CHAPTER 11

# The Measurement of Resilience Capacities Through the Integration of Macrolevel and Microlevel Indicators

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**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.

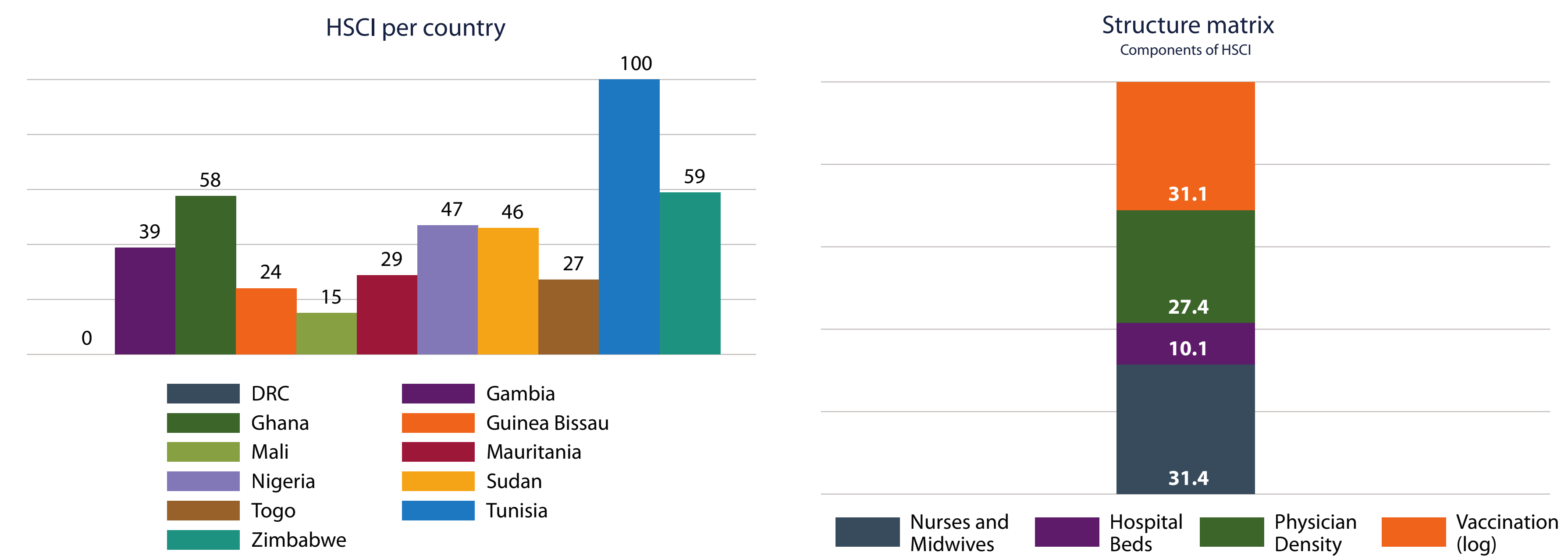
2 See http://www.ipcinfo.org/ipcinfo-website/ipc-overview-and-classification-system/en/.

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

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} w_{ik} \; || \; x^i - \mu_k \; ||^2,$$

where $w_{ik} = 1$ for data point $x^i$ if it belongs to cluster $k$, and otherwise, $w_{ik} = 0$. $\mu_k$ 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 $\gamma$ 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 $\beta$ 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<br>(0.00422) | 2.40e-05<br>(0.00421) | 0.181<br>(0.318) | 0.252<br>(0.319) |
| AST | -0.00333<br>(0.00487) | -0.00332<br>(0.00486) | -2.163***<br>(0.357) | -2.167***<br>(0.356) |
| SSN | 0.00328<br>(0.00311) | 0.00342<br>(0.00311) | 1.663***<br>(0.278) | 1.636***<br>(0.276) |
| AC | -0.00211<br>(0.00395) | -0.00221<br>(0.00395) | 3.346***<br>(0.304) | 3.366***<br>(0.302) |
| HSCI | | -0.000323*<br>(0.000190) | | 0.0680***<br>(0.0141) |
| Conflict | 0.294***<br>(0.00670) | 0.290***<br>(0.00565) | -10.65***<br>(0.518) | -9.909***<br>(0.557) |
| EVI | 0.0358***<br>(0.000518) | 0.0359***<br>(0.000512) | | |
| hhsize | -0.0219***<br>(0.000991) | -0.0222***<br>(0.000996) | 0.105*<br>(0.0547) | 0.158***<br>(0.0559) |
| femhead | 0.102***<br>(0.0134) | 0.0993***<br>(0.0137) | -0.210<br>(0.991) | 0.301<br>(0.996) |
| hhcompo | -8.49e-05<br>(0.000443) | -4.36e-05<br>(0.000441) | -0.0312<br>(0.0355) | -0.0406<br>(0.0355) |
| Constant | 0.217***<br>(0.0244) | 0.232***<br>(0.0250) | 95.48***<br>(1.338) | 91.85***<br>(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*

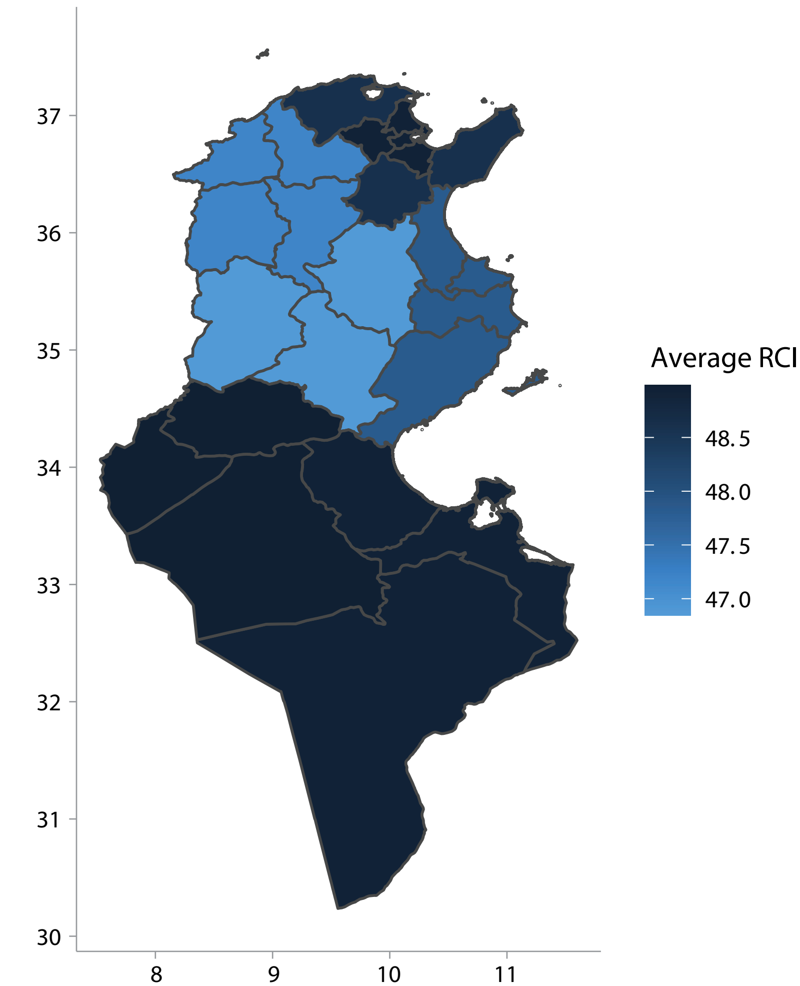
We present two case studies that illustrate the relevance and potential use of our methodologies. As a result of our ranking, Tunisia emerged as the safest and Mali as the most exposed to COVID-19 (Figure 11A.1 in the appendix). This finding is not trivial nor granted, since neither of the countries 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.

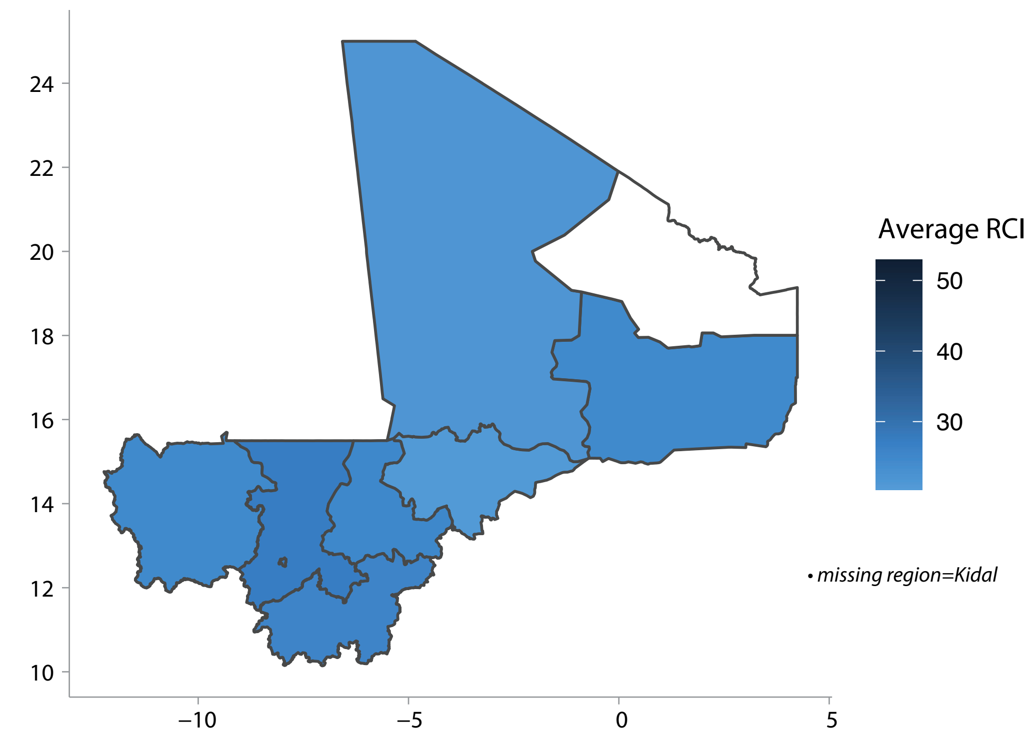
the political transition, however, there is still much to do in terms of Tunisia's economic resilience, which lags in comparison with its neighboring regional peers. In 2020, the GDP growth of the country contracted by 8.8 percent, while unemployment increased to 17.8 percent from its previous level 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.

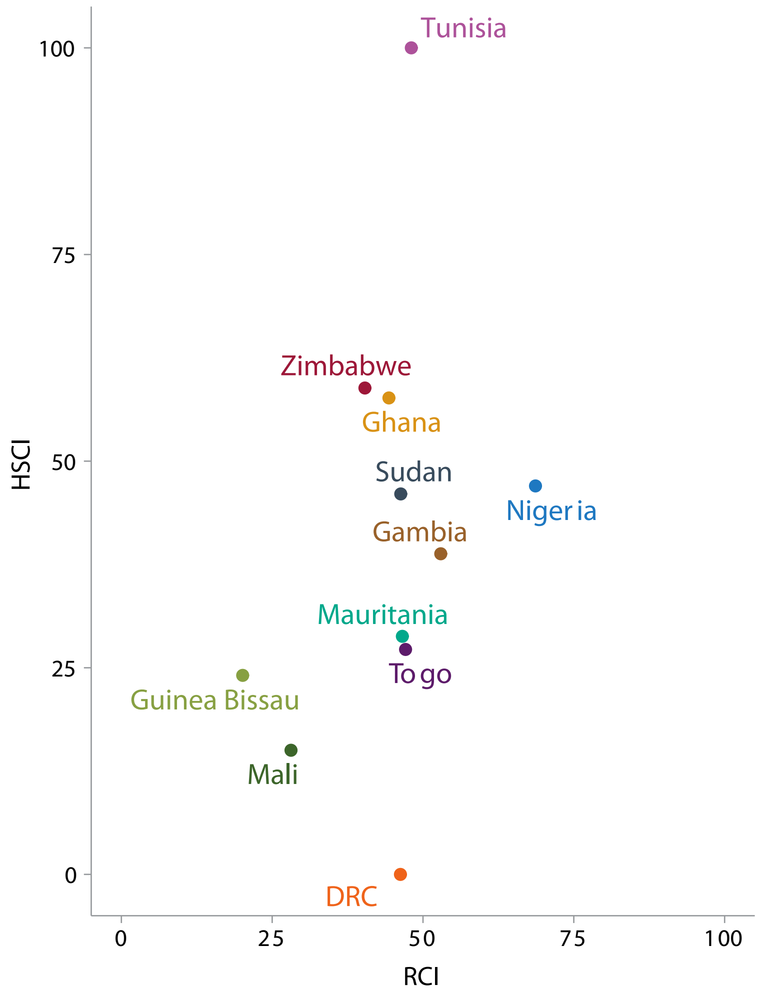
# Appendix

## 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 | HSCI: Low |
|---|---|---|---|
| RCI | **High** | Cluster 1:<br>Ghana<br>Tunisia | Cluster 3:<br>Gambia<br>Mauritania<br>Nigeria<br>Zimbabwe<br>Sudan |
| RCI | **Low** | Cluster 2:<br>DRC<br>Togo | Cluster 4:<br>Mali<br>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.