
More favorable agriculture conditions	49.7	-1.7	46.3	43.8	-2.1	39.2	-1.9	34.5	-2.4	32.9
Mineral-rich countries	44.9	-1.0	43.7	43.2	-0.6	41.2	-0.7	39.7	-0.8	38.9
Lower-middle-income countries	37.3	-1.2	35.6	34.5	-0.8	31.3	-2.8	28.7	-1.0	27.7
Upper-middle-income countries	28.1	-0.5	27.4	26.8	-1.2	26.2	-0.2	25.2	-1.3	24.5
CEN-SAD	36.8	-1.2	35.2	34.5	-0.7	31.6	-2.0	29.6	-0.6	29.1
COMESA	45.3	-1.4	42.9	41.8	-0.5	38.3	-2.4	34.5	-1.4	33.4
EAC	42.7	-0.9	40.6	40.5	-0.9	36.7	-2.3	34.4	-0.2	34.0
ECCAS	46.4	-1.3	44.5	43.1	-1.5	40.4	-1.3	37.8	-1.6	36.4
ECOWAS	39.7	-0.9	38.1	37.1	-1.4	33.9	-1.7	32.1	-0.3	31.7
IGAD	49.8	-1.6	46.4	44.6	-1.8	39.3	-2.5	35.2	-1.3	34.1
SADC	46.7	-1.4	44.3	42.6	-1.3	39.4	-2.0	35.9	-1.8	34.5
UMA	22.9	-1.5	21.4	19.3	-2.9	16.8	-2.3	14.8	-4.1	13.5
CAADP Compact 2007-09 (CC1)	45.6	-1.2	43.2	41.4	-1.9	37.3	-2.0	34.6	-0.7	33.8
CAADP Compact 2010-12 (CC2)	43.6	-1.2	41.6	40.7	-0.6	37.7	-1.9	34.7	-1.1	33.9
CAADP Compact 2013-15 (CC3)	43.6	-1.2	41.6	40.7	-0.6	37.7	-1.9	34.7	-1.1	33.9
CAADP Compact not yet (CC0)	26.2	-2.5	24.2	23.8	1.6	21.9	-2.9	19.3	-2.8	18.3
CAADP Level 0 (CL0)	26.2	-2.5	24.2	23.8	1.6	21.9	-2.9	19.3	-2.8	18.3
CAADP Level 1 (CL1)	43.1	-1.6	40.8	39.0	-1.6	35.8	-2.8	31.9	-2.4	30.2
CAADP Level 2 (CL2)	43.1	-1.0	42.0	41.6	-0.7	39.6	-0.7	38.0	-0.8	37.2
CAADP Level 3 (CL3)	43.7	-1.2	41.1	39.6	-1.5	36.3	-1.1	33.9	-1.5	33.0
CAADP Level 4 (CL4)	45.6	-1.2	43.3	41.7	-1.6	37.5	-2.3	34.4	-0.6	33.6
NAIP00 (N00)	33.0	-1.7	31.3	30.3	-0.5	27.8	-2.7	24.5	-2.9	23.1
NAIP10 (N10)	45.3	-1.2	43.4	42.3	-0.6	39.7	-1.5	37.2	-1.3	36.0
NAIP11 (N11)	43.8	-1.2	41.6	40.1	-1.6	36.1	-2.1	33.2	-0.7	32.6

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Data only available up to 2019. For regions or groups, level is weighted average, where weight is country's share in population under 5 years for the region or group.

ANNEX 1f: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.2.2C

TABLE L1.2.2C—PREVALENCE OF WASTING, WEIGHT FOR HEIGHT (% of children under 5)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	9.6	-1.1	9.1	8.8	-1.2	8.0	-2.0	7.2	-1.9	6.8
Central	11.2	-0.3	10.4	9.9	-2.1	8.6	-2.5	7.3	-3.2	6.9
Eastern	9.4	-0.9	9.0	8.9	-1.1	8.2	-1.7	7.7	-1.3	7.3
Northern	5.8	1.2	6.3	6.1	0.8	6.7	2.0	7.3	0.1	7.4
Southern	6.2	-2.2	5.7	5.4	-1.4	4.6	-1.8	3.9	-4.3	3.5
Western	12.3	-2.3	11.2	10.7	-1.5	9.4	-3.2	8.1	-2.3	7.5
Less favorable agriculture conditions	14.6	-2.6	13.4	12.6	-2.8	11.3	-1.3	10.0	-4.4	9.3
More favorable agriculture conditions	9.0	-1.8	8.3	8.0	-2.6	6.9	-2.2	6.1	-3.6	5.5
Mineral-rich countries	12.3	0.1	11.7	11.3	-1.4	10.3	-1.7	9.3	-1.8	9.1
Lower-middle-income countries	8.9	-1.1	8.5	8.3	-0.3	7.6	-2.4	7.0	-0.6	6.7
Upper-middle-income countries	4.5	-0.5	4.4	4.5	2.2	4.4	-2.5	4.0	-0.4	4.0
CEN-SAD	10.8	-1.1	10.3	10.1	-0.7	9.4	-2.0	8.7	-1.0	8.4
COMESA	8.9	-0.1	8.7	8.7	-0.4	8.2	-1.0	7.8	-1.2	7.5
EAC	6.2	-2.2	5.5	5.5	0.2	4.9	-3.1	4.3	-0.1	4.2
ECCAS	10.4	-0.7	9.6	9.2	-1.9	7.9	-2.6	6.7	-3.0	6.3
ECOWAS	12.3	-2.3	11.2	10.7	-1.5	9.4	-3.2	8.1	-2.3	7.5
IGAD	10.0	-0.5	9.7	9.8	-0.5	9.2	-1.6	8.8	-0.7	8.5
SADC	8.2	-1.2	7.5	7.1	-2.2	6.0	-2.2	5.0	-4.2	4.6
UMA	6.0	1.5	6.7	5.6	-6.9	4.9	-0.5	4.6	-3.3	4.4
CAADP Compact 2007-09 (CC1)	12.0	-2.2	11.0	10.6	-1.8	9.3	-2.9	8.1	-3.1	7.3
CAADP Compact 2010-12 (CC2)	8.7	-1.5	7.9	7.6	-1.3	6.7	-2.7	5.7	-2.1	5.5
CAADP Compact 2013-15 (CC3)	8.7	-1.5	7.9	7.6	-1.3	6.7	-2.7	5.7	-2.1	5.5
CAADP Compact not yet (CC0)	6.4	0.4	6.7	6.5	0.5	6.6	0.0	6.7	-0.5	6.7
CAADP Level 0 (CL0)	6.4	0.4	6.7	6.5	0.5	6.6	0.0	6.7	-0.5	6.7
CAADP Level 1 (CL1)	10.3	0.4	10.7	10.6	-0.9	10.1	-0.4	9.8	-0.1	9.8
CAADP Level 2 (CL2)	11.2	-0.3	10.3	9.8	-2.6	8.3	-2.6	7.0	-3.5	6.6
CAADP Level 3 (CL3)	9.2	-2.0	8.6	8.3	-1.9	7.6	-0.3	7.1	-3.4	6.7
CAADP Level 4 (CL4)	10.4	-2.2	9.4	9.1	-1.3	8.0	-3.4	6.9	-2.2	6.3
NAIP00 (N00)	7.2	0.3	7.6	7.3	-0.6	7.0	-0.6	6.8	-0.7	6.8
NAIP10 (N10)	9.6	-0.7	8.9	8.6	-1.3	7.9	-1.2	7.0	-2.6	6.7
NAIP11 (N11)	10.8	-2.0	9.9	9.6	-1.4	8.5	-3.0	7.5	-2.2	7.0

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Data only available up to 2019. For regions or groups, level is weighted average, where weight is country's share in population under 5 years for the region or group.

ANNEX 1g: *Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.2.3*

TABLE L1.2.3—CEREAL IMPORT DEPENDENCY RATIO (%)

Region	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014–2017)	Annual avg. change (2014–2017)	2017
Africa	25.1	25.6	1.2	26.4	-0.1	27.6	2.3	28.1
Central	30.5	29.8	-0.8	29.9	0.5	29.8	0.0	29.8
Eastern	13.3	13.7	2.6	15.6	-3.7	14.8	4.0	15.4
Northern	44.0	45.9	3.8	50.5	0.0	53.9	3.7	55.4
Southern	25.0	26.0	-0.5	23.2	-0.2	27.4	4.4	28.3
Western	22.6	22.5	-0.7	23.0	2.3	23.8	-0.3	23.7
Less favorable agriculture conditions	10.3	10.8	0.8	11.7	0.4	9.4	-5.3	9.0
More favorable agriculture conditions	13.4	13.4	-1.4	12.9	-1.0	14.0	4.7	14.6
Mineral-rich countries	30.0	28.3	-1.2	26.9	2.3	35.1	7.1	37.3
Lower-middle-income countries	33.1	33.8	1.8	36.3	0.2	37.0	1.2	37.3
Upper-middle-income countries	16.9	19.0	3.1	14.7	-2.3	22.3	16.5	24.9
CEN-SAD	25.7	26.6	2.6	29.3	0.9	31.2	2.6	31.9
COMESA	18.7	19.4	3.6	22.4	-2.0	23.1	4.9	24.1
EAC	13.8	16.4	6.2	19.7	-2.8	18.5	2.6	19.0
ECCAS	37.4	37.7	-0.2	38.7	1.0	34.9	-4.1	33.6
ECOWAS	22.6	22.5	-0.7	23.0	2.3	23.8	-0.3	23.7
IGAD	13.4	13.7	3.6	15.9	-4.9	16.0	5.7	16.7
SADC	21.1	21.9	-0.6	19.9	-0.4	22.0	3.3	22.7
UMA	58.0	58.7	2.2	59.4	-0.6	63.6	3.3	65.0
CAADP Compact 2007-09 (CC1)	16.9	16.5	-1.1	17.3	1.2	17.9	0.1	18.0
CAADP Compact 2010-12 (CC2)	22.3	22.9	0.3	22.9	-1.3	23.3	4.2	24.1
CAADP Compact 2013-15 (CC3)	22.3	22.9	0.3	22.9	-1.3	23.3	4.2	24.1
CAADP Compact not yet (CC0)	35.9	37.8	3.7	39.9	-0.2	44.9	5.4	46.8
CAADP Level 0 (CL0)	35.9	37.8	3.7	39.9	-0.2	44.9	5.4	46.8
CAADP Level 1 (CL1)	35.8	37.1	1.3	39.4	0.3	36.7	-4.1	35.3
CAADP Level 2 (CL2)	32.1	30.9	-0.8	31.8	2.3	34.5	1.2	34.9
CAADP Level 3 (CL3)	15.1	14.7	-5.7	9.4	-4.6	7.8	4.8	8.1
CAADP Level 4 (CL4)	19.2	19.3	0.4	21.0	0.4	21.9	1.8	22.3
NAIP00 (N00)	34.9	36.8	3.3	39.0	-0.1	41.9	3.0	42.9
NAIP10 (N10)	25.2	24.8	-3.0	22.3	-0.6	22.5	3.2	23.2
NAIP11 (N11)	18.9	18.8	0.2	20.0	0.4	20.5	1.4	20.8

Source: ReSAKSS based on FAO (2021), World Bank (2021), and ILO (2021).

Note: Data are only available from 2000 to 2017. For regions or groups, level is weighted average, where weight is country's share in total population for the region or group.

ANNEX 1h: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.3.1A

TABLE L1.3.1A—EMPLOYMENT RATE (% of labor force, 15-64 years)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	92.2	0.0	92.4	93.1	0.3	93.5	-0.1	93.2	-0.04	90.0
Central	95.6	0.0	95.8	96.2	0.1	95.9	-0.1	95.9	0.1	93.2
Eastern	95.1	0.0	95.2	95.6	0.1	95.8	0.0	96.1	0.1	93.0
Northern	85.4	0.2	86.3	88.2	0.9	88.9	-0.5	88.4	0.4	85.5
Southern	84.8	-0.1	84.5	86.1	0.9	87.6	-0.2	86.8	-0.2	82.8
Western	95.8	-0.1	95.6	95.7	0.0	95.6	0.0	94.5	-0.4	90.9
Less favorable agriculture conditions	96.4	-0.1	95.7	95.4	0.0	96.0	0.1	96.2	0.0	94.8
More favorable agriculture conditions	96.5	0.0	96.7	97.0	0.1	97.1	0.0	97.4	0.0	94.7
Mineral-rich countries	93.5	0.0	93.5	93.5	0.0	92.7	-0.3	92.4	0.1	89.3
Lower-middle-income countries	91.7	0.1	92.1	93.0	0.4	93.2	-0.2	92.4	-0.1	89.0
Upper-middle-income countries	71.8	-0.4	71.0	74.1	1.9	77.3	-0.3	75.5	-0.7	68.2
CEN-SAD	93.4	0.0	93.2	93.4	0.2	93.3	-0.2	92.6	-0.1	89.5
COMESA	94.2	0.0	94.2	94.5	0.2	94.4	-0.2	94.6	0.2	91.6
EAC	96.7	0.0	96.6	96.8	0.1	96.7	0.0	97.3	0.1	94.8
ECCAS	95.9	0.0	96.2	96.4	0.1	95.7	-0.2	95.6	0.1	92.8
ECOWAS	95.8	-0.1	95.6	95.7	0.0	95.6	0.0	94.5	-0.4	90.9
IGAD	94.5	0.0	94.6	95.0	0.1	95.0	0.0	95.3	0.1	91.4
SADC	90.2	0.0	90.2	91.2	0.5	92.0	-0.1	91.7	-0.1	88.8
UMA	80.9	0.4	83.6	86.7	1.3	88.9	-0.1	88.5	-0.1	83.7
CAADP Compact 2007-09 (CC1)	96.2	0.0	96.3	96.5	0.1	96.7	0.0	95.7	-0.3	91.8
CAADP Compact 2010-12 (CC2)	96.0	0.0	95.8	95.9	0.1	95.7	0.0	96.1	0.0	93.8
CAADP Compact 2013-15 (CC3)	91.5	0.1	92.3	93.0	0.3	92.9	-0.1	93.0	0.1	90.1
CAADP Compact not yet (CC0)	81.5	0.0	81.9	84.2	1.2	85.7	-0.4	84.7	0.0	80.4
CAADP Level 0 (CL0)	81.5	0.0	81.9	84.2	1.2	85.7	-0.4	84.7	0.0	80.4
CAADP Level 1 (CL1)	91.2	0.1	91.7	92.3	0.2	92.1	-0.1	92.1	0.1	89.1
CAADP Level 2 (CL2)	95.6	0.1	95.9	96.3	0.1	95.7	-0.1	95.7	0.1	92.9
CAADP Level 3 (CL3)	95.3	-0.2	94.5	94.8	0.3	95.8	0.2	96.0	-0.1	93.9
CAADP Level 4 (CL4)	96.3	0.0	96.3	96.5	0.1	96.5	0.0	96.0	-0.2	92.6
NAIP00 (N00)	84.8	0.1	85.4	87.2	0.9	88.4	-0.3	87.8	0.1	84.0
NAIP10 (N10)	93.7	0.0	93.8	94.1	0.2	94.1	-0.1	94.1	0.0	92.3
NAIP11 (N11)	96.2	0.0	96.2	96.3	0.1	96.4	0.0	95.9	-0.2	92.2

Source: ReSAKSS based on ILO (2021).

Note: For regions or groups, level is weighted average, where weight is country's share in total labor force for the region or group.

ANNEX 1i: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.3.1B

TABLE L1.3.1B—EMPLOYMENT RATE (% of population, 15+ years)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	59.9	-0.1	59.8	60.3	0.3	60.0	-0.5	58.8	-0.1	56.7
Central	70.6	0.0	70.6	70.2	-0.5	66.4	-0.9	65.3	0.0	63.2
Eastern	70.6	0.0	70.7	71.0	0.2	71.3	0.0	71.1	-0.1	68.4
Northern	39.6	-0.1	39.8	41.1	1.3	42.2	-0.3	40.6	-0.8	37.8
Southern	58.4	-0.2	58.2	59.3	0.9	59.5	-0.3	59.5	0.0	57.1
Western	61.6	-0.3	61.0	60.7	-0.1	59.1	-1.2	55.7	-0.3	53.9
Less favorable agriculture conditions	70.6	-0.3	69.6	69.2	-0.1	69.1	-0.3	67.9	-0.1	66.4
More favorable agriculture conditions	77.1	0.1	77.7	78.0	0.1	77.0	-0.3	75.8	-0.2	73.1
Mineral-rich countries	61.0	0.0	60.9	60.4	-0.6	57.3	-1.1	55.9	0.0	53.7
Lower-middle-income countries	54.1	-0.2	53.7	54.2	0.5	54.1	-0.6	52.3	-0.3	50.2
Upper-middle-income countries	39.2	-0.5	38.6	40.4	2.2	41.6	-0.3	42.0	-0.2	38.5
CEN-SAD	55.0	-0.2	54.4	54.6	0.3	54.3	-0.7	52.3	-0.3	50.3
COMESA	62.9	0.0	62.8	63.3	0.3	63.4	-0.1	63.1	-0.1	60.5
EAC	75.5	-0.3	74.3	74.2	0.1	74.7	0.1	75.1	0.0	72.9
ECCAS	72.3	0.0	72.2	71.8	-0.4	68.5	-0.8	67.6	0.0	65.3
ECOWAS	61.6	-0.3	61.0	60.7	-0.1	59.1	-1.2	55.7	-0.3	53.9
IGAD	66.3	0.0	66.2	66.4	0.2	67.0	0.1	67.3	-0.1	64.3
SADC	66.2	0.0	66.3	66.9	0.4	65.9	-0.5	65.3	0.0	63.2
UMA	38.0	0.1	38.8	40.1	1.0	40.9	-0.2	39.7	-0.4	37.1
CAADP Compact 2007-09 (CC1)	66.4	0.0	66.5	66.7	0.1	65.7	-0.9	63.0	-0.2	60.7
CAADP Compact 2010-12 (CC2)	70.8	-0.2	70.0	69.5	-0.3	67.8	-0.5	67.1	-0.1	65.0
CAADP Compact 2013-15 (CC3)	65.4	0.0	65.7	66.2	0.2	65.5	-0.3	65.1	0.0	62.9
CAADP Compact not yet (CC0)	40.5	-0.2	40.4	41.9	1.5	43.0	-0.3	41.9	-0.6	39.0
CAADP Level 0 (CL0)	40.5	-0.2	40.4	41.9	1.5	43.0	-0.3	41.9	-0.6	39.0
CAADP Level 1 (CL1)	63.2	0.0	63.5	63.9	0.2	63.8	-0.2	63.4	0.0	61.1
CAADP Level 2 (CL2)	68.9	0.0	69.0	68.5	-0.6	64.3	-1.0	62.9	-0.1	60.7
CAADP Level 3 (CL3)	69.2	-0.2	68.6	68.7	0.2	68.8	-0.2	67.7	-0.3	65.7
CAADP Level 4 (CL4)	68.6	-0.1	68.3	68.2	0.0	67.2	-0.7	65.1	-0.1	62.9
NAIP00 (N00)	46.4	-0.1	46.5	47.8	1.2	48.9	-0.1	48.4	-0.3	45.8
NAIP10 (N10)	69.3	0.0	69.3	69.1	-0.2	66.5	-0.8	65.2	-0.1	63.5
NAIP11 (N11)	66.2	-0.1	65.8	65.8	0.0	65.2	-0.6	63.3	-0.2	60.9

Source: ReSAKSS based on ILO (2021).

Note: For regions or groups, level is weighted average, where weight is country's share in total population for the region or group.

ANNEX 1j: Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.3.3

TABLE L1.3.3—POVERTY GAP AT $1.90/ DAY (2011 PPP) (%)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	19.4	-2.5	17.4	16.4	-2.4	14.1	-3.0	12.0	-3.9	10.8
Central	24.0	-3.4	21.6	20.1	-2.8	17.2	-2.7	14.3	-4.3	13.1
Eastern	23.1	-2.3	20.0	18.8	-2.0	15.9	-3.3	13.5	-4.4	12.1
Northern	1.1	-4.6	0.9	0.8	-5.7	0.4	-13.1	0.3	-9.2	0.2
Southern	20.4	-1.3	19.3	18.6	-3.1	17.5	0.6	16.7	-1.6	16.4
Western	24.4	-3.3	21.5	20.1	-2.8	16.7	-4.6	13.0	-5.3	11.2
Less favorable agriculture conditions	36.4	-4.1	30.8	27.8	-5.0	19.1	-8.3	14.0	-3.5	12.2
More favorable agriculture conditions	27.4	-2.7	23.6	22.0	-2.2	18.6	-3.4	15.3	-5.1	13.7
Mineral-rich countries	38.2	-4.1	31.7	27.9	-5.3	18.4	-9.1	9.5	-15.4	6.5
Lower-middle-income countries	13.6	-1.8	12.8	12.5	-1.5	11.9	-1.6	10.9	-2.2	10.1
Upper-middle-income countries	11.1	-4.2	9.0	7.6	-9.9	5.4	0.4	3.6	-15.6	2.5
CEN-SAD	16.7	-2.8	15.0	14.3	-2.4	12.1	-4.0	10.0	-4.0	8.8
COMESA	16.0	-1.6	14.6	14.3	-0.9	12.9	-2.2	11.6	-2.7	11.0
EAC	25.6	-1.4	23.1	21.6	-2.8	18.0	-2.9	15.6	-3.1	14.6
ECCAS	22.9	-1.8	21.3	20.1	-3.1	18.3	-0.6	17.1	-1.6	16.7
ECOWAS	24.4	-3.3	21.5	20.1	-2.8	16.7	-4.6	13.0	-5.3	11.2
IGAD	18.6	-3.4	15.3	14.3	-2.1	11.3	-4.8	8.8	-7.2	7.3
SADC	24.1	-1.0	22.5	21.7	-2.3	20.2	-0.3	19.2	-1.5	18.7
UMA	1.6	-5.7	1.2	0.9	-9.5	0.4	-19.3	0.1	-38.2	0.0
CAADP Compact 2007-09 (CC1)	24.4	-3.5	20.9	19.6	-2.7	16.2	-4.8	12.5	-6.2	10.6
CAADP Compact 2010-12 (CC2)	25.6	-2.1	23.1	21.8	-2.6	18.3	-3.0	15.3	-3.6	14.3
CAADP Compact 2013-15 (CC3)	25.6	-2.1	23.1	21.8	-2.6	18.3	-3.0	15.3	-3.6	14.3
CAADP Compact not yet (CC0)	4.2	-4.4	3.4	2.8	-9.1	1.9	-1.8	1.7	-12.1	0.9
CAADP Level 0 (CL0)	4.2	-4.4	3.4	2.8	-9.1	1.9	-1.8	1.7	-12.1	0.9
CAADP Level 1 (CL1)	21.5	2.1	23.1	23.2	0.4	25.8	2.7	28.8	2.3	30.2
CAADP Level 2 (CL2)	21.0	-4.5	17.7	15.9	-4.6	11.4	-6.2	7.2	-10.6	5.7
CAADP Level 3 (CL3)	30.1	-2.8	26.8	24.7	-3.7	18.7	-5.5	14.9	-3.2	13.9
CAADP Level 4 (CL4)	23.6	-2.9	20.6	19.5	-2.3	16.8	-3.4	13.6	-5.2	11.9
NAIP00 (N00)	7.3	-0.3	7.1	6.9	-1.9	7.0	2.5	7.9	1.2	7.8
NAIP10 (N10)	30.9	-2.3	27.4	25.8	-3.2	21.6	-2.9	18.1	-4.0	16.7
NAIP11 (N11)	22.9	-3.2	20.0	18.7	-2.5	15.6	-4.3	12.2	-5.4	10.6

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Data only available up to 2019. For regions or groups, level is weighted average, where weight is country's share in total population for the region or group.

ANNEX 1k: *Level 1—Agriculture's Contribution to Economic Growth and Inclusive Development, Indicator 1.3.4*

TABLE L1.3.4—POVERTY HEADCOUNT RATIO AT $1.90/ DAY (2011 PPP, % of population)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	45.9	-1.4	43.2	41.7	-1.5	38.1	-1.9	35.2	-1.1	34.2
Central	55.1	-2.7	51.3	49.1	-1.8	44.1	-1.8	39.0	-2.9	36.9
Eastern	58.0	-1.6	52.7	50.7	-1.4	45.2	-2.1	40.8	-2.4	38.5
Northern	5.6	-4.2	4.9	4.3	-4.4	2.6	-11.6	1.7	-3.4	1.4
Southern	45.9	-0.7	44.6	43.2	-1.9	40.6	-0.2	39.9	-0.2	40.0
Western	54.8	-1.6	51.7	49.9	-1.6	45.6	-2.3	40.3	-2.5	37.5
Less favorable agriculture conditions	74.9	-2.1	68.9	65.9	-2.1	55.9	-3.4	48.3	-2.3	44.9
More favorable agriculture conditions	64.9	-1.8	58.9	56.1	-1.5	50.0	-2.3	44.4	-2.6	42.1
Mineral-rich countries	68.3	-1.3	65.5	62.0	-2.7	51.3	-3.6	41.6	-5.2	36.7
Lower-middle-income countries	33.7	-0.9	32.9	32.3	-1.0	31.1	-1.2	30.4	0.7	30.7
Upper-middle-income countries	30.7	-3.3	26.0	23.0	-7.3	17.5	-0.5	13.2	-9.7	10.8
CEN-SAD	38.8	-1.3	37.2	36.3	-1.3	33.6	-2.0	31.3	-0.3	30.7
COMESA	41.6	-1.1	39.2	38.3	-0.8	35.1	-1.8	32.8	-1.4	31.8
EAC	59.2	-0.8	56.4	54.4	-1.4	49.6	-1.4	46.7	-1.2	45.5
ECCAS	51.4	-1.3	49.6	48.1	-1.5	45.7	-0.4	44.1	-0.9	43.5
ECOWAS	54.8	-1.6	51.7	49.9	-1.6	45.6	-2.3	40.3	-2.5	37.5
IGAD	52.0	-2.2	45.8	43.6	-1.7	37.4	-3.0	32.3	-3.6	29.4
SADC	53.4	-0.6	51.6	50.3	-1.4	47.4	-0.6	46.3	-0.4	46.0
UMA	6.8	-5.5	5.2	4.2	-8.5	2.2	-16.5	0.5	-50.5	0.1
CAADP Compact 2007-09 (CC1)	57.8	-2.0	52.8	50.5	-2.0	44.9	-2.9	38.4	-3.6	35.0
CAADP Compact 2010-12 (CC2)	56.8	-0.9	54.4	52.8	-1.1	48.9	-1.3	46.2	-0.9	45.4
CAADP Compact 2013-15 (CC3)	56.8	-0.9	54.4	52.8	-1.1	48.9	-1.3	46.2	-0.9	45.4
CAADP Compact not yet (CC0)	13.4	-3.7	11.4	10.0	-6.4	7.1	-3.6	6.1	-4.1	4.9
CAADP Level 0 (CL0)	13.4	-3.7	11.4	10.0	-6.4	7.1	-3.6	6.1	-4.1	4.9
CAADP Level 1 (CL1)	48.4	1.5	51.3	52.3	0.7	52.5	-0.8	55.5	2.1	58.1
CAADP Level 2 (CL2)	48.2	-3.0	44.0	41.0	-2.4	34.1	-3.1	30.0	-3.2	28.0
CAADP Level 3 (CL3)	65.3	-1.2	62.4	59.7	-1.9	51.8	-2.6	46.3	-1.6	44.6
CAADP Level 4 (CL4)	55.8	-1.7	51.6	49.7	-1.5	45.6	-2.1	40.6	-2.6	38.0
NAIP00 (N00)	19.7	-1.0	19.0	18.4	-1.8	17.8	1.1	19.8	3.7	21.2
NAIP10 (N10)	65.0	-1.4	60.9	58.5	-1.7	53.0	-1.7	49.6	-1.1	48.4
NAIP11 (N11)	54.7	-1.7	50.8	48.9	-1.6	44.1	-2.4	38.8	-2.8	36.2

Source: ReSAKSS based on World Bank (2021) and ILO (2021).

Note: Data only available up to 2019. For regions or groups, level is weighted average, where weight is country's share in total population for the region or group.

ANNEX 2a: *Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.1*

TABLE L2.1.1—AGRICULTURE VALUE ADDED (billion, constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	184.0	4.6	222.3	229.9	2.3	289.8	3.5	351.4	3.0	384.9
Central	12.6	-4.1	10.7	12.7	6.9	17.1	4.8	20.9	2.2	23.7
Eastern	39.8	1.2	41.2	45.3	4.5	66.9	7.4	87.8	3.1	98.0
Northern	38.6	8.7	49.7	50.3	0.3	59.3	3.0	74.0	4.1	84.5
Southern	19.6	1.3	20.3	21.3	3.7	25.1	1.9	28.6	-1.7	30.1
Western	73.3	6.6	100.4	100.2	1.5	121.2	1.8	140.1	3.4	148.6
Less favorable agriculture conditions	7.3	4.1	8.3	11.1	10.5	14.8	5.3	18.4	2.7	15.2
More favorable agriculture conditions	24.9	-0.8	25.4	30.5	7.8	46.2	5.5	58.8	4.9	69.9
Mineral-rich countries	21.7	1.5	21.8	21.6	1.4	29.3	7.3	34.2	-2.4	32.3
Lower-middle-income countries	118.5	6.5	153.5	153.9	0.9	187.6	2.7	227.8	3.5	254.3
Upper-middle-income countries	11.5	2.3	13.3	12.8	1.6	11.9	-2.8	12.2	0.4	13.3
CEN-SAD	128.0	5.5	162.0	165.0	1.8	203.1	2.9	238.8	2.8	253.2
COMESA	67.6	1.9	70.8	74.8	2.9	96.4	4.5	117.1	2.7	132.4
EAC	17.9	-0.8	18.0	19.9	3.9	30.6	7.0	43.5	7.1	52.0
ECCAS	16.2	-2.8	14.6	17.3	6.6	24.4	6.1	32.1	1.1	35.5
ECOWAS	73.3	6.6	100.4	100.2	1.5	121.2	1.8	140.1	3.4	148.6
IGAD	30.7	2.1	31.7	34.7	4.6	52.8	8.0	68.6	2.3	76.5
SADC	33.5	-1.6	32.2	34.3	3.8	42.2	2.9	51.4	1.7	56.2
UMA	18.7	13.9	27.3	26.9	-1.6	32.0	5.5	43.5	4.2	48.5
CAADP Compact 2007-09 (CC1)	70.5	6.5	97.1	99.4	2.7	125.3	2.4	145.9	3.2	166.8
CAADP Compact 2010-12 (CC2)	38.0	-0.9	37.1	39.4	2.6	54.2	5.1	72.9	6.7	76.8
CAADP Compact 2013-15 (CC3)	27.7	2.8	29.0	31.2	3.2	40.5	7.1	48.9	-3.5	47.0
CAADP Compact not yet (CC0)	47.8	7.1	59.1	59.9	1.0	69.9	2.1	83.7	3.3	94.3
CAADP Level 0 (CL0)	47.8	7.1	59.1	59.9	1.0	69.9	2.1	83.7	3.3	94.3
CAADP Level 1 (CL1)	25.1	2.8	26.2	28.5	3.6	37.1	7.2	44.2	-4.4	41.5
CAADP Level 2 (CL2)	11.4	-4.3	9.6	9.6	0.8	12.1	4.2	16.1	5.9	19.1
CAADP Level 3 (CL3)	12.6	3.3	14.0	15.5	4.7	21.5	3.7	24.4	3.4	21.9
CAADP Level 4 (CL4)	87.1	5.0	113.5	116.3	2.4	149.2	3.1	183.0	4.3	208.1
NAIP00 (N00)	58.4	5.8	69.5	72.8	2.1	85.9	2.7	104.2	2.3	116.5
NAIP10 (N10)	33.2	0.1	33.4	34.5	2.1	46.6	6.4	56.7	0.1	56.1
NAIP11 (N11)	92.4	5.4	119.5	122.6	2.4	157.3	3.0	190.5	4.2	212.4

Source: ReSAKSS based on World Bank (2021) and FAO (2021).

Note: Aggregate value for a group is the sum of agriculture value added for countries in the group.

ANNEX 2b: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.2

TABLE L2.1.2—AGRICULTURAL PRODUCTION INDEX (API) (2014-2016 = 100)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	61.5	2.9	69.6	76.1	3.1	88.4	3.2	103.6	2.3	108.6
Central	53.0	0.8	55.5	60.3	3.5	81.3	7.5	104.2	2.9	110.3
Eastern	59.8	3.0	68.0	74.3	3.3	89.4	3.8	103.0	2.1	108.3
Northern	62.2	2.1	69.6	77.0	3.2	91.4	2.9	102.4	1.4	105.7
Southern	66.5	2.1	71.0	76.4	3.0	94.7	3.4	104.8	2.4	110.9
Western	61.9	3.6	71.3	78.1	3.0	86.2	2.4	104.4	2.8	109.7
Less favorable agriculture conditions	51.6	3.9	59.9	65.4	4.0	86.6	4.6	107.9	5.3	119.2
More favorable agriculture conditions	57.9	3.2	66.0	71.5	3.0	89.0	4.5	103.2	1.9	108.1
Mineral-rich countries	53.3	1.3	56.7	60.0	2.4	80.0	8.6	105.1	3.2	113.7
Lower-middle-income countries	62.4	2.8	70.7	78.1	3.2	88.4	2.6	103.3	2.1	107.5
Upper-middle-income countries	72.2	2.2	77.5	82.0	2.5	94.4	2.2	101.7	0.4	102.7
CEN-SAD	62.6	3.5	71.9	78.8	3.1	88.5	2.4	103.8	2.4	108.8
COMESA	65.5	2.8	73.2	79.6	3.2	91.7	2.6	102.7	1.8	106.9
EAC	64.8	3.5	74.5	80.1	2.5	91.7	3.7	102.3	1.4	106.7
ECCAS	51.1	1.9	56.5	62.1	3.9	85.4	6.5	104.4	2.9	110.8
ECOWAS	61.9	3.6	71.3	78.1	3.0	86.2	2.4	104.4	2.8	109.7
IGAD	60.9	3.2	69.8	76.2	3.0	89.5	3.3	103.2	2.2	108.6
SADC	61.5	1.9	66.0	71.0	3.1	89.6	5.0	103.6	1.9	108.8
UMA	56.4	0.8	61.7	68.1	1.6	87.3	5.1	104.0	2.4	109.8
CAADP Compact 2007-09 (CC1)	60.0	3.9	70.7	77.4	3.1	86.4	2.6	103.8	2.5	108.3
CAADP Compact 2010-12 (CC2)	60.2	2.6	66.4	72.2	2.8	88.1	4.7	104.4	2.5	110.9
CAADP Compact 2013-15 (CC3)	60.2	2.6	66.4	72.2	2.8	88.1	4.7	104.4	2.5	110.9
CAADP Compact not yet (CC0)	64.0	1.9	70.8	77.8	3.2	91.9	2.7	102.3	1.3	105.3
CAADP Level 0 (CL0)	64.0	1.9	70.8	77.8	3.2	91.9	2.7	102.3	1.3	105.3
CAADP Level 1 (CL1)	68.9	1.2	71.3	75.3	1.9	90.4	3.5	104.7	3.1	112.8
CAADP Level 2 (CL2)	52.5	0.8	55.0	60.2	3.4	80.5	7.7	103.9	2.5	109.1
CAADP Level 3 (CL3)	67.0	2.3	73.7	78.5	1.9	91.6	3.1	104.4	2.6	110.2
CAADP Level 4 (CL4)	59.5	3.9	69.6	76.4	3.2	86.7	3.0	103.9	2.6	109.0
NAIP00 (N00)	64.9	1.7	70.8	77.2	2.9	91.8	2.9	102.5	1.5	106.0
NAIP10 (N10)	52.0	1.9	57.5	62.8	3.5	84.5	6.8	104.5	2.8	112.3
NAIP11 (N11)	61.4	3.5	70.8	77.6	3.1	87.2	2.7	104.0	2.6	108.9

Source: ReSAKSS based on FAO (2021) and World Bank (2021).
Note: Data only available up to 2019. For regions or groups, level is weighted average, where weight is country's share in total agriculture value added for the region or group.

ANNEX 2c: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.3

TABLE L2.1.3—LABOR PRODUCTIVITY (agriculture value-added per agricultural worker, constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	1,297.7	1.5	1,393.9	1,332.3	-1.1	1,493.9	2.5	1,690.7	1.1	1,820.8
Central	642.9	-6.4	488.3	529.1	2.1	594.2	3.3	652.7	-0.5	672.5
Eastern	700.1	-2.0	636.8	651.6	1.9	857.3	5.3	995.7	0.4	1,019.2
Northern	3,553.3	4.5	3,896.3	3,681.6	-1.8	4,433.9	4.3	6,128.4	7.4	7,723.5
Southern	1,092.9	-2.2	950.0	932.6	1.0	985.5	0.2	1,007.3	-3.8	987.2
Western	2,052.2	4.5	2,642.2	2,390.1	-3.7	2,513.8	2.5	2,984.8	2.7	3,848.2
Less favorable agriculture conditions	600.4	1.4	628.2	730.5	3.0	764.9	3.6	860.8	-0.1	890.6
More favorable agriculture conditions	419.0	-3.5	381.7	431.9	5.7	595.9	3.6	677.6	2.6	748.4
Mineral-rich countries	1,089.1	-1.3	979.1	932.5	0.0	1,162.5	6.6	1,250.3	-5.6	1,056.3
Lower-middle-income countries	2,466.2	3.2	2,803.7	2,516.4	-4.2	2,662.5	2.7	3,226.2	3.0	3,698.9
Upper-middle-income countries	7,287.5	1.2	7,975.0	7,970.8	2.5	8,368.0	-2.6	7,727.0	-0.9	8,040.0
CEN-SAD	2,306.7	3.0	2,660.8	2,433.7	-3.5	2,553.4	3.0	2,992.8	1.8	3,470.9
COMESA	907.8	-1.5	819.4	805.7	0.3	953.4	3.1	1,044.5	0.4	1,097.7
EAC	616.1	-3.7	548.3	571.5	1.5	761.8	4.2	933.8	4.4	1,025.9
ECCAS	702.9	-6.4	520.7	559.5	1.8	653.5	4.2	771.4	-1.5	779.2
ECOWAS	2,052.2	4.5	2,642.2	2,390.1	-3.7	2,513.8	2.5	2,984.8	2.7	3,848.2
IGAD	858.7	-1.5	766.4	769.0	1.5	1,021.4	5.5	1,150.6	-0.8	1,162.2
SADC	692.3	-4.4	583.5	588.2	1.7	665.5	1.5	731.5	-0.5	742.7
UMA	3,327.5	5.8	3,885.2	3,839.6	-0.9	5,131.2	7.5	7,574.4	5.4	8,803.7
CAADP Compact 2007-09 (CC1)	1,279.1	3.5	1,597.1	1,487.8	-1.3	1,666.5	1.7	1,857.4	1.5	2,171.5
CAADP Compact 2010-12 (CC2)	678.8	-3.4	598.7	602.1	0.1	723.7	3.4	871.6	4.4	887.8
CAADP Compact 2013-15 (CC3)	1,549.3	-1.1	1,324.8	1,266.4	-2.5	1,367.1	5.9	1,503.9	-6.6	1,296.4
CAADP Compact not yet (CC0)	3,967.9	3.6	4,300.1	4,088.3	-0.9	4,904.0	3.4	6,421.3	6.3	7,973.9
CAADP Level 0 (CL0)	3,967.9	3.6	4,300.1	4,088.3	-0.9	4,904.0	3.4	6,421.3	6.3	7,973.9
CAADP Level 1 (CL1)	1,832.3	-1.5	1,509.2	1,433.6	-3.1	1,484.0	5.6	1,584.9	-7.7	1,321.1
CAADP Level 2 (CL2)	596.8	-6.9	448.5	430.9	-0.6	500.0	3.0	610.7	3.8	674.6
CAADP Level 3 (CL3)	665.0	0.5	660.2	681.1	1.6	820.3	1.3	806.3	0.7	823.4
CAADP Level 4 (CL4)	1,127.0	2.3	1,338.9	1,266.7	-1.2	1,432.8	2.3	1,662.6	2.7	1,837.4
NAIP00 (N00)	2,706.4	1.2	2,588.0	2,421.8	-3.0	2,489.1	1.9	2,881.7	1.8	3,161.8
NAIP10 (N10)	725.4	-2.1	670.0	665.7	0.6	838.6	5.7	940.1	-2.6	850.7
NAIP11 (N11)	1,249.1	2.4	1,456.2	1,363.8	-1.6	1,514.7	1.9	1,690.7	1.1	1,820.8

Source: ReSAKSS based on World Bank (2021).

ANNEX 2d: *Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.4*

TABLE L2.1.4—LAND PRODUCTIVITY (agriculture value-added per hectare of arable land, constant 2010 US$)										
Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	212.8	3.2	246.5	251.9	1.9	297.6	1.5	349.5	3.8	432.3
Central	128.1	-3.9	108.7	129.6	6.8	160.1	2.7	186.4	2.1	204.9
Eastern	273.4	0.5	275.0	294.9	3.6	341.1	-1.1	409.4	8.2	596.8
Northern	361.0	1.2	384.6	392.1	0.5	474.0	3.2	593.6	4.1	677.9
Southern	67.0	0.9	68.7	71.3	3.4	82.9	1.7	92.9	-2.0	97.0
Western	334.3	5.7	445.4	433.4	0.6	506.3	1.4	576.2	3.2	845.1
Less favorable agriculture conditions	55.1	3.5	62.2	80.1	9.4	105.8	5.1	129.9	2.5	158.9
More favorable agriculture conditions	141.9	-1.7	139.4	163.1	6.9	235.7	4.7	293.2	4.6	343.9
Mineral-rich countries	505.3	0.9	490.4	481.0	1.0	367.4	-12.7	322.0	8.9	536.6
Lower-middle-income countries	338.9	4.2	414.4	411.2	0.5	491.1	2.4	589.3	3.3	691.2
Upper-middle-income countries	66.8	0.3	68.0	67.9	3.2	71.4	-1.7	74.4	0.4	81.1
CEN-SAD	337.2	4.8	415.5	418.3	1.4	459.0	-0.9	514.8	5.0	738.9
COMESA	361.8	0.8	360.4	376.9	2.6	405.1	-2.5	449.6	6.8	627.0
EAC	234.2	-1.2	229.9	250.2	3.2	364.3	6.0	508.3	7.0	599.5
ECCAS	110.3	-2.9	98.2	115.0	6.1	150.4	4.3	188.4	0.7	202.4
ECOWAS	334.3	5.7	445.4	433.4	0.6	506.3	1.4	576.2	3.2	845.1
IGAD	435.6	1.8	439.2	463.4	3.5	478.0	-6.2	533.9	11.4	946.4
SADC	85.7	-2.1	81.1	85.5	3.4	102.7	2.3	122.3	1.5	131.9
UMA	174.1	5.4	209.0	209.1	-1.2	262.6	6.0	359.8	4.2	401.5
CAADP Compact 2007-09 (CC1)	351.4	5.6	468.9	464.8	1.6	564.0	1.8	643.0	2.9	915.9
CAADP Compact 2010-12 (CC2)	147.9	-1.2	142.2	149.1	2.0	193.4	4.0	253.0	6.6	283.2
CAADP Compact 2013-15 (CC3)	159.1	2.2	162.8	173.1	2.7	181.8	-0.3	200.2	0.5	245.7
CAADP Compact not yet (CC0)	204.5	3.5	230.4	235.2	1.3	282.3	2.5	339.9	3.4	383.7
CAADP Level 0 (CL0)	204.5	3.5	230.4	235.2	1.3	282.3	2.5	339.9	3.4	383.7
CAADP Level 1 (CL1)	151.1	2.2	153.7	165.2	3.1	173.4	-0.4	187.4	-0.2	227.1
CAADP Level 2 (CL2)	127.5	-4.2	107.7	107.6	0.6	124.6	2.1	157.8	5.8	182.1
CAADP Level 3 (CL3)	105.3	2.1	111.6	119.8	3.5	158.6	3.1	176.8	3.2	239.3
CAADP Level 4 (CL4)	339.5	4.6	433.8	436.0	1.7	537.2	2.5	645.8	4.1	783.7
NAIP00 (N00)	149.9	3.3	165.7	174.1	2.1	208.3	2.8	251.2	2.2	279.5
NAIP10 (N10)	182.1	-0.1	181.4	185.8	1.7	197.9	-1.4	218.1	4.1	267.6
NAIP11 (N11)	313.3	4.6	393.8	392.9	1.5	485.5	2.5	578.2	4.0	803.7

Source: ReSAKSS based on World Bank (2021) and FAO (2021).

ANNEX 2e: *Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.5A*

TABLE L2.1.5A—YIELD, CASSAVA (metric tons per hectare)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	8.6	1.0	8.9	9.3	1.8	9.1	-2.4	8.8	0.1	8.9
Central	7.8	-0.2	7.6	7.8	1.3	8.1	0.4	8.3	0.3	8.4
Eastern	8.0	0.1	7.7	7.6	1.0	6.2	-3.2	5.2	-0.6	5.6
Northern										
Southern	6.4	8.3	8.1	8.5	2.8	9.4	0.6	9.7	5.1	11.0
Western	10.1	-0.4	10.3	10.8	1.5	10.4	-4.5	9.8	-0.5	9.6
Less favorable agriculture conditions	7.1	7.1	8.3	7.4	-6.0	7.0	5.8	8.8	-2.6	7.9
More favorable agriculture conditions	7.5	3.0	7.7	7.6	0.6	6.9	-0.9	6.4	0.9	7.0
Mineral-rich countries	7.6	-0.2	7.5	7.4	-0.1	7.8	1.5	8.1	0.4	8.2
Lower-middle-income countries	9.8	0.1	10.2	11.0	2.7	10.9	-4.8	10.1	-0.1	10.1
Upper-middle-income countries	4.2	0.5	4.3	4.3	0.9	4.5	0.9	4.7	0.4	4.7
CEN-SAD	9.8	-0.3	10.0	10.5	1.4	10.1	-4.2	9.7	-0.5	9.5
COMESA	8.1	2.4	8.6	8.7	-0.4	8.1	-0.8	8.0	-0.1	8.0
EAC	8.4	0.2	8.1	7.7	-0.5	5.8	-3.2	5.2	-0.6	5.6
ECCAS	7.6	1.9	8.3	8.7	2.4	9.2	-1.7	8.4	-0.2	8.4
ECOWAS	10.1	-0.4	10.3	10.8	1.5	10.4	-4.5	9.8	-0.5	9.6
IGAD	10.3	9.2	12.8	12.1	-7.3	5.7	-12.2	3.3	-6.8	3.0
SADC	7.3	1.3	7.5	7.8	2.7	8.3	0.3	8.3	2.2	8.9
UMA										
CAADP Compact 2007-09 (CC1)	10.3	-0.7	10.4	10.9	1.5	10.6	-4.4	10.1	-0.6	9.9
CAADP Compact 2010-12 (CC2)	7.4	1.4	7.5	7.4	0.0	7.0	0.6	7.3	1.4	7.7
CAADP Compact 2013-15 (CC3)	7.3	4.3	8.5	9.7	6.5	11.2	-2.3	9.5	0.4	10.0
CAADP Compact not yet (CC0)	7.1	0.7	7.3	7.3	-0.1	7.4	0.3	7.5	0.2	7.5
CAADP Level 0 (CL0)	7.1	0.7	7.3	7.3	-0.1	7.4	0.3	7.5	0.2	7.5
CAADP Level 1 (CL1)	6.9	6.5	8.9	9.6	4.6	10.7	-3.3	8.4	0.0	8.8
CAADP Level 2 (CL2)	7.8	-0.5	7.6	7.9	1.7	8.2	0.1	8.3	0.2	8.4
CAADP Level 3 (CL3)	8.2	5.3	9.1	8.6	-4.7	6.2	-3.0	6.5	2.4	6.8
CAADP Level 4 (CL4)	9.2	0.1	9.4	9.8	2.1	9.6	-2.6	9.5	-0.1	9.6
NAIP00 (N00)	6.8	7.0	8.8	9.6	4.9	10.7	-3.7	8.2	0.0	8.6
NAIP10 (N10)	7.3	-0.9	6.8	6.8	1.5	7.0	2.4	7.9	2.6	8.6
NAIP11 (N11)	10.0	0.8	10.5	10.9	0.9	10.3	-4.6	9.4	-1.3	9.1

Source: ReSAKSS based on FAO (2021).

Note: Data only available up to 2019. Cassava production data are not available in Northern Africa and UMA.

ANNEX 2f: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.5B

TABLE L2.1.5B—YIELD, YAMS (metric tons per hectare)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	10.0	-0.5	10.3	10.6	0.3	9.3	-5.4	8.6	-1.0	8.4
Central	7.4	0.1	7.2	7.7	3.4	8.3	-0.2	8.4	0.4	8.5
Eastern	4.4	0.3	4.3	4.2	0.8	4.1	-8.1	3.0	0.8	3.0
Northern	6.3	-0.1	6.3	6.3	0.0	6.3	-0.1	6.3	0.1	6.3
Southern										
Western	10.3	-0.6	10.5	10.8	0.2	9.4	-5.6	8.7	-1.1	8.4
Less favorable agriculture conditions	8.8	1.7	9.3	9.8	2.3	10.3	1.1	10.2	-0.6	10.0
More favorable agriculture conditions	10.3	2.2	11.5	11.1	-0.1	12.1	0.4	12.4	0.3	12.2
Mineral-rich countries	5.1	-1.9	4.7	4.7	1.0	5.0	-1.6	4.8	1.8	5.0
Lower-middle-income countries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Upper-middle-income countries	10.2	-0.8	10.4	10.8	0.2	9.3	-5.9	8.5	-1.1	8.3
CEN-SAD	10.1	-0.5	10.4	10.7	0.2	9.3	-5.5	8.6	-1.0	8.4
COMESA	4.6	-0.7	4.3	4.3	0.6	4.2	-6.0	3.4	1.0	3.4
EAC	5.3	0.5	5.4	5.6	-0.3	5.6	-2.4	4.4	-2.1	4.3
ECCAS	7.4	0.1	7.1	7.7	3.3	8.3	0.1	8.5	0.4	8.5
ECOWAS	10.3	-0.6	10.5	10.8	0.2	9.4	-5.6	8.7	-1.1	8.4
IGAD	4.4	0.3	4.3	4.2	0.7	3.9	-11.3	2.6	1.4	2.6
SADC	5.9	-5.6	4.5	4.5	0.1	4.5	-0.1	4.5	0.5	4.6
UMA	6.3	-0.1	6.3	6.3	0.0	6.3	-0.1	6.3	0.1	6.3
CAADP Compact 2007-09 (CC1)	10.4	-0.4	10.8	11.3	0.8	10.0	-6.4	9.1	-0.8	9.0
CAADP Compact 2010-12 (CC2)	8.8	-1.2	8.4	8.1	-2.3	6.8	-1.5	6.1	-2.2	5.8
CAADP Compact 2013-15 (CC3)	5.8	0.9	5.8	6.4	4.0	6.8	-1.4	6.6	0.3	6.7
CAADP Compact not yet (CC0)	5.3	0.2	5.3	5.4	0.2	4.2	-14.3	2.6	0.5	2.6
CAADP Level 0 (CL0)	5.3	0.2	5.3	5.4	0.2	4.2	-14.3	2.6	0.5	2.6
CAADP Level 1 (CL1)	5.2	-0.1	5.2	5.3	1.4	5.3	-1.5	5.1	0.3	5.2
CAADP Level 2 (CL2)	7.3	-0.6	6.8	7.5	4.7	8.6	0.0	8.9	1.7	9.2
CAADP Level 3 (CL3)	10.0	3.2	10.6	10.7	0.6	9.9	-3.4	9.3	1.4	9.3
CAADP Level 4 (CL4)	10.2	-0.6	10.5	10.8	0.2	9.4	-5.6	8.7	-1.1	8.4
NAIP00 (N00)	8.4	0.4	8.5	8.6	0.5	8.3	-1.0	7.9	-1.0	7.7
NAIP10 (N10)	5.3	0.1	5.2	5.7	3.9	6.1	-1.7	6.0	1.1	6.1
NAIP11 (N11)	10.2	-0.6	10.5	10.8	0.2	9.4	-5.6	8.7	-1.1	8.4

Source:ReSAKSS based on FAO (2021).

Note: Data only available up to 2019. Yam production data are not available for Southern Africa.

ANNEX 2g: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.5C

TABLE L2.1.5C—YIELD, MAIZE (metric tons per hectare)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	1.7	1.5	1.7	1.7	2.2	2.0	0.6	2.0	0.4	2.0
Central	1.1	0.3	1.1	1.1	1.6	1.1	-1.1	1.1	-0.1	1.1
Eastern	1.6	0.2	1.6	1.5	4.5	1.8	3.6	2.2	4.4	2.4
Northern	5.5	3.6	6.1	6.3	0.8	6.5	1.4	6.7	-0.2	6.6
Southern	1.6	2.0	1.6	1.7	2.2	2.2	2.9	2.1	-2.1	2.0
Western	1.4	1.9	1.5	1.6	2.0	1.7	-2.6	1.7	1.7	1.7
Less favorable agriculture conditions	1.1	0.4	1.2	1.3	2.4	1.8	2.5	2.0	3.5	2.1
More favorable agriculture conditions	1.4	0.2	1.3	1.3	5.5	1.7	3.6	1.9	1.4	2.0
Mineral-rich countries	0.9	0.9	0.9	0.9	0.0	0.9	-1.3	0.9	0.8	0.9
Lower-middle-income countries	1.8	1.9	1.9	1.9	0.2	2.0	-0.2	1.9	-1.1	1.9
Upper-middle-income countries	2.4	5.1	2.8	3.3	6.7	4.5	0.3	4.8	3.4	4.9
CEN-SAD	1.9	2.3	2.0	2.1	0.6	2.1	-2.1	2.0	0.3	2.0
COMESA	1.8	0.7	1.8	1.9	1.8	2.2	3.2	2.3	0.9	2.4
EAC	1.6	-0.6	1.5	1.4	4.3	1.6	2.1	1.8	1.1	1.8
ECCAS	0.9	0.5	0.9	1.0	1.3	1.1	1.5	1.1	-0.8	1.1
ECOWAS	1.4	1.9	1.5	1.6	2.0	1.7	-2.6	1.7	1.7	1.7
IGAD	1.6	1.3	1.6	1.7	2.4	2.1	4.3	2.5	5.9	2.9
SADC	1.5	1.1	1.5	1.5	3.0	1.8	1.5	1.8	-0.9	1.8
UMA	0.6	2.9	0.8	0.7	-1.9	0.8	-1.1	0.8	0.9	0.8
CAADP Compact 2007-09 (CC1)	1.4	1.4	1.5	1.6	3.7	1.8	-0.2	2.0	3.0	2.1
CAADP Compact 2010-12 (CC2)	1.4	-0.2	1.3	1.3	3.3	1.5	2.0	1.5	-1.2	1.5
CAADP Compact 2013-15 (CC3)	1.0	0.0	1.0	1.0	-3.2	1.1	5.9	1.2	1.0	1.2
CAADP Compact not yet (CC0)	3.0	4.6	3.5	4.0	5.8	4.9	-0.8	5.1	2.8	5.2
CAADP Level 0 (CL0)	3.0	4.6	3.5	4.0	5.8	4.9	-0.8	5.1	2.8	5.2
CAADP Level 1 (CL1)	0.9	-1.5	0.8	0.8	-6.0	0.9	8.9	1.0	2.2	1.1
CAADP Level 2 (CL2)	1.1	1.3	1.1	1.1	0.9	1.2	-1.8	1.1	0.3	1.1
CAADP Level 3 (CL3)	1.4	1.5	1.5	1.6	3.2	2.1	1.5	2.3	0.2	2.3
CAADP Level 4 (CL4)	1.4	0.4	1.4	1.5	3.9	1.7	1.5	1.8	1.1	1.8
NAIP00 (N00)	2.3	3.6	2.5	2.6	1.6	3.1	1.9	3.1	-0.6	3.0
NAIP10 (N10)	1.3	-0.8	1.2	1.1	3.7	1.3	1.4	1.4	-1.8	1.3
NAIP11 (N11)	1.4	1.2	1.5	1.6	3.4	1.8	0.7	2.0	2.0	2.0

Source: ReSAKSS based on FAO (2021).
Note: Data only available up to 2019.

ANNEX 2h: *Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.5D*

TABLE L2.1.5D—YIELD, MEAT (indigenous cattle, kilograms per head)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014–2019)	Annual avg. change (2014–2019)	2019
Africa	145.8	0.7	152.8	156.8	0.9	157.1	-0.5	157.4	0.0	156.9
Central	134.4	-0.2	133.0	132.4	0.0	127.8	-0.9	125.0	-0.3	124.2
Eastern	116.6	1.0	125.6	129.8	1.0	128.7	-0.8	130.6	0.3	129.6
Northern	191.7	3.0	223.6	228.6	1.7	237.0	-0.1	257.7	2.8	276.4
Southern	222.3	-0.4	217.3	228.6	1.1	235.3	0.2	238.9	0.4	241.3
Western	129.2	0.4	130.8	130.9	0.1	128.9	-0.4	124.1	-1.1	122.7
Less favorable agriculture conditions	124.6	1.2	129.3	129.0	-0.3	126.0	-0.3	124.9	-0.1	124.5
More favorable agriculture conditions	115.5	-0.5	112.4	113.7	0.5	114.6	0.0	119.0	2.5	126.1
Mineral-rich countries	118.1	1.4	123.9	123.6	0.0	125.7	0.5	129.4	0.6	131.0
Lower-middle-income countries	157.0	2.0	178.3	185.5	1.5	182.7	-1.3	179.0	-1.5	171.4
Upper-middle-income countries	244.9	-0.5	240.9	258.8	1.6	285.6	1.4	295.3	1.2	305.8
CEN-SAD	136.5	1.7	151.1	155.2	1.2	154.6	-1.1	150.0	-1.1	145.6
COMESA	136.2	1.7	152.4	157.3	1.1	157.4	-1.2	150.8	-1.5	144.4
EAC	122.3	1.8	142.2	152.4	2.1	147.8	-1.7	151.3	0.4	148.8
ECCAS	139.9	0.2	138.3	135.7	-0.4	130.3	-0.8	126.9	-0.6	125.5
ECOWAS	129.2	0.4	130.8	130.9	0.1	128.9	-0.4	124.1	-1.1	122.7
IGAD	118.2	1.7	132.4	138.2	1.2	137.6	-1.1	134.4	-1.5	126.8
SADC	175.7	-0.1	174.5	181.1	0.9	183.5	0.2	192.3	1.8	200.5
UMA	180.5	1.1	184.4	185.6	0.8	189.4	0.9	226.0	4.1	239.7
CAADP Compact 2007-09 (CC1)	124.1	0.3	125.3	125.8	0.1	122.3	-0.7	119.0	-1.0	117.5
CAADP Compact 2010-12 (CC2)	125.4	0.8	135.8	141.9	1.5	142.3	-0.7	144.3	0.3	142.7
CAADP Compact 2013-15 (CC3)	131.7	1.0	135.1	134.1	-0.2	129.8	-1.3	124.2	-0.3	123.5
CAADP Compact not yet (CC0)	206.6	1.2	222.2	232.9	1.7	242.6	-0.6	249.5	1.8	261.0
CAADP Level 0 (CL0)	206.6	1.2	222.2	232.9	1.7	242.6	-0.6	249.5	1.8	261.0
CAADP Level 1 (CL1)	131.1	1.2	135.0	133.9	-0.3	131.2	-1.0	126.4	-0.2	126.0
CAADP Level 2 (CL2)	136.6	-0.7	133.0	131.3	-0.1	128.5	-0.3	130.0	0.3	130.7
CAADP Level 3 (CL3)	148.4	2.5	159.5	159.0	-0.3	155.5	-0.4	154.0	0.1	154.1
CAADP Level 4 (CL4)	119.3	0.4	125.5	129.9	1.2	127.5	-1.2	126.8	-0.3	124.6
NAIP00 (N00)	184.3	1.0	194.3	199.1	0.8	204.8	0.2	209.6	0.6	213.0
NAIP10 (N10)	120.8	0.3	121.2	121.6	0.3	122.0	0.0	129.3	2.5	136.9
NAIP11 (N11)	125.4	0.9	134.8	139.3	1.0	137.4	-0.9	132.3	-1.9	125.0

Source: ReSAKSS based on FAO (2021).
Note: Data only available up to 2019.

ANNEX 2i: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.1.5E

TABLE L2.1.5E—YIELD, MILK (whole fresh cow, kilograms per head)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	517.1	1.5	552.7	544.1	-0.6	540.9	1.3	552.9	1.1	575.2
Central	310.8	-0.9	299.1	300.6	0.6	312.8	2.0	302.8	-5.6	274.2
Eastern	377.8	2.8	435.1	407.4	-2.5	379.1	-0.2	384.7	3.8	426.6
Northern	1104.7	5.0	1302.2	1510.6	5.4	1825.2	2.7	1783.7	-1.0	1748.6
Southern	1326.8	-1.1	1337.5	1403.8	0.9	1421.2	1.3	1459.5	-1.2	1423.6
Western	236.4	-1.3	225.3	233.0	1.9	244.9	0.2	242.7	-1.6	235.9
Less favorable agriculture conditions	285.2	-1.6	265.4	275.1	1.6	282.5	0.1	276.7	-2.9	262.5
More favorable agriculture conditions	303.9	4.5	398.4	378.7	-2.6	328.7	-0.4	336.4	3.9	379.2
Mineral-rich countries	439.8	-1.4	411.8	373.9	-2.2	369.3	0.5	360.6	0.5	363.0
Lower-middle-income countries	664.3	4.4	773.9	818.9	2.1	923.5	1.2	935.0	1.5	970.8
Upper-middle-income countries	2293.2	-1.8	2281.7	2433.0	0.5	2331.7	1.6	2581.7	0.1	2583.3
CEN-SAD	478.7	1.3	495.6	488.2	0.1	521.3	1.7	540.1	0.8	548.9
COMESA	467.0	2.6	535.9	513.3	-1.7	478.1	-0.4	471.3	3.4	518.9
EAC	386.6	3.1	429.4	416.9	-1.7	429.1	1.3	466.1	3.8	511.0
ECCAS	374.8	-0.4	364.8	366.6	0.4	383.9	2.3	363.8	-3.8	340.9
ECOWAS	236.4	-1.3	225.3	233.0	1.9	244.9	0.2	242.7	-1.6	235.9
IGAD	415.8	2.7	480.9	446.2	-2.7	407.3	-0.6	404.8	4.1	454.9
SADC	667.8	-0.7	641.2	630.4	-1.3	620.2	1.6	671.9	0.7	680.2
UMA	1067.1	5.4	1240.9	1416.3	5.8	1805.2	4.6	1858.6	-1.4	1817.8
CAADP Compact 2007-09 (CC1)	287.0	5.7	416.2	395.4	-2.8	318.7	-2.3	296.8	2.7	328.6
CAADP Compact 2010-12 (CC2)	392.4	2.2	423.2	410.0	-1.5	417.7	1.1	447.9	3.3	485.2
CAADP Compact 2013-15 (CC3)	423.6	-0.4	411.4	379.1	-1.9	372.8	0.5	363.3	-0.2	362.6
CAADP Compact not yet (CC0)	1209.8	2.0	1300.1	1461.9	3.7	1656.0	2.1	1676.8	-0.5	1655.3
CAADP Level 0 (CL0)	1209.8	2.0	1300.1	1461.9	3.7	1656.0	2.1	1676.8	-0.5	1655.3
CAADP Level 1 (CL1)	418.4	-0.3	407.3	375.0	-1.9	367.7	0.4	357.1	-0.2	356.5
CAADP Level 2 (CL2)	331.1	-0.5	321.9	322.7	0.7	336.7	1.3	331.5	-1.7	317.4
CAADP Level 3 (CL3)	438.2	-1.7	408.7	405.8	0.2	402.3	0.2	408.2	-1.1	410.4
CAADP Level 4 (CL4)	334.6	5.1	435.0	414.1	-2.9	368.0	-0.7	377.3	5.0	429.6
NAIP00 (N00)	910.6	2.2	999.9	1102.4	3.0	1232.2	2.2	1218.9	-1.4	1184.2
NAIP10 (N10)	418.3	-0.5	402.7	372.1	-2.1	367.9	1.1	395.0	2.4	416.2
NAIP11 (N11)	345.0	4.3	440.1	422.5	-2.3	375.9	-1.3	367.1	3.2	405.4

Source: ReSAKSS based on FAO (2021).
Note: Data only available up to 2019.

ANNEX 2j: Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.2.1A

TABLE L2.2.1A—INTRA-AFRICAN AGRICULTURAL TRADE, EXPORTS (billion, constant 2010 US$)										
Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	5.2	5.4	6.1	6.8	7.9	12.2	9.0	15.3	2.1	15.8
Central	0.1	0.4	0.2	0.2	2.1	0.2	-4.6	0.2	-0.8	0.2
Eastern	0.9	3.7	1.1	1.3	11.8	2.0	7.5	2.9	12.4	3.6
Northern	0.5	8.5	0.7	1.0	18.1	1.9	5.6	2.3	5.2	2.5
Southern	2.9	4.7	3.1	3.1	4.9	6.3	12.7	8.0	-1.6	7.6
Western	0.9	9.0	1.1	1.2	4.8	1.9	4.0	1.9	0.5	1.9
Less favorable agriculture conditions	0.2	7.4	0.2	0.2	11.1	0.3	-8.3	0.3	7.8	0.3
More favorable agriculture conditions	0.6	8.8	0.8	1.1	12.9	1.8	9.0	2.3	6.2	2.6
Mineral-rich countries	0.1	3.0	0.2	0.1	-10.4	0.1	6.5	0.6	46.2	1.0
Lower-middle-income countries	2.5	7.6	3.0	3.4	8.0	5.3	6.3	6.2	1.7	6.3
Upper-middle-income countries	1.9	1.7	1.9	1.9	5.8	4.7	13.9	5.9	-2.2	5.5
CEN-SAD	1.9	6.3	2.3	2.8	9.0	4.4	3.8	5.1	5.9	5.6
COMESA	1.9	8.2	2.3	2.6	8.3	4.0	7.6	5.3	6.7	5.9
EAC	0.7	2.6	0.8	1.1	13.6	1.7	5.3	2.0	7.7	2.4
ECCAS	0.2	-0.3	0.2	0.3	6.8	0.3	1.2	0.3	6.9	0.4
ECOWAS	0.9	9.0	1.1	1.2	4.8	1.9	4.0	1.9	0.5	1.9
IGAD	0.7	4.3	0.8	1.0	10.6	1.5	6.5	2.2	14.6	2.7
SADC	3.1	4.4	3.4	3.4	5.3	6.8	12.4	8.6	-1.1	8.4
UMA	0.7	10.2	0.9	1.4	18.3	2.4	6.7	2.7	-5.8	2.4
CAADP Compact 2007-09 (CC1)	0.4	7.5	0.6	0.6	8.8	1.1	5.5	1.1	1.4	1.2
CAADP Compact 2010-12 (CC2)	1.9	6.5	2.4	2.9	8.3	4.0	5.8	4.9	2.8	5.1
CAADP Compact 2013-15 (CC3)	0.7	6.5	0.7	0.6	0.7	0.8	10.6	1.5	15.6	1.9
CAADP Compact not yet (CC0)	2.2	3.5	2.4	2.7	9.0	6.2	11.7	7.8	-0.5	7.6
CAADP Level 0 (CL0)	2.2	3.5	2.4	2.7	9.0	6.2	11.7	7.8	-0.5	7.6
CAADP Level 1 (CL1)	1.0	6.5	1.0	0.9	0.6	1.1	6.7	1.8	14.4	2.3
CAADP Level 2 (CL2)	0.2	-3.5	0.2	0.3	9.7	0.4	2.6	0.4	3.0	0.4
CAADP Level 3 (CL3)	0.5	14.8	0.8	1.0	13.0	1.5	6.3	2.0	4.7	2.0
CAADP Level 4 (CL4)	1.4	5.8	1.7	1.9	6.7	3.1	7.0	3.3	0.6	3.4
NAIP00 (N00)	2.7	4.2	3.0	3.1	7.7	6.8	12.0	8.6	0.0	8.5
NAIP10 (N10)	0.9	6.1	1.1	1.4	7.5	1.8	5.4	2.7	8.8	3.2
NAIP11 (N11)	1.6	7.1	2.0	2.3	8.3	3.6	5.5	4.0	2.6	4.1

Source: ReSAKSS based on UNCTAD (2021) and World Bank (2021).

Note: : Aggregate value for a group is the sum of intra-African agricultural exports for countries in the group. The values of intra-African agricultural exports and imports for Africa as a whole are expected to be equal. However, Tables TL2.2.1A and TL2.2.1B show differing values, due to differences in commodities categorized as agricultural by different countries, year of shipment of exports and arrival of imports, treatment of the origin of export versus shipment, and valuation of exports and imports (for details see UNCTAD: http://unctadstat.unctad.org/EN?FAQ.html). Data only available up to 2019.

ANNEX 2k: *Level 2—Agricultural Transformation and Sustained Inclusive Agricultural Growth, Indicator 2.2.1B*

TABLE L2.2.1B—INTRA-AFRICAN AGRICULTURAL TRADE, IMPORTS (billion, constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	6.0	6.8	7.6	8.2	4.5	12.1	5.2	15.1	5.4	17.1
Central	0.6	0.9	0.7	0.9	7.5	1.1	3.9	1.2	-2.6	1.1
Eastern	0.7	10.3	1.1	1.2	6.3	1.9	6.7	2.4	7.6	2.8
Northern	0.7	11.7	1.0	1.0	5.0	1.6	6.0	2.9	23.5	4.7
Southern	3.1	4.9	3.7	3.7	3.8	5.5	4.0	6.1	-0.5	6.0
Western	1.0	10.9	1.2	1.3	2.2	2.0	7.6	2.5	1.8	2.5
Less favorable agriculture conditions	0.3	10.7	0.4	0.5	6.8	0.8	7.9	0.9	-0.5	0.9
More favorable agriculture conditions	0.7	1.7	0.9	1.1	3.9	1.3	8.1	1.8	5.0	2.0
Mineral-rich countries	0.4	2.1	0.6	0.7	7.1	1.1	8.0	1.4	5.1	1.6
Lower-middle-income countries	3.3	7.6	4.0	4.2	4.0	5.7	1.3	7.0	8.7	8.6
Upper-middle-income countries	1.3	9.0	1.7	1.8	4.2	3.2	10.4	3.9	1.2	4.0
CEN-SAD	1.8	12.8	2.6	2.7	3.1	4.4	7.3	5.6	3.8	5.9
COMESA	2.3	7.7	3.3	3.8	7.1	5.0	2.4	5.6	2.0	5.7
EAC	0.4	4.9	0.6	0.8	10.8	1.1	4.3	1.2	4.8	1.3
ECCAS	1.2	6.0	1.4	1.4	0.8	1.7	3.1	1.7	-3.5	1.6
ECOWAS	1.0	10.9	1.2	1.3	2.2	2.0	7.6	2.5	1.8	2.5
IGAD	0.5	12.8	0.7	0.8	6.5	1.3	5.3	1.6	9.7	1.9
SADC	3.6	4.6	4.3	4.5	4.2	6.4	3.8	7.1	-0.2	7.0
UMA	0.5	13.8	0.7	0.7	3.4	1.2	9.2	2.3	24.7	4.0
CAADP Compact 2007-09 (CC1)	0.8	9.9	1.0	1.0	1.1	1.6	9.2	2.0	0.1	1.9
CAADP Compact 2010-12 (CC2)	1.8	4.8	2.3	2.7	4.9	3.4	4.4	4.1	2.7	4.3
CAADP Compact 2013-15 (CC3)	1.8	7.0	2.2	2.3	3.9	3.1	0.9	3.2	-0.6	3.1
CAADP Compact not yet (CC0)	1.7	7.4	2.2	2.3	5.9	4.0	8.2	5.9	12.3	7.9
CAADP Level 0 (CL0)	1.7	7.4	2.2	2.3	5.9	4.0	8.2	5.9	12.3	7.9
CAADP Level 1 (CL1)	2.1	6.8	2.5	2.5	3.1	3.3	0.9	3.3	-1.1	3.2
CAADP Level 2 (CL2)	0.4	-0.2	0.4	0.6	12.7	0.8	1.8	0.9	2.4	1.0
CAADP Level 3 (CL3)	0.6	8.0	0.8	0.9	2.9	1.0	5.2	1.4	4.1	1.5
CAADP Level 4 (CL4)	1.3	7.8	1.7	1.9	3.0	2.9	7.7	3.6	1.5	3.5
NAIP00 (N00)	3.2	7.3	4.0	4.2	5.0	6.4	4.1	7.9	7.4	9.6
NAIP10 (N10)	1.4	3.8	1.7	1.9	2.8	2.6	6.5	3.3	4.0	3.6
NAIP11 (N11)	1.4	8.8	1.9	2.2	4.7	3.1	6.4	3.8	2.3	3.9

Source: ReSAKSS based on UNCTAD (2021) and World Bank (2021).

Note: Aggregate value for a group is the sum of intra-African agricultural imports for countries in the group. The values of intra-African agricultural exports and imports for Africa as a whole are expected to be equal. However, Tables TL2.2.1A and TL2.2.1B show differing values, due to differences in commodities categorized as agricultural by different countries, year of shipment of exports and arrival of imports, treatment of the origin of export versus shipment, and valuation of exports and imports (for details see UNCTAD: http://unctadstat.unctad.org/EN?FAQ.html). Data only available up to 2019.

ANNEX 3a: Level 3—Strengthening Systemic Capacity to Deliver Results, Indicator 3.5.1

TABLE L3.5.1—GOVERNMENT AGRICULTURE EXPENDITURE (billion, constant 2010 US$)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	10.1	2.7	11.4	13.2	6.1	14.7	1.6	16.1	-1.5	15.5
Central	0.5	-24.3	0.2	0.3	11.5	0.6	9.9	0.7	0.4	0.8
Eastern	1.4	3.7	1.8	2.4	10.1	2.8	-0.8	3.2	4.8	3.5
Northern	4.8	4.1	5.3	5.0	-3.1	3.9	-1.3	3.9	-1.3	4.1
Southern	1.6	5.0	2.1	3.0	15.2	4.0	1.0	3.9	-7.4	3.0
Western	1.7	4.1	2.0	2.5	10.9	3.5	6.6	4.3	-0.9	4.2
Less favorable agriculture conditions	0.4	1.1	0.4	0.5	1.9	0.6	10.4	0.9	4.6	1.2
More favorable agriculture conditions	1.0	3.5	1.3	1.8	13.7	2.7	4.4	3.6	2.4	3.9
Mineral-rich countries	0.8	-16.3	0.6	0.8	10.0	0.6	0.2	0.8	5.5	0.9
Lower-middle-income countries	6.7	3.5	7.4	7.9	3.8	8.3	0.9	8.4	-3.7	7.6
Upper-middle-income countries	1.1	14.9	1.8	2.2	8.2	2.5	-0.4	2.4	-3.5	2.0
CEN-SAD	6.3	1.9	6.6	6.6	1.3	7.1	3.5	8.3	-0.3	8.5
COMESA	3.9	-1.8	3.8	4.2	4.3	4.5	1.4	5.1	-2.6	4.8
EAC	0.5	4.5	0.7	0.7	6.1	1.1	0.8	1.4	9.1	1.7
ECCAS	0.6	-17.8	0.4	0.7	26.2	1.1	2.0	1.1	-1.2	1.2
ECOWAS	1.7	4.1	2.0	2.5	10.9	3.5	6.6	4.3	-0.9	4.2
IGAD	1.1	4.2	1.5	2.0	11.7	2.1	0.2	2.5	2.4	2.4
SADC	2.3	-1.7	2.4	3.4	13.5	4.5	-0.1	4.5	-5.2	3.8
UMA	5.7	3.8	6.8	6.8	0.7	5.6	-3.0	5.6	2.0	5.9
CAADP Compact 2007-09 (CC1)	1.4	12.2	2.1	2.8	12.7	3.8	6.0	4.8	-0.3	4.7
CAADP Compact 2010-12 (CC2)	2.5	-6.3	2.1	2.4	6.4	3.1	3.5	3.9	-0.3	3.7
CAADP Compact 2013-15 (CC3)	1.0	-7.6	0.9	1.5	18.9	1.8	-4.4	1.4	-4.5	1.4
CAADP Compact not yet (CC0)	5.2	7.3	6.3	6.5	0.9	6.0	-0.2	6.0	-2.4	5.7
CAADP Level 0 (CL0)	5.2	7.3	6.3	6.5	0.9	6.0	-0.2	6.0	-2.4	5.7
CAADP Level 1 (CL1)	0.9	-8.4	0.9	1.4	18.2	1.5	-7.5	1.0	-3.7	1.1
CAADP Level 2 (CL2)	1.4	-11.0	0.9	0.9	-2.5	0.8	0.2	0.8	-2.0	0.7
CAADP Level 3 (CL3)	0.5	8.7	0.6	0.9	12.3	1.2	9.3	2.2	0.7	2.1
CAADP Level 4 (CL4)	2.1	5.9	2.7	3.5	12.9	5.2	4.9	6.1	-0.8	5.9
NAIP00 (N00)	5.8	5.0	6.6	7.1	3.0	7.0	-1.0	6.7	-2.5	6.6
NAIP10 (N10)	1.9	-6.6	1.8	2.1	6.1	2.1	-0.4	2.2	-4.6	1.9
NAIP11 (N11)	2.4	5.2	3.0	3.9	12.4	5.6	5.8	7.1	0.5	7.1

Source: ReSAKSS based on IFPRI (2019), World Bank (2021), and national sources.
Note: Aggregate value for a group is the sum of government agriculture expenditure for countries in the group.

ANNEX 3b: Level 3—Strengthening Systemic Capacity to Deliver Results, Indicator 3.5.2

TABLE L3.5.2—GOVERNMENT AGRICULTURE EXPENDITURE AS SHARE OF TOTAL GOVERNMENT EXPENDITURE (%)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	3.6	3.4	3.8	3.6	-3.2	2.7	-2.5	2.5	-3.7	2.1
Central	3.0	0.7	2.5	2.6	-5.2	2.2	0.2	2.1	-1.7	1.3
Eastern	5.6	1.9	6.0	6.4	2.4	6.0	-5.5	5.2	0.9	4.6
Northern	5.4	-1.5	4.5	3.7	-10.2	2.1	-4.5	1.8	-1.4	1.9
Southern	1.7	6.4	2.2	2.5	4.0	2.3	-3.9	1.9	-7.1	1.4
Western	4.0	-4.0	3.8	4.1	0.4	3.2	3.6	3.3	-9.1	2.4
Less favorable agriculture conditions	15.1	-5.2	11.7	10.5	-5.4	6.6	1.1	7.2	0.2	3.1
More favorable agriculture conditions	7.5	-2.5	7.5	8.9	6.5	9.6	-3.5	4.4	-22.5	6.8
Mineral-rich countries	4.6	10.4	5.3	4.9	-15.1	1.3	-2.5	1.8	7.6	0.8
Lower-middle-income countries	4.1	-1.2	3.8	3.4	-4.3	2.5	-3.4	1.9	-7.1	2.2
Upper-middle-income countries	1.6	14.5	2.3	2.4	-2.3	1.8	-3.7	1.8	5.5	1.0
CEN-SAD	5.5	-3.5	4.6	3.8	-7.4	2.7	0.3	2.8	-5.0	2.3
COMESA	5.2	8.3	5.3	4.6	-5.1	3.6	-3.2	3.4	-3.6	2.9
EAC	4.8	-1.6	4.1	3.7	1.0	4.3	-7.6	3.7	4.5	3.8
ECCAS	1.9	-3.7	1.5	2.1	8.4	1.8	-7.4	1.7	6.4	1.4
ECOWAS	4.0	-4.0	3.8	4.1	0.4	3.2	3.6	3.3	-9.1	2.4
IGAD	5.5	2.8	6.3	6.9	3.7	6.3	-3.6	5.9	-0.6	4.6
SADC	2.0	6.5	2.4	2.6	2.6	2.4	-5.1	2.0	-5.0	1.6
UMA	5.1	-3.1	4.3	3.9	-5.0	2.3	-5.8	2.1	2.0	2.2
CAADP Compact 2007-09 (CC1)	3.7	0.8	4.3	5.0	1.8	3.6	2.9	3.9	-8.5	2.9
CAADP Compact 2010-12 (CC2)	6.8	4.4	5.1	4.9	1.4	4.8	-3.6	4.3	-4.2	3.4
CAADP Compact 2013-15 (CC3)	2.7	-3.1	2.8	3.5	3.4	2.5	-11.0	1.8	1.1	1.5
CAADP Compact not yet (CC0)	3.2	4.6	3.5	3.0	-7.5	2.0	-3.3	1.7	-3.7	1.5
CAADP Level 0 (CL0)	3.2	4.6	3.5	3.0	-7.5	2.0	-3.3	1.7	-3.7	1.5
CAADP Level 1 (CL1)	2.6	-3.2	2.8	3.4	2.2	2.1	-13.7	1.4	2.5	1.3
CAADP Level 2 (CL2)	11.7	9.2	5.6	4.7	-5.4	3.4	-6.0	2.7	-1.5	2.2
CAADP Level 3 (CL3)	5.9	0.2	6.1	6.5	-7.8	2.6	2.5	2.9	-15.0	1.7
CAADP Level 4 (CL4)	4.1	-1.9	4.2	4.8	6.5	5.1	1.2	5.5	-1.2	4.9
NAIP00 (N00)	3.1	3.5	3.4	3.0	-6.4	2.0	-5.0	1.6	-2.7	1.5
NAIP10 (N10)	5.9	7.1	5.2	5.2	-1.2	4.0	-5.1	3.2	-5.6	2.3
NAIP11 (N11)	4.5	-2.9	4.4	4.8	3.0	4.1	1.5	4.1	-6.8	3.3

Source: ReSAKSS based on IFPRI (2019), World Bank (2021), and national sources.

ANNEX 3c: Level 3—Strengthening Systemic Capacity to Deliver Results, Indicator 3.5.3

TABLE L3.5.3—GOVERNMENT AGRICULTURE EXPENDITURE AS SHARE OF AGRICULTURE GDP (%)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	5.6	-1.5	5.3	5.8	3.4	5.1	-1.8	4.6	-4.4	4.0
Central	3.9	-21.1	2.1	2.3	2.2	3.2	5.5	3.5	-1.7	3.3
Eastern	3.5	2.4	4.5	5.4	5.6	4.3	-7.8	3.7	1.5	3.5
Northern	13.0	-3.7	11.2	10.2	-3.7	6.7	-4.5	5.4	-5.2	4.8
Southern	9.0	5.8	11.5	15.5	9.4	15.9	-0.9	13.8	-5.8	10.1
Western	2.4	-2.4	2.0	2.5	9.3	2.8	4.7	3.1	-4.2	2.8
Less favorable agriculture conditions	5.1	-3.1	5.1	4.6	-7.7	3.8	4.5	4.9	1.8	7.7
More favorable agriculture conditions	4.1	4.3	5.1	5.9	5.4	5.9	-1.0	6.1	-2.4	5.5
Mineral-rich countries	4.0	-17.6	2.7	3.6	8.3	2.3	-6.3	2.4	7.7	2.7
Lower-middle-income countries	5.8	-2.8	4.9	5.1	2.0	4.3	-1.9	3.5	-6.6	2.9
Upper-middle-income countries	11.3	14.4	16.9	21.1	3.8	21.4	1.3	19.4	-3.8	14.8
CEN-SAD	5.0	-3.3	4.1	4.1	-0.6	3.5	0.5	3.5	-3.1	3.4
COMESA	6.1	-2.7	5.7	5.9	0.7	4.7	-3.3	4.4	-5.2	3.6
EAC	3.0	5.3	3.6	3.6	2.4	3.7	-5.9	3.3	1.3	3.3
ECCAS	4.1	-15.5	2.6	4.0	16.6	4.7	-3.4	3.6	-2.3	3.4
ECOWAS	2.4	-2.4	2.0	2.5	9.3	2.8	4.7	3.1	-4.2	2.8
IGAD	3.5	2.0	4.7	5.8	7.0	4.2	-7.4	3.6	-0.1	3.1
SADC	7.2	1.1	8.1	10.5	8.4	10.7	-2.9	8.8	-6.8	6.8
UMA	17.1	-7.9	13.6	13.6	1.8	9.1	-8.5	6.4	-2.1	6.1
CAADP Compact 2007-09 (CC1)	2.0	5.3	2.2	2.8	9.8	3.0	3.5	3.3	-3.4	2.8
CAADP Compact 2010-12 (CC2)	6.5	-5.5	5.7	5.9	3.5	5.7	-1.4	5.4	-6.6	4.8
CAADP Compact 2013-15 (CC3)	3.9	-9.1	3.5	5.2	13.5	4.6	-10.7	2.9	-0.9	2.9
CAADP Compact not yet (CC0)	11.1	0.7	11.2	11.3	-0.2	8.8	-2.7	7.2	-5.8	6.0
CAADP Level 0 (CL0)	11.1	0.7	11.2	11.3	-0.2	8.8	-2.7	7.2	-5.8	6.0
CAADP Level 1 (CL1)	4.2	-9.8	3.7	5.3	12.1	4.1	-13.7	2.4	0.8	2.7
CAADP Level 2 (CL2)	12.0	-7.0	9.9	9.1	-4.3	6.5	-3.0	5.1	-7.4	3.9
CAADP Level 3 (CL3)	3.7	5.2	4.6	5.5	7.3	5.7	5.3	8.8	-2.6	9.6
CAADP Level 4 (CL4)	2.4	0.8	2.4	3.0	10.2	3.5	1.8	3.4	-5.0	2.8
NAIP00 (N00)	10.4	0.1	10.4	10.4	0.1	8.3	-3.9	6.5	-4.7	5.6
NAIP10 (N10)	5.7	-6.7	5.4	6.1	3.7	4.6	-6.2	3.9	-4.9	3.3
NAIP11 (N11)	2.7	-0.2	2.5	3.2	9.7	3.5	2.7	3.8	-3.6	3.3

Source: ReSAKSS based on IFPRI (2019), World Bank (2021), and national sources.

ANNEX 3d: *Level 3—Strengthening Systemic Capacity to Deliver Results*

TABLE L 3(a)—PROGRESS IN CAADP IMPLEMENTATION PROCESS AS OF SEPTEMBER 2021

			Second generation investment plan				Inaugural biennial review (BR) process		Second biennial review (BR) process		Third biennial review (BR) process
Country/Region	JSR assessment conducted/ initiated	First generation NAIP drafted, reviewed, and validated	Malabo domestication event held	Malabo status assessment and profile finalized	Malabo goals and milestones report finalized	Malabo compliant NAIP drafted, reviewed, and/or validated	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR data reviewed, validated, and submitted to REC
AFRICA*	**26**	**36**	**25**	**31**	**25**	**42**	**47**	**20**	**49**	**4**	**51**
Central Africa*	***1***	***6***	***2***	***2***	***2***	***5***	***9***	***1***	***8***		***8***
Burundi		Yes				Yes	Yes	On track	Yes		Yes
Cameroon		Yes		Yes	Yes	Yes	Yes		Yes		Yes
Central African Republic		Yes					Yes		Yes		Yes
Chad						Yes	Yes		Yes		Yes
Congo, Dem. Republic	Yes	Yes	Yes				Yes		Yes		Yes
Congo, Republic		Yes				Yes	Yes		Yes		Yes
Equatorial Guinea							Yes		Yes		Yes
Gabon			Yes	Yes	Yes	Yes	Yes		Yes		Yes
Sao Tome and Principe		Yes					Yes				
Eastern Africa*	***7***	***9***	***5***	***6***	***1***	***12***	***10***	***6***	***13***	***1***	***12***
Comoros						Yes					Yes
Djibouti		Yes				Yes	Yes		Yes		Yes
Eritrea						Yes			Yes		Yes
Ethiopia	Yes	Yes	Yes	Yes		Yes	Yes	On track	Yes		Yes
Kenya	Yes	Yes	Yes	Yes	Yes	Yes	Yes	On track	Yes		Yes
Madagascar						Yes	Yes		Yes		Yes
Mauritius	Yes					Yes	Yes	On track	Yes		
Rwanda		Yes	Yes	Yes		Yes	Yes	On track	Yes	On track	Yes
Seychelles	Yes	Yes		Yes			Yes	On track	Yes		Yes
Somalia									Yes		
South Sudan		Yes				Yes			Yes		Yes
Sudan		Yes				Yes	Yes		Yes		Yes
Tanzania	Yes	Yes	Yes	Yes		Yes	Yes		Yes		Yes
Uganda	Yes	Yes	Yes	Yes		Yes	Yes	On track	Yes		Yes

ANNEX 3d: Level 3—Strengthening Systemic Capacity to Deliver Results, continued

TABLE L 3(a)—PROGRESS IN CAADP IMPLEMENTATION PROCESS AS OF SEPTEMBER 2021 *continued*

			Second generation investment plan				Inaugural biennial review (BR) process		Second biennial review (BR) process		Third biennial review (BR) process
Country/Region	JSR assessment conducted/ initiated	First generation NAIP drafted, reviewed, and validated	Malabo domestication event held	Malabo status assessment and profile finalized	Malabo goals and milestones report finalized	Malabo compliant NAIP drafted, reviewed, and/or validated	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR data reviewed, validated, and submitted to REC
Northern Africa*		***1***				***5***	***4***	***2***	***3***	***1***	***6***
Algeria											Yes
Egypt						Yes	Yes				Yes
Libya						Yes					Yes
Mauritania		Yes				Yes	Yes	On track	Yes		Yes
Morocco						Yes	Yes	On track	Yes	On track	Yes
Tunisia						Yes	Yes		Yes		Yes
Saharawi Arab Dem. Republic											
Southern Africa*	***8***	***5***	***9***	***8***	***7***	***5***	***10***	***6***	***10***		***10***
Angola	Yes		Yes	Yes	Yes		Yes		Yes		Yes
Botswana			Yes	Yes	Yes	Yes	Yes	On track	Yes		Yes
Eswatini	Yes	Yes	Yes	Yes	Yes		Yes	On track	Yes		Yes
Lesotho			Yes	Yes	Yes		Yes		Yes		Yes
Malawi	Yes	Yes	Yes	Yes		Yes	Yes	On track	Yes		Yes
Mozambique	Yes	Yes	Yes			Yes	Yes	On track	Yes		Yes
Namibia			Yes	Yes	Yes		Yes	On track	Yes		Yes
South Africa							Yes	On track	Yes		Yes
Zambia	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Zimbabwe	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Western Africa*	***10***	***15***	***9***	***15***	***15***	***15***	***14***	***5***	***15***	***2***	***15***
Benin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	On track	Yes		Yes
Burkina Faso	Yes	Yes	Yes	Yes	Yes	Yes	Yes	On track	Yes		Yes
Cabo Verde		Yes		Yes	Yes	Yes	Yes	On track	Yes		Yes
Côte d'Ivoire	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Gambia		Yes		Yes	Yes	Yes	Yes		Yes		Yes
Ghana	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes	On track	Yes
Guinea		Yes		Yes	Yes	Yes	Yes		Yes		Yes
Guinea Bissau		Yes		Yes	Yes	Yes			Yes		Yes

ANNEX 3d: *Level 3—Strengthening Systemic Capacity to Deliver Results, continued*

TABLE L 3(a)—PROGRESS IN CAADP IMPLEMENTATION PROCESS AS OF SEPTEMBER 2021 *continued*

			Second generation investment plan				Inaugural biennial review (BR) process		Second biennial review (BR) process		Third biennial review (BR) process
Country/Region	JSR assessment conducted/ initiated	First generation NAIP drafted, reviewed, and validated	Malabo domestication event held	Malabo status assessment and profile finalized	Malabo goals and milestones report finalized	Malabo compliant NAIP drafted, reviewed, and/or validated	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR report drafted, validated, and submitted to REC	Country on track to meet Malabo Commitments	BR data reviewed, validated, and submitted to REC
Western Africa* *cont'd*	***10***	***15***	***9***	***15***	***15***	***15***	***14***	***5***	***15***	***2***	***15***
Liberia		Yes		Yes	Yes	Yes	Yes		Yes		Yes
Mali	Yes	Yes	Yes	Yes	Yes	Yes	Yes	On track	Yes	On track	Yes
Niger	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Nigeria		Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Senegal	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes		Yes
Sierra Leone		Yes		Yes	Yes	Yes	Yes		Yes		Yes
Togo	Yes	Yes	Yes	Yes	Yes	Yes	Yes	On track	Yes		Yes
RECS**	***2***	***3***									
CEN-SAD											
COMESA											
EAC	Yes										
ECCAS		Yes									
ECOWAS	Yes	Yes									
IGAD		Yes									
SADC											
UMA											

Source: Authors' compilation based on NEPAD (2015), AUC (2021), and ReSAKSS (2021).
Note: * The items in this row are the number of countries in the subregion that have achieved the milestone. ** The items in this row are the number of RECs that have achieved the milestone.
JSR=Joint Sector Review; NAIP= National Agriculture Investment Plan; BR=Biennial Review.

ReSAKSS-ECA

Burundi (COMESA, EAC, ECCAS)
Central African Rep. (CEN-SAD, ECCAS)
Comoros (CEN-SAD, COMESA)
Congo, D.R. (COMESA, ECCAS, SADC)
Congo, R. (ECCAS)
Djibouti (CEN-SAD, COMESA, IGAD)
Egypt (CEN-SAD, COMESA)
Eritrea (COMESA, IGAD)
Ethiopia (COMESA, IGAD)
Gabon (ECCAS)
Kenya (CEN-SAD, COMESA, EAC, IGAD)
Libya (CEN-SAD, COMESA, UMA)
Rwanda (COMESA, EAC, ECCAS)
Seychelles (COMESA, SADC)
South Sudan (IGAD, EAC)
Sudan (CEN-SAD, COMESA, IGAD)
Tanzania (SADC)
Uganda (COMESA, EAC, IGAD)

ReSAKSS-SA

Angola (ECCAS, SADC)
Botswana (SADC)
Eswatini (COMESA, SADC)
Madagascar (COMESA, SADC)
Malawi (COMESA, SADC)
Mauritius (COMESA, SADC)
Mozambique (SADC)
Namibia (SADC)
Lesotho (SADC)
Zambia (COMESA, SADC)
Zimbabwe (COMESA, SADC)

ReSAKSS-WA

Benin (CEN-SAD, ECOWAS)
Burkina Faso (CEN-SAD, ECOWAS)
Cameroon (ECCAS)
Cabo Verde (ECOWAS)
Chad (CEN-SAD, ECCAS)
Côte d'Ivoire (CEN-SAD, ECOWAS)
Gambia (CEN-SAD, ECOWAS)
Ghana (CEN-SAD, ECOWAS)
Guinea (CEN-SAD, ECOWAS)
Guinea-Bissau (CEN-SAD, ECOWAS)
Liberia (CEN-SAD, ECOWAS)
Mali (CEN-SAD, ECOWAS)
Mauritania (CEN-SAD, UMA)
Niger (CEN-SAD, ECOWAS)
Nigeria (CEN-SAD, ECOWAS)
Senegal (CEN-SAD, ECOWAS)
Sierra Leone (CEN-SAD, ECOWAS)
Togo (CEN-SAD, ECOWAS)

ANNEX 3d: Level 3—Strengthening Systemic Capacity to Deliver Results

TABLE L 3(b)—PROGRESS IN STRENGTHENING SYSTEMIC CAPACITY

Country/region	L2.4.2-Existence of food reserves, local purchases for relief programs, early warning systems and school feeding programs**	L3.1.1-Existence of a new NAIP/NAFSIP developed through an inclusive and participatory process	L3.2.1-Existence of inclusive institutionalized mechanisms for mutual accountability and peer review	L3.3.1-Existence of and quality in the implementation of evidence-informed policies and corresponding human resources	L3.4.1-Existence of a functional multisectoral and multistakeholder coordination body	L3.4.2-Cumulative number of agriculture-related public-private partnerships (PPPs) that are successfully undertaken	L3.4.3-Cumulative value of investments in the PPPs	L3.4.6-Existence of an operational country SAKSS
AFRICA*	**42**	**42**	**28**	**36**	**31**	**22**	**22**	**14**
Central Africa*	***4***	***5***	***2***	***3***	***1***	***3***	***3***	***1***
Burundi	Yes	Yes	Yes	Yes	Yes	Several PPPs	€18 million	
Cameroon		Yes						
Central African Republic	Yes					Two	US$1.25	
Chad		Yes						
Congo, Dem. Rep.	Yes		Yes	Yes		Several PPPs	Not stated	Yes
Congo, Rep.	Yes	Yes		Yes				
Equatorial Guinea								
Gabon		Yes						
Sao Tome and Principe								
Eastern Africa*	***14***	***12***	***6***	***12***	***8***	***8***	***8***	***4***
Comoros	Yes	Yes		Yes				
Djibouti	Yes	Yes		Yes		Several PPPs	Not stated	
Eritrea	Yes	Yes						
Ethiopia	Yes	Yes	Yes	Yes	Yes	Several PPPs	Over US$10 million	
Kenya	Yes	Yes		Yes	Yes	Several PPPs	Over US$200 million	Yes
Madagascar	Yes	Yes	Yes	Yes	Yes	Four	Not stated	
Mauritius	Yes	Yes	Yes	Yes	Yes	One	Not stated	
Rwanda	Yes	Yes	Yes	Yes	Yes	Several PPPs	Over US$20 million	Yes
Seychelles	Yes			Yes	Yes			
Somalia	Yes							
South Sudan	Yes	Yes		Yes				
Sudan	Yes	Yes		Yes				

ANNEX 3d: Level 3—Strengthening Systemic Capacity to Deliver Results, continued

TABLE L 3(b)—PROGRESS IN STRENGTHENING SYSTEMIC CAPACITY *continued*

Country/region	L2.4.2-Existence of food reserves, local purchases for relief programs, early warning systems and school feeding programs**	L3.1.1-Existence of a new NAIP/NAFSIP developed through an inclusive and participatory process	L3.2.1-Existence of inclusive institutionalized mechanisms for mutual accountability and peer review	L3.3.1-Existence of and quality in the implementation of evidence-informed policies and corresponding human resources	L3.4.1-Existence of a functional multisectoral and multistakeholder coordination body	L3.4.2-Cumulative number of agriculture-related public-private partnerships (PPPs) that are successfully undertaken	L3.4.3-Cumulative value of investments in the PPPs	L3.4.6-Existence of an operational country SAKSS
***Eastern Africa** cont'd*	***14***	***12***	***6***	***12***	***8***	***8***	***8***	***4***
Tanzania	Yes	Yes	Yes	Yes	Several PPPs across the country and many of them in SAGCOT with several projects	US$ 3.2 billion by 2030	Yes	Yes
Uganda	Yes	Yes	Yes	Yes	Several PPPs	Over US$ 218 million	Yes	Yes
Northern Africa*	***2***	***5***		***2***	***1***	***1***	***1***	
Algeria								
Egypt	Yes	Yes		Yes	Yes	Several PPPs	Over US$30 million	
Libya	Yes	Yes		Yes				
Mauritania		Yes						
Morocco		Yes						
Tunisia		Yes						
Saharawi Arab Dem. Republic								
Southern Africa*	***10***	***5***	***10***	***10***	***9***	***7***	***7***	***2***
Angola	Yes		Yes	Yes	Yes	Five	Not stated	
Botswana	Yes	Yes	Yes	Yes	Yes	Three	Not stated	
Eswatini	Yes		Yes	Yes	Yes	Four	Not stated	
Lesotho	Yes		Yes	Yes	Yes	Four	Over US$87 million	
Malawi	Yes	Yes	Yes	Yes	Yes	Four	Not stated	
Mozambique	Yes	Yes	Yes	Yes	Yes	Four	Not stated	Yes
Namibia	Yes		Yes	Yes		One	Not stated	
South Africa	Yes		Yes	Yes	Yes			
Zambia	Yes	Yes	Yes	Yes	Yes			
Zimbabwe	Yes	Yes	Yes	Yes	Yes			Yes

TABLE L 3(b)—PROGRESS IN STRENGTHENING SYSTEMIC CAPACITY *continued*

Country/region	L2.4.2-Existence of food reserves, local purchases for relief programs, early warning systems and school feeding programs**	L3.1.1-Existence of a new NAIP/NAFSIP developed through an inclusive and participatory process	L3.2.1-Existence of inclusive institutionalized mechanisms for mutual accountability and peer review	L3.3.1-Existence of and quality in the implementation of evidence-informed policies and corresponding human resources	L3.4.1-Existence of a functional multisectoral and multistakeholder coordination body	L3.4.2-Cumulative number of agriculture-related public-private partnerships (PPPs) that are successfully undertaken	L3.4.3-Cumulative value of investments in the PPPs	L3.4.6-Existence of an operational country SAKSS
Western Africa*	***12***	***15***	***10***	***9***	***12***	***3***	***3***	***7***
Benin	Yes	Yes	Yes		Yes			Yes
Burkina Faso	Yes	Yes		Yes	Yes			Yes
Cabo Verde		Yes						
Côte d'Ivoire		Yes		Yes	Yes	two	Not stated	
Gambia	Yes	Yes	Yes	Yes	Yes			
Ghana	Yes	Yes	Yes	Yes	Yes			Yes
Guinea	Yes	Yes	Yes	Yes				
Guinea-Bissau		Yes						
Liberia	Yes	Yes			Yes			
Mali	Yes	Yes	Yes	Yes	Yes	Three	More than 50 billion FCFA	Yes
Niger	Yes	Yes	Yes	Yes	Yes			Yes
Nigeria	Yes	Yes	Yes		Yes			
Senegal	Yes	Yes	Yes	Yes	Yes			Yes
Sierra Leone	Yes	Yes	Yes		Yes			
Togo	Yes	Yes	Yes	Yes	Yes	Four	Not stated	Yes

Note: * The figures in this row are the number of countries in Africa of the sub region corresponding to each indicator.
** This indicator is from level 2 of the CAADP Results Framework
SAKSS = Strategic Analysis and Knowledge Support System
NAIP = National Agricultural Investment Plan
NAFSIP = National Agriculture and Food Security Investment Plans

ANNEX 4: Country Categories by Geographic Regions, Economic Classification, and Regional Economic Communities

TABLE 4.1—GEOGRAPHIC REGIONS

Western Africa	Eastern Africa	Southern Africa	Central Africa	Northern Africa
Benin	Comoros	Angola	Burundi	Algeria
Burkina Faso	Djibouti	Botswana	Cameroon	Egypt
Cabo Verde	Eritrea	Eswatini	Central African Republic	Libya
Côte d'Ivoire	Ethiopia	Lesotho	Chad	Mauritania
Gambia	Kenya	Malawi	Congo, Dem. Rep.	Morocco
Ghana	Madagascar	Mozambique	Congo, Rep.	Sahrawi, Arab Dem. Rep.
Guinea	Mauritius	Namibia	Equatorial Guinea	Tunisia
Guinea-Bissau	Rwanda	South Africa	Gabon	
Liberia	Seychelles	Zambia	Sao Tome and Principe	
Mali	Somalia	Zimbabwe		
Niger	Sudan			
Nigeria	Tanzania			
Senegal	Uganda			
Sierra Leone	South Sudan			
Togo				

ANNEX 4: *Country Categories by Geographic Regions, Economic Classification, and Regional Economic Communities*

TABLE 4.2—ECONOMIC CLASSIFICATIONS

Mineral-rich countries	Less favorable agriculture conditions	More favorable agriculture conditions	Lower middle-income countries	Upper middle-income countries
Central African Republic	Burundi	Benin	Algeria	Botswana
Congo, Dem. Rep.	Chad	Burkina Faso	Angola	Equatorial Guinea
Guinea	Eritrea	Ethiopia	Cameroon	Gabon
Liberia	Mali	Gambia	Cabo Verde	Libya
Sierra Leone	Niger	Guinea-Bissau	Comoros	Mauritius
South Sudan	Rwanda	Madagascar	Congo, Rep.	Namibia
Sudan	Somalia	Malawi	Côte d'Ivoire	South Africa
		Mozambique	Djibouti	Seychelles
		Tanzania	Egypt	
		Togo	Eswatini	
		Uganda	Ghana	
			Kenya	
			Lesotho	
			Mauritania	
			Morocco	
			Nigeria	
			Sahrawi, Arab Dem. Rep.	
			Sao Tome and Principe	
			Senegal	
			Tunisia	
			Zambia	
			Zimbabwe	

ANNEX 4: *Country Categories by Geographic Regions, Economic Classification, and Regional Economic Communities*

TABLE 4.3—REGIONAL ECONOMIC COMMUNITIES

CEN-SAD	COMESA	SADC	ECOWAS	ECCAS	IGAD	EAC	UMA
Benin	Burundi	Angola	Benin	Angola	Djibouti	Burundi	Algeria
Burkina Faso	Comoros	Botswana	Burkina Faso	Burundi	Eritrea	Kenya	Libya
Cent. African Republic	Congo, Dem. Rep.	Congo, Dem. Rep.	Cabo Verde	Cameroon	Ethiopia	Rwanda	Mauritania
Chad	Djibouti	Eswatini	Côte d'Ivoire	Cent. African Republic	Kenya	Tanzania	Morocco
Comoros	Egypt	Lesotho	Gambia	Chad	Somalia	Uganda	Tunisia
Côte d'Ivoire	Eritrea	Madagascar	Ghana	Congo, Dem. Rep.	Sudan	South Sudan	
Djibouti	Eswatini	Malawi	Guinea	Congo, Rep.	Uganda		
Egypt	Ethiopia	Mauritius	Guinea-Bissau	Equatorial Guinea	South Sudan		
Gambia	Kenya	Mozambique	Liberia	Gabon			
Ghana	Libya	Namibia	Mali	Rwanda			
Guinea	Madagascar	Seychelles	Niger	Sao Tome and Principe			
Guinea-Bissau	Malawi	South Africa	Nigeria				
Kenya	Mauritius	Tanzania	Senegal				
Liberia	Rwanda	Zambia	Sierra Leone				
Libya	Seychelles	Zimbabwe	Togo				
Mali	Sudan						
Mauritania	Uganda						
Morocco	Zambia						
Niger	Zimbabwe						
Nigeria							
Sao Tome and Principe							
Senegal							
Sierra Leone							
Somalia							
Sudan							
Togo							
Tunisia							
South Sudan							

Note: CEN-SAD = Community of Sahel-Saharan States; COMESA = Common Market for Eastern and Southern Africa; EAC = East African Community; ECCAS = Economic Community of Central African States; ECOWAS = Economic Community of West African States; IGAD = Intergovernmental Authority for Development; SADC = Southern African Development Community; UMA = Arab Maghreb Union.

ANNEX 5: Distribution of Countries by Year of Signing CAADP Compact and Level of CAADP Implementation Reached by End of 2015

TABLE 5.1—CAADP COMPACT SIGNING AND LEVEL OF CAADP IMPLEMENTATION

PERIOD WHEN CAADP COMPACT WAS SIGNED				LEVEL OR STAGE OF CAADP IMPLEMENTATION REACHED BY END OF 2015				
2007–2009	2010–2012	2013–2015	Not signed	LEVEL 0 Not started or pre-compact	LEVEL 1 Signed compact	LEVEL 2 Level 1 plus NAIP	LEVEL 3 Level 2 plus one external funding source	LEVEL 4 Level 3 plus other external funding source
CC1	**CC2**	**CC3**	**CC0**	**CL0**	**CL1**	**CL2**	**CL3**	**CL4**
Benin	Burkina Faso	Angola	Algeria	Algeria	Angola	Cameroon	Burundi	Benin
Burundi	Central Afr. Rep.	Cameroon	Comoros	Comoros	Chad	Cabo Verde	Gambia	Burkina Faso
Cabo Verde	Congo, Dem. Rep.	Chad	Egypt	Egypt	Congo, Rep.	Central Afr. Rep.	Liberia	Côte d'Ivoire
Ethiopia	Côte d'Ivoire	Congo, Rep.	Eritrea	Eritrea	Eswatini	Congo, Dem. Rep.	Mali	Ethiopia
Gambia	Djibouti	Equatorial Guinea	Libya	Libya	Equatorial Guinea	Djibouti	Niger	Ghana
Ghana	Eswatini	Gabon	Morocco	Morocco	Gabon	Guinea	Sierra Leone	Kenya
Liberia	Guinea	Lesotho	Saharawi Arab Dem. Republic	Saharawi Arab Dem. Republic	Lesotho	Guinea Bissau	Togo	Malawi
Mali	Guinea Bissau	Madagascar	Somalia	Somalia	Madagascar	Mauritania	Uganda	Mozambique
Niger	Kenya	Mauritius	South Africa	South Africa	Mauritius	Sao Tome and Principe	Zambia	Nigeria
Nigeria	Malawi	Sudan	South Sudan	South Sudan	Seychelles			Rwanda
Rwanda	Mauritania	Sao Tome and Principe	Tunisia	Tunisia	Sudan			Senegal
Sierra Leone	Mozambique	Zimbabwe			Zimbabwe			Tanzania
Togo	Senegal							
	Seychelles							
	Tanzania							
	Uganda							
	Zambia							
Count								
13	17	12	11	11	12	9	9	12
AgShare in GDP (%)								
25.8	22.2	15.1	7.6	7.6	15.0	18.0	25.5	24.9

Note: NAIP = national agricultural investment plan. There are three external funding sources considered—Grow Africa, New Alliance Cooperation, and the Global Agriculture and Food Security Program (GAFSP). AgShare in GDP is the average share of agricultural GDP in total GDP for 2003-2020.

ANNEX 6: *Distribution of Countries in Formulating First-Generation Investment Plan (NAIP1.0) and Second-Generation Investment Plan (NAIP2.0) Reached by September of 2021*

TABLE 6.1—PROGRESS IN NAIP FORMULATION

NAIP00	NAIP10	NAIP11
Algeria	Burundi	Benin
Angola	Cameroon	Burkina Faso
Chad	Central African Republic	Cabo Verde
Comoros	Congo Rep.	Côte d'Ivoire
Egypt	Congo, Dem. Republic	Ethiopia
Equatorial Guinea	Djibouti	Gambia
Eritrea	Eswatini	Ghana
Gabon	Mauritania	Guinea
Lesotho	Mozambique	Guinea Bissau
Libya	São Tomé and Principe	Kenya
Madagascar	Seychelles	Liberia
Mauritius	South Sudan	Malawi
Morocco	Sudan	Mali
Saharawi Arab Dem. Republic	Tanzania	Niger
Somalia	Zambia	Nigeria
South Africa	Zimbabwe	Rwanda
Tunisia		Senegal
		Sierra Leone
		Togo
		Uganda
Count		
17	16	20
AgShare in GDP (%)		
8.1	20.7	24.3

Note: NAIP00 = countries that have neither NAIP1.0 nor NAIP2.0, NAIP10 = countries that have a NAIP1.0 but do not have NAIP2.0, NAIP11 = countries that have both NAIP1.0 and NAIP2.0.

AgShare in GDP is the average share of agricultural GDP in total GDP for 2009-2020.

ANNEX 7: Supplementary Data Tables

TABLE O.1.1A—AGRICULTURAL ODA (% total ODA)

Region	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	3.8	3.7	2.9	5.6	5.7	6.7	-0.5	6.6
Central	2.1	2.1	20.7	3.2	16.9	4.3	2.8	4.8
Eastern	4.6	4.3	-1.0	6.1	4.5	7.4	-2.0	7.0
Northern	3.8	3.7	-3.4	4.8	8.2	5.3	-6.0	4.5
Southern	2.9	3.5	3.7	5.4	6.3	6.2	-2.5	5.6
Western	5.4	4.2	-0.8	6.9	3.5	8.2	2.1	8.5
Less favorable agriculture conditions	6.3	5.8	-0.2	8.4	5.1	9.6	4.6	10.5
More favorable agriculture conditions	5.1	5.3	-1.7	7.0	3.6	8.0	-2.4	7.3
Mineral-rich countries	1.3	1.3	15.3	3.5	19.8	3.6	-9.7	3.0
Lower-middle-income countries	3.9	3.3	3.5	5.5	3.9	6.7	0.7	6.8
Upper-middle-income countries	3.8	3.6	-12.2	2.0	3.1	1.7	0.6	1.8
CEN-SAD	4.9	3.9	-2.6	6.0	5.5	6.9	-0.5	6.8
COMESA	3.2	3.5	7.7	5.6	8.3	7.2	-4.3	6.6
EAC	4.3	5.1	6.8	6.1	0.5	7.7	7.6	8.9
ECCAS	1.9	2.3	25.5	4.0	11.9	5.5	3.5	6.0
ECOWAS	5.4	4.2	-0.8	6.9	3.5	8.2	2.1	8.5
IGAD	4.3	4.0	-0.8	6.1	8.0	7.2	-4.6	6.6
SADC	2.7	3.4	10.4	4.8	3.8	5.8	-0.6	5.5
UMA	5.1	4.0	-11.1	4.9	7.7	4.2	3.8	4.0
CAADP Compact 2007-09 (CC1)	4.3	3.5	-2.4	6.8	6.5	8.3	2.8	8.7
CAADP Compact 2010-12 (CC2)	3.8	4.6	11.0	5.7	1.8	7.1	0.1	6.9
CAADP Compact 2013-15 (CC3)	3.7	2.7	-4.4	5.5	16.5	5.7	-9.5	4.8
CAADP Compact not yet (CC0)	3.4	3.1	-6.1	3.9	13.0	4.6	-5.4	4.0
CAADP Level 0 (CL0)	3.4	3.1	-6.1	3.9	13.0	4.6	-5.4	4.0
CAADP Level 1 (CL1)	3.8	2.9	-3.7	5.7	15.8	5.5	-12.5	4.3
CAADP Level 2 (CL2)	2.8	2.7	13.1	3.1	3.0	3.9	8.2	4.5
CAADP Level 3 (CL3)	4.3	4.7	3.0	7.0	7.2	7.8	3.2	8.4
CAADP Level 4 (CL4)	4.6	4.3	1.6	6.6	2.3	8.4	0.3	8.2
NAIP00 (N00)	3.8	3.5	-4.5	4.5	8.4	4.8	-2.6	4.5
NAIP10 (N10)	2.7	2.8	9.7	4.7	9.0	5.7	-5.9	5.0
NAIP11 (N11)	4.9	4.5	1.2	6.9	3.4	8.4	1.9	8.6

Source: ReSAKSS based on OECD (2021) and World Bank (2021).
Note: Data are from 2002 to 2019. ODA refers to gross disbursements.

ANNEX 7: Supplementary Data Tables

TABLE O.1.1B—AGRICULTURAL ODA DISBURSEMENTS (as % of agricultural ODA commitments)

Region	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	81.0	77.3	-5.2	73.5	3.1	75.5	-0.5	78.4
Central	72.3	79.2	12.5	69.5	1.7	74.6	3.3	91.0
Eastern	71.7	80.9	-1.6	78.6	3.2	73.1	0.7	80.5
Northern	116.0	70.2	-19.5	69.2	21.1	120.6	5.7	199.5
Southern	85.0	89.2	-1.7	83.2	0.2	86.9	-10.4	65.9
Western	86.8	77.3	-7.7	73.1	-1.8	73.7	1.4	74.5
Less favorable agriculture conditions	92.5	89.0	-7.9	76.9	3.1	70.8	5.3	76.9
More favorable agriculture conditions	82.2	89.7	-1.7	82.6	-2.2	73.0	-1.9	74.2
Mineral-rich countries	55.7	55.2	-3.6	86.4	18.1	77.9	-18.9	51.5
Lower-middle-income countries	86.4	66.5	-8.8	69.3	5.3	86.6	3.4	97.6
Upper-middle-income countries	83.7	119.7	7.6	106.7	15.0	105.8	-16.7	86.9
CEN-SAD	87.7	68.2	-9.2	69.9	6.0	75.0	0.1	78.6
COMESA	74.9	80.9	-3.7	72.5	2.7	76.3	1.8	88.2
EAC	59.0	86.8	15.2	85.3	-0.6	74.2	5.0	84.7
ECCAS	74.7	78.3	6.6	72.7	1.2	75.6	2.0	84.6
ECOWAS	86.8	77.3	-7.7	73.1	-1.8	73.7	1.4	74.5
IGAD	65.0	78.6	-3.8	77.5	6.4	70.2	-2.0	71.2
SADC	81.5	88.3	2.2	86.1	-1.4	83.5	-3.6	82.7
UMA	98.9	76.7	-22.3	106.3	48.3	111.4	-16.9	102.6
CAADP Compact 2007-09 (CC1)	82.8	77.0	-11.4	74.8	-1.2	73.9	5.9	83.2
CAADP Compact 2010-12 (CC2)	73.4	85.9	7.2	79.7	-0.8	79.0	-4.0	74.3
CAADP Compact 2013-15 (CC3)	92.6	80.0	-8.3	73.6	9.5	67.5	-6.7	68.8
CAADP Compact not yet (CC0)	121.3	86.6	-25.1	69.4	24.7	126.9	3.7	207.3
CAADP Level 0 (CL0)	121.3	86.6	-25.1	69.4	24.7	126.9	3.7	207.3
CAADP Level 1 (CL1)	82.0	75.3	-9.4	81.4	15.1	68.4	-10.6	62.6
CAADP Level 2 (CL2)	82.4	88.2	7.1	77.3	-8.6	70.1	-1.7	78.3
CAADP Level 3 (CL3)	79.9	103.5	-0.3	79.0	-0.2	64.2	0.1	60.7
CAADP Level 4 (CL4)	78.2	72.0	-2.4	76.8	-1.6	83.5	2.0	88.1
NAIP00 (N00)	109.3	85.3	-16.8	72.4	15.4	82.3	0.5	101.3
NAIP10 (N10)	74.6	76.9	2.1	79.0	5.0	80.5	-5.8	75.0
NAIP11 (N11)	76.5	79.7	-3.7	75.0	-1.3	73.5	1.4	76.2

Source: ReSAKSS based on OECD (2021) and World Bank (2021).
Note: Data are from 2002 to 2019.

ANNEX 7: Supplementary Data Tables

TABLE O.1.1C—EMERGENCY FOOD AID (% of total ODA)

Region	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014–2019)	2019
Africa	4.4	4.9	-0.5	4.5	-10.1	4.2	10.9	5.0
Central	1.7	3.0	27.4	5.1	0.5	6.1	9.7	7.3
Eastern	10.1	10.8	-8.9	8.3	-11.9	6.1	3.4	6.5
Northern	1.2	1.6	8.6	1.6	-14.9	1.3	20.2	1.9
Southern	4.3	3.7	2.9	2.6	-18.6	1.9	9.3	2.1
Western	0.9	0.8	-6.0	1.6	24.2	3.6	18.5	4.6
Less favorable agriculture conditions	3.9	4.8	-11.5	6.7	8.6	5.4	-4.8	5.2
More favorable agriculture conditions	5.5	5.4	-15.2	3.7	-12.1	4.0	10.9	4.3
Mineral-rich countries	8.1	12.1	14.7	9.5	-5.4	8.1	5.8	9.4
Lower-middle-income countries	3.3	3.2	12.4	3.1	-17.7	3.0	23.5	4.3
Upper-middle-income countries	0.2	0.1	-10.8	0.3	18.2	0.5	59.2	0.7
CEN-SAD	3.8	5.1	8.6	5.5	-8.3	4.9	10.9	6.2
COMESA	7.1	9.2	4.3	8.1	-12.3	6.0	4.0	6.4
EAC	3.6	4.0	-4.0	3.2	-8.2	2.7	7.4	3.1
ECCAS	3.9	3.3	1.6	4.3	0.2	5.1	9.8	6.0
ECOWAS	0.9	0.8	-6.0	1.6	24.2	3.6	18.5	4.6
IGAD	14.6	15.7	-9.1	11.7	-12.1	8.4	0.5	8.4
SADC	2.7	2.7	11.4	2.5	-13.3	2.4	15.9	2.9
UMA	1.2	1.6	8.6	1.6	-14.9	1.3	20.2	1.9
CAADP Compact 2007-09 (CC1)	5.6	4.8	-14.0	4.4	-6.3	5.5	11.4	6.1
CAADP Compact 2010-12 (CC2)	1.7	2.3	8.8	2.6	-3.0	2.8	7.7	3.1
CAADP Compact 2013-15 (CC3)	12.0	12.5	5.3	13.8	-9.4	9.1	1.5	10.0
CAADP Compact not yet (CC0)	4.4	3.4	-43.8	0.6	-13.9	0.5	30.9	0.8
CAADP Level 0 (CL0)	4.4	3.4	-43.8	0.6	-13.9	0.5	30.9	0.8
CAADP Level 1 (CL1)	15.4	15.5	5.5	15.6	-9.1	10.2	1.5	11.2
CAADP Level 2 (CL2)	1.3	2.2	20.7	3.3	1.0	4.6	7.8	5.2
CAADP Level 3 (CL3)	3.2	3.1	-8.1	3.0	8.8	3.6	1.8	3.7
CAADP Level 4 (CL4)	3.8	3.7	-9.9	3.4	-10.6	3.9	13.8	4.3
NAIP00 (N00)	7.6	6.2	-1.8	4.6	-25.6	2.4	22.4	3.6
NAIP10 (N10)	3.9	5.8	12.1	5.5	-6.2	4.9	8.4	6.1
NAIP11 (N11)	4.3	4.2	-9.7	3.9	-6.5	4.4	7.9	4.7

Source: ReSAKSS based on OECD (2021) and World Bank (2021).
Note: Data are from 2002 to 2019. ODA and food aid refer to gross disbursements.

ANNEX 7: *Supplementary Data Tables*

TABLE O.1.2A—GENERAL GOVERNMENT GROSS DEBT (% of GDP)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	54.1	-2.4	46.2	31.8	-14.8	23.6	2.3	30.9	4.3	33.2
Central	88.9	-0.6	79.7	51.8	-19.3	20.4	-6.8	31.9	13.3	38.5
Eastern	92.0	-4.2	79.8	53.4	-19.1	39.7	4.6	43.6	-1.3	40.4
Northern	47.1	-6.2	37.7	26.6	-15.4	16.9	-0.2	21.2	8.3	23.3
Southern	42.7	-3.2	34.3	27.2	-5.0	31.5	6.6	45.9	3.5	48.1
Western	52.6	3.7	48.6	29.3	-20.7	15.5	-3.1	19.4	6.2	20.4
Less favorable agriculture conditions	78.3	-2.2	63.4	39.4	-22.0	26.5	3.8	34.8	5.9	38.6
More favorable agriculture conditions	81.4	-5.2	70.1	46.6	-22.1	28.6	4.5	40.1	3.9	40.7
Mineral-rich countries	133.9	3.2	140.5	101.3	-15.3	53.8	-4.7	42.5	-6.1	35.2
Lower-middle-income countries	53.9	-3.9	43.1	27.8	-18.2	17.1	-0.1	22.8	6.2	24.0
Upper-middle-income countries	27.6	0.1	24.6	22.2	2.6	32.0	8.4	44.9	4.1	48.5
CEN-SAD	54.9	-0.3	50.4	34.8	-15.7	22.2	-0.7	26.1	4.3	27.5
COMESA	64.6	-2.0	62.3	44.9	-15.9	29.0	-0.1	34.1	3.6	42.6
EAC	62.9	-5.7	53.9	35.5	-20.8	26.3	6.3	37.8	6.1	42.8
ECCAS	99.8	-5.3	72.7	44.5	-22.2	20.6	-1.1	33.7	8.4	37.1
ECOWAS	52.6	3.7	48.6	29.3	-20.7	15.5	-3.1	19.4	6.2	20.4
IGAD	96.3	-2.2	88.9	59.8	-18.6	40.8	3.0	42.7	-2.9	37.2
SADC	47.0	-3.2	38.7	30.2	-7.0	32.2	5.5	45.3	3.6	47.9
UMA	55.2	-6.3	40.1	25.6	-17.8	18.2	3.2	22.8	3.8	23.3
CAADP Compact 2007-09 (CC1)	42.4	7.2	43.5	24.1	-25.9	11.8	0.9	17.6	7.0	18.6
CAADP Compact 2010-12 (CC2)	93.7	-1.9	82.4	57.4	-16.0	36.4	-2.0	45.9	5.1	49.0
CAADP Compact 2013-15 (CC3)	107.0	-6.1	79.2	51.7	-18.8	35.2	3.2	42.8	-0.4	38.7
CAADP Compact not yet (CC0)	36.3	-3.9	30.6	24.2	-7.1	23.2	4.4	30.5	5.0	35.8
CAADP Level 0 (CL0)	36.3	-3.9	30.6	24.2	-7.1	23.2	4.4	30.5	5.0	35.8
CAADP Level 1 (CL1)	109.0	-5.8	81.6	54.1	-17.7	38.1	2.7	44.9	-0.9	39.9
CAADP Level 2 (CL2)	88.1	2.9	90.0	64.0	-16.2	29.4	-8.9	32.7	7.5	38.5
CAADP Level 3 (CL3)	109.2	3.1	108.7	63.7	-26.0	26.8	-0.3	44.9	9.2	49.8
CAADP Level 4 (CL4)	53.1	-0.4	46.1	27.9	-21.2	17.2	1.1	24.2	6.0	25.7
NAIP00 (N00)	42.3	-5.1	33.4	25.4	-9.1	23.9	4.7	32.0	4.5	36.7
NAIP10 (N10)	125.4	-2.7	109.0	72.4	-18.4	41.2	-1.0	49.1	0.9	47.1
NAIP11 (N11)	53.5	2.7	50.2	30.4	-21.6	17.2	-0.2	23.1	6.4	24.6

Source: ReSAKSS based on AfDB (2021) and World Bank (2021).

TABLE O.1.2B—GENERAL GOVERNMENT GROSS REVENUE (% OF GDP)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	24.2	3.4	26.5	27.0	-0.3	24.4	-1.7	20.5	-1.8	20.1
Central	18.4	3.8	20.8	26.6	9.7	23.7	-0.6	18.8	-5.3	17.6
Eastern	15.7	1.8	18.1	18.9	-0.8	16.1	-3.0	15.2	0.9	15.6
Northern	27.7	1.5	29.8	32.8	2.7	31.3	-2.3	24.6	-2.8	23.7
Southern	26.1	0.5	25.8	27.1	1.6	28.6	0.5	28.7	0.7	29.4
Western	22.3	11.4	27.8	23.1	-9.7	15.6	-2.1	11.0	-4.3	10.6
Less favorable agriculture conditions	16.7	2.4	18.8	22.5	7.1	20.8	1.1	19.4	-0.9	19.4
More favorable agriculture conditions	17.1	1.3	18.4	19.0	-0.2	17.3	-0.6	17.7	1.2	18.2
Mineral-rich countries	9.4	7.3	14.5	16.0	0.9	14.6	-3.3	11.2	-4.9	10.5
Lower-middle-income countries	25.8	4.0	28.1	27.4	-2.3	23.6	-2.0	18.3	-3.5	17.6
Upper-middle-income countries	25.6	2.2	27.6	30.6	3.4	30.7	-0.7	29.7	1.3	30.5
CEN-SAD	22.6	5.8	26.3	25.5	-2.7	21.1	-3.2	15.2	-4.3	14.3
COMESA	21.6	2.3	24.7	26.6	1.1	24.0	-3.5	17.9	-4.6	16.5
EAC	18.5	-0.3	19.0	19.5	-0.7	17.1	-0.9	17.8	2.1	18.6
ECCAS	26.4	2.7	27.0	31.9	6.4	30.5	-2.2	20.5	-6.0	19.1
ECOWAS	22.3	11.4	27.8	23.1	-9.7	15.6	-2.1	11.0	-4.3	10.6
IGAD	15.5	2.6	18.6	19.0	-1.6	15.5	-3.9	14.1	-0.1	14.2
SADC	24.5	0.7	24.5	25.9	1.6	27.1	0.5	26.9	0.4	27.3
UMA	29.9	3.3	33.8	37.8	3.5	35.9	-2.4	28.1	-0.2	28.8
CAADP Compact 2007-09 (CC1)	22.7	13.1	28.9	23.7	-10.6	15.3	-2.5	10.3	-5.6	9.6
CAADP Compact 2010-12 (CC2)	18.3	0.3	19.2	19.6	-0.1	18.6	0.9	19.3	0.3	19.6
CAADP Compact 2013-15 (CC3)	23.9	2.3	25.3	28.8	4.0	26.9	-2.7	18.4	-4.9	17.5
CAADP Compact not yet (CC0)	26.1	1.2	27.3	29.6	2.5	29.6	-1.0	27.1	-0.6	27.0
CAADP Level 0 (CL0)	26.1	1.2	27.3	29.6	2.5	29.6	-1.0	27.1	-0.6	27.0
CAADP Level 1 (CL1)	25.4	1.7	26.5	29.1	2.5	27.9	-2.8	18.7	-5.3	17.6
CAADP Level 2 (CL2)	13.2	5.3	16.1	21.4	8.9	17.4	2.1	16.8	-3.1	16.2
CAADP Level 3 (CL3)	18.9	1.1	19.9	20.9	0.8	16.6	0.0	18.1	1.4	18.7
CAADP Level 4 (CL4)	22.1	9.7	26.9	22.7	-9.1	16.1	-1.7	12.4	-3.0	12.1
NAIP00 (N00)	26.8	1.1	27.7	30.0	2.5	30.0	-1.2	26.3	-1.2	26.0
NAIP10 (N10)	15.2	3.8	18.4	21.1	3.4	18.4	-0.3	16.5	-2.0	16.4
NAIP11 (N11)	21.8	9.5	26.6	22.7	-8.6	16.0	-2.0	12.4	-2.8	12.1

Source: ReSAKSS based on AfDB (2021) and World Bank (2021).
Note: Data only available up to 2019.

ANNEX 7: Supplementary Data Tables

TABLE O.1.3—ANNUAL INFLATION, GDP DEFLATOR (%)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	10.7	-2.5	8.9	9.8	0.7	8.3	-0.6	7.9	0.9	12.8
Central	4.9	-0.6	3.0	9.5	2.8	4.1	-2.0	0.4	-0.7	-5.0
Eastern	14.7	-4.0	7.6	10.1	1.4	14.1	0.1	13.3	2.4	32.4
Northern	6.5	-1.3	5.8	8.4	1.1	7.6	-0.9	7.0	-0.4	1.7
Southern	9.0	-0.7	8.7	7.2	0.5	7.0	-0.4	7.8	2.7	24.6
Western	17.4	-5.9	14.5	14.0	-0.1	8.1	-0.6	7.5	0.4	7.4
Less favorable agriculture conditions	6.2	-1.7	3.0	7.3	1.8	4.4	-1.3	1.6	-0.2	0.2
More favorable agriculture conditions	12.3	-2.3	8.1	8.4	1.5	11.5	-1.1	6.7	0.1	7.2
Mineral-rich countries	23.1	-9.3	10.3	12.6	0.8	18.5	2.5	28.1	8.6	91.7
Lower-middle-income countries	10.9	-3.1	9.5	10.8	0.6	8.0	-0.8	8.0	0.9	11.2
Upper-middle-income countries	8.1	-0.5	7.7	7.5	0.9	6.4	-0.6	4.7	-0.2	4.1
CEN-SAD	12.2	-3.8	10.0	10.8	0.5	8.9	-0.3	9.8	0.7	12.7
COMESA	9.6	-2.1	8.3	9.9	1.0	13.2	0.0	15.6	3.1	35.0
EAC	11.9	-1.1	6.3	9.2	1.1	11.3	-1.0	5.4	-0.3	4.5
ECCAS	5.2	-0.7	3.3	9.6	2.6	4.2	-2.0	0.6	-0.5	-3.7
ECOWAS	17.4	-5.9	14.5	14.0	-0.1	8.1	-0.6	7.5	0.4	7.4
IGAD	14.8	-4.6	7.5	10.6	1.4	16.4	0.5	16.5	3.4	43.2
SADC	9.5	-0.9	8.6	7.4	0.6	7.2	-0.5	7.4	2.2	21.4
UMA	7.3	-1.7	4.9	7.7	1.1	4.5	-1.5	1.8	-0.3	-1.6
CAADP Compact 2007-09 (CC1)	19.0	-6.5	15.8	15.1	-0.1	9.2	-0.7	8.1	0.5	9.1
CAADP Compact 2010-12 (CC2)	11.1	-1.3	7.3	8.6	0.9	8.6	-0.9	5.8	0.1	5.7
CAADP Compact 2013-15 (CC3)	11.1	-1.3	7.3	8.6	0.9	8.6	-0.9	5.8	0.1	5.7
CAADP Compact not yet (CC0)	7.3	-0.9	6.8	7.7	0.9	7.2	-0.7	6.3	-0.3	3.0
CAADP Level 0 (CL0)	7.3	-0.9	6.8	7.7	0.9	7.2	-0.7	6.3	-0.3	3.0
CAADP Level 1 (CL1)	12.4	-4.3	7.5	10.6	1.7	11.9	0.2	2.4	11.9	3.1
CAADP Level 2 (CL2)	4.1	-0.3	3.4	8.1	1.1	4.3	-1.2	5.0	0.4	7.2
CAADP Level 3 (CL3)	10.2	-1.2	8.4	8.5	0.5	10.4	-0.8	7.8	0.5	8.0
CAADP Level 4 (CL4)	17.5	-5.3	13.9	13.5	0.2	8.9	-0.7	7.5	0.3	8.3
NAIP00 (N00)	7.1	-7.3	6.7	7.9	8.4	7.1	-0.8	6.9	0.8	10.6
NAIP10 (N10)	16.8	-21.1	8.6	9.3	3.3	11.6	0.3	13.9	3.6	39.3
NAIP11 (N11)	16.1	-9.8	13.3	13.4	-3.0	9.1	-0.7	7.6	0.4	8.1

Source: ReSAKSS based on World Bank (2021).

ANNEX 7: Supplementary Data Tables

TABLE O.2.1A—AGRICULTURAL EXPORTS (% of total merchandise exports)										
Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	12.2	-4.2	10.3	8.2	-7.1	8.8	3.1	12.1	1.7	11.8
Central	5.1	-8.8	3.4	2.9	-5.6	2.9	-3.7	3.6	2.9	3.6
Eastern	47.2	-6.2	35.1	29.6	-5.8	30.3	6.7	41.5	2.8	42.6
Northern	6.8	-10.2	4.8	4.5	-0.3	6.1	5.3	9.7	3.5	9.9
Southern	11.2	-1.8	10.2	7.9	-9.2	8.1	3.9	10.1	-0.6	9.5
Western	14.9	1.0	15.1	11.4	-8.5	10.5	-2.2	14.1	-0.3	12.4
Less favorable agriculture conditions	13.6	-6.0	9.2	6.5	2.4	8.0	-6.4	10.8	9.2	11.1
More favorable agriculture conditions	51.6	-3.3	43.3	41.6	-0.2	37.7	-2.2	35.7	-2.2	33.5
Mineral-rich countries	31.4	6.3	29.7	16.9	-19.3	9.9	-2.7	28.0	31.2	41.3
Lower-middle-income countries	15.7	-2.5	14.2	10.8	-9.5	10.2	1.6	14.0	0.4	13.1
Upper-middle-income countries	6.6	-7.2	4.8	3.7	-5.8	5.0	7.0	7.2	0.3	6.9
CEN-SAD	15.9	-4.5	12.8	10.0	-7.6	10.2	1.9	15.2	1.6	14.5
COMESA	26.8	-10.7	15.0	11.5	-7.4	13.9	8.3	20.5	-1.5	18.9
EAC	57.6	-3.7	46.0	44.0	-0.6	40.4	-2.7	41.8	2.4	42.3
ECCAS	3.0	-9.2	2.1	1.6	-8.8	1.5	-0.2	2.4	2.6	2.2
ECOWAS	14.9	1.0	15.1	11.4	-8.5	10.5	-2.2	14.1	-0.3	12.4
IGAD	51.0	-7.7	34.2	27.5	-7.6	29.3	9.7	44.0	3.7	45.7
SADC	12.5	-2.1	11.5	9.1	-8.8	9.1	3.4	11.2	-0.4	10.6
UMA	6.5	-12.2	3.9	3.6	-0.7	4.6	7.1	8.0	4.1	8.3
CAADP Compact 2007-09 (CC1)	8.3	1.9	9.2	7.2	-8.3	7.2	-1.4	9.8	0.6	8.7
CAADP Compact 2010-12 (CC2)	43.1	-0.7	39.2	34.8	-4.1	31.0	-2.1	30.6	-2.9	28.1
CAADP Compact 2013-15 (CC3)	9.9	-5.6	7.5	4.6	-16.4	3.8	8.0	8.4	11.3	9.5
CAADP Compact not yet (CC0)	8.2	-5.5	6.7	5.7	-3.6	7.3	4.3	10.0	2.1	10.1
CAADP Level 0 (CL0)	8.2	-5.5	6.7	5.7	-3.6	7.3	4.3	10.0	2.1	10.1
CAADP Level 1 (CL1)	10.3	-5.2	7.7	4.8	-16.3	3.9	9.0	8.5	11.3	9.6
CAADP Level 2 (CL2)	17.1	-2.2	16.2	14.4	-6.0	13.2	-4.3	14.9	0.6	14.4
CAADP Level 3 (CL3)	23.2	-0.9	23.4	23.1	-0.5	19.2	-6.0	19.1	0.2	17.6
CAADP Level 4 (CL4)	52.2	-1.2	49.9	45.4	-3.2	40.1	-3.6	37.7	-3.2	34.6
NAIP00 (N00)	8.3	-5.7	6.6	5.3	-6.2	6.3	5.2	9.1	2.3	9.1
NAIP10 (N10)	19.7	-4.7	15.5	13.0	-5.6	12.1	2.7	17.5	6.3	19.4
NAIP11 (N11)	19.6	-0.5	18.5	15.1	-5.6	14.4	-1.3	18.4	-1.4	16.0

Source: ReSAKSS based on UNCTAD (2021) and World Bank (2021).
Note: Data only available up to 2019.

ANNEX 7: *Supplementary Data Tables*

TABLE O.2.1B—AGRICULTURAL IMPORTS (% of total merchandise imports)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	15.1	-0.5	14.7	13.3	-3.3	14.0	1.3	14.5	1.5	14.6
Central	17.1	-1.4	16.7	17.1	-1.0	15.4	-0.1	18.0	8.3	20.5
Eastern	14.7	0.2	14.4	12.8	-4.3	14.6	2.0	16.5	4.8	17.6
Northern	20.0	-3.1	17.6	15.6	-2.2	16.1	2.0	16.4	-1.1	15.9
Southern	9.4	1.0	9.6	8.6	-3.5	9.5	-0.7	9.8	2.4	9.8
Western	17.5	2.5	18.5	16.8	-4.7	16.8	2.1	16.5	-0.3	15.8
Less favorable agriculture conditions	20.2	-1.4	18.3	18.7	-3.1	17.3	-0.4	17.5	1.7	17.5
More favorable agriculture conditions	16.3	-1.7	16.4	14.5	-6.1	13.0	-0.8	14.6	5.9	15.6
Mineral-rich countries	18.9	-2.7	16.5	14.4	-2.9	19.6	4.6	22.6	2.6	23.7
Lower-middle-income countries	18.4	-0.3	17.9	16.0	-3.0	16.3	1.3	15.9	-0.3	15.7
Upper-middle-income countries	7.4	2.6	8.1	7.4	-2.8	8.9	3.5	10.3	1.7	10.1
CEN-SAD	16.7	-0.3	16.1	14.6	-2.9	15.9	2.5	16.1	-0.4	15.7
COMESA	17.0	-0.1	17.1	15.3	-2.7	17.0	1.8	17.4	0.4	17.2
EAC	13.3	-3.5	11.8	11.4	-1.9	11.6	0.0	12.3	3.1	12.3
ECCAS	20.1	-0.7	19.3	17.8	-3.3	16.2	0.6	18.0	7.8	20.5
ECOWAS	17.5	2.5	18.5	16.8	-4.7	16.8	2.1	16.5	-0.3	15.8
IGAD	14.1	0.9	13.7	12.0	-4.9	14.6	2.3	16.9	5.8	18.5
SADC	10.1	0.4	10.4	9.5	-3.3	10.2	-0.6	10.4	2.4	10.5
UMA	19.6	-3.9	16.5	14.8	-1.3	14.7	1.6	15.6	-0.8	15.2
CAADP Compact 2007-09 (CC1)	16.1	3.0	17.1	15.3	-5.9	15.5	2.9	15.2	0.6	14.8
CAADP Compact 2010-12 (CC2)	17.7	-0.6	17.3	15.8	-2.8	14.5	-2.9	14.6	1.9	14.6
CAADP Compact 2013-15 (CC3)	17.2	0.7	17.5	16.0	-2.4	17.6	2.6	20.1	5.2	21.9
CAADP Compact not yet (CC0)	13.5	-1.9	12.7	11.5	-2.3	12.6	1.6	13.1	0.7	13.1
CAADP Level 0 (CL0)	13.5	-1.9	12.7	11.5	-2.3	12.6	1.6	13.1	0.7	13.1
CAADP Level 1 (CL1)	17.4	0.7	17.6	16.0	-2.6	17.6	3.0	20.1	4.7	21.7
CAADP Level 2 (CL2)	22.0	-0.3	21.6	21.4	0.5	20.6	-3.2	20.7	3.3	21.8
CAADP Level 3 (CL3)	15.9	-2.5	15.3	13.6	-4.8	11.7	-2.4	12.2	3.5	12.6
CAADP Level 4 (CL4)	16.2	2.2	16.8	15.1	-5.1	15.0	1.1	14.8	1.0	14.5
NAIP00 (N00)	14.2	-1.4	13.6	12.3	-2.6	13.2	1.5	13.7	0.9	13.7
NAIP10 (N10)	17.6	-0.4	16.6	14.9	-3.4	15.2	0.0	16.8	5.2	18.3
NAIP11 (N11)	16.5	1.9	17.1	15.5	-4.8	15.5	1.2	15.4	1.1	15.2

Source: ReSAKSS based on UNCTAD (2021) and World Bank (2021).
Note: Data only available up to 2019.

ANNEX 7: Supplementary Data Tables

TABLE O.2.2—RATIO OF AGRICULTURAL EXPORTS TO AGRICULTURAL IMPORTS

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2019
Africa	0.8	-1.6	0.8	0.7	-5.1	0.6	-1.1	0.7	1.1	0.7
Central	0.5	-6.3	0.4	0.4	-4.6	0.3	-8.8	0.3	0.1	0.3
Eastern	1.7	-4.6	1.4	1.2	-4.4	1.0	-1.4	1.0	-0.8	1.0
Northern	0.3	0.1	0.3	0.4	1.1	0.3	-3.2	0.4	5.8	0.4
Southern	1.3	-2.8	1.1	1.0	-4.3	0.9	4.0	1.1	-0.3	1.1
Western	1.1	-0.6	1.2	1.0	-8.2	0.8	-4.0	0.9	-0.3	0.8
Less favorable agriculture conditions	0.3	-5.9	0.3	0.3	7.7	0.3	-6.4	0.4	8.3	0.4
More favorable agriculture conditions	1.6	-3.5	1.2	1.2	2.8	1.2	-0.7	1.2	-3.3	1.1
Mineral-rich countries	0.8	-2.9	0.6	0.4	-16.8	0.2	-0.1	0.5	17.6	0.6
Lower-middle-income countries	0.7	-0.4	0.7	0.6	-7.3	0.5	-2.0	0.6	1.3	0.6
Upper-middle-income countries	1.3	-4.8	1.0	0.9	-4.2	0.9	-1.1	0.9	1.4	0.9
CEN-SAD	0.9	-1.4	0.9	0.8	-7.6	0.6	-4.0	0.7	2.3	0.7
COMESA	1.0	-3.5	0.8	0.7	-5.4	0.6	-1.4	0.6	0.8	0.6
EAC	2.3	-1.1	2.2	1.8	-6.7	1.4	-3.1	1.5	-1.3	1.4
ECCAS	0.3	-9.1	0.2	0.2	-0.1	0.2	-4.9	0.2	1.3	0.2
ECOWAS	1.1	-0.6	1.2	1.0	-8.2	0.8	-4.0	0.9	-0.3	0.8
IGAD	1.8	-6.1	1.4	1.2	-2.9	0.9	-1.9	0.9	-0.7	0.9
SADC	1.3	-2.7	1.1	1.0	-4.8	0.9	3.6	1.1	0.0	1.1
UMA	0.4	-2.6	0.3	0.4	2.3	0.3	-2.5	0.4	7.6	0.4
CAADP Compact 2007-09 (CC1)	0.7	-0.6	0.8	0.7	-7.0	0.6	-4.0	0.6	0.9	0.6
CAADP Compact 2010-12 (CC2)	2.0	-1.8	1.8	1.6	-4.7	1.4	-0.7	1.4	-2.5	1.4
CAADP Compact 2013-15 (CC3)	0.8	-4.7	0.6	0.5	-9.9	0.3	0.8	0.5	7.3	0.5
CAADP Compact not yet (CC0)	0.6	0.5	0.5	0.5	-2.7	0.5	-0.5	0.6	2.2	0.6
CAADP Level 0 (CL0)	0.6	0.5	0.5	0.5	-2.7	0.5	-0.5	0.6	2.2	0.6
CAADP Level 1 (CL1)	0.8	-3.8	0.7	0.5	-9.3	0.3	1.7	0.5	7.5	0.6
CAADP Level 2 (CL2)	0.9	-7.1	0.7	0.6	-5.7	0.5	-2.8	0.6	2.0	0.6
CAADP Level 3 (CL3)	1.0	-0.9	0.9	1.0	5.7	1.1	-0.4	1.0	-2.9	0.9
CAADP Level 4 (CL4)	1.5	-2.4	1.5	1.2	-6.1	1.0	-3.1	1.0	-1.6	1.0
NAIP00 (N00)	0.6	-1.1	0.5	0.5	-3.8	0.5	0.4	0.6	2.5	0.6
NAIP10 (N10)	1.1	-3.1	0.9	0.8	-2.0	0.7	-3.1	0.8	1.8	0.8
NAIP11 (N11)	1.4	-2.2	1.4	1.1	-5.8	1.0	-3.0	1.0	-1.8	0.9

Source: ReSAKSS based on UNCTAD (2021) and World Bank (2021).
Note: Data only available up to 2019.

ANNEX 7: Supplementary Data Tables

TABLE O.3.1—TOTAL FERTILIZER CONSUMPTION (kilograms per hectare)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2018)	Annual avg. change (2014-2018)	2018
Africa	21.4	1.6	23.3	22.8	-0.2	22.8	0.6	26.5	5.5	29.0
Central	3.8	5.0	4.8	3.6	-1.4	4.0	4.5	5.6	9.7	6.5
Eastern	10.9	-0.7	10.0	11.0	7.6	13.6	-0.1	15.6	6.6	16.9
Northern	76.8	3.9	92.9	95.5	-0.2	94.0	2.0	108.5	1.6	112.0
Southern	35.3	-0.5	35.3	33.7	1.1	34.6	1.5	39.7	3.5	43.3
Western	6.1	1.4	6.3	6.8	-1.0	8.5	7.8	13.5	15.8	16.7
Less favorable agriculture conditions	3.0	7.9	4.2	4.4	5.9	4.8	1.0	8.0	1.4	7.6
More favorable agriculture conditions	8.0	-2.5	7.6	8.5	9.7	12.4	5.5	16.9	9.4	19.1
Mineral-rich countries	0.6	-10.8	0.4	0.5	23.7	1.6	26.1	4.8	22.4	6.0
Lower-middle-income countries	29.2	3.2	33.1	33.2	-1.6	34.1	2.9	40.9	4.8	44.6
Upper-middle-income countries	52.4	-0.9	53.1	51.3	1.2	53.6	2.3	59.1	3.1	64.4
CEN-SAD	24.2	2.7	27.4	27.7	-1.3	26.1	-0.9	29.1	5.6	31.8
COMESA	42.8	1.1	45.7	43.2	-0.1	37.4	-6.2	36.4	4.2	38.6
EAC	8.4	3.6	9.3	10.4	1.9	12.4	5.9	12.8	-1.6	12.5
ECCAS	3.3	4.2	4.1	3.7	5.3	4.9	5.3	6.4	5.7	7.2
ECOWAS	6.1	1.4	6.3	6.8	-1.0	8.5	7.8	13.5	15.8	16.7
IGAD	14.1	-0.2	12.5	13.7	9.7	16.3	-4.0	16.8	5.3	17.8
SADC	24.2	-0.2	25.0	22.7	0.5	22.7	0.1	25.3	4.9	28.1
UMA	29.3	5.6	36.2	36.1	0.4	38.3	5.8	42.5	-1.8	43.0
CAADP Compact 2007-09 (CC1)	6.2	-0.1	5.9	6.8	8.2	10.1	6.3	15.7	16.0	19.4
CAADP Compact 2010-12 (CC2)	9.1	2.5	10.9	11.1	1.2	12.7	5.0	15.3	0.7	15.5
CAADP Compact 2013-15 (CC3)	9.1	2.5	10.9	11.1	1.2	12.7	5.0	15.3	0.7	15.5
CAADP Compact not yet (CC0)	67.5	2.4	77.7	78.8	0.3	78.9	2.0	90.3	2.2	94.8
CAADP Level 0 (CL0)	67.5	2.4	77.7	78.8	0.3	78.9	2.0	90.3	2.2	94.8
CAADP Level 1 (CL1)	21.3	-1.7	15.9	14.4	-2.7	11.7	-12.7	11.3	14.8	13.6
CAADP Level 2 (CL2)	3.4	5.2	4.4	3.3	-2.2	3.6	3.8	4.7	9.2	5.6
CAADP Level 3 (CL3)	4.3	4.7	6.0	6.2	3.9	7.8	5.1	11.7	3.8	11.8
CAADP Level 4 (CL4)	9.2	0.4	9.3	10.4	4.2	14.0	6.8	19.3	10.0	22.5
NAIP00 (N00)	58.5	2.1	64.7	64.5	-0.3	63.2	1.5	71.9	2.7	76.2
NAIP10 (N10)	4.9	3.1	6.5	6.4	5.6	8.0	0.4	10.3	10.8	11.7
NAIP11 (N11)	8.1	1.0	8.4	9.2	3.7	12.0	6.3	16.8	9.1	19.2

Source: : ReSAKSS based on World Bank (2021).
Note: Data only available up to 2018.

ANNEX 7: Supplementary Data Tables

TABLE O.3.2—AGRICULTURAL VALUE ADDED (% GDP)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	17.3	-1.2	16.9	15.2	-3.5	14.7	-0.7	15.0	1.2	15.5
Central	21.6	-5.3	16.6	16.1	-2.4	15.2	-0.1	15.7	1.1	17.3
Eastern	34.0	-3.2	29.2	27.0	-3.0	28.1	1.9	27.7	-1.9	27.3
Northern	14.0	-3.3	12.5	11.4	-4.1	11.0	0.2	11.6	0.9	12.5
Southern	5.6	-1.7	5.1	4.7	-2.0	4.5	-1.3	4.5	-2.5	5.0
Western	28.3	1.9	31.5	27.1	-4.3	23.6	-4.0	21.6	1.0	23.7
Less favorable agriculture conditions	37.9	-1.0	34.7	38.3	3.8	38.0	-0.1	36.9	-1.1	36.6
More favorable agriculture conditions	34.0	-5.3	28.4	28.6	0.5	30.3	-0.9	27.6	-1.0	27.7
Mineral-rich countries	39.9	-2.1	33.8	28.5	-6.0	27.3	2.9	25.6	-5.4	22.6
Lower-middle-income countries	19.2	-0.8	19.4	17.0	-4.6	15.6	-1.8	15.7	1.2	17.3
Upper-middle-income countries	3.7	-2.6	3.4	2.9	-2.7	2.6	-4.1	2.4	-0.4	2.8
CEN-SAD	23.7	0.7	24.7	21.9	-3.9	20.1	-1.7	19.2	-0.1	19.9
COMESA	24.2	-2.3	21.5	20.0	-2.9	19.5	0.2	18.6	-1.9	18.5
EAC	30.6	-4.6	25.7	24.2	-2.9	26.3	1.1	28.1	2.1	29.1
ECCAS	16.9	-5.7	12.9	12.1	-3.9	11.7	1.1	13.1	0.7	14.6
ECOWAS	28.3	1.9	31.5	27.1	-4.3	23.6	-4.0	21.6	1.0	23.7
IGAD	36.8	-2.3	31.7	28.9	-3.4	30.4	2.4	29.5	-2.7	28.8
SADC	8.5	-4.4	7.2	6.6	-2.0	6.6	-0.6	6.9	0.6	7.8
UMA	12.8	-5.2	10.8	9.8	-5.1	10.1	2.7	11.8	1.9	13.3
CAADP Compact 2007-09 (CC1)	30.4	1.4	33.3	28.9	-3.9	25.3	-3.9	23.1	0.8	25.4
CAADP Compact 2010-12 (CC2)	27.3	-3.7	23.4	21.8	-2.9	22.2	-0.5	22.2	1.4	23.2
CAADP Compact 2013-15 (CC3)	19.5	-1.0	17.6	15.6	-5.4	14.5	2.6	15.1	-4.2	14.8
CAADP Compact not yet (CC0)	8.6	-0.6	8.3	7.5	-3.6	7.3	-0.4	7.7	1.3	8.6
CAADP Level 0 (CL0)	8.6	-0.6	8.3	7.5	-3.6	7.3	-0.4	7.7	1.3	8.6
CAADP Level 1 (CL1)	19.5	-0.9	17.6	15.7	-5.5	14.4	2.7	14.9	-4.8	14.6
CAADP Level 2 (CL2)	26.9	-5.6	20.6	18.4	-4.0	17.7	-1.0	17.7	1.2	18.7
CAADP Level 3 (CL3)	31.0	-1.8	28.0	26.9	-1.5	26.6	-2.0	23.2	-0.9	21.5
CAADP Level 4 (CL4)	28.9	0.6	30.7	26.9	-3.8	24.4	-3.0	23.0	1.2	25.5
NAIP00 (N00)	9.1	-1.1	8.6	8.0	-3.2	7.7	-0.2	8.1	0.5	9.1
NAIP10 (N10)	29.2	-3.5	24.7	21.8	-4.4	21.2	1.4	20.5	-2.8	19.0
NAIP11 (N11)	29.3	0.8	31.1	27.3	-3.7	24.9	-3.0	23.3	1.0	25.7

Source: ReSAKSS based on World Bank (2021).

ANNEX 7: Supplementary Data Tables

TABLE O.4.1—GROSS DOMESTIC PRODUCT (constant 2010 US$, trillion)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014-2019)	Annual avg. change (2014-2019)	2020
Africa	1.1	4.6	1.4	1.6	6.0	2.0	3.8	2.4	2.5	2.5
Central	0.1	2.7	0.1	0.1	6.0	0.1	4.7	0.1	1.0	0.1
Eastern	0.1	4.5	0.1	0.2	8.5	0.2	4.5	0.3	4.7	0.4
Northern	0.4	6.6	0.4	0.5	5.2	0.6	2.0	0.7	3.6	0.7
Southern	0.4	3.0	0.4	0.5	5.8	0.6	3.3	0.6	0.8	0.6
Western	0.3	4.7	0.3	0.4	6.0	0.5	6.0	0.6	2.3	0.7
Less favorable agriculture conditions	0.0	4.9	0.0	0.0	6.1	0.0	4.4	0.0	3.8	0.1
More favorable agriculture conditions	0.1	4.7	0.1	0.1	7.3	0.2	6.5	0.2	6.1	0.3
Mineral-rich countries	0.1	3.7	0.1	0.1	9.4	0.1	2.8	0.1	2.1	0.1
Lower-middle-income countries	0.7	4.2	0.8	0.9	5.8	1.2	4.7	1.5	2.5	1.5
Upper-middle-income countries	0.3	5.5	0.4	0.4	5.4	0.5	1.2	0.5	1.3	0.5
CEN-SAD	0.6	5.9	0.7	0.8	6.3	1.1	3.8	1.3	3.1	1.4
COMESA	0.3	6.4	0.4	0.4	6.3	0.6	3.1	0.7	4.9	0.8
EAC	0.1	4.0	0.1	0.1	8.6	0.1	4.5	0.2	4.3	0.2
ECCAS	0.1	3.9	0.1	0.2	8.7	0.2	4.8	0.2	0.4	0.2
ECOWAS	0.3	4.7	0.3	0.4	6.0	0.5	6.0	0.6	2.3	0.7
IGAD	0.1	4.4	0.1	0.1	9.3	0.2	4.3	0.2	4.4	0.3
SADC	0.4	2.9	0.5	0.5	5.9	0.6	3.5	0.7	1.4	0.7
UMA	0.4	7.5	0.6	0.6	4.7	0.7	1.4	0.8	2.9	0.8
CAADP Compact 2007-09 (CC1)	0.2	5.0	0.3	0.3	6.8	0.5	6.5	0.6	2.4	0.7
CAADP Compact 2010-12 (CC2)	0.1	2.8	0.2	0.2	5.6	0.2	5.5	0.3	5.4	0.4
CAADP Compact 2013-15 (CC3)	0.1	4.4	0.2	0.2	7.7	0.3	4.4	0.3	0.7	0.3
CAADP Compact not yet (CC0)	0.6	4.9	0.7	0.8	5.3	1.0	2.0	1.1	2.3	1.1
CAADP Level 0 (CL0)	0.6	4.9	0.7	0.8	5.3	1.0	2.0	1.1	2.3	1.1
CAADP Level 1 (CL1)	0.1	4.4	0.2	0.2	8.1	0.3	4.3	0.3	0.3	0.3
CAADP Level 2 (CL2)	0.0	1.5	0.0	0.1	4.9	0.1	4.9	0.1	4.6	0.1
CAADP Level 3 (CL3)	0.0	5.2	0.0	0.1	6.3	0.1	5.8	0.1	4.3	0.1
CAADP Level 4 (CL4)	0.3	4.5	0.4	0.4	6.4	0.6	6.3	0.8	3.2	0.9
NAIP00 (N00)	0.7	4.8	0.8	1.0	5.5	1.2	2.5	1.3	2.1	1.3
NAIP10 (N10)	0.1	3.8	0.1	0.2	7.7	0.2	4.1	0.3	2.8	0.3
NAIP11 (N11)	0.3	4.5	0.4	0.5	6.3	0.6	6.2	0.8	3.2	0.9

Source: ReSAKSS based on World Bank (2021).
Note: Aggregate value for a group is the sum of gross domestic product for countries in the group.

ANNEX 7: Supplementary Data Tables

TABLE O.5.1—GLOBAL HUNGER INDEX (GHI)

Region	Annual avg. level (1995–2003)	Annual avg. change (1995–2003)	2003	Annual avg. level (2003–2008)	Annual avg. change (2003–2008)	Annual avg. level (2008–2014)	Annual avg. change (2008–2014)	Annual avg. level (2014–2019)	Annual avg. change (2014–2019)	2020
Africa	34.5	-1.7	31.9	30.3	-2.1	26.6	-2.6	23.2	-2.9	21.7
Central	35.6	-2.2	32.5	30.7	-2.4	26.0	-3.2	22.0	-3.5	20.2
Eastern	47.7	-2.3	43.1	40.2	-2.8	33.8	-3.5	28.0	-4.0	25.5
Northern	15.4	-1.7	14.4	13.7	-1.9	12.2	-2.2	10.8	-2.5	9.9
Southern	38.5	-1.9	35.2	33.2	-2.4	28.6	-3.1	24.7	-3.1	24.1
Western	39.8	-1.6	37.2	35.4	-1.9	31.8	-2.1	28.3	-2.3	26.7
Less favorable agriculture conditions	45.0	-2.1	40.8	38.2	-2.7	32.3	-3.4	27.1	-3.7	25.0
More favorable agriculture conditions	48.7	-2.2	44.2	41.3	-2.7	35.0	-3.3	29.1	-3.8	26.4
Mineral-rich countries	57.7	-2.3	52.6	49.6	-2.5	42.2	-3.1	35.3	-3.5	31.0
Lower-middle-income countries	29.4	-1.5	27.4	26.2	-1.8	23.5	-2.2	20.9	-2.4	20.0
Upper-middle-income countries	21.6	-1.4	20.5	19.9	-1.4	18.0	-1.7	16.6	-1.5	15.6
CEN-SAD	31.4	-1.5	29.3	28.0	-1.8	25.2	-2.1	22.4	-2.3	21.1
COMESA	34.5	-1.8	31.7	30.0	-2.3	26.0	-2.9	22.2	-3.2	20.7
EAC	28.0	-1.8	25.6	23.9	-2.6	20.3	-3.4	17.3	-3.5	16.9
ECCAS	48.2	-2.4	43.1	39.9	-3.1	32.8	-4.0	26.4	-4.7	24.2
ECOWAS	39.8	-1.6	37.2	35.4	-1.9	31.8	-2.1	28.3	-2.3	26.7
IGAD	48.5	-2.3	43.8	40.8	-2.8	34.2	-3.5	28.2	-4.0	25.4
SADC	38.3	-1.9	35.1	33.1	-2.3	28.6	-3.0	24.7	-3.1	24.0
UMA	14.5	-2.2	13.2	12.5	-2.4	10.5	-3.4	8.9	-3.5	8.4
CAADP Compact 2007-09 (CC1)	21.8	-1.6	20.3	19.4	-2.0	17.8	-3.5	26.6	-3.0	24.7
CAADP Compact 2010-12 (CC2)	24.5	-2.4	21.9	20.3	-3.0	18.1	-3.8	15.0	-2.7	14.5
CAADP Compact 2013-15 (CC3)	10.4	-1.7	9.7	9.3	-1.8	8.7	-2.1	13.6	-4.6	12.3
CAADP Compact not yet (CC0)	41.5	-2.3	37.5	34.9	-2.9	31.2	-3.5	7.4	-2.3	6.8
CAADP Level 0 (CL0)	10.4	-1.7	9.7	9.3	-1.8	8.3	-2.0	8.4	5.4	10.0
CAADP Level 1 (CL1)	24.2	-2.0	22.1	20.8	-2.4	17.8	-3.1	19.2	7.9	22.7
CAADP Level 2 (CL2)	7.3	-2.2	6.7	6.2	-2.8	5.2	-3.6	12.5	45.7	19.8
CAADP Level 3 (CL3)	21.3	-1.8	19.7	18.7	-2.3	15.9	-3.2	20.9	18.5	26.0
CAADP Level 4 (CL4)	42.4	-1.8	39.1	36.9	-2.2	32.4	-2.6	28.2	-2.8	26.6
NAIP00 (N00)	17.3	-2.3	15.7	14.7	-2.6	13.3	-3.1	10.7	-3.3	9.8
NAIP10 (N10)	14.0	-1.4	13.1	12.5	-1.8	11.5	-3.3	9.9	-2.4	9.9
NAIP11 (N11)	43.4	-1.8	40.0	37.7	-2.3	34.5	-2.7	23.8	-17.6	13.0

Source: ReSAKSS based on von Grebmer et al. (2020), World Bank (2021), and ILO (2021).

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ARRANGED BY CHAPTER

Chapter 1

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