CHAPTER 3

# The Effects of Widespread Adoption of Climate-Smart Agriculture in Africa South of the Sahara under Changing Climate Regimes

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Current scenarios for "business-as-usual" (BAU) farming under climate change project increasing food shortages by 2050. The worst hit will be underdeveloped economic regions of the world where food security is already problematic and populations are vulnerable to shocks (Rosegrant et al. 2014). Without substantial measures to adapt to increasing temperatures and more frequent extreme weather events, losses in crop and livestock productivity are expected to undermine the rate of gain from technological and management improvements (Lobell and Gourdji 2012). Furthermore, climate change not only is threatening the productivity of the world's agricultural systems but is also expected to have consequences on a wide range of ecosystem services (Knight and Harrison 2012).

Developing countries are expected to bear the brunt of climate change (Morton 2007). The Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC AR5) projects that under more optimistic scenarios, climate change could reduce food crop yields in parts of Africa by between 10 and 20 percent, a large drop for already at-risk populations and regions. The outlook for key food crops across the African continent under climate change is mostly negative. Low productivity, together with increasing global demand, will likely drive up the prices of staple foods, which may rise by 42 to 131 percent for maize, 11 to 78 percent for rice, and 17 to 67 percent for wheat between 2010 and 2050 (Hachigonta et al. 2013; Jalloh et al. 2013; Nelson et al. 2010; Waithaka et al. 2013). Moreover, localized weather shocks and emerging pest and disease outbreaks are already compromising stability in crop production, highlighting the urgency for immediate and adaptable management responses (FAO 2016).

Agriculture not only is affected by climate change but also significantly contributes to the problem. Yearly greenhouse gas (GHG) emissions from the agricultural sector range from 5.0 to 5.8 gigatons[9] of carbon dioxide ($CO_2$) equivalent, or about 11 percent of total anthropogenic GHG emissions, not including land use change (Smith et al. 2014). Poor soil management and land conversion from tropical forests to poorly productive agricultural systems also have a large climate footprint. Combined with forestry and other land uses, anthropogenic land activities contribute about a quarter of annual GHG emissions, three-fourths of which are estimated to originate in the developing world (Smith et al. 2014). Importantly, smallholder farming systems worldwide contribute 3.4 percent of total global emissions (Vermeulen and Wollenberg 2017).

Considering existing expectations for agricultural production in developing countries, including the production of smallholder producers—for example, Sustainable Development Goal (SDG) 2.3 calls for doubling the agricultural productivity and incomes of small-scale food producers by 2030—it is undisputed that farmers need options to increase production under a changing climate and, ideally, to reduce emissions.

Climate-smart agriculture (CSA) is an approach that addresses these problems jointly. After years of dichotomy in the climate change research community between climate change adaptation and mitigation, the two concepts were combined in the term *CSA*. CSA was introduced in 2009 (FAO 2009a, 2009b) and became prominent a year later at the first Global Conference on Agriculture, Food Security and Climate Change (FAO 2010). It is an umbrella term that includes many approaches built upon geographically specific solutions, and it is recognized as a potential means to help achieve the SDGs. It is composed of agricultural systems that contribute to three objectives: (1) sustainable and equitable increases in agricultural

9 *Tons* refers to metric tons throughout the chapter; 1 gigaton = $10^9$ tons.

productivity and incomes; (2) greater resilience of food systems and farming livelihoods; and (3) reduction, removal, or both of greenhouse gas emissions associated with agriculture (including the relationship between agriculture and ecosystems), where possible.

Agricultural production systems that follow the general principles of CSA are expected to be not only more productive and efficient, but also more resilient to short-, medium-, and long-term shocks and risks associated with climate change and climate variability. There is a general consensus that CSA, albeit with limits (Wheeler and von Braun 2013), helps to advance the discussion on future agricultural production under a significantly different climate environment.

Indeed, CSA is an important departure from the single-objective analysis that has supported most food policies so far. CSA is expected to address climate-related risks by simultaneously considering three main objectives and by fully accounting for the trade-offs and synergies among them (Rosenstock et al. 2016). CSA's broader and more flexible approach is supposed to distinguish it from more prescriptive practices such as conservation agriculture or agroforestry. Furthermore, its multi-objective approach has the potential to spur productive conversations and negotiations among ministries that often do not share or coordinate objectives.

Many operational aspects of CSA are still under investigation. Agricultural practices may be climate smart in particular circumstances, but local contexts determine the enabling environment and the trade-offs and synergies across the multiple objectives (Below et al. 2012). As a consequence, conditions for adoption are highly context and location specific, and farmers need access to considerable information to make the approach operational (Mccarthy, Lipper, and Branca 2011). The literature has also focused on technical aspects related to economic feasibility (Sain et al. 2017), the emission reduction and adaptation benefits (de Nijs et al. 2015), and the local-level impacts (Zougmoré et al. 2016) of CSA.

However, to our knowledge, no study has produced a comprehensive analysis of the effects that widespread adoption of CSA practices and technologies may have on the production of key crops, on GHG emissions, and on key food security metrics, regionally or globally. This chapter investigates the potential broad benefits of a widespread adoption of CSA practices, focusing its analysis on Africa south of the Sahara (SSA).

Results of this analysis indicate that there might be significant challenges for CSA to deliver across the three objectives, particularly the abatement of GHG emissions. So-called win-win outcomes, cases in which both productivity and reduction of emissions are achieved, do exist but are not as common as often believed. In order to achieve significant GHG emission abatement, mechanisms that incentivize a reduction in emission intensity must be in place. Importantly, the current results indicate that CSA should not be interpreted simply as a list of acceptable practices from which farmers can choose. If the CSA approach is to have a significant impact on food security, sustainable development, and GHG emission reduction, it should consider activities across production systems as well as the interaction of agricultural land use with carbon-rich land uses such as forests.

## *Background*

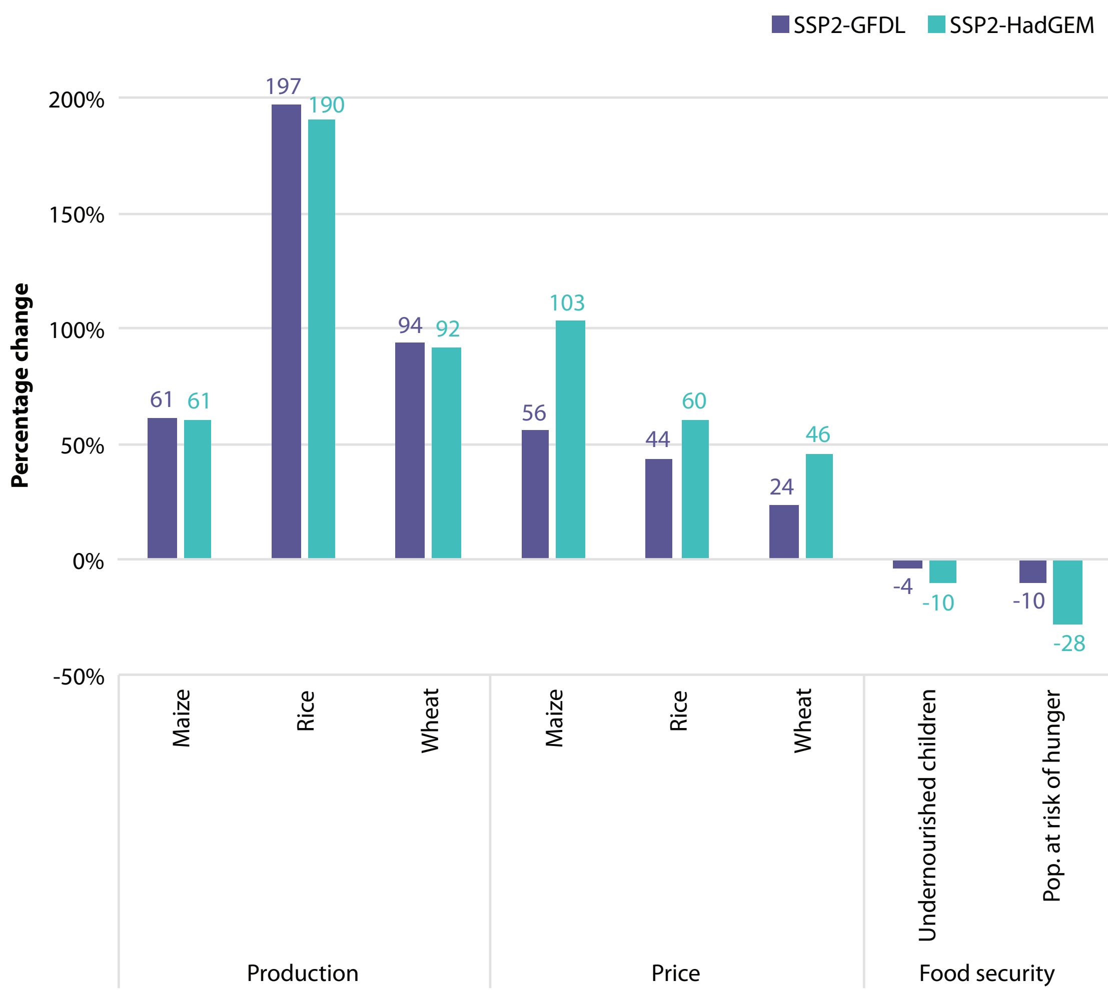
Uncertainties in climate change scenarios make it difficult to determine the precise impacts of climate change on future agricultural productivity. However, although the expectations are mixed, studies have consistently found that under the most severe scenarios of climate change, significant losses should be expected worldwide (Darwin et al. 1995, 1996; Easterling et al. 2007; Fischer et al. 1993; Fischer and van Velthuizen 1996; Nelson et al. 2010; Rosenthal and Kurukulasuriya 2003; Rosenzweig and Parry 1994). Regional differences in crop production are expected to grow stronger through time, potentially widening the gap between the haves and have-nots and increasing hunger among the poorer nations (Parry et al. 2004; Nelson et al. 2010). Interregional trade flows, as a result, may expand from their current location in mid- to high-latitude regions into low-latitude regions, although trade alone might not be a sufficient strategy for adaptation to climate change (Elbehri, Elliott, and Wheele 2015).

SSA is expected to be strongly affected by climate change. Niang and colleagues (2014) found that climate change is very likely to have negative effects on yields of major cereal crops in the African region, albeit with strong subregional variation. Schlenker and Lobell (2010) indicated that in a "worst-case" scenario, a warming of about 2°C above preindustrial levels by midcentury, losses of 27–32 percent for maize, sorghum, millet, and groundnut should be expected. Thornton and others (2010) estimated mean yield losses of 24 percent for maize and 71 percent for beans under a warming scenario exceeding 4°C. Rosenzweig and colleagues (2014) found yield decreases of more than 50 percent for maize in the Sahel region and in the range of 10–20 percent in other regions south of the Sahara. On the other hand, crops like cassava, are likely to be more resistant to higher temperatures and the increasing seasonality of precipitation, compared with cereal crops (Niang et al. 2014); furthermore, alternative practices and cropping systems are expected to reduce the risk of crop failure (Waha et al. 2013).

Thomas and Rosegrant (2015) found that production of some crops in SSA may rise faster under climate change than under a scenario without climate change. This seemingly counterintuitive result is due to the market effects resulting from the global negative impact of climate change on yields. Reduced global yields have the effect of boosting world crop prices, making increasing production attractive to some African farmers. Yet even with increased production in some crops, Thomas and Rosegrant (2015) found, the price increase will ultimately cause food insecurity to rise. According to their calculations, SSA could have a malnutrition rate of 21.7 percent among children younger than five years in 2050 without climate change, but this rate may rise to 24.4 percent with climate change, an increase of more than 4 million children.

Projections of future production for maize, wheat, and rice in SSA for the period 2010–2050 obtained using the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (Robinson et al. 2015) indicate that their output is expected to increase by 61 percent, 92–94 percent, and 190–197 percent, respectively, depending on the particular general circulation model used. During the same 40-year period, prices are projected to increase by 56–103 percent for maize, 24–46 percent for wheat, and 44–60 percent for rice. Growth in world prices, combined with regional growth in production and income, and changing diets, will have an effect on hunger and nutrition. In SSA, the number of undernourished children younger than five years is anticipated to decrease by 4–7 percent and the population at risk of hunger by 10–22 percent by 2050. These results, summarized in Figure 3.1, constitute the BAU scenario against which we will evaluate the performance of CSA practices and technologies. The BAU scenario was generated using two particular climate scenarios:

FIGURE 3.1—CHANGES IN PRODUCTION, PRICES, UNDERNOURISHED CHILDREN YOUNGER THAN FIVE YEARS, AND POPULATION AT RISK OF HUNGER , 2010–2050, UNDER TWO CLIMATE SCENARIOS WITH BUSINESS-AS-USUAL FARMING PRACTICES




Source: Authors.

Note: SSP2-GFDL = Geophysical Fluid Dynamics Laboratory model under shared socioeconomic pathway 2; SSP2-HadGEM = Hadley Centre Global Environment Model under shared socioeconomic pathway 2. Production and food security results are specific for SSA, cereal prices are global.

GFDL-ESM2M (Geophysical Fluid Dynamics Laboratory Earth System Model version 2M) (Dunne et al. 2012) and HadGEM2-ES (Hadley Centre Global Environment Model version 2—Earth System) (Jones et al. 2011), both under a representative concentration pathway (RCP) of 8.5 and coupled with trends of population and income growth obtained through the shared socioeconomic pathways (SSPs) 2 scenario (O'Neill et al. 2014) developed for the IPCC AR5.

## *Methods and Data*

To perform an ex ante assessment of the effects of adoption of CSA practices and technologies in SSA, we linked the inputs and outputs of three models: the Spatial Production Allocation Model (SPAM) (You, Wood, and Wood-Sichra 2006), the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al. 2003), and IMPACT version 3.3 (Robinson et al. 2015). The analysis focuses on three widely grown crops—wheat (Triticum aestivum), maize (Zea mays), and rice (Oryza sativa)—which represent about 41 percent of the global harvested area and 20 percent of the harvested area in SSA. They also represent about 64 percent of GHG emissions generated by crop production globally (Carlson et al. 2016). The simulations in the ex ante assessment use the same climate scenarios considered under the BAU scenario: GFDL-ESM2M and HadGEM2-ES, with an RCP of 8.5 and SSP 2.

The SPAM model spatially disaggregates subnational statistics on crop production and cropland (for the period 2004–2006) into either 0.08 or 0.5-degree grid cells by analyzing biophysical crop "suitability" assessments, population density, and all other available knowledge regarding the spatial distribution of specific crops or crop systems. We used the model to geographically locate the area allocated to the three considered crops. For each SPAM grid cell, we assembled a database of existing dominant management practices and inputs used (that is, varieties employed, application rates of inorganic fertilizers, organic amendment availability, and water management practices). Furthermore, we linked climate scenario data to each 0.5-degree grid cell (a square of approximately 56 km by 56 km at the equator). Finally, we treated each grid cell as an individual farm, assuming that it can properly represent as many farms as are actually contained in its area.

The DSSAT crop model simulates crop yields by accounting for the interaction between the biophysical elements of crop systems (for example, soil, weather, and crop type) and management options (for example, tillage, nutrient application, and water availability). Data from the SPAM model and climate projections from the GFDL and HadGEM models are used as inputs into DSSAT to simulate changes in yields due to adoption of CSA practices compared with the BAU scenario, the latter assuming a continued use of current agricultural practices. All simulations were performed for a 40-year period (2011–2050; see "Simulation of Technology Adoption" in the appendix[10]).

The yield changes derived from the crop simulation in DSSAT, reflecting climate change effects as well as adoption of CSA technologies, form the basis for the simulations of the adoption of CSA practices carried out in the IMPACT model (see "Yield Responses" in the appendix). IMPACT is a partial equilibrium model of the agricultural sector that approximates the behavior of a global competitive agricultural market and simulates supply, demand, and prices for agricultural commodities at the country level. The model has a long record of application, having been employed in a wide range of analyses, from assessing the potential effects of climate change on global food production and nutrition (Springmann et al. 2016) to evaluating the global effects of biofuel production (Rosegrant 2008). The yield changes simulated in DSSAT that result from adoption of CSA practices function as shifters for the crop-specific supply curves and also change yield growth rates under climate change.

Along with the yield responses, we also calculate changes in GHG emissions. Spatial and temporal changes in soil carbon stocks and direct nitrous oxide ($N_2O$) emissions, which account for $N_2O$ emitted directly from the soils to which the nitrogen has been added and then released, were simulated in soil organic matter modules embedded into the DSSAT crop model. For the rice production system, we also calculated methane ($CH_4$) emissions by combining the DSSAT-simulated rice biomass with the approach proposed by Yan and colleagues (2009), whereby emission coefficients from

10 The starting year for the simulations in IMPACT is 2010 but the first year of possible adoption in DSSAT is 2011.

IPCC Tier 1 methods are used to estimate the global $CH_4$ emissions from rice fields. Finally, we converted all GHG emissions into kilograms of $CO_2$ equivalent by using the global warming potential over a 100-year time horizon for each GHG: 1, 28, and 265 for $CO_2$, $CH_4$, and $N_2O$, respectively.

# *Simulation Scenarios*

Figures 3.1, 3.2, and 3.3 present results for the BAU scenario. These results determine, although indirectly, the effects of adopting alternative technologies on both yields and GHG emissions.[11]

## Calibration of DSSAT for the Business-as-Usual Scenario

The BAU scenario in DSSAT reflects the use of current agronomic practices and technologies, assuming that farmers are not adopting any of the assessed CSA alternatives throughout the simulation period of 2010–2050. We made considerable efforts to calibrate DSSAT to ensure that the simulated yields in the reference year would match national statistical data as accurately as possible (see "Calibration of DSSAT for the Business-as-Usual Scenario" in the appendix).

After calibration, simulated yields for maize and wheat are comparable to yields in the database of the Food and Agriculture Organization of the United Nations (FAO), known as FAOSTAT (FAO 2017), with very good fits—$R^2$ values of 0.85 and 0.80, respectively. The fit is lower but still adequate for rice, with an $R^2$ of 0.63 (Figure 3.2). However, when only the SSA region is considered, the fit of the simulated yields is worse, especially for rice. This outcome might be related to higher uncertainties about the model inputs (for example, soil characteristics and highly localized farming practices) compiled for the simulations of the SSA region.

It must be noted that only monoculture systems were simulated, thereby providing a stylized representation of worldwide agricultural systems. This limitation should be addressed in future research through including intercropping and rotation practices.

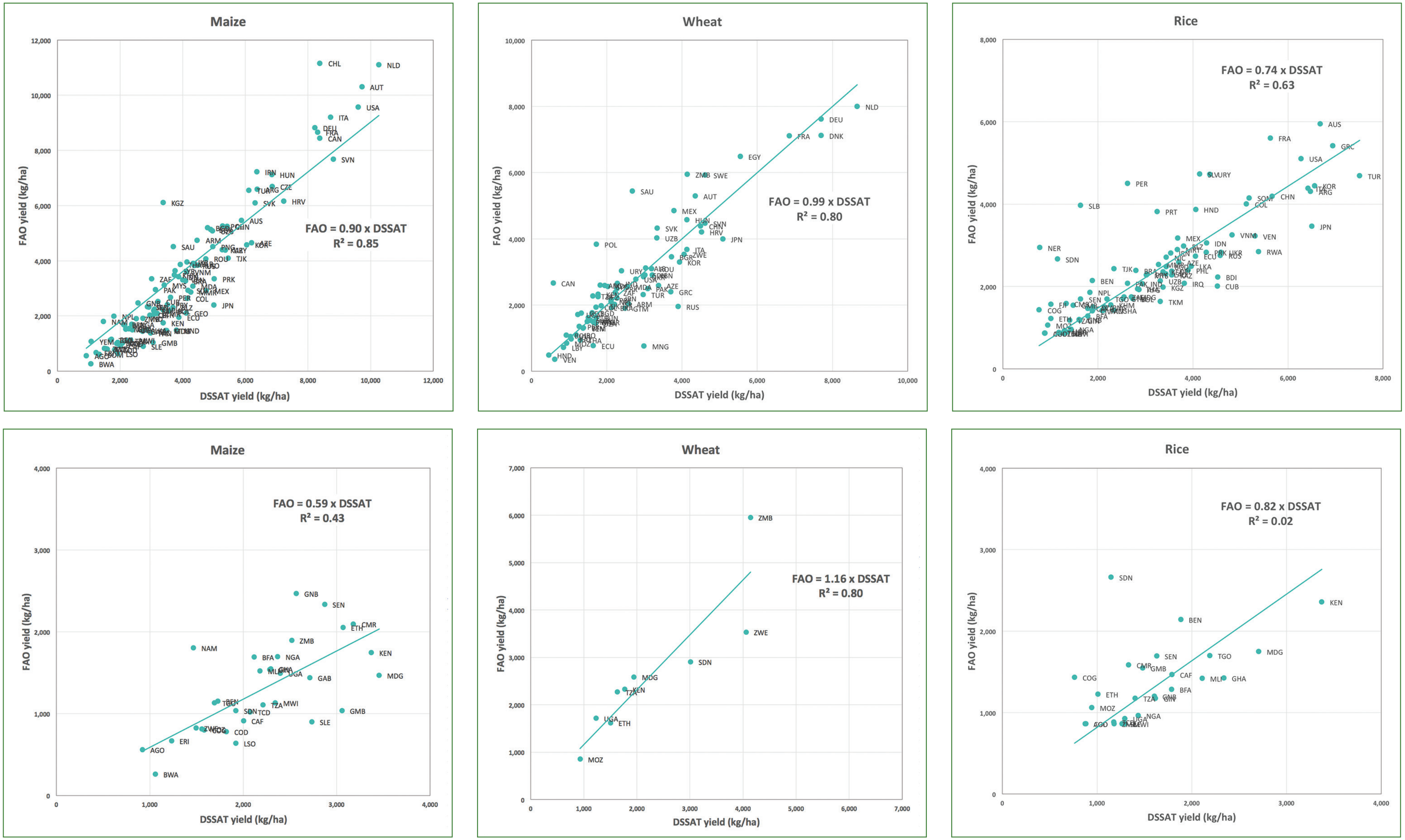
## Climate-Smart Alternatives Scenario

We identified four specific technologies to use in simulations for the climate-smart scenario. These are practices with a potential for large-scale adoption, and most of them are already being utilized or tested in some regions, including SSA. The technologies considered for maize and wheat are no tillage (NT) and integrated soil fertility management (ISFM), and those for rice are alternate wetting and drying (AWD) and urea deep placement (UDP) (Table 3.1). For this study, we assume that CSA practices are adopted across the entire SSA region but not the rest of the world. Although this assumption is clearly unrealistic, it allows us to better appreciate the effects of adoption of CSA practices on the African continent.

Examples from SSA and other regions show that unlike continuous tillage, which leaves soils prone to soil erosion and is a major source of soil carbon loss (Reicosky et al. 2005), NT combined with crop rotation and retention of crop residues reduces erosion and improves general soil fertility through retention of water and nutrients as well as benefits to soil aeration and soil biota, with potential direct effects on agricultural productivity (Hobbs, Sayre, and Gupta 2008; Kassam et al. 2009). The existing literature on conservation agriculture, of which NT is an essential component, points

11 It should be noted that both the BAU and alternative scenarios reflect the yield responses to the projected changes in climate (precipitation and temperature) but do not consider potentially important changes in the incidence and impact of pests and diseases.

## FIGURE 3.2—DSSAT CALIBRATION RESULTS FOR THE WORLD (TOP) AND AFRICA SOUTH OF THE SAHARA (BOTTOM), BUSINESS-AS-USUAL SCENARIO




Source: Authors.

Note: The dry-matter weight used in the DSSAT yield was converted into the fresh-matter weight of yield typically reported in FAOSTAT and SPAM by correcting for harvesting and threshing losses and grain moisture contents (see "Calibration of DSSAT for the Business-as-Usual Scenario" in the appendix). DSSAT = Decision Support System for Agrotechnology Transfer; FAOSTAT = the database of the Food and Agriculture Organization of the United Nations; SPAM = Spatial Production Allocation Model.

to an increase in yields, as evidenced by the effects on soil quality, soil moisture, and maize yields gathered at two different farm sites in Zambia (Thierfelder, Mwila, and Rusinamhodzi 2013). In general, however, the effects are quite variable because they depend on a range of location-specific exogenous conditions (such as climate and learning processes) and endogenous conditions (such as soil type) (Erenstein et al. 2012; Lal 2015; Pittelkow, Liang, et al. 2015). In some conditions, short-term productivity may even decrease under conservation agriculture (Pittelkow, Liang, et al. 2015). A review of case studies across SSA (Burkina Faso, Kenya, Madagascar, Malawi, Tanzania, Zambia, and Zimbabwe) showed that yields are more stable and often increase with time under such practices, especially in dry or drought-stressed conditions (Corbeels et al. 2014).

ISFM has been especially studied in SSA (Vanlauwe et al. 2010). ISFM is a set of locally adapted practices that utilize crop residues along with both synthetic fertilizers and organic inputs (such as animal manure, green manure, or both), aiming at increasing productivity through the efficient use of nutrients (Vanlauwe et al. 2011). It has been recognized that ISFM contributes toward improving the resilience of soils and agricultural production to weather variability, but much depends on the different benefits that synthetic fertilizers and organic inputs bring to the soil.

AWD has been used in paddy rice cultivation, which is one of the main sources of non-$CO_2$ GHG emissions from the agriculture sector, after livestock and soil (Smith et al. 2014), to significantly reduce $CH_4$ emissions from rice paddies (FAO 2013; Tyagi, Kumari, and Singh 2010) and in some instances also increase yields (Rejesus et al. 2011; Lampayan 2012). The technology has been validated and promoted across several countries in Asia, and adopted widely in Bangladesh, the Philippines, and Viet Nam. The water savings associated with AWD make this technology particularly suited to testing in the SSA context, and some positive results have been already reported in the Sahel region (de Vries et al. 2010; Comas et al. 2012).

### TABLE 3.1—CLIMATE-SMART AGRICULTURE TECHNOLOGIES CONSIDERED IN THIS STUDY

| Technology | Definition | Crop | Potential effects on yields and GHG emissions | References |
|---|---|---|---|---|
| No tillage (NT) | Minimal or no soil disturbance; often used in combination with residue retention, crop rotation, and cover crops | Maize, wheat | • Positive or neutral effect on yields<br>• Uncertain effect on GHG emissions | • Erenstein et al. 2008, 2012; Hobbs, Sayre, and Gupta 2008; Pittelkow, Linquist, et al. 2015<br>• Powlson et al. 2014 |
| Integrated soil fertility management (ISFM) | Combination of chemical fertilizers, crop residues, and manure or compost | Maize, wheat | • Positive effect on yields<br>• Variable effects on GHG emissions | • Agegnehu, vanBeek, and Bird 2014; Chivenge, Vanlauwe, and Six 2011; Vanlauwe et al. 2011<br>• Gentile et al. 2008 |
| Alternate wetting and drying (AWD) | Repeated interruptions of flooding during the season, causing the water to decline as the upper soil layer dries out before subsequent reflooding | Rice | • Low to no significant changes in yields<br>• High confidence in lower GHG emissions due to reduction of methane emissions | • Devkota et al. 2013; Huda et al. 2016; Rejesus et al. 2010<br>• Pandey et al. 2014; Tyagi, Kumari, and Singh 2010 |
| Urea deep placement (UDP) | Strategic burial of urea "supergranules" near the root zones of crop plants | Rice | • Positive results on yields<br>• Reduction of GHG emissions | • Bandaogo et al. 2015; Huda et al. 2016<br>• Gaihre et al. 2015 |

Source: Authors.
Note: GHG = greenhouse gas.

UDP aims at the efficient use of nitrogen, which is the key to both increased production and reduced emissions (FAO 2013). Broadcast application of nitrogen in rice fields leads to loss of 60 to 70 percent of the nitrogen, directly contributing to both water pollution and GHG emissions. The placement of urea "supergranules" deep in the soil provides a slow release of fertilizer near the root system of rice plants, thereby improving the efficiency of nutrient uptake and limiting nitrogen losses. The result is an increase in yields, combined with a significant reduction in leached nitrates and therefore a lower likelihood of $N_2O$ emissions. At the same time, UDP increases the resilience of agricultural systems by making them less susceptible to economic shocks due to changes in energy prices. The International Fertilizer Development Center reports that UDP was introduced for testing in West Africa in 2009 (IFDC 2011). Experiments conducted in Burkina Faso revealed the potential for a significant increase in rice yields (Bandaogo et al. 2015).

### *Adoption of Alternative Technologies*

The alternatives to the BAU scenario were constructed by assuming that farmers who are cultivating either maize, wheat, or rice are offered a portfolio of alternatives (that is, the four CSA practices considered) from which to choose. We constructed two scenarios based on two alternative conditions for adoption. In the first, the prerequisite for adoption is that the CSA technology or practice must return a yield gain over the status quo (i.e. the BAU scenario). In the second, CSA practices are adopted if they generate higher yields than current practices *and* reduce emission intensity.[12] In both cases, farmers are assumed to choose the alternative that increases yields the most. If none of the alternatives increases yields, farmers retain their current practices.

Clearly, in real-world conditions, adoption of alternatives to the status quo depends on many other factors. Yields, which could be considered a crude proxy for profitability, are only one of the aspects of production that enter the farmer's decision process. The literature on the socioeconomic determinants of adoption is extensive and considers factors related to the characteristics of farmers and their farms, market access, technology, the quality of extension services, and risk factors (Bewket 2007; Enfors and Gordon 2008; Shiferaw, Okello, and Reddy 2009; Teklewold and Kohlin 2011). However, we consider the yield increase assumption to be justified because it is difficult to imagine that countries would favor the widespread use of technologies that reduce yields, given the pressure of population growth and changing diets.

The analysis also assumes that when an alternative provides better yields in a particular grid cell, *all* farmers in that cell adopt the best alternative. This assumption departs significantly from previous studies (such as Rosegrant et al. 2014), in which adoption depends on other socioeconomic factors and has a ceiling lower than 100 percent. It is important therefore to consider the results of this study as an upper bound of the changes induced by the widespread adoption of CSA practices. As a sensitivity analysis, we

12 Emission intensity is defined as emissions per unit of output (yield). There are connections between reduction of emission intensity, efficient use of energy, and total factor productivity (Ayres et al. 2002). These linkages should be explored further, but they are not the target of this analysis. Still, farmers' adoption of CSA practices that reduce emission intensity could be in response to policies that target GHG emission reduction or to more general policies that aim at increasing total factor productivity.

simulated several other scenarios, including (following Rosegrant et al. 2014) lower adoption rates and adoption of AWD based on a reduction of production costs, not just an increase in yields. Although the results are numerically different, there are no qualitative differences between these additional scenarios and the two presented in this chapter.

## Greenhouse Gas Emissions and Emission Intensity

One of the pillars of CSA is the reduction of GHG emissions. Even though the CSA practices considered are expected to reduce emissions, given the high heterogeneity of soil characteristics and growing conditions, there is no assurance that adopting these practices actually reduces emissions on a given farm. Furthermore, to appreciate the complexities related to the reduction of GHGs it is necessary to take a closer look at what determines total emissions. Total emissions from crop production ($E$) are determined by a multiplicative combination of emission intensity ($e$, emissions per unit of output), yield ($y$, output per hectare), and area ($a$, hectares allocated to crop production):

$$E = f(e, y, a) = e * y * a. \quad (1)$$

Equation (1) indicates that reducing total emissions depends not only on the effectiveness of the alternative practices in reducing emissions per unit of output but also on their effects on yields. In principle, it is possible for yields and area to increase sufficiently to offset any reduction in emission intensity.[13]

[13] This can be easily observed by taking the total derivative of equation (1), $dE = \frac{\partial f}{\partial e}\, de + \frac{\partial f}{\partial y} dy + \frac{\partial f}{\partial a} da$, noting that $\frac{\partial f}{\partial e} > 0$, $\frac{\partial f}{\partial y} > 0$, and $\frac{\partial f}{\partial a} > 0$.

# Results

Results for the scenarios that simulate global adoption of CSA practices and technologies are dependent on how widely CSA practices and technologies are adopted. The adoption rates for the two scenarios are shown in Table 3.2.

**TABLE 3.2—ADOPTION RATE BY CROP UNDER VARIOUS CLIMATE AND ADOPTION SCENARIOS**

| Scenario | Adoption rate of alternative practice: MAIZE (GFDL / HadGEM) | Adoption rate of alternative practice: WHEAT (GFDL / HadGEM) | Adoption rate of alternative practice: RICE (GFDL / HadGEM) |
|---|---|---|---|
| Adoption of CSA practices dependent on increased yields | 94.0% / 94.2% | 90.0% / 90.1% | 22.2% / 20.9% |
| Adoption of CSA practices dependent on reduction of emission intensity *and* increased yields | 79.0% / 78.1% | 26.8% / 26.5% | 20.8% / 20.2% |

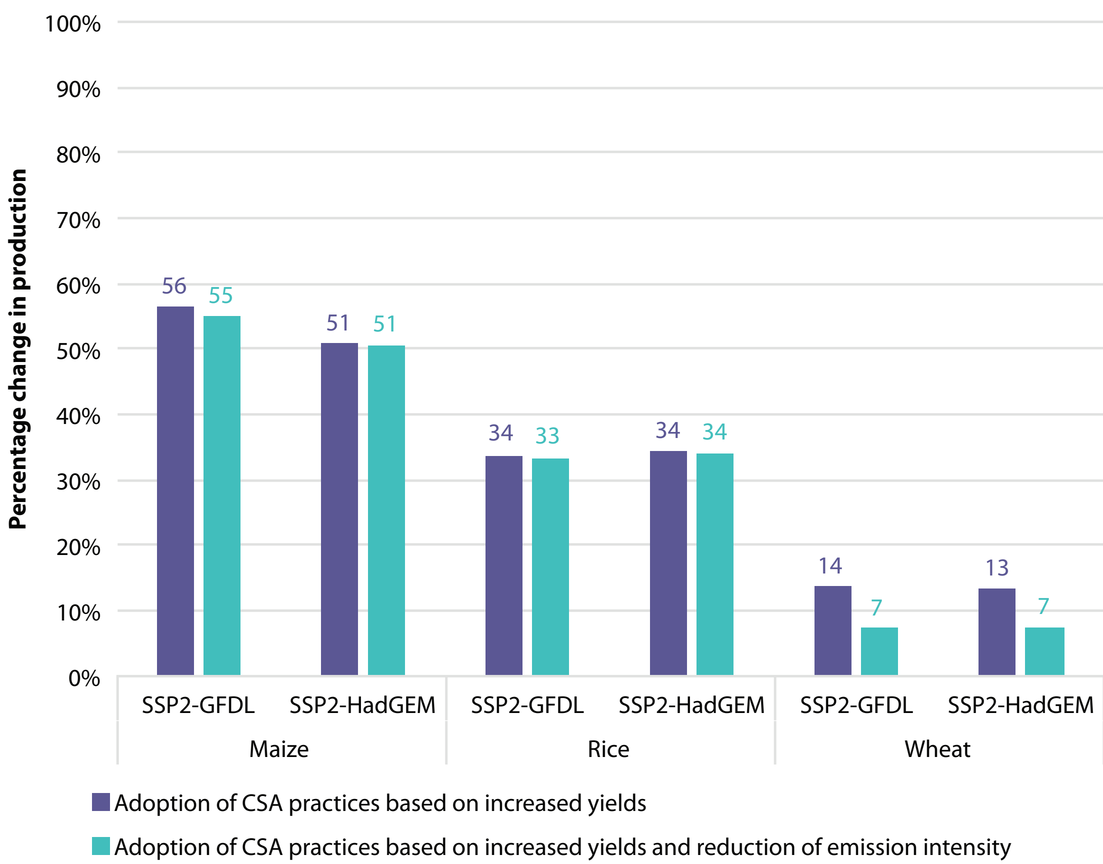
Source: Authors.

Note: CSA = climate-smart agriculture; GFDL = Geophysical Fluid Dynamics Laboratory Earth System Model version 2M; HadGEM = Hadley Centre Global Environment Model version 2—Earth System.

As expected, adoption rates are lower when two conditions (increase in yields and reduction of emission intensity) must be satisfied. Adoption seems to drop the most for wheat with the addition of a second condition, indicating that the CSA practices considered do not automatically lead to a reduction of emissions for this crop.

Overall, when compared with a BAU scenario, CSA technology adoption in SSA is estimated to increase production of maize by more than 50 percent, wheat production by between 7 and 14 percent, and rice production by more than 30 percent (Figure 3.3). There is almost no difference in effect between the two adoption scenarios, with the exception of wheat, for which production is about 6 percent larger when only yield increases are a condition for adoption. Results for maize are particularly important. CSA technologies appear to be able to offset the negative effects of climate change (Figure 3.3). When CSA practices are adopted under the GFDL simulated climate, for instance, production may increase by 55–56 percent over BAU.

FIGURE 3.3—PERCENTAGE CHANGE IN PRODUCTION (TOTAL OUTPUT) IN 2050, CLIMATE-SMART AGRICULTURE SCENARIOS COMPARED WITH BUSINESS-AS-USUAL SCENARIO




Source: Authors.

Note: CSA = climate-smart agriculture; SSP2-GFDL = Geophysical Fluid Dynamics Laboratory Earth System Model version 2M under shared socioeconomic pathway 2; SSP2-HadGEM = Hadley Centre Global Environment Model version 2—Earth System under shared socioeconomic pathway 2.

Not surprisingly, because we limit adoption of CSA to SSA, the increase in crop productivity has only a small effect on the world prices of maize, rice, and wheat (Table 3.3), especially when compared with the changes in global prices projected for the period 2010–2050 under SSP2-GFDL or SSP2-HadGEM and BAU (Figure 3.1). A result of the unchanged upward trend in prices is that producers can take advantage of higher productivity by expanding production area. Projections indicate that harvested area for maize, rice, and wheat is expected to increase in SSA with the adoption of CSA practices. The IMPACT simulations show an increase of up to 12 percent for maize, 3 percent for wheat, and 2 percent for rice by 2050 (Table 3.3). These are important changes to consider even though the current model framework does not allow us to discern what other land uses would be affected by this expansion. Further research is necessary to explore these issues.

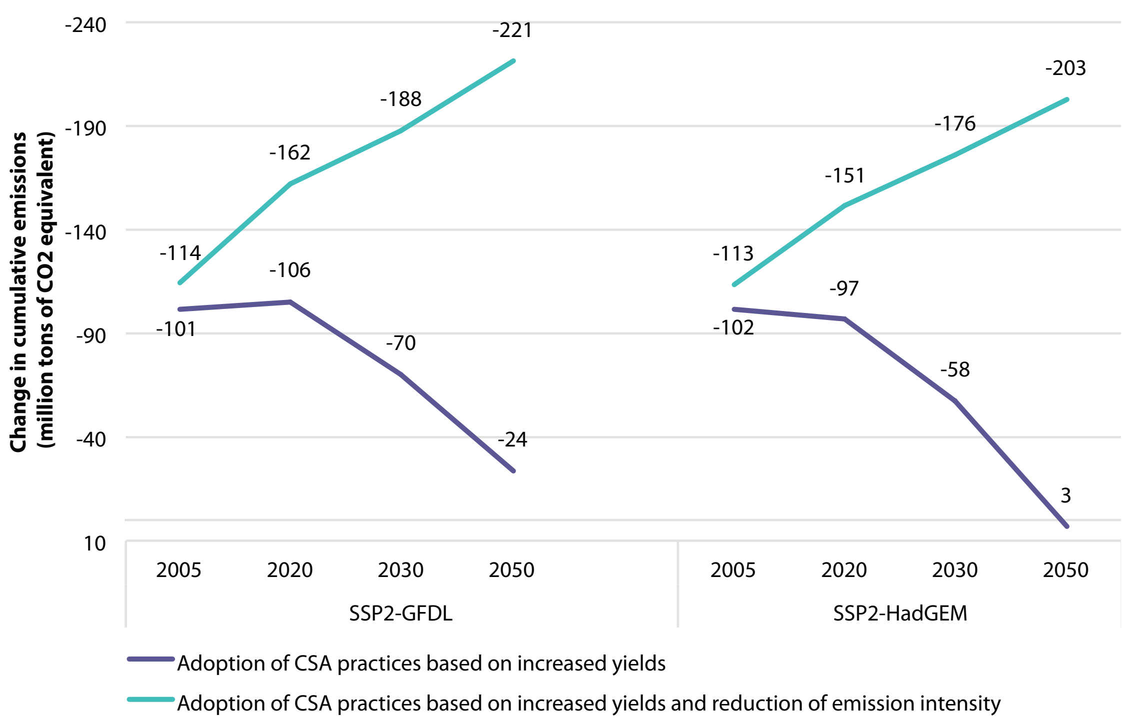
## TABLE 3.3—PERCENTAGE CHANGE IN 2050 WORLD PRICES UNDER TWO SCENARIOS, COMPARED WITH BUSINESS-AS-USUAL

| Scenario | MAIZE (GFDL / HadGEM) | WHEAT (GFDL / HadGEM) | RICE (GFDL / HadGEM) |
|---|---|---|---|
| Adoption rate of CSA practices predicated on increased yields | -2.80% / -3.00% | -1.30% / -2.00% | -3.20% / -3.40% |
| Adoption rate of CSA practices predicated on increased yields and reduction of emission intensity | -2.70% / -3.00% | -1.20% / -1.80% | -3.20% / -3.30% |

Source: Authors.

Note: GFDL = Geophysical Fluid Dynamics Laboratory Earth System Model version 2M; HadGEM = Hadley Centre Global Environment Model version 2—Earth System.

## FIGURE 3.4—CHANGE IN GREENHOUSE GAS EMISSIONS FROM BASELINE UNDER TWO ADOPTION AND TWO CLIMATE SCENARIOS




Source: Authors.

Note: CSA = climate-smart agriculture; SSP2-GFDL = Geophysical Fluid Dynamics Laboratory Earth System Model version 2M under shared socioeconomic pathway 2; SSP2-HadGEM = Hadley Centre Global Environment Model version 2—Earth System under shared socioeconomic pathway 2.

Consistent with the production results,[14] the population at risk of hunger in SSA is projected to decrease by between 1.8 and 2.5 percent, with little difference between the two adoption scenarios. However, the decrease in undernourished children younger than five years is low under both adoption scenarios, ranging between 0.2 and 0.3 percent (equivalent to approximately 100,000 children).

Overall, the considered CSA practices also appear to be beneficial for soil fertility, for sustainability, and potentially for resilience in general. The soil organic carbon concentration, which increases not only fertility but also soil water retention, is estimated to increase by an average of 0.16–0.17 tons/ha$^{-1}$/year$^{-1}$ over BAU across the area that adopts the alternative practices, depending on which scenario is considered. Soil organic carbon "gains" should be interpreted mostly as avoided soil carbon losses rather than actual gains from the initial conditions.

Significant differences are apparent between the two adoption scenarios when we consider GHG emissions. When the choice to adopt is based only on yields, total GHG emissions remain basically unchanged or decrease minimally, at an estimated 0.01 tons/ha$^{-1}$/year$^{-1}$ and results depend largely on the climate scenario used (Figure 3.4). Importantly, although CSA practices reduce emissions during the first two decades simulated, during the latter two decades they appear to increase emissions. This happens

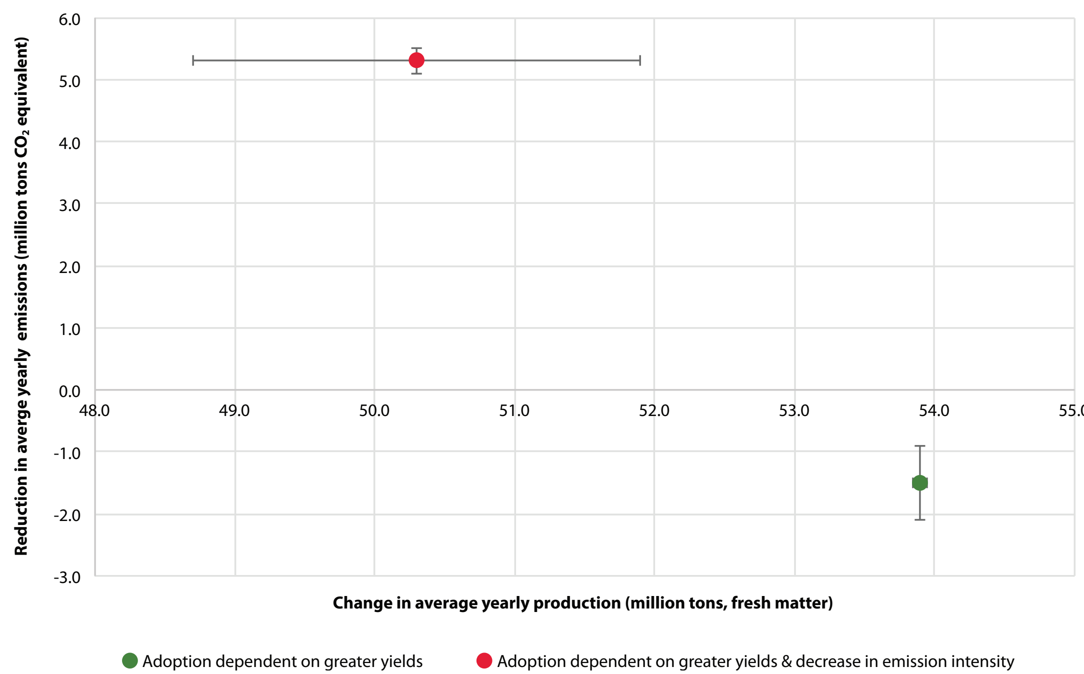
14 On exception is wheat, for which results change significantly across scenarios. However, wheat area by 2050 is about one-third of rice area and one-seventh of maize area, and therefore its contribution to overall production and calories is limited.

because soils reach a steady-state condition wherein no more soil organic carbon sequestration occurs even though $N_2O$ emissions continue at relatively constant rates over the entire 40 years. This leads to an actual increase in GHG emissions during the final decade simulated, compared with the baseline, estimated at 1.5 million tons of $CO_2$ equivalent annually.

Results from the second simulation show that it is possible, in principle, to increase production while reducing GHG emissions. By enforcing a reduction of emission intensity, it is possible to reduce GHG emissions by more than 200 million tons for the period under consideration (Figure 3.4), equivalent to an average per-hectare yearly reduction of approximately 0.17 tons of $CO_2$ equivalent. Significantly, even during the final decade modeled, emissions are reduced at an average rate of 5.5 million tons of $CO_2$ equivalent annually.

Figure 3.5 summarizes the results of comparing the two adoption scenarios for the final decade under consideration. The change in total production is computed using the cumulative fresh weight of the three crops considered, and yearly GHG emissions are computed using the yearly average for the final decade (2040–2050). The whisker bars indicate the range of simulation results obtained using the two different climate projections, with the average of the two estimates marked by a colored dot. Two messages can be drawn from the results displayed in Figure 3.5. First of all, although the CSA practices and technologies simulated have overall positive effects on production, reducing emissions while also increasing production is possible but depends on being able to enforce a reduction in emission intensity. This result is consistent with field findings reported in the literature indicating that CSA practices do not reduce emissions in all conditions and require careful tailoring to the specific local soil and weather conditions. In other words, there appears to be substantial room for CSA practices to increase yields but not necessarily to reduce GHG emissions. Second, there appears to be a trade-off between crop production and reduction of GHG emissions. Simulation results reveal that total annual output is reduced by some 4 million tons of fresh matter when a reduction in GHG

**FIGURE 3.5—EFFECTS OF ADOPTION OF THE BEST CLIMATE-SMART AGRICULTURE PRACTICE DURING THE PERIOD 2040–2050 ON TOTAL ANNUAL YIELD AND GREENHOUSE GAS EMISSIONS**




Source: Authors.

emissions is achieved. In order to resolve these trade-offs in an economically efficient manner, a correct pricing of the factors of production and a price for carbon are necessary.

## *Discussion and Conclusions*

A growing body of literature analyzes the effects of CSA practices and technologies in terms of agronomic, economic, and environmental benefits. Though most of the literature focuses on these effects at the farm and household levels, this study takes a broader geographic perspective, performing an ex ante evaluation of the effects of widespread adoption of selected CSA practices on three cereals: maize, wheat, and rice. Household-level analyses are important to determine, among other things, the viability of new practices and their benefits for households' well-being. However, a broader outlook provides insights into issues related to changes in prices, accessibility of food products, and the cumulative effects on GHG reduction. This broader perspective is necessary when the changes in production affect global prices and consequently cause changes in demand, potential substitution among food products, and increases in production area needed to satisfy demand, all of which must be accounted for.

We therefore carried out an ex ante assessment of the effects of widespread adoption of CSA practices and technologies compared with the outcomes of a BAU scenario in which the climate-smart practices are not adopted. Notwithstanding the broad generalizations necessary to carry out such a large-scale analysis, several insights into the benefits and limits of the CSA approach come to light.

Results indicate that widespread adoption of CSA practices has a positive effect on production and total agricultural output, with a consequent reduction in prices and decrease in the number of people at risk of hunger and the number of children younger than five years at risk of malnutrition. Soil organic carbon appears to grow, compared with the BAU scenario, indicating that productivity can be increased while making production more sustainable than it is with current practices.

These results indicate that CSA practices can positively affect yields and production, induce a reduction in prices, and decrease the number of people at risk of hunger and the number of undernourished children younger than five years. Adoption of CSA practices also induces an increase in soil organic carbon content, or at least reduces soil organic carbon losses, indicating that productivity can be increased in a more sustainable manner than with the current practices. Taken together, all of these outcomes suggest an increase in resilience to climate change.

Importantly, however, the relatively modest effect on world prices does not lead to reduced pressure for cropland expansion. Given the increased productivity, producers might find bringing additional land into production profitable even with the projected decrease in prices, potentially endangering environmentally sensitive and carbon-rich areas.

It is important to recall that these results reflect the upper-bound effects of adoption of CSA practices and that the overall-positive outcomes strongly depend on the uptake of CSA practices by farmers, which we purposely assume to be unrealistically high. The effects of CSA practices would be increasingly marginal with lower adoption rates. In addition, CSA alone does not solve long-standing problems related to the adoption of new beneficial technologies, such as the necessity of well-functioning extension services, the amount and quality of the information provided to farmers, and the removal of a host of other barriers to adoption. These caveats point to the importance of putting in place policies and incentives that promote climate-smart agricultural development.

The effects on GHG emissions are mixed and mostly depend on how much emphasis is given to reduction of emissions. Results for the scenario that simulates adoption of alternative practices based only on yield increases suggest that GHG emission reduction is minimal or nonexistent, depending on which climate scenario is used, highlighting the highly context- and location-specific nature of CSA practices as well as the fact that their use alone does not assure a reduction in emissions. Conversely, when adoption depends on yield increase *and* emission intensity reduction, GHG emissions decrease while some increase in productivity is preserved. This result is important because it appears to indicate that the reduction of GHG emissions is compatible with increased productivity—although it depends on how feasible it is to enforce and control the actual achievement of in-the-field emission intensity reductions.

Not surprisingly, simulations point to an overall trade-off between increasing total output and reducing GHG emissions. Resolving this trade-off in an economically efficient manner depends on correctly pricing the factors of production and possibly creating a price for carbon. Given the multi-objective nature of the approach and the highly context-specific performance of CSA practices, simply offering farmers a portfolio of options from which to choose and educating them about their benefits appears not to lead automatically to meeting the goals of CSA—particularly if significant levels of GHG reduction must be achieved.

Although the insights on emission reduction offered by this analysis are limited by construction (that is, the study focuses on three crops and only on crop production), results point to the importance of broadening the interpretation of CSA and making sure its interactions with other land uses (for example, forests and mangroves) are considered and that agroforestry, livestock, and value chains are included in any analysis. The focus on crop production seems to be limiting and could potentially omit other and more important opportunities for carbon sequestration.

Frelat and colleagues (2016) suggested that targeting poverty through improving market access and off-farm opportunities is a better strategy to increase food security than focusing on agricultural production and closing yield gaps. Wheeler and von Braun (2013) suggested that the whole food system (that is, trade, stocks, nutrition, and social policies) needs to adjust to climate change. These authors make important calls for an approach that is much broader than a narrow focus on increasing yields, and this approach can be applied to CSA as well. CSA is too often reduced to a list of viable agricultural practices and technologies identified as acceptable. The results offered by this study suggest that although beneficial, the adoption of a set of CSA practices only marginally addresses poverty, food security, and most of all, emission reduction, indicating that broader interventions are necessary.

# Appendix

## Simulation of Technology Adoption

In order to simulate changes in yields, crop area, and production due to adoption of CSA practices and technologies compared with the BAU scenario, IMPACT must be linked with the DSSAT crop model through several steps (Robinson et al. 2015).

First, the IMPACT's BAU scenario begins in the year 2005, with yield values taken from FAOSTAT, which contains statistics and data compiled by the FAO Statistics Division (FAO 2017). Whereas early yield trends are calibrated to reproduce observed historical data, long-term yield trends or intrinsic productivity growth rates (IPRs) are estimated using the expected increases in inputs (for example, fertilizers and water) and general improvements in investments in agriculture. These IPRs differ for developing countries, where there is considerable scope to narrow the gap in yields compared with developed countries, and are exogenous to the model. As a result, changes in the IPRs are specified in the definitions of the various scenarios. Second, on top of these IPRs, the effects of temperature and precipitation (climate shocks) and CSA practices and technologies on crop yields (yield responses) are estimated through the DSSAT crop model. These climate shocks and yield responses are combined as shifters and then aggregated from the DSSAT area unit (a 0.5-degree grid cell, a square of approximately 56 km by 56 km at the equator) to the food producing unit (FPU) used in IMPACT. Finally, yield estimates in IMPACT are adjusted by way of an endogenous link between yields and estimated changes in commodity prices. The link hinges on the underlying assumption that farmers will respond to changes in prices by varying their use of inputs, such as fertilizer, chemicals, and labor, which will in turn change yields.

## Yield Responses

We analyzed yields estimated through DSSAT runs at global grid levels to calculate yield responses (percentages) due to any CSA practices and technologies, compared with the BAU scenario:

$$\Delta yield^{t,i} = \frac{\left(Yield_{CSA}^{t,i} - Yield_{BAU}^{t,i}\right)}{Yield_{BAU}^{t}} \times 100, \qquad (2)$$

where $t$ indicates time and $i$ identifies the 0.5-degree grid cell.

The yield responses for the first 10 years and the final 10 years were averaged to represent two specific years, 2005 and 2050. Because IMPACT operates on a regional basis, that of FPUs, we aggregated the detailed gridded crop modeling results of each pixel to the FPU level by calculating area-weighted average yield responses and applying them to the IMPACT yields. This approach allowed us to capture the direction and magnitude of change due to technologies (or climate change) seen in the crop models while maintaining the observed agricultural productivity reported in the FAOSTAT database.

## Calibration of DSSAT for the Business-as-Usual Scenario

To improve estimates of yield responses calculated from DSSAT-simulated yields under the respective scenarios of BAU and CSA practices/technologies, we calibrated the DSSAT crop model to ensure that its simulated yields would be compatible with those used in IMPACT as baseline yields in any given reference year. Because the yields of both IMPACT and SPAM at the reference year, 2005, are derived from FAOSTAT, we utilized disaggregated yields of SPAM as observed baseline yields for the purpose of calibration.

First, we adjusted the SPAM yields to account for harvesting and threshing losses and grain moisture contents. This step is necessary because FAO crop yield data are for harvested production, defined as production minus harvesting and threshing losses per unit of harvested area. Correcting for grain moisture content is necessary to convert FAO fresh-matter weight yields into the dry-matter weight yields simulated in DSSAT. Second, we selected one model parameter (the soil fertility factor, or SLPF, a growth reduction and fertility factor that accounts for the effects of soil nutrients—other than nitrogen—on the daily plant growth rate, on a scale of 0 to 1) and two model inputs (planting density and nitrogen fertilization rate) that would be sensitive to simulated yields yet could still be derived in spite of some uncertainties in the DSSAT database. Third, we varied the parameter and each input using three levels. For example, the SLPF was assigned a value of either 0.6, 0.8, or 1.0, whereas planting density and nitrogen rates were assigned either the original values derived from the DSSAT database or 50 percent or 150 percent of these original values. These levels resulted in 27 possible combinations of model parameter and input values for each grid cell. Fourth, we ran DSSAT to simulate yields corresponding to all of these combinations for five continuous years, and then selected the combination of parameter and input levels that gave the lowest relative difference between simulated and observed yields ($Yield_{sim}$ and $Yield_{obs}$):

$$\text{Relative difference} = \frac{Yield_{sim} - Yield_{obs}}{\frac{Yield_{sim} + Yield_{obs}}{2}}. \qquad (3)$$

Finally, within the irrigated and the rainfed grid cells, respectively, for each crop, we identified SPAM cells that were statistically deemed as outliers based on the method by Leys and others (2013). To do so, we calculated the relative difference (positive or negative) between simulated and observed yields and then removed grid cells with too large a relative difference, assuming that DSSAT would not be capable of simulating yields comparable to the observed yields for those grid cells.