CHAPTER 5

Trade, Climate Change, and Climate-Smart Agriculture

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The eradication of poverty in Africa south of the Sahara (SSA), whose poverty rate is the highest in the world, and of its food and nutrition insecurity necessitates structural transformation of the agricultural sector. Meanwhile, global climate change models suggest an overall warming trend and increased incidence of extreme weather events that vary by altitude (Serdeczny et al. 2017). These changes are expected to have a significant impact on agricultural productivity and the availability of productive resources globally and in SSA, a region that relies heavily on rainfed agriculture (Knox et al. 2012; Müller and Robertson 2014).

At the same time, agriculture affects climate change through anthropogenic greenhouse gas (GHG) emissions and by acting as a greenhouse gas sink. GHG emissions result, for instance, from enteric fermentation, application of synthetic fertilizers, land use change, and deforestation, while a sink removes atmospheric GHG by storing (sequestering) it in other forms through photosynthesis. Africa accounted for 15 percent of the world's agriculture-related GHG emissions in 2012, making it the third most important contributor, after Asia (45 percent) and the Americas (25 percent) (Tubiello et al. 2014). Considering the pressure on agricultural production driven by population growth, growth in gross domestic product (GDP) and a consequent change in diets toward higher consumption of animal-source foods, and the risks posed by climate change, farmers need options to sustainably increase production.

Climate-smart agriculture (CSA) is one approach that has been promoted to enhance agricultural productivity, food security, and adaptive capacity, while at the same time reducing GHG emissions and increasing carbon sequestration (Campbell et al. 2014; Huang, Lampe, and Tongeren 2011). The CSA approach, which became prominent during the First Global Conference on Agriculture, Food Security and Climate Change (FAO 2013), is an umbrella term that includes many strategies built upon location-specific solutions that are expected to contribute toward achievement of the Sustainable Development Goals (SDGs). It relies on agricultural systems that contribute to three outcomes: (1) sustainable and equitable increases in agricultural productivity and income; (2) greater resilience of food systems and farming livelihoods, and (3) reduction and removal of GHG emissions associated with agriculture, wherever possible. Agricultural production systems that follow the tenets of CSA are expected to be not only more productive and efficient, but also resilient to short-, medium-, and long-term shocks and risks associated with climate change and variability.

The CSA approach represents a departure from the single-objective approach that underlies most work to ensure food and nutrition security. CSA's multi-objective approach facilitates important conversations, negotiations, and coordination of interventions among different ministries. Many operational aspects of CSA, however, are still under investigation. Local contexts determine the enabling environment, the trade-offs, and the synergies of CSA, so practices and technologies may be climate smart in some circumstances and conditions but not in others. Therefore, how these practices deliver across the three pillars of CSA, and the conditions for their adoption, are highly specific to contexts and locations, with fundamental implications for the operational aspects of CSA (McCarthy, Lipper, and Branca 2011). Indeed, short-term productivity may even decrease under CSA (Pittelkow et al. 2015), with more stable and often increasing yields observed over time, especially under dry or drought-stressed conditions (Corbeels et al. 2014; Pittelkow et al. 2015).

Another approach being promoted to ensure the eradication of extreme poverty and promote inclusive and sustainable development, especially in the face of climate-induced changes in the amount and distribution of production, is trade (Sommer and Luke 2016). Trade is recognized as a cross-cutting means of implementing the 2030 Agenda for Sustainable Development under SDG 17. Agricultural commodity trade in Africa has increased steadily over the past 30 years, with net exports (exports minus imports) rising from 2 to 6 percent of GDP between 1980 and 2014 (IMF 2016). Despite these improvements, the region not only accounts for a small share of the global commodity trade but has one of the lowest intraregional trades in goods (16 percent, versus 17 percent for South and Central America, 42 percent for North America, 62 percent for the European Union, and 64 percent for Asia) (Davis 2016; Khandelwal 2005; Tamiotti et al. 2009).

Although a number of regional economic communities (RECs) have been established to promote economic integration and trade, including the Common Market for Eastern and Southern Africa (COMESA),[17] the Economic Community of West African States (ECOWAS),[18] and the Southern African Development Community (SADC),[19] intraregional trade remains staggeringly low. For example, between 2001 and 2010, intraregional trade grew at 2 percent, 1.3 percent, and 0.9 percent per year, on average, for ECOWAS, SADC, and COMESA, respectively, and intraregional trade accounted for 9 percent, 9.8 percent, and 5.6 percent of the total trade, on average, for ECOWAS, SADC, and COMESA, respectively (Seid 2013). But intraregional trade is expected to increase in the coming decades, thanks to an emerging favorable trade environment including the establishment of the African Continental Free Trade Area (UNCTAD 2016); the Malabo declaration, aimed at tripling intracontinental trade in agricultural commodities and services by 2025; and the African Union's Agenda 2063, which aims to increase intracontinental trade from 12 percent to 50 percent and the continent's share of global trade from 2 percent to 12 percent between 2013 and 2045 (African Union Commission 2015).

This chapter examines the role of CSA in mitigating the negative effects of climate change on yields and commodity trade flows in SSA. The analysis is disaggregated by the three RECs—SADC, ECOWAS, and COMESA—to capture possible region-specific factors that could mediate the interaction between agricultural production and trade flow as well as potential location specificity in the effectiveness of CSA practices. We simulate the expected effects of adoption of four CSA practices for the period 2018–2025: no tillage (NT) and integrated soil fertility management (ISFM) for maize, and urea deep placement (UDP) and alternate wetting and drying (AWD) for rice. These practices are found to increase agricultural productivity and net exports, highlighting the potential that CSA has in mitigating climate-induced risks in agricultural production, food security, and foreign currency.

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17 COMESA includes Burundi, Comoros, Democratic Republic of the Congo, Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia, and Zimbabwe.

18 ECOWAS includes Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, and Togo.

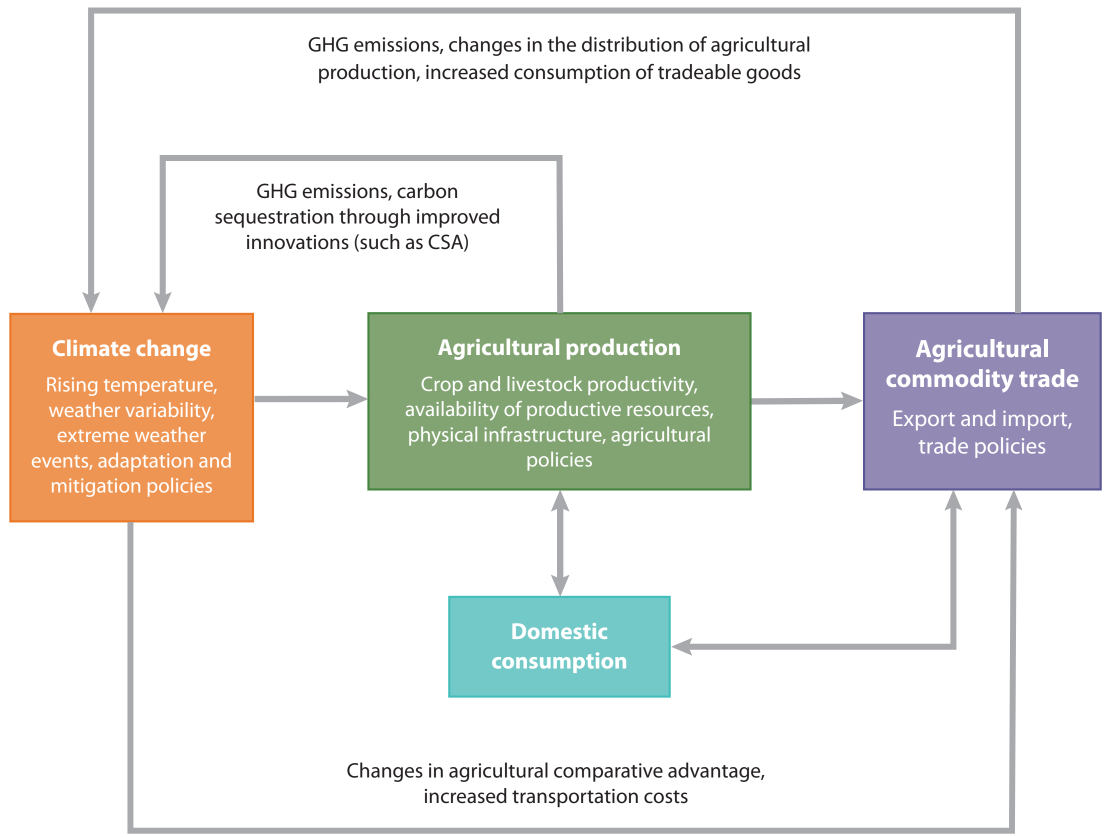
19 SADC includes Angola, Botswana, Democratic Republic of the Congo, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, United Republic of Tanzania, Zambia, and Zimbabwe, of which eight also belong to COMESA.

Conceptual Framework

The linkage between climate change, agricultural production, and trade flow is quite complex, as summarized in Figure 5.1. Given the reliance of Africa's agriculture on weather and its role in the region's trade, climatic changes such as rising temperature, weather variability, and extreme weather events (such as El Niño and La Niña) will have a significant impact on the availability of productive resources, productivity, food security, foreign exchange, and physical infrastructure (Müller and Robertson 2014). Important drivers of the relationship between agriculture and trade in the region are the production landscape and the biophysical conditions. Favorable climatic and weather conditions increase net exports by affecting the supply of exportable commodities, whereas climate changes and variability that reduce the supply of agricultural production have the opposite effect, given the possibility of substitution between internally produced and externally procured goods.

Climate change affects not only yields but also the pattern of production, the latter by changing countries' comparative advantage in the production of certain crops. By changing precipitation patterns and reservoir storage, it will also impact water availability for power production and irrigation (You et al. 2011). The effects of climate change will vary by agroecology and by countries' adaptive capability (Hebebrand 2009; Kang et al. 2009;

FIGURE 5.1—LINKAGES BETWEEN CLIMATE CHANGE, AGRICULTURAL PRODUCTION, AND AGRICULTURAL COMMODITY TRADE



Source: Authors, based on review of relevant literature.
Note: CSA = climate-smart agriculture; GHG = greenhouse gas.

Wheeler 2011). For example, rising temperatures will lengthen the growing period in mid- and high-latitude areas, with lower temperatures having the opposite effect in low-latitude areas. In this regard, a widespread adoption of improved agricultural technologies and management practices that reduce GHG emissions, improve the sequestration of carbon in agricultural soils, and curtail undesirable land use changes could play a crucial role in mitigating the effects of climate change.

Unlike continuous tillage, which leaves soils prone to erosion and is a major source of soil carbon loss (Reicosky et al. 2005), NT practices improve general soil fertility through retention of water and nutrients, at the same time benefiting soil aeration and biota, with potential direct effects on agricultural productivity (Hobbs, Sayre, and Gupta 2008; Thierfelder, Mwila, and Rusinamhodzi 2013). The existing literature on conservation agriculture, of which NT is an essential component, points to an increase in yields, but the effects are notably variable, dependent on a range of location-specific factors such as climate and soil type (Pittelkow et al. 2015; Lal 2015; Erenstein et al. 2012). Similarly, ISFM, a set of locally adapted practices using residues along with both organic and inorganic inputs (for instance, animal manure and green manure) to promote the efficient use of nutrients, can significantly increase productivity (Vanlauwe et al. 2011).

Given that agriculture is a crucial foreign exchange earner in SSA, climatic changes that affect productivity and the distribution of production will ultimately impact the region's trade flow. In addition, extreme weather events such as La Niña and El Niño, which interfere with ship navigation and port operations as well as damaging physical infrastructure, could hamper the flow of trade locally, regionally, and internationally. At the same time, trade contributes to climate change through increased GHG emissions due to the transportation of commodities and increased consumption of tradable goods. Free trade can help offset climate-induced changes in agricultural production and food supply, and trade liberalization and investments can encourage the introduction of more (energy-) efficient production processes that emit fewer GHGs per unit of output produced and traded. Thus, trade can serve as both a mitigation and an adaptation strategy to climate change.[20]

Finally, trade and agricultural policies can either worsen or mitigate climatic changes, depending on whether they encourage or limit the production and distribution of GHG-intensive goods (IPCC 2007). Similarly, large-scale adoption of improved technologies and practices can cause an agricultural glut if local, regional, and international markets are too weak to absorb the boost, potentially inducing suboptimal adoption in subsequent cropping seasons. Although disentangling these complex linkages between climate change, agriculture, and trade is beyond the scope of this study, the chapter examines the potential role of CSA in enhancing yields and trade flow in SSA in the face of expected climatic changes.

Data and Summary

The analysis uses secondary data from several sources. A time series (1993–2010) of country-level data on the gross value of agricultural production in purchasing power parity (PPP) (constant 2004–2006 international

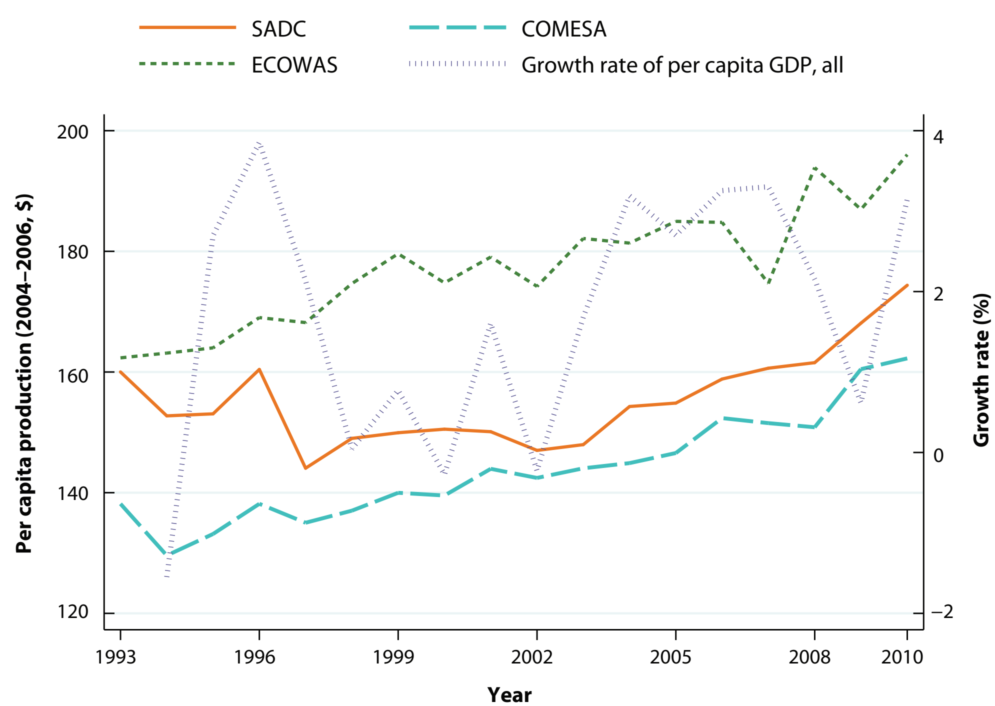
20 Mitigation aims at reducing GHG emissions sources or enhancing GHG sinks, whereas adaptation refers to adjustments to mitigate detrimental effects of actual or anticipated climatic changes and to seize opportunities induced by climate change (IPCC 2007).

dollars)[21] and trade flow in US dollars comes from the Food and Agriculture Organization's trade statistics database, FAOSTAT (FAO 2017). Data on population and GDP per capita in PPP (constant 2011 international dollars) are obtained from the World Bank (World Bank 2017a, 2017b).

For crop modeling, we use a time series of site-specific weather data from the US National Aeronautics and Space Administration's (NASA's) AgMERRA database (Ruane, Goldberg, and Chryssanthacopoulos 2015). AgMERRA (based on NASA's Modern-Era Retrospective Analysis for Research and Applications, or MERRA) compiles satellite-measured weather data for 30-arc-minute grid squares, including minimum temperature, maximum temperature, solar radiation, and precipitation. Our source for high-resolution (in 5-arc-minute grid squares) soil property data is the Global High-Resolution Soil Profile Database (IRI et al. 2015). The geography of the two crops we simulate (maize and rice) is based on the Spatial Production Allocation Model (SPAM) (IFPRI and IIASA 2016).[22]

Figure 5.2 summarizes the per capita gross value of agricultural production (constant 2004–2006 international dollars). Per capita gross value has been rising steadily over the years, with ECOWAS reaching consistently higher production than the other two RECs. The population of the region grew at about 2.3 percent per year, whereas per capita GDP (constant 2011 international dollars) grew at about 1.7 percent, with a much faster growth observed from the first years

FIGURE 5.2—HISTORICAL PER CAPITA GROSS PRODUCTION VALUE (LEFT AXIS) AND GROWTH RATE OF PER CAPITA GROSS DOMESTIC PRODUCT (RIGHT AXIS), SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES, 1993–2010



Source: Authors' own calculations based on agricultural production data from FAO (FAO 2017) and population data from the World Bank (World Bank 2017b).

Note: COMESA = Common Market for Eastern and Southern Africa; ECOWAS = Economic Community of West African States; GDP = gross domestic product; I $ = international dollars; SADC = Southern African Development Community.

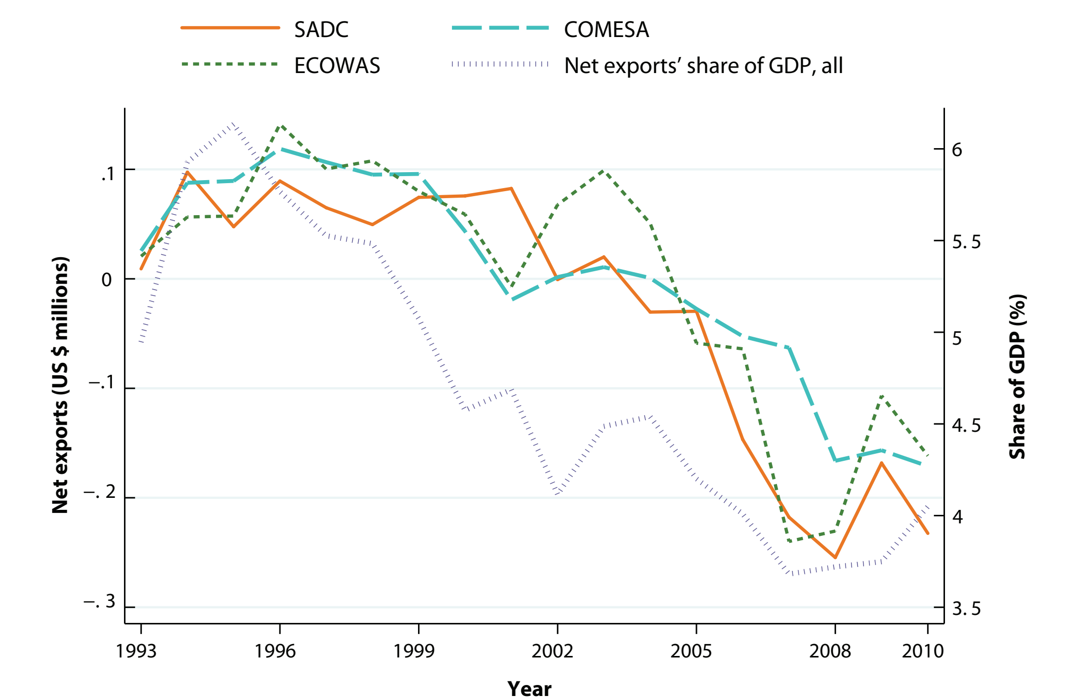
21 An international dollar has the same purchasing power as the U.S. dollar has in the United States. Values and costs in local currency are converted to international dollars using purchasing power parity (PPP) exchange rates. The PPP between two countries A and B measures the amount of A's local currency needed to purchase a basket of commodities in A as compared to one unit of B's currency needed to purchase a similar basket of commodities in B (World Bank, 2017c).

22 The analysis excludes the following countries due to incomplete data on trade, simulated yields, or both: Benin, Cabo Verde, Comoros, Djibouti, Egypt, Liberia, Mauritius, Seychelles, and Sierra Leone.

of the new millennium until the dip in 2009, following the 2007–2008 financial crisis.

Figure 5.3 summarizes net agricultural exports (in millions of US dollars) by REC. Overall, the region has been a net importer of agricultural commodities since just after the turn of the 21st century, with net exports (in absolute value) accounting for about 4.5 percent of GDP, on average. Although the gross value of agricultural production has been rising, the relatively faster economic growth since the early years of the century has created a strong demand for consumer-oriented agricultural products such as prepared foods, dairy, poultry, and vegetables (USDA 2014). What is more, many of the net importers were unable to pay for their imports. For example, the export revenues of only one-third of African countries were large enough to pay their food import bills, with the rest of them resorting to external funding (Rakotoarisoa, Iafrate, and Paschali 2011). Cereals, oilseeds, and dairy products accounted for more than 60 percent of the region's total imports, whereas coffee, cocoa, tea, and fruits and vegetables accounted for more than 55 percent of total exports (Rakotoarisoa, Iafrate, and Paschali 2011).

FIGURE 5.3—HISTORICAL TOTAL AGRICULTURAL NET EXPORTS, SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES, 1993–2010



Source: Authors' own calculations based on trade flow data from FAO (FAO 2017) and GDP data from the World Bank (World Bank 2017a).
Note: COMESA = Common Market for Eastern and Southern Africa; ECOWAS = Economic Community of West African States; GDP = gross domestic product; SADC = Southern African Development Community.

Method

Climate-Smart Agriculture and Yields

Crop growth is affected by several factors, including weather condition, soil type, and farmers' management practices. Process-based crop models simulate crop growth by dynamically interacting these factors. Since the 1970s, as plant science has rapidly advanced with a better understanding of how plant photosynthesis and respiration processes work, various forms of dynamic crop models have been developed and used to support farm management decision making. Given the complex nature of CSA implementation in the fields and its potential impacts, this study uses the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al. 2015; Jones et al. 2003) to simulate the effects of the adoption of selected CSA practices.

DSSAT combines a suite of complex and dynamic crop system models to estimate the biophysical responses of crops under various scenarios, in our case, scenarios of large-scale CSA technology adoption by farmers. DSSAT integrates the effects of crop system components and management options to simulate the states of all the components of the cropping system and their interactions. DSSAT crop models are designed based on a systems approach, which provides a framework for users to understand how the overall cropping system and its components function throughout cropping season(s) on a daily basis. Table 5.1 summarizes the CSA practices we focus on.

TABLE 5.1—SUMMARY OF CLIMATE-SMART AGRICULTURAL PRACTICES CONSIDERED

CSA technology	Definition	Crop
No tillage	Minimal or no soil disturbance, often in combination with residue retention, crop rotation, and use of cover crops	Maize
Integrated soil fertility management	Combination of chemical fertilizers, crop residues, and manure or compost	Maize
Alternative wetting and drying	Repeated interruptions of flooding during the season, causing water to decline as the upper soil layer dries out before subsequent reflooding	Rice
Urea deep placement	Strategic burial of urea "supergranules" near the root zones of crop plants	Rice

Source: Authors' review of the relevant literature.
Note: CSA = climate-smart agriculture.

It has been shown that ISFM improves the resilience of soils and agricultural production systems to weather variability (Roobroeck et al., 2016). This finding is dependent on the fact that synthetic fertilizers and organic inputs bring diverse benefits to the soil. AWD has been used in paddy rice cultivation, one of the main sources of non–carbon dioxide GHG emissions from the agriculture sector, after livestock and soil (Smith et al. 2014), to significantly reduce methane emissions from rice paddies (FAO 2013; Tyagi, Kumari, and Singh 2010) and, in some instances, also to increase yields (Rejesus et al. 2011).

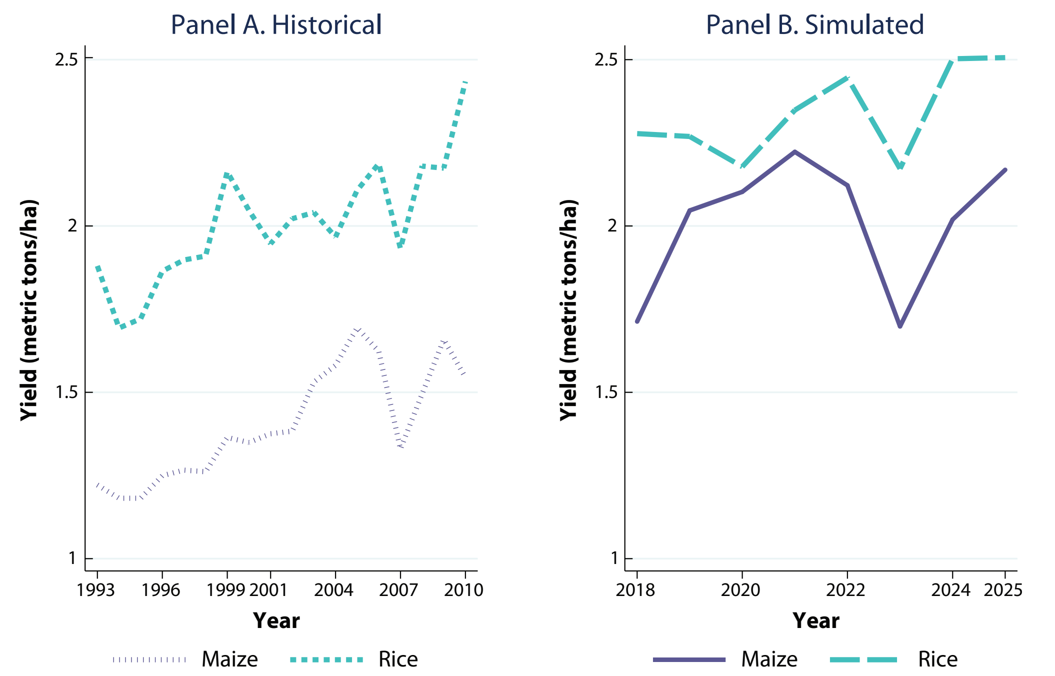
UDP aims at the efficient use of nitrogen, key to both increased production and reduced emissions (FAO 2013). Broadcast application of nitrogen in rice fields leads to 60 to 70 percent nitrogen losses, directly contributing to both water pollution and GHG emissions. The placement of urea "supergranules" 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 nitrous oxide 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.

Conditions for adoption of CSA practices are highly context and location specific, highlighting the need for information and data to make a true CSA approach to agricultural development operational (McCarthy, Lipper, and Branca 2011). From the farmers' perspective, however, the problem is quite different. Adoption of practices and technologies that are alternatives to the status quo depends on many factors. An extensive literature has investigated the socioeconomic determinants of adoption of alternative practices, attempting to account for farmers' and farms' characteristics by considering access to markets and credit, the characteristics of the technology, the quality of extension services, and risk factors as important factors of adoption (Bewket 2007; Enfors and Gordon 2008; Shiferaw, Okello, and Reddy 2009; Teklewold and Kohlin 2011).

We assume that farmers who are currently using a determinate set of practices to produce either maize or rice have the option to choose from a portfolio of alternatives (that is, the four CSA practices considered). In addition, we assume that they have complete information regarding potential yields and are able choose the alternative that provides the highest yield for their grid square compared with business-as-usual practices, a scenario we refer to as a "smart farmer option." Depending on the location, therefore, the CSA practice that corresponds with the smart farmer option could be one of the four CSA practices we are considering (NT or ISFM for maize and UDP or AWD for rice). In cases in which the alternatives are not projected to produce yield gains, farmers are assumed to retain the current practices. Although these assumptions are an extreme simplification of the conditions for adoption of alternative practices, it is difficult to imagine that countries would favor the widespread use of technologies that reduce yields in the face of high population growth rates and changing diets. Therefore, the yield-increase assumption on which adoption is based is considered justified with the understanding that the analysis could overestimate CSA adoption rates and hence their effects.

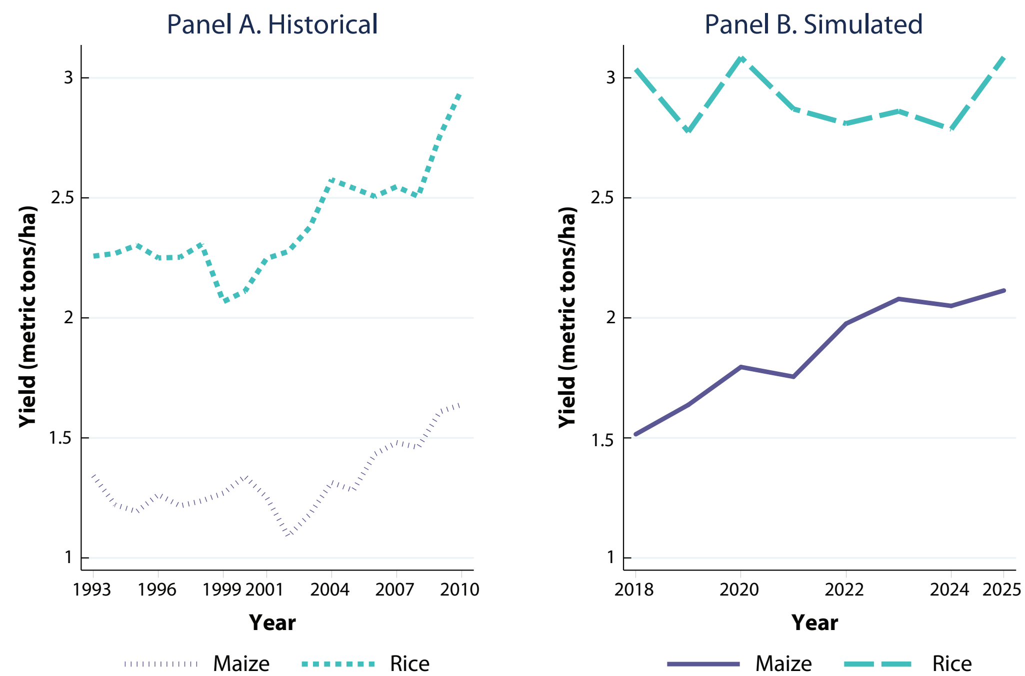
For each grid-cell level and crop, yields were simulated for alternative CSA practices for 2018–2025 based on AgMERRA weather data for 2003–2010, assuming the weather patterns for 2018–2025 will be identical

FIGURE 5.4—HISTORICAL (1993–2010) AND SIMULATED (2018–2025) YIELDS UNDER THE SMART FARMER OPTION, ECOWAS



Source: Authors' own calculation based on historical yield data from FAO (FAO, 2017) and DSSAT-simulated yields.

FIGURE 5.5—HISTORICAL (1993–2010) AND SIMULATED (2018–2025) YIELDS UNDER THE SMART FARMER OPTION, COMESA



Source: Authors' own calculation based on historical yield data from FAO (FAO, 2017) and DSSAT-simulated yields.

to those of the earlier period. To simulate the effects of CSA on agricultural commodity trade flow, simulated yields are converted into monetary values using crop-specific FAOSTAT data on cultivated area and a PPP conversion factor.[23]

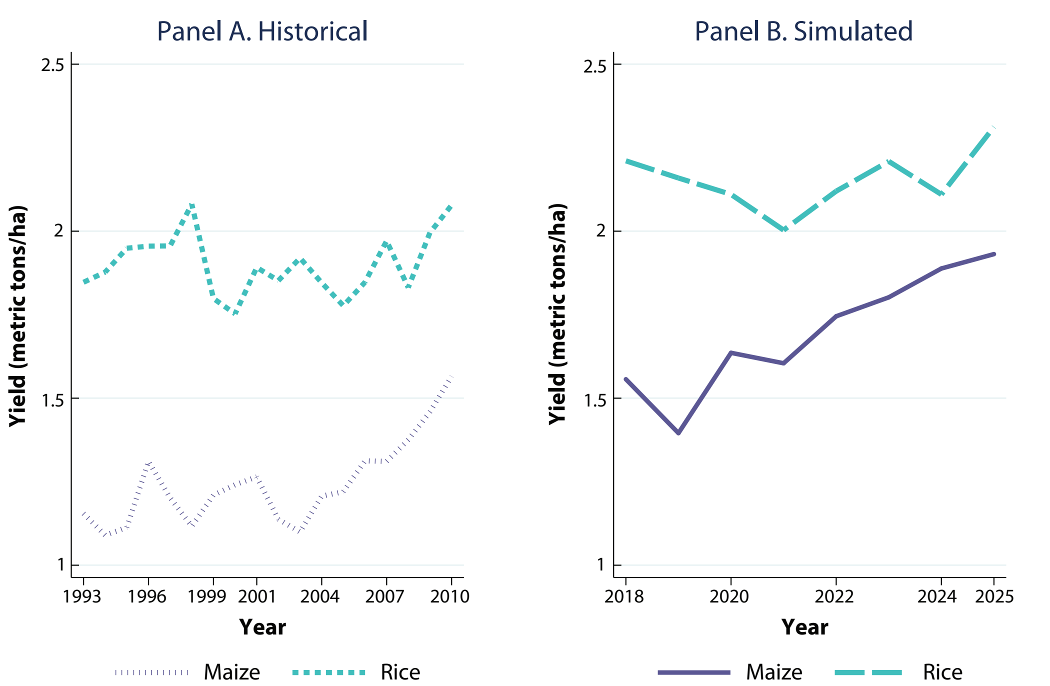
A summary of historical and simulated yields (in tons/hectare)[24] associated with the smart farmer option for each REC is shown in Figures 5.4–5.6. The ECOWAS region has witnessed a steady increase in maize yield over the years, except for 2007 (Figure 5.4, panel A), whereas the increasing trend in maize yield observed for COMESA (Figure 5.5, panel A) and

23 The PPP conversion rate is calculated as the ratio between production value in thousands of constant 2004–2006 international dollar per metric ton and the quantity of production in metric tons.

24 Throughout the chapter, tons refers to metric tons.

SADC (Figure 5.6, panel A) begins after the early years of the 21st century. Compared with maize yields, rice yields show more temporal variation. Nonetheless, given the projected climatic changes, these increasing trends in yields may not be sustained (Lesk and Ramankutty 2016). On the other hand, large-scale adoption of CSA practices has the potential to increase yields, as summarized in panel B of the respective figures.

FIGURE 5.6—HISTORICAL (1993–2010) AND SIMULATED (2018–2025) YIELDS UNDER THE SMART FARMER OPTION, SADC



Source: Authors' own calculation based on historical yield data from FAO (FAO, 2017) and DSSAT-simulated yields.

Climate-Smart Agriculture and Trade Flow

To examine the link between agricultural production and trade flow, we estimate Equation (1) using historical data:

$$NX_{ct}=\alpha_0 + \alpha_1 Y_{ct} + \Lambda' Z_{c(t)}+\gamma t + \varepsilon_{ct}, \quad (1)$$

where c and t are country and year indexes, respectively; NX is the gross value of total agricultural net exports (in millions of US dollars); Y is the logarithm (log) of the gross value of agricultural production (in constant 2004–2006 international dollars, thousands); Z is a matrix of time-varying or time-invariant factors that could affect net exports, including the log of per capita GDP (in constant 2011 international dollars), population (in millions), price indexes of agricultural imports and exports, and crop land area (millions of hectares); t is a linear time trend to capture overall temporal trends in NX; and ε is the (composite) error term.

For the sake of comparability, Equation (1) is estimated using pooled ordinary least squares (OLS) and random-effects (RE) estimators, the latter assuming Y and Z to be exogenous (see Cameron and Trivedi 2005 and Wooldridge 2010 for general discussions). Since we are estimating a level-log model, a percent increase in Y is associated with $\widehat{\alpha_1}/100$ change in NX, where $\widehat{\alpha_1}$ is the coefficient estimate of Y. Robust standard errors are clustered at the country level to correct for intracountry serial correlation and cross-country heteroscedasticity. Next, OLS point estimates from Equation (1) and the projected increase in the gross value of agricultural production are used to simulate the effects of CSA on net agricultural exports for the period 2018–2025. To simulate net exports, we assume that the values of Z during the forecast period will remain the same as those during 2003–2010. A similar assumption is made about the value of all other agricultural commodities (except maize and rice) that constitute Y, so that simulated Y (Y^s) is calculated as $Y_s = Y - Y_c^b + Y_c^s$, where b, s, and c index baseline, simulation, and crop (either maize or rice), respectively.

Results and Discussion

Table 5.2 presents OLS and RE estimates of Equation (1). Overall, coefficient estimates are jointly significant, although only at the 10 percent level for the RE estimator. The model fitness statistic from the OLS estimation shows that the conditioning variables explain about 40 percent of the model variance. The overall model fitness in the RE estimation (R-squared overall) is about 23 percent and the fact that "R-squared overall" and "R-squared within" are not quite close suggests the importance of country fixed effects. The fraction of the variance due to country fixed effect (rho) is 0.76. Depending on the estimator, a 1 percent increase in the gross value of agricultural production (in constant 2004–2006 international dollars, thousands) increases total agricultural net exports by about US$4,000 to US$4,500. Alternatively, climatic changes that cause a 1 percent reduction in the value of agricultural production will reduce net agricultural exports by about the same amount.

TABLE 5.2—NET AGRICULTURAL EXPORTS (IN MILLIONS OF US DOLLARS) AND GROSS VALUE OF AGRICULTURAL PRODUCTION, SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES,1993–2010

Dependent variable: agricultural net exports (millions of US $)	OLS		Random-effects	
	Coef.	Std. err.	Coef.	Std. err.
Log. gross production value (thousands of constant 2004–2006 international $)	0.410***	0.139	0.448**	0.180
Population (millions)	-0.000	0.000	-0.000**	0.000
Per capita gross domestic product (2011 international $)	0.000	0.000	-0.000	0.000
Import value index (2004–2006 = 100)	-0.002	0.002	-0.002*	0.001
Export value index (2004–2006 = 100)	0.001	0.001	0.001**	0.001
Total cereal area harvested (millions of hectares)	-0.105**	0.044	0.037	0.060
Linear time trend	-0.005	0.007	0.008	0.008
Constant	3.862	14.109	-21.846	15.385
Number of observations (N*T)	450		450	
Adjusted R-squared	0.407		n.a.	
R-squared within	n.a.		0.367	
R-squared between	n.a.		0.224	
R-squared overall	n.a.		0.228	
Chi-squared	n.a.		13.104	
F-statistic	3.959		n.a.	
Panel-level std. dev.	n.a.		0.520	
Rho	n.a.		0.767	
Log-likelihood	-379.13		n.a.	

Source: Authors' own calculation.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. n.a. = not applicable; OLS = ordinary least squares; Std. err. = cluster-robust standard error.

This increase amounts to about 0.27 percent, 0.39 percent, and 0.02 percent, in absolute value, of the yearly average total agricultural net exports for COMESA, ECOWAS, and SADC, respectively, for 1993–2010. Indeed, as noted above, climate change is projected to have an overall negative effect on yields of major food-security crops across SSA, with effects on yields expected to experience significant spatial variation (Berg et al. 2013; Sultan et al. 2013). Thus, the adoption of yield-enhancing CSA practices could be one promising approach to mitigate these effects.

Summaries of simulated production values and net exports under the smart farmer option for maize and rice, disaggregated by REC, are shown in Table 5.3. The average production value of maize under the smart farmer option is 0.33 million (in constant 2004–2006 international dollar) (Table 5.3, column 4), whereas that of rice is 0.21 million (in constant 2004–2006 international dollar) (Table 5.3, column 8). Using average annual production values during 2003–2010 as a benchmark scenario, these results represent a 73 percent (from 0.19 million to 0.33 million for maize) and 40 percent (from 0.15 million to 0.21 million for rice) increase in production value, on average, for the whole sample. For both maize and rice, the percentage increase in production value from the benchmark scenario is highest for SADC and lowest for ECOWAS.

Compared with the benchmark scenarios, the simulated net exports under the smart farmer option are significantly higher, especially for SADC, yet ECOWAS's net exports appear to decline (Figures 5.7 and 5.8). Further research is needed to identify possible factors behind these inter-REC differences in the elasticity of net agricultural exports to CSA-induced increases in the value of agricultural production.

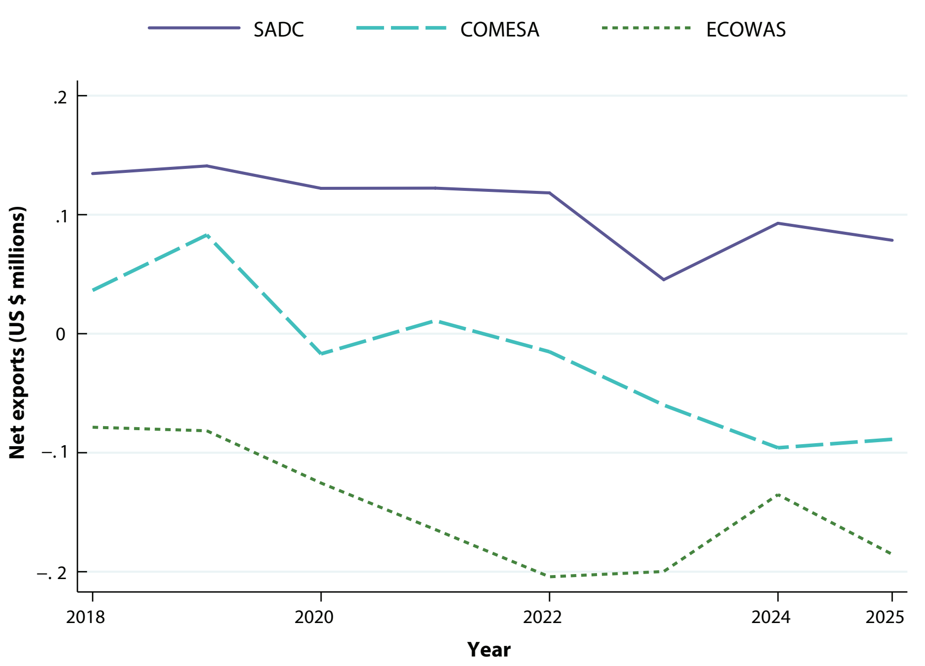
TABLE 5.3—CLIMATE-SMART AGRICULTURE PRODUCTION VALUE AND NET EXPORTS, SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES, 2018–2025 PROJECTIONS

	1	2	3	4	5	6	7	8
	Smart farmer option—maize				Smart farmer option—rice			
	2018–2025				2018–2025			
	ECOWAS	SADC	COMESA	All	ECOWAS	SADC	COMESA	All
Maize production value	0.22	0.47	0.28	0.33	n.a.	n.a.	n.a.	n.a.
	(0.40)	(0.61)	(0.32)	(0.49)				
Rice production value	n.a.	n.a.	n.a.	n.a.	0.22	0.49	0.22	0.21
					(0.31)	(0.69)	(0.51)	(0.39)
Gross production value	5.32	3.63	3.81	4.60	5.29	3.44	3.76	4.49
	(9.57)	(3.84)	(3.25)	(6.97)	(9.44)	(3.77)	(3.21)	(6.88)
Total agricultural net exports	-0.15	0.11	-0.02	-0.06	-0.15	0.18	0.04	-0.04
	(0.64)	(0.20)	(0.38)	(0.50)	(0.64)	(0.18)	(0.37)	(0.52)

Source: Authors' own calculation.

Note: Production values expressed in millions (in constant 2004–2006 international dollars). Agricultural net exports expressed in millions of US dollars. COMESA = Common Market for Eastern and Southern Africa; ECOWAS = Economic Community of West African States; n.a. = not applicable; SADC = Southern African Development Community.

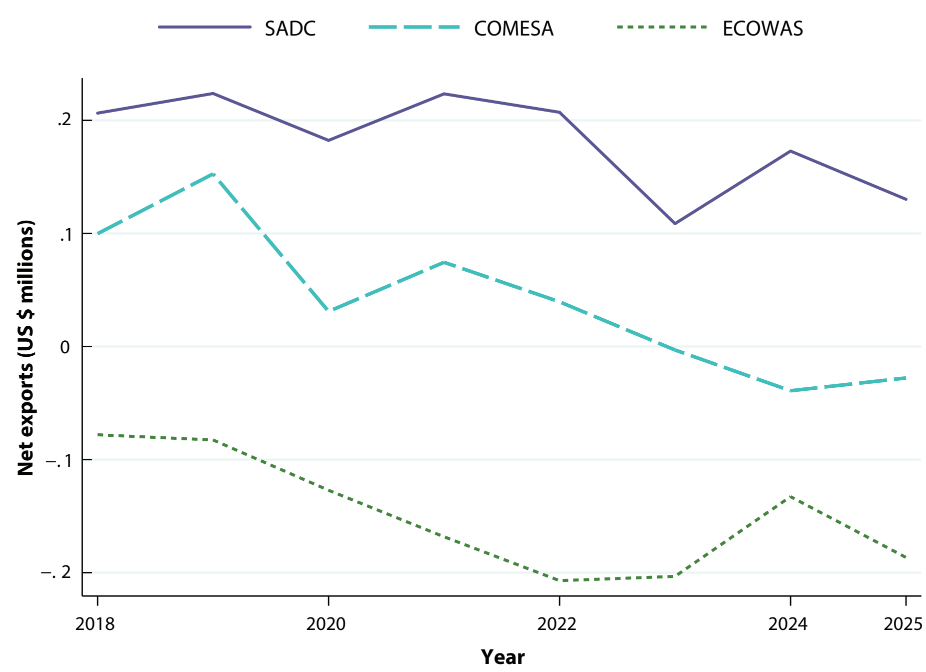
FIGURE 5.7—SIMULATED TOTAL AGRICULTURAL NET EXPORTS WITH SMART FARMER OPTION, MAIZE, SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES, 2018–2025



Source: Authors' own calculation.

Note: COMESA = Common Market for Eastern and Southern Africa; ECOWAS = Economic Community of West African States; SADC = Southern African Development Community.

FIGURE 5.8—SIMULATED TOTAL AGRICULTURAL NET EXPORTS WITH SMART FARMER OPTION, RICE, SELECTED AFRICAN REGIONAL ECONOMIC COMMUNITIES, 2018–2025



Source: Authors' own calculation.

Note: COMESA = Common Market for Eastern and Southern Africa; ECOWAS = Economic Community of West African States; SADC = Southern African Development Community.

Conclusion

Given its heavy reliance on rainfed agriculture and projected climatic and weather changes, SSA faces multidimensional challenges in ensuring food and nutrition security as well as preserving its ecosystems. In this regard, CSA can play an important role in addressing the interlinked challenges of food security and climate change. The dominance of agricultural commodities in the region's exports also implies that agroclimatic changes will affect countries' ability to fully benefit from international trade.

This chapter combines crop modeling and econometric analysis to simulate the effects of CSA on maize and rice yields and net agricultural exports (exports minus imports) in SSA, with a focus on three RECs: ECOWAS, COMESA, and SADC. The analysis assumes that farmers have complete information regarding potential yields associated with alternative CSA practices and can choose the alternative that produces the highest yields for their agroecology. Expected effects of CSA are simulated for the period 2018–2025, by the end of which countries have committed to tripling intra-Africa trade in agricultural commodities and services as part of the 2014 Malabo Declaration. We find that CSA significantly increases both yields and agricultural trade flow, suggesting a potential role for CSA in improving resilience and spreading out agricultural production risks. The evidence also suggests a heterogeneous response of trade flows to CSA by REC.

Finally, although these findings are informative, it is worth noting that even if famers have complete information about a portfolio of CSA practices and their agronomic potential, adoption may be suboptimal due to, for example, limited budget, missing or imperfect markets, and institutional barriers (see Barrett 2008; Dillon and Barrett 2016; Foster and Rosenzweig 2010; and Suri 2011 for some discussions). Given that CSA practices have more complex sets of tangible and intangible components, relative to a single and discrete class of technologies, adoption of all the components is necessary to benefit from all the synergistic effects of CSA on productivity and sustainability. Additional research is therefore needed to examine the possible general equilibrium effects of large-scale adoption of CSA practices and to identify location-specific factors that mediate the interaction between climate change, agriculture, and trade.