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Climate Change Adaptation in Agriculture

Ex Ante Analysis of Promising and Alternative Crop Technologies Using DSSAT and IMPACT

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This complex, multidisciplinary study was built on the work of many researchers over an extended period of time as a part of the first phase of the GFSF project. We especially want to acknowledge the contributions of the CGIAR centers that collaborated with IFPRI in this study, namely the International Center for Tropical Agriculture (CIAT), the International Maize and Wheat Improvement Center (CIMMYT), the International Potato Center (CIP), the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), and the International Rice Research Institute (IRRI). Several of the study's coauthors have changed affiliation since this work began: Bernardo Creamer was previously at CIAT, Arthur Gueneau was previously at IFPRI, Ulrich Kleinwechter was previously at CIP, Khondoker Mottaleb was previously at IRRI, and Gbegbelegbe Sika was previously at CIMMYT.

ABSTRACT

Achieving and maintaining global food security is challenged by changes in population, income, and climate, among other drivers. Assessing these challenges and possible solutions over the coming decades requires a rigorous multidisciplinary approach. To answer this challenge, the International Food Policy Research Institute (IFPRI) has developed a system of linked simulation models of global agriculture to do long-run scenario analysis of the effects of climate change and various adaptation strategies. This system includes the core International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT), which is linked to water models (global hydrology, water basin management, and water stress on crops) and crop simulation models.

The Global Futures and Strategic Foresight program, a CGIAR initiative led by IFPRI in collaboration with other CGIAR research centers, is working to improve these tools and conducting ex ante assessments of promising technologies, investments, and policies under alternative global futures. Baseline projections from IMPACT set the foundation with the latest outlook on long-term trends in food demand and agricultural production based on projected changes in population, income, technology, and climate. On top of the baseline, scenarios are developed for assessing the impacts of promising climate-adapted technologies for maize, wheat, rice, potatoes, sorghum, groundnut, and cassava on yields, area, production, trade, and prices in 2050 at a variety of scales. Yield gains from adoption of the selected technologies vary by technology and region, but are found to be generally comparable in scale to (and thus able to offset) the adverse effects of climate change under a high-emissions representative concentration pathway (RCP 8.5). Even more important in this long-term climate change scenario are effects of growth in population, income, and investments in overall technological change, highlighting the importance of linked assessment of biophysical and socioeconomic drivers to better understand climate impacts and responses. For all crops in the selected countries, climate change impacts are negative with the baseline technology. All new technologies have beneficial effects on yields under climate change, with combined traits (drought and heat tolerance) showing the greatest benefit.

Keywords: interdisciplinary research, agricultural productivity, yields, climate change, adaptation, climate-smart technology

1. INTRODUCTION

The goal of achieving and maintaining global food security is challenged by a number of stresses directly stemming from population and income growth, climate change, and other factors. The agriculture sector is confronted with increasing demand, competition for natural resources, and climate impacts, both abiotic (for example, changes in temperature and precipitation, and extreme weather events) and biotic (for example, damages from pests and diseases). Complicating the challenge, these impacts are characterized by large geographic and temporal variability and uncertainty.

A recent study, using crop simulation models to examine the effects of abiotic stresses, estimated that the long-term changes in temperature and rainfall due to climate change could reduce global maize, rice, and wheat yields in 2050 by as much as 25 percent compared with 2010 yields in the absence of technological change and market effects (Rosegrant et al. 2014).[1] Clearly, new technologies will be developed and economic agents will respond to changes in prices over time due to changes in population, income, and climate. Nevertheless, significant increases in prices may occur. Higher prices would particularly hurt marginalized populations, as well as those who spend a large share of their income on food. The authors found that a range of technology improvements could help reduce some of these adverse impacts. Other recent work has examined the impact of climate change on crop yields, production, and prices in 2050 relative to a baseline without climate change. Drawing on multiple climate, crop, and economic models, Nelson and others (2013) estimated that yields of four major crops (maize, rice, wheat, and soybeans) in 2050 would be around 11 percent lower due to the effects of climate change once economic responses were considered. Together, these studies indicate the importance of improved modeling to disentangle the complex interactions between multiple drivers of change. Improved understanding of emerging technologies must be used to explore alternative strategies to achieve and sustain increases in agricultural productivity and food security.

Basic and applied research in agronomy, soil science, ecology, and entomology has generated a wealth of technologies and practices to increase the resilience of agroecosystems to both abiotic and biotic stresses, and ultimately to protect and increase productivity. However, in order to inform prioritization of research and investments in agriculture, more work needs to be done to explore the potential of the various options, for specific crops and under specific local soil and climatic conditions. Meeting the challenge of feeding a growing population requires analysis of how to better allocate scarce resources, both financial and natural. To this goal, empirical analysis and modeling efforts are useful to assess the potential of different technologies and practices to increase agricultural productivity and alleviate poverty and hunger, while also using limited resources more efficiently. This analysis needs to be performed at various levels of aggregation, from global to national to subnational scales.

The goal of the CGIAR Global Futures and Strategic Foresight (GFSF) program is to support increases in agricultural productivity and environmental sustainability in developing countries by evaluating potential long-run impacts of promising technologies, investments, and policy reforms.[2] The present study focuses on the evaluation of selected promising and alternative technologies for crops, specifically drought- and heat-tolerant varieties not currently available at large scale but needed to adapt to climatic change, and also analysis of the effects of crop protection measures, with a focus on the mealybug pest on cassava. The assessment relies on the Decision Support System for Agrotechnology Transfer (DSSAT) family of crop models;[3] hydrology and water supply-demand models; and a multimarket economic model, the International Model for Policy Analysis of Agricultural Commodities

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[1] Average percent changes are calculated across two climate change scenarios (MIROC A1B and CSIRO A1B) and across rainfed and irrigated cropping systems.

[2] GFSF is a CGIAR initiative led by IFPRI in collaboration with 12 other CGIAR centers, with funding from the Bill and Melinda Gates Foundation; the CGIAR Research Program on Policies, Institutions, and Markets; and the CGIAR Research Program on Climate Change, Agriculture and Food Security. For more information, visit globalfutures.cgiar.org.

[3] DSSAT is a software application that includes models to simulate the growing stages and productivity output for more than 28 crops (as of version 4.5) (Hoogenboom et al 2012, and Jones et al 2003)

and Trade (IMPACT). These models are linked in order to estimate future production, consumption, and trade of key agricultural commodities, following different scenarios of climate change, water availability, and population and income growth (among other factors). The result is a powerful simulation tool to assess the potential impact of selected promising technologies on some of the world's most important agricultural commodities.

The current analysis improves on previous research by incorporating detailed location-specific data; climate, soil type, crop variety, and other critical variables; detailed models of crop, hydrology, and water supply and demand; improved measurement of effects on human welfare; and the impact of potential agricultural investments on economic growth, incomes, and poverty alleviation.

2. APPROACH

Ex ante analysis of technologies and markets several decades into the future requires a flexible scenario–based approach, which involves assessment of the impacts of long-run drivers (such as changes in population, incomes, and climate) whose nature is still uncertain and of technologies (such as drought- and heat-tolerant crop varieties) that are still being developed. To do this, we rely on a suite of linked crop, water, and economic simulation models to analyze the performance of new crop varieties with desirable traits that are currently being developed but not yet widely available. The models provide a framework for analyzing alternative scenarios about how population, income, climate, and technologies may change over time. The projections in the various scenarios are not "predictions" or "forecasts" but instead are simulated scenarios conditional on different sets of assumptions regarding potential drivers of change.

New Promising and Alternative Crop Varieties

In view of the climate change challenges discussed in the introduction, GFSF team members in four participating CGIAR centers—the International Maize and Wheat Improvement Center (CIMMYT), the International Potato Center (CIP), the International Crops Research Institute for the Semi-arid Tropics (ICRISAT), and the International Rice Research Institute (IRRI)—identified drought and heat tolerance traits as priorities to be simulated for maize, wheat, rice, potatoes, sorghum, and groundnut. Table 2.1 summarizes the traits and regions that the GFSF participating centers prioritized. Each center also identified target areas where varieties with these traits are expected to be adopted. CIMMYT targeted Africa south of the Sahara for drought-tolerant (DT) maize and South Asia for the heat-tolerant (HT) technology. For wheat, the DT variety was targeted for adoption in western Asia, the HT variety in South Asia, and the drought- and heat-tolerant (DTHT) variety in Argentina and South Africa. Because South and Southeast Asia are major rice-producing regions, a DT variety was targeted in both regions. CIP targeted DT, HT, and DTHT potato varieties in South Asia, central Asia, and parts of Southeast Asia. ICRISAT focused on a DT sorghum variety to be adopted in the semiarid tropics of Asia and Africa. DT, HT, and DTHT groundnut varieties were targeted for adoption across 11 countries spanning Asia and Africa.

Cassava is a resilient crop, well adapted to potential future abiotic stresses (temperature and precipitation). Therefore, the International Center for Tropical Agriculture (CIAT) focused on modeling the effects of an expansion in pest damages and then in pest management practices. For this scenario, the introduction of a mealybug pest was simulated in the Southeast Asia region and three different management scenarios were tested. These promising crops or management practices will be described further in Section 3.

Table 2.1 Promising and alternative crops and traits considered in this report

Crop	Trait	Center	Countries	Region name
Maize	Drought tolerance	CIMMYT	Angola, Benin, Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Uganda, United Republic of Tanzania, Zambia, Zimbabwe	M1
	Heat tolerance		Bangladesh, India, Nepal, Pakistan	M2
Wheat	Drought tolerance	CIMMYT	Iran, Turkey	W1
	Heat tolerance		India, Pakistan	W2
	Drought and heat tolerance		Argentina, South Africa	W3
Rice	Drought tolerance	IRRI	Bangladesh, Cambodia, India, Lao People's Democratic Republic, Nepal, Sri Lanka, Thailand	R1
Potatoes	Drought tolerance Heat tolerance Drought and heat tolerance	CIP	Bangladesh, China, India, Kyrgyzstan, Nepal, Pakistan, Tajikistan, Uzbekistan, Vietnam	P1
Sorghum	Drought tolerance	ICRISAT	Burkina Faso, Eritrea, Ethiopia, India, Mali, Nigeria, Sudan, United Republic of Tanzania	S1
Groundnut	Drought tolerance Heat tolerance Drought and heat tolerance, high yield	ICRISAT	Burkina Faso, Ghana, India, Malawi, Mali, Myanmar, Niger, Nigeria, Uganda, United Republic of Tanzania, Vietnam	G1
Cassava	Scenarios include impact of mealybug and control methods	CIAT	China, India, Indonesia, Lao People's Democratic Republic, Myanmar, Thailand	C1

Source: Compiled by authors.

Notes: CIMMYT = International Maize and Wheat Improvement Center; CIP = International Potato Center; ICRISAT = International Crops Research Institute for the Semi-arid Tropics; IRRI = International Rice Research Institute.

The IMPACT System of Models

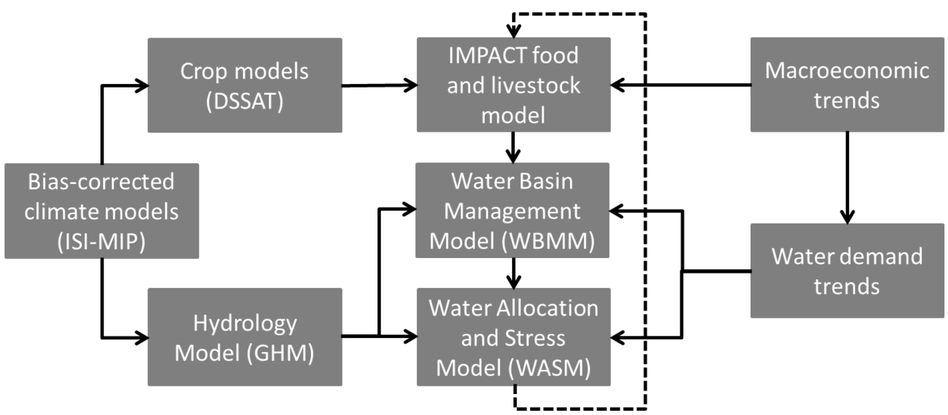
The International Food Policy Research Institute (IFPRI) has developed a suite of linked economic, water, and crop simulation models to do long-run scenario analysis. The economic multimarket model of global agriculture, IMPACT, integrates information from climate models (general circulation models, or GCMs), crop simulation models (DSSAT), and water models in a consistent equilibrium framework that supports long-run scenario analysis. The IMPACT model simulates the operation of national and international markets, solving for production, demand, and prices that equate supply and demand across the globe. Some of the model communication is one-way, with no feedback links (for example, GCM scenarios to hydrology models to crop models), while other links require capturing feedback loops (for example, water demand from the economic model and water supply from the water models must be reconciled to estimate water stress impacts on crop yields). Figure 2.1 describes the links between the different models that constitute the IMPACT network of models.

This flexible framework of models supports integrated analysis of the implications of physical, biophysical, and socioeconomic trends and phenomena, allowing for varied and in-depth analysis on a variety of key issues of interest to policymakers. As a flexible policy analysis tool, IMPACT has been used to research linkages between agriculture production and food security at the national[4] and regional[5] levels. IMPACT has also been used in commodity-level[6] analyses, and has contributed to thematic and interdisciplinary scenario-based projects.[7] Additional details on DSSAT, IMPACT, and the linkages between the two models are provided in Appendix A.

Promising Crops and Crop Simulation Models

To analyze the impacts of introducing new climate-resilient crop varieties, we incorporate both the new technologies and climate change effects in the IMPACT model. The impacts of new crop varieties are first simulated using DSSAT. These process-based models provide a purely biophysical assessment of yield changes, which can then be used as inputs to the economic model. The crop models use weather data to simulate plant growth, providing the entry point for climate change scenarios to be added to the models. The characteristics of particular varieties or cultivars are encoded in genetic parameters within the crop models, providing a way to create new alternative cultivars that reflect potentially desirable traits. Management specifications (for example, planting dates, irrigation plans, tillage regimes, and so on) open the possibility of representing further technology options. Once these are defined, the crop model can be run on a gridded basis across the relevant geographic regions, treating each pixel as an individual field.

Figure 2.1 The IMPACT system of models



Source: Authors.

Notes: DSSAT = Decision Support System for Agrotechnology Transfer; GHM = global hydrological model; IMPACT = International Model for Policy Analysis of Agricultural Commodities and Trade; ISI-MIP = Inter-Sectoral Impact Model Intercomparison Project.

[4] For example, (1) Africa Agriculture and Climate Change Research Monographs: Waithaka and others (2013); Hachigonta and others (2013); Jalloh and others (2013); and (2) a variety of country reports such as Takle and others (2013) and Ye and others (2014).

[5] For example, (1) food security issues in the Arab region (Sulser et al. 2011); and (2) the discussion paper *Looking Ahead: Long-Term Prospects for Africa's Food and Nutrition Security* (Rosegrant et al. 2005).

[6] For example, (1) "Alternative Futures for World Cereal and Meat Consumption" (Rosegrant, Leach, and Gerpacio 1999); (2) "Global Projections for Root and Tuber Crops to the Year 2020" (Scott, Rosegrant, and Ringler 2000); (3) *Livestock to 2020: The Next Food Revolution* (Delgado et al. 1999).

[7] For example, (1) the IFPRI-IWMI book *World Water and Food to 2025: Dealing with Scarcity* (Rosegrant, Cai, and Cline 2002); (2) food security and climate change (Nelson et al. 2010); (3) global assessments such as the International Assessment of Agricultural Science and Technology for Development (IAASTD 2009), *World Development Report 2008: Agriculture for Development* (World Bank 2007), the CGIAR's Strategic Results Framework (SRF Process Team 2009), and the Agriculture Model Intercomparison and Improvement Project (Nelson et al. 2013).

A final yield map is constructed by determining where the alternative cultivar could be beneficial. The particular parameters defining the cultivars are obtained from known values in the literature, calibrated based on raw experimental data, or deduced by modifying previously calibrated varieties to reflect known characteristics in the absence of quality trial data. Each cultivar may have specific details concerning planting densities, spacing, time to harvest, and so on. Additionally, rules must be developed to allocate the desired total fertilizer application throughout the growing season (for example, all at the beginning or in split applications). Irrigation also needs to be specified. For use in IMPACT, the irrigation cases are meant to reflect a minimum water stress situation. Any constraints on water availability and the associated yield penalties are included in the water allocation and stress model that is part of the IMPACT suite of models.

Once the pixel-level yields are generated, they are aggregated to the regional level for use in IMPACT. Using maps of existing production areas by crop and water source, we compute the area-weighted average yield typical of each subnational unit. From these yields, yield growth rates are calculated and applied into the IMPACT model as biophysical "shifters," which include the effects of climate and specific promising technologies. These biophysical shifters are combined in IMPACT with other productivity shifters, called intrinsic productivity growth rates (IPRs), which summarize general trends on improvements in crop yields due to new technologies and management practices (discussed further below).

For this report, the crops modeled on a global grid are rice, wheat, maize, groundnut, soybeans, potatoes, and sorghum. Three alternative varieties of the crops have been modeled. A drought tolerance mechanism involving deeper and more efficient roots has been applied to all of the crops except soybeans (not part of the original set of mandated crops in CGIAR). Heat tolerance has been modeled for wheat, maize, and potatoes. Drought tolerance was combined with heat tolerance for wheat, maize, and potatoes. Finally, the combination of drought tolerance, heat tolerance, and a high-yielding variation has been modeled for groundnut and sorghum.

The IMPACT Multimarket Model

The IMPACT model was developed at IFPRI at the beginning of the 1990s to address a lack of long-term vision and consensus among policymakers and researchers about the actions that are necessary to feed the world in the future, reduce poverty, and protect the natural resource base. Over time, this economic model has been expanded and improved, and IMPACT is now a network of linked economic, water, and crop models. At IMPACT's core is the original partial equilibrium multimarket model of global production, demand, and trade, which is linked to a suite of water models. The multimarket model focuses on national and global markets, including those of 159 countries.[8] Agricultural production is specified by models of land supply, allocation of land (irrigated and rainfed) to crops, and determination of yields (which is described in more detail below). Production is modeled at a subnational level, including 320 regions called "food production units" or FPUs. The FPUs are defined to link to the water models and correspond to river basins within national boundaries—154 basins and 159 countries.

The multimarket model simulates 62 agricultural commodity markets, which represent the bulk of food and cash crops. The multimarket model is integrated with the IMPACT water models, which simulate the availability of water for irrigation and the effects of changes in water availability on agricultural production. Similar to the global multimarket model, the water models operate at disaggregated scales. However, the regions of interest for the water models are hydrological basins (Nile, Amazon, Mississippi, and so on), of which there are 154. To allow communication between the multimarket and water models, the IMPACT suite of models operates on a subnational unit, focusing on the 320 FPUs created by the intersection of the 159 geopolitical and 154 hydrological regions.

[8] Some "countries," for example Other Indian Ocean, are aggregates designed to achieve complete global coverage.

The IMPACT core is additionally connected to a series of modules integrating information from climate models (GCMs), crop simulation models, population and demographic models, and economic growth models. These models are not dynamically linked in the way the water and multimarket models are, but instead their results operate only in one direction, serving as IMPACT scenario inputs. Figure 2.1 describes the links between the different models that constitute the IMPACT system of models. All models except the climate models are run by IFPRI.

Climate and Economic Scenarios to 2050

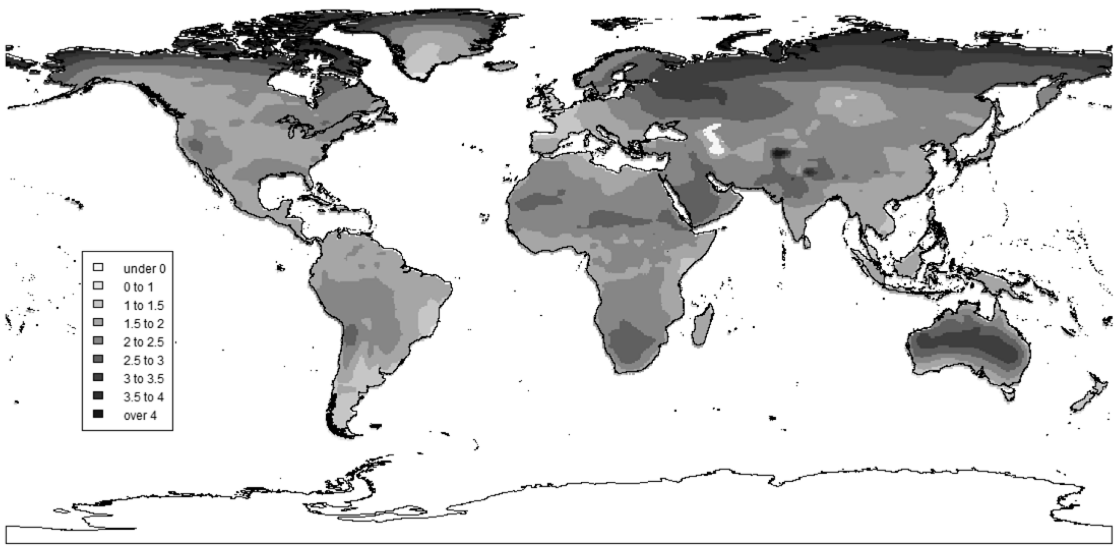
The climate and economic scenarios used in IMPACT draw on work developed for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC 2013). The climate model results used are the trend-preserving bias-corrected projections developed for the First Inter-sectoral Impact Model Intercomparison Project (ISI-MIP) (Hempel et al. 2013) based on the climate models experiment run for the Fifth Coupled Model Intercomparison Project (CMIP5) (Taylor, Stouffer, and Meehl 2012). The current GCMs used for IMPACT are HadGEM2-ES (Jones et al. 2011), IPSL-CM5A-LR (Dufresne et al. 2013), MIROC-ESM-CHEM (Watanabe et al. 2011), and GFDL-ESM2M (Dunne et al. 2012).

Economic scenarios used in IMPACT are based on the Shared Socioeconomic Pathways (SSPs) (O'Neill et al. 2014) developed for AR5. We use the projections of the International Institute for Applied Systems Analysis (IIASA) for population and those of the Organization for Economic Co-operation and Development (OECD) for gross domestic production (GDP) (Chateau et al. 2012).

Overall we compare a no-climate-change scenario (which is noted as the baseline below) and a climate change scenario that is expected to cause significant changes to the agricultural system. The SSP2 is a middle-of-the-road projection and is used in all of the scenarios included in this report. For climate change projections, we use a scenario that results from the GFDL-ESM2M climate model (noted as climate change scenario below) under an RCP of 8.5 (Meinshausen et al. 2011; Riahi et al 2011). This climate scenario was chosen for this analysis because it appeared to be on average across the globe the driest of the four GCMs considered.

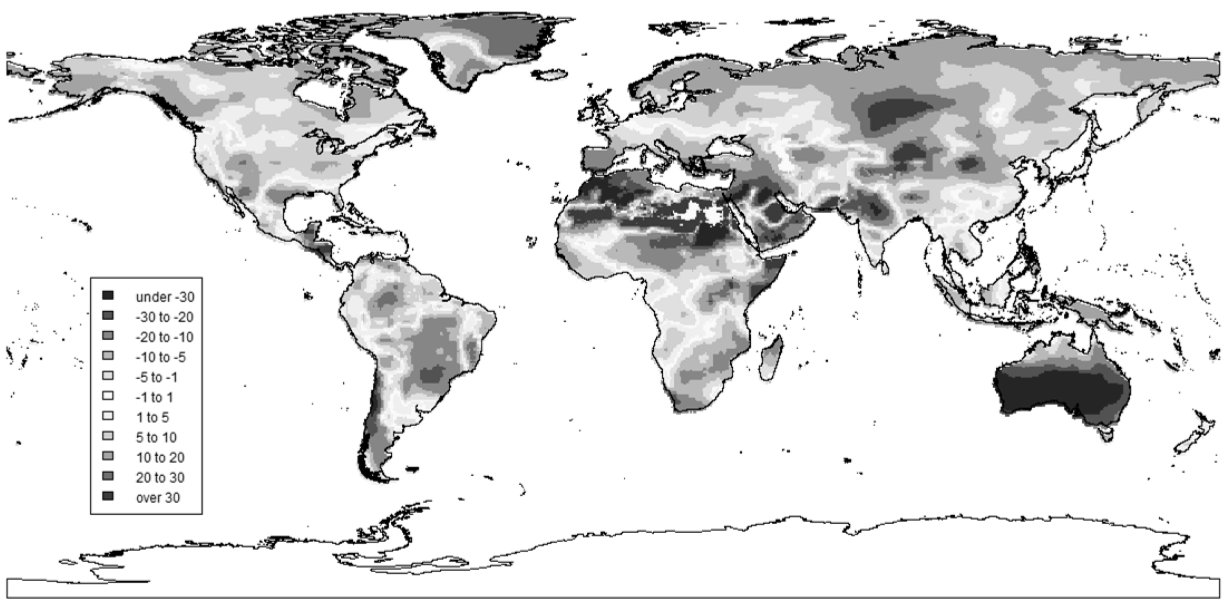
Figures 2.2, 2.3, and 2.4 describe changes in temperature, precipitation, and evapotranspiration in 2050 under the climate change scenario compared with an unchanged 2005 climate. As shown in Figure 2.2, the temperature increase is between 1.5 and 2.5 degrees for most major agricultural areas of the world, with some areas showing even stronger increases, especially in the northern latitudes and Australia. Precipitation changes vary significantly by region, as seen in Figure 2.3. Regions with large declines in annual precipitation include the Mediterranean region, South America, northern India, and Australia, whereas North America and much of eastern and central Asia would expect greater precipitation. Figure 2.4 shows the change in potential evapotranspiration (PET) for the climate change scenario as calculated by the IMPACT Global Hydrology Model (IGHM). As expected, the map resembles the temperature change map (Figure 2.2), with PET increasing by 3 to 5 percent annually in most areas.

Figure 2.2 Change in temperature in 2050 in the climate change scenario compared with the baseline in 2050 (in degrees Celsius)



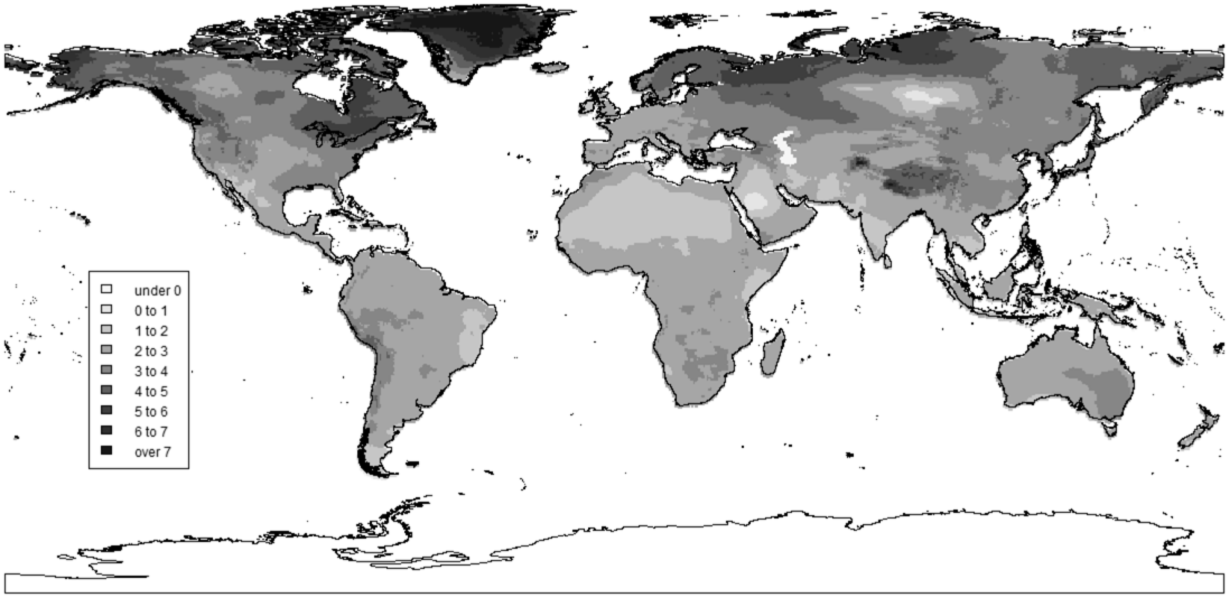
Source: Authors' calculations.

Figure 2.3 Change in precipitation in 2050 in climate change scenario compared with the baseline in 2050 (percent)



Source: Authors' calculations.

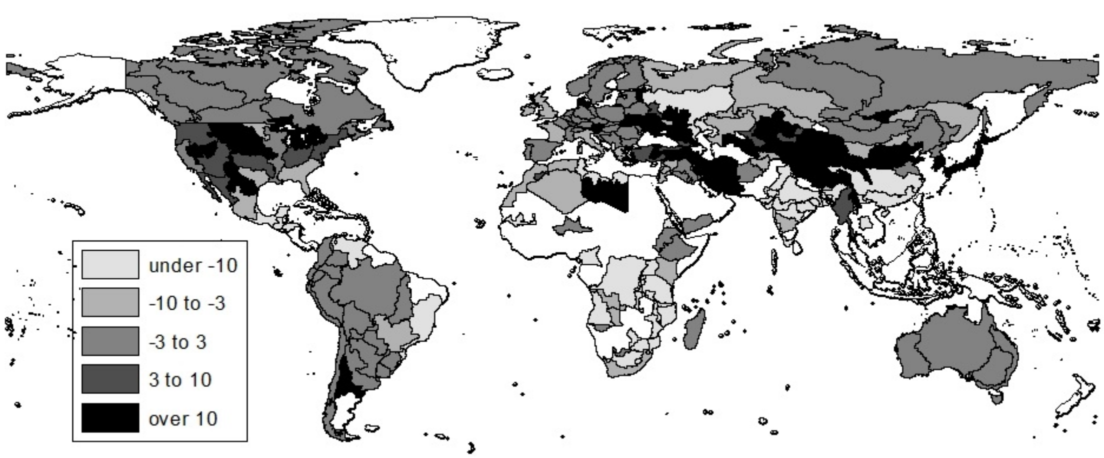
Figure 2.4 Change in potential evapotranspiration in 2050 in the climate change scenario compared with the baseline in 2050 (percent)



Source: Authors' calculations.

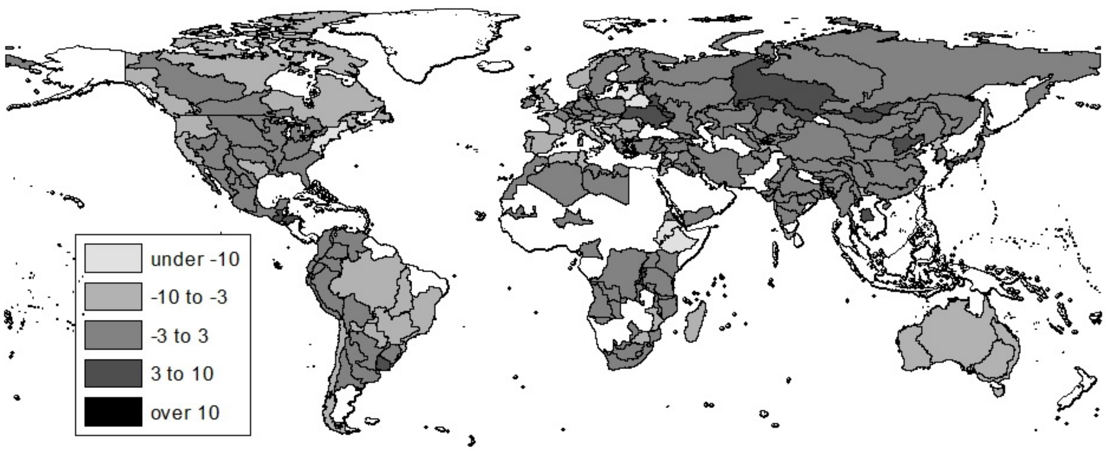
Figures 2.5, 2.6, and 2.7 detail how climate shocks to crop yields are estimated, using rainfed wheat cultivation as an example. It should be noted that these figures reflect only biophysical effects of climate and do not yet include market effects from IMPACT. All maps show the relative difference in crop yields computed for the climate change scenario in 2050 as compared with the crop yields in an unchanged 2005 climate. For example, a -20 percent change in water stress impact means that the wheat yield in 2050 under the climate change scenario will be reduced by 20 percent compared with the yield in 2050 under the baseline scenario (that is, the non–climate change scenario).

Figure 2.5 Temperature stress impact on rainfed wheat yields in climate change scenario before market effects are considered (in percent change compared with 2050 base value)



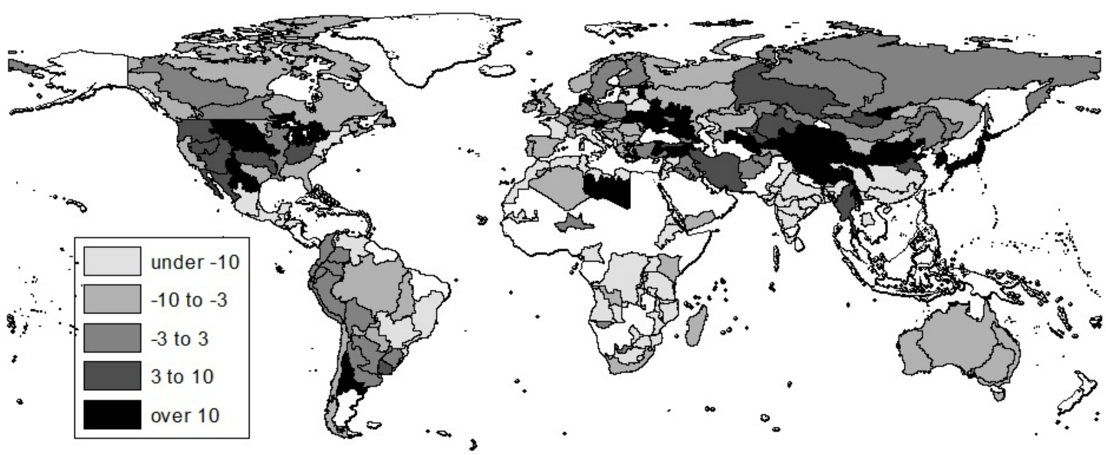
Source: Authors' calculations.

Figure 2.6 Water stress impact on rainfed wheat yields in climate change scenario before market effects are considered (in percent change compared with 2050 base value)



Source: Authors' calculations.

Figure 2.7 Total climate stress impact on rainfed wheat yields in climate change scenario before market effects are considered (in percent change compared with 2050 base value)



Source: Authors' calculations.

Climate shocks consist of two different components, temperature stress and water stress. We run DSSAT under two management assumptions (irrigated and rainfed), which allows us to isolate the temperature stress and water stress globally. Figure 2.5 illustrates the yield stress to rainfed wheat globally. It should be noted that climate change may not always be negative. Temperature increases in higher latitudes may lengthen the growing season and lead to higher yields.

The IMPACT Crop Water Allocation and Stress Model (ICWASM) calculates the crop-specific water stress for both irrigated and rainfed crops, which determines the water stress–induced shock (Figure 2.6). For rainfed wheat under climate change, the patterns are heterogeneous but follow loosely the patterns of precipitation change. These two shocks are multiplied to create an overall climate shock applied to the base yield of the crop (Figure 2.7). Under the climate change scenario, rainfed wheat sees its yield decrease in Latin America, the Mediterranean basin, southern Africa, India, central China, and Australia (among others) but increase in North America, northern Europe, and Siberia. These patterns are specific to the GFDL model and denote the particular representation of climate change at the time of the year when rainfed wheat is grown. Other models and other crops would show different patterns.

3. NEW PROMISING AND ALTERNATIVE TECHNOLOGIES

We used DSSAT to simulate improved varieties of maize, rice, wheat, sorghum, and groundnut, as well as changes in yields following the adoption of these varieties in specific geographical areas of the world before market effects are considered (refer to Table 2.1). As mentioned in the methodology section, the DSSAT simulations were performed under the GDFL climate change scenario and, through the changes in yields, they capture the interaction of the improved varieties with biophysical conditions, specifically soil type and climate conditions. Results of these scenarios are described in Section 4.

Maize

Maize is the major food, feed, and industrial crop globally, and the leading staple food crop in many developing countries. The area coverage, production, and yield of maize have increased over the last 50 years, and much of the increase was recorded in the developing world. Despite these improvements, demand for maize has been outpacing production, partly due to growing demand (for food, feed, and energy and other industry). The demand for maize is expected to double by 2050, which signals the need to drastically increase productivity. Yet maize production and productivity is constrained by several biotic and abiotic factors whose magnitudes are expected to increase under climate change. The major abiotic constraints are recurrent drought, low soil fertility, high soil acidity, soil erosion, heat stress, and waterlogging. Climate change is exacerbating the existing problems and posing new challenges (Pingali and Pandey 2000; Shiferaw et al. 2011; Cairns et al. 2012). Insect pests, diseases, and weeds are the most common biotic challenges.

Most farmers in Africa rely on rainfall to grow maize; hence, production is very vulnerable to climate shocks, and dry conditions can have disastrous consequences. In 2011, more than 12.5 million people were affected by drought that ravaged the Horn of Africa. Through the Drought-Tolerant Maize for Africa (DTMA) initiative, CIMMYT, IITA (the International Institute for Tropical Agriculture), and their partners have developed DT varieties adapted to the various ecologies of Africa. The DT maize varieties (both hybrids and open-pollinated varieties) provide insurance against climate risks and are currently being deployed across 13 African countries (Angola, Benin, Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Nigeria, Tanzania, Uganda, Zambia, and Zimbabwe) (Shiferaw et al. 2014). It has been estimated that DT maize varieties have 30 to 40 percent better yield under severe stress than commercial varieties. Additionally, under optimal rainfall conditions, these varieties match or exceed the yields of popular commercial varieties. In 2010 DT maize occupied close to 1.5 million hectares in Africa (Prasanna et al. 2012).

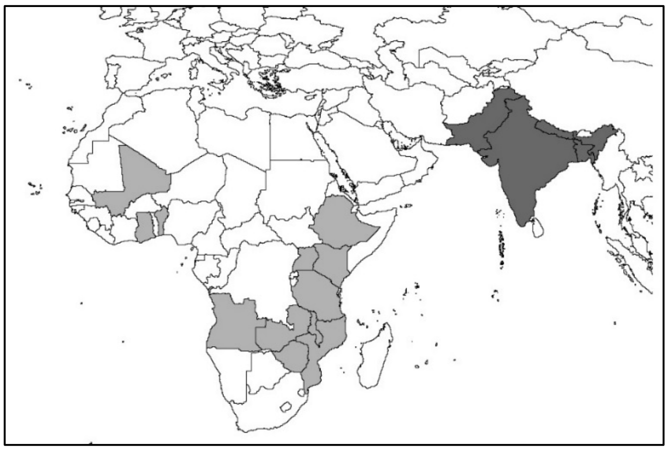
In recent years, evidence has emerged demonstrating the negative effect of high temperatures on the performance of maize. Research in Africa south of the Sahara has shown that a decrease in rainfall by 20 percent is less detrimental to maize yields than a 2-degree Celsius increase in temperatures (Lobell and Burke 2010). Elevated temperatures impact maize yields by shortening the life cycle, reducing light interception, and increasing sterility (Stone 2001; Cairns et al. 2012). Heat stress under future climate is also expected to affect large maize-growing areas in South Asia. In 2013, CIMMYT and its partners launched the Heat-Tolerant Maize for Asia (HTMA) initiative. The goal is to use conventional breeding to develop maize germplasm with tolerance to heat stress, specifically for the South Asia region.

Using the CERES (Crop Environment Resource Synthesis) maize model embedded in DSSAT, CIMMYT assessed the potential yield benefits of incorporating DT and HT traits. These traits were modeled by identifying characteristics that are suspected to provide improved performance. For example, root mass is thought to be an important indicator for drought tolerance; consequently, the DT variety was implemented in DSSAT by simulating an increase in the share of root mass within a unit volume of soil and making the plant better able to extract water from the soil.

The countries targeted by the DTMA initiative are the same used in this study to assess the –ex ante impact of DT maize across African countries (Figure 3.1). We assume all the targeted countries begin adoption of DT maize varieties in 2013, with slower adoption in the early years than in the later years, reaching 30 percent of maize area adopting DT varieties by 2050.

The countries targeted by the HTMA initiative and used in this study to assess the impact from adoption of HT maize varieties are Bangladesh, Nepal, India, and Pakistan. Adoption in all four countries is expected to reach a maximum of 30 percent of maize area in 2032, with adoption starting in 2017. Similar to the DT technology adoption, adoption of HT varieties is expected to be slower in earlier years.

Figure 3.1 Countries whose adoption of alternative maize varieties is simulated in this analysis



Source: Authors.

Note: Light gray = drought tolerance; dark gray = heat tolerance.

Wheat

Wheat is one of the most important staple foods across the globe; it provides 20 percent of total calories and proteins consumed by humans globally (Braun, Atlin, and Payne 2010; Curtis, Rajaram, and Gómez Macpherson 2002, 602; Shiferaw et al. 2011). Fifteen countries accounted for 80 percent of global wheat production between 2007 and 2011; and over the same period 28 countries consumed 80 percent of wheat.

Wheat is an important food and cash crop for populations in the developing world. Today, 72 percent of wheat produced is consumed in the developing world. Developing countries, however, produce only 48 percent of global wheat production, meaning that many developing countries must rely on global trade to satisfy their total wheat demand. The major wheat-producing regions in the developing world are central and western Asia and North Africa, East and Southeast Asia, and South Asia.

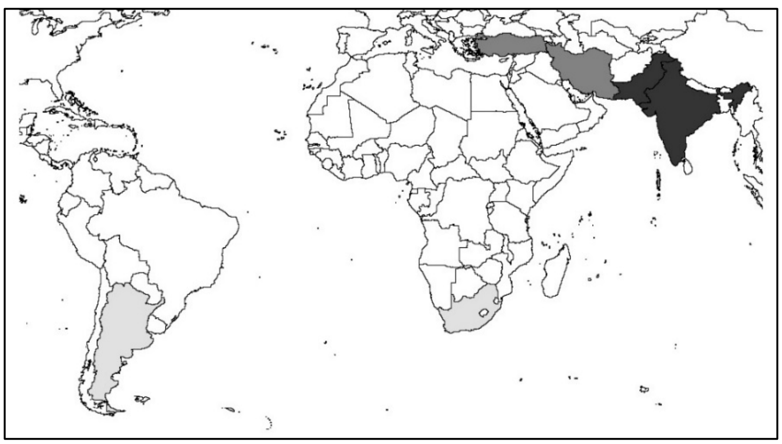
Wheat production across the developing world faces various challenges, including stagnating yields, distorted national agricultural policies that hinder the adoption of improved wheat technologies by farmers, increased water scarcity, and increasing fertilizer prices. In addition, climate change is projected to bring about new abiotic and biotic stresses. Rising temperatures negatively affect wheat production and, in low-latitude countries, wheat production losses from global climate change are expected to be higher than for any other staple crop (CIMMYT and ICARDA 2011, 189). Climate change might also lead to new or more virulent races of wheat pests and diseases. The incidence of Ug99 (a race of wheat stem rust) demonstrates the importance of such threats to global wheat production (Singh et al. 2011).

Various studies have shown that international wheat breeding conducted by CIMMYT and its partners has contributed substantially to increasing wheat production in the developing world in the face of various stresses (Heisey, Lantican, and Dubin 2002, 73; Lantican, Dubin, and Morris 2005, 54). Some of the knowledge and tools needed to address the new challenges brought by climate change include the following:

1. Characterization of wheat-growing regions affected by the stresses brought by climate change
2. Identification and propagation of the trait or combination of traits most needed to address the new or augmented stresses (both abiotic and biotic)
3. Making available genetic resources to allow selection of the proper traits from a wider pool of mechanisms for adaptation to stress (these resources can be used for strategic crossing/breeding)
4. Development of tools to facilitate yield dissection in terms of both genetic and physiological elements

Some of the promising wheat technologies being developed through international wheat breeding include wheat tolerant to drought stress, heat stress, and combined heat and drought stress. The CSM-CERES wheat model was used to assess the potential yield benefits of DT, HT, and DTHT wheat varieties. In this study, targeted regions for these three technologies were chosen among the developing countries that stand to be most vulnerable to the abiotic stresses due to climate change (see Figures 2.5, 2.6, and 2.7). More specifically, DT wheat is targeted for Turkey and Iran, HT wheat is targeted for India and Pakistan, and DTHT wheat is targeted for Argentina and South Africa (Figure 3.2).

Figure 3.2 Countries whose adoption of alternative wheat varieties is simulated in this analysis



Source: Authors.

Note: Medium gray = drought tolerance; dark gray = heat tolerance; light gray = drought and heat tolerance.

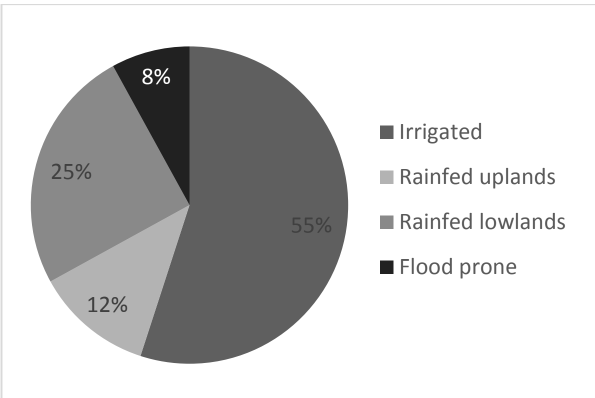
Adoption of the promising wheat technologies in the targeted countries is expected to start in 2015 for DT wheat, 2020 for HT wheat, and 2022 for DTHT wheat. For all technologies, adoption is expected to be quicker in the initial years. The maximum adoption rate of the promising technologies is 35 percent of wheat area for DT wheat and 30 percent for each of the other technologies.

Rice

Rice is the staple food for more than half of the world's population. Approximately 3.3 billion people depend on rice for more than 20 percent for their daily caloric intake. Rice is a critical economic crop with nearly 1 billion people depending on rice for their livelihood. Global rice production is one of the great success stories of the Green Revolution, having more than doubled since 1965 (from 256 million to 680 million tons by 2008, according to the Food and Agriculture Organization of the United Nations, (2012). Nevertheless, rice productivity is facing a variety of biotic and abiotic stresses that threaten these gains. Climate change further threatens rice productivity mostly from water shortages, low water quality, thermal stress, rising sea levels, and extreme weather events. To meet the demand of a growing global population, 25 percent more rice may be needed by 2050 compared with today. Therefore, increasing rice yields while using less water, chemicals, land, and labor is a critical challenge.

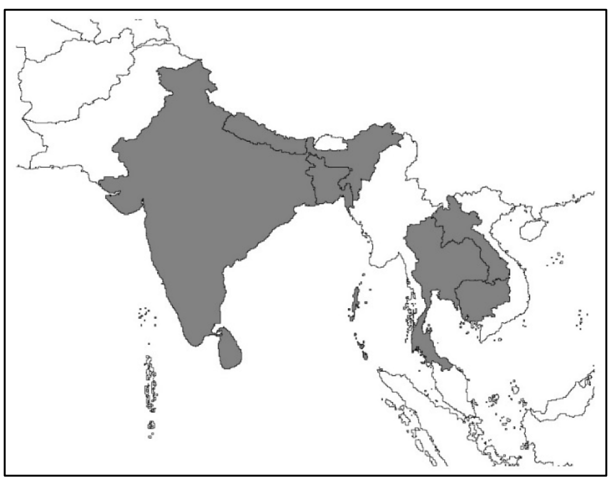
Rice is produced under a variety of agromanagement systems (see Figure 3.3), and while irrigated rice is the more productive, rainfed production systems are very important, and are the most at risk to climate change. It is these rainfed production systems that were targeted with the modeling of DT rice varieties. More than 90 percent of rice is produced and consumed in Asia, and rainfed rice is important economically and for food security in South and Southeast Asia, which is where IRRI focused on modeling the DT rice varieties (Figure 3.4).

Figure 3.3 Global rice production by production system (percentage of total cultivated area)



Source: Singh (2009).

Figure 3.4 Countries whose adoption of an alternative rice variety is simulated in this analysis



Source: Authors.
Note: Gray = drought tolerance adoption.

Potatoes

Since their diffusion from the Andean region of South America in the 16th century, potatoes have become the third most important food crop in the world in terms of human consumption, following only rice and wheat. In 2009, world production reached 330 million tons, of which 18 million tons were produced in Africa, 16 million tons in South and Central America, 59 million tons in South and West Asia, 9 million tons in central Asia and the Caucasus, and 89 million tons in East Asia and the Pacific (FAO 2011). While total production area has declined slightly for the world as a whole, the importance of potatoes in developing countries has steadily increased, reflecting a shift in production away from developed countries. The total harvested area was almost 20 million hectares in 2009, of which more than half was in developing countries. This growth in area in developing countries involves a greater diversity of agroecological zones and a greater number of varieties adapted to these conditions. The growth of production in developing countries also reflects the fact that potatoes are the one commodity in the developing world with consistent increases in quantities consumed per capita (Bruinsma 2003).

By providing income generation opportunities as a cash crop, potatoes contribute to alleviating poverty. Further, potatoes represent an important source of energy, with a high delivery of energy per unit of land, water, and time, and are a valuable source of minerals and vitamins for the diet (Anderson et al. 2010).

During the food price crisis in 2007/2008, potato prices were significantly less affected by the price increases in international markets than were prices of other crops (FAO 2008), highlighting the contribution of the crop to a more stable world food system in regions with high incidences of poverty, malnutrition, and food insecurity, such as the tropical highlands of Africa, the Andes of South America, or the Indo-Gangetic basin of southern Asia (Thiele et al. 2010).

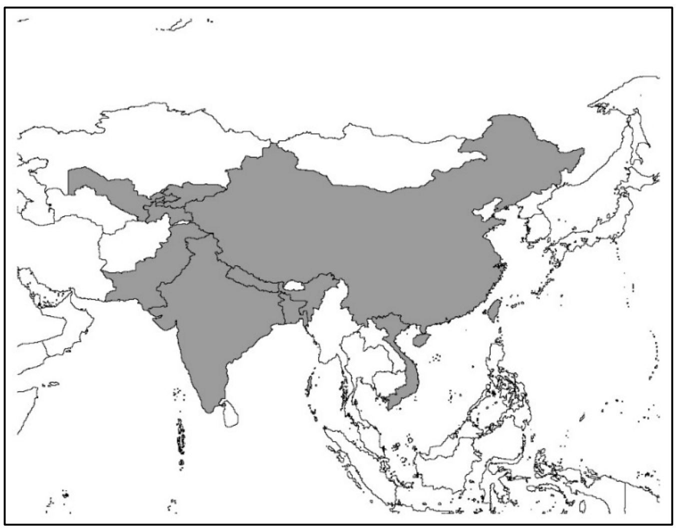
A broad range of factors affect potato productivity. The potential yield level is determined by a variety's genetic characteristics, including its growth, tuberization, and partitioning response to prevailing environmental conditions such as day length, temperature, soil fertility, and availability of water. Actual productivity and yield stability are influenced by abiotic factors, such as drought and heat, as well as biotic factors, including diseases such as late blight (the most important biotic constraint to potato production in the world), and a number of important viruses that can affect yields directly or by reducing seed quality (Lutaladio et al. 2009). Drought is the major abiotic factor affecting potato productivity. Depending on the genotype and the timing and extent of drought, water stress might accelerate or delay flowering and tuberization, or slow down canopy growth and tuber fill or bulking. A second important abiotic factor affecting both total potato yield and yield variability is temperature. High temperature affects the rates of photosynthesis and respiration, with the former being reduced and the latter increased. Increases in either day or night temperature above optimal levels (18 to 20 degrees Celsius) reduce tuber yields, with high night temperature being deleterious to tuber bulking and dry matter accumulation. High temperatures also cause physiological disorders such as irregular shape, premature sprouting, cracking, and elevated concentrations of glycoalkaloids in tubers, leading to bitter tubers that can be toxic (Gastelo, Kleinwechter, and Bonierbale 2014; Levy and Veilleux 2007).

One of the flagship technologies defined by CIP and the CGIAR Research Program on Roots, Tubers and Bananas is the "agile" potato, a variety with short growth cycles of 70 to 90/100 days to be incorporated into the rice- and wheat-based cropping systems of central and South Asia and parts of China. Adopted by poor and vulnerable rural households, it is expected to contribute to the sustainable intensification of cereal-based cropping systems and thereby to improve farm revenues, reduce vulnerability, improve diets, and bring income opportunities from on- and off-farm employment through emerging markets for fresh potatoes and in processing industries (CIP 2013). While the shorter growth cycle is the defining characteristic of this product, this variety is also characterized by heat and drought tolerance and virus resistance. Given the current capabilities of the crop modeling framework, the current assessment focuses on the elementary traits of heat and drought tolerance and a combination of these.

For central Asia, the baseline cultivar used for the assessment is Atlantic. The improved cultivar is expected to be introduced into wheat-based irrigated systems of the temperate lowlands and the main cropping season of the temperate highlands of Tajikistan, Kyrgyzstan, and Uzbekistan. In South and Southeast Asia, traits of tolerance to heat, drought, or both are expected to be a component of improved potato varieties to be introduced into rice-based systems of Bangladesh, East India, the plains of Nepal, and North Vietnam; into wheat-based systems in North and West India and Pakistan; and into potato-potato systems of Bangladesh, India, and Pakistan. The crop agroecology can be described as a subtropical lowland environment. The baseline cultivar for that region is Kufri Bahar. In China, four provinces in Southwest and central China are the target region for the improved varieties. The provinces under consideration are Yunnan, Guangxi, Gansu, and Qinghai. The baseline cultivar for the Chinese provinces is Tacna.

In all regions, heat tolerance, drought tolerance, and a combination of the two is modeled in the DSSAT-SUBSTOR potato model (Figure 3.5). Crop model coefficients for the three technologies were calibrated based on a set of yield trial data obtained from CIP breeders. Heat tolerance is modeled by adjusting the genetic coefficient that governs the heat response of the plant for the three baseline cultivars (Atlantic, Kufri Bahar, Tacna) by +2 degrees. Drought tolerance was modeled by increasing the root density and the plant's capacity to absorb water from the soil. Adoption estimates were taken from the ex ante assessment in Fuglie (2007) for similar technology. Where data were not available, adoption estimates for virus-resistant varieties were used as a proxy.

Figure 3.5 Countries whose adoption of alternative potato varieties is simulated in this analysis



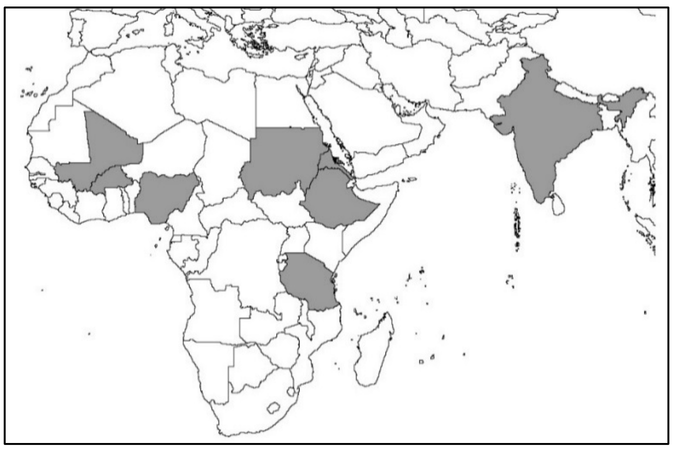
Source: Authors.
Note: Gray = drought tolerance, heat tolerance, and drought and heat tolerance adoption.

Sorghum

More than half a billion people in the world rely on sorghum as a dietary mainstay and, given its diversity of uses, as an important source of income. The grain is used mainly for food by many poor people, and the stalks are a vital source of fodder for livestock. Sorghum is also used for a wide range of industrial purposes. Sorghum grain is nutritious and contains relatively high levels of iron and zinc. This cereal grows over a wide range of temperatures and elevations. Given that sorghum requires less water, it is usually grown instead of maize in the hotter and drier areas of Africa, South Asia, and Central America. This hardy crop is now grown on some 42 million hectares in countries spread across Africa, Asia, Oceania, and the Americas. In India, it is grown on 8.02 million hectares with an average productivity of 920 kilograms per hectare. In West Africa, Nigeria is the largest producer of sorghum, followed by Burkina Faso and Mali. In Mali, it is grown on 1.06 million hectares with an average productivity of 1,020 kilograms per hectare (mean of 2006–2010 production data, FAO 2012).

Major biotic constraints for sorghum production include shoot fly, stem borer, head bug, and aphid insect pests, as well as grain mold, anthracnose diseases, leaf blight, weed competition, and (in Africa) the parasitic plant *Striga* spp. (ICRISAT 2004). Major abiotic stresses are drought, high temperatures, acid soils, and low soil fertility. As droughts and temperature hikes intensify with projected climate changes, they are expected to have even more negative effects on productivity, especially in the arid and semiarid regions (Sultan 2012). In the semiarid tropics, where sorghum is currently grown during the rainy season, the mean crop-season temperatures are already close to or above these optimum temperatures. Based on a metadata analysis, Knox and colleagues (2012) assessed the impact of projected climate change by the 2050s on sorghum productivity for both Africa and South Asia. They reported a 15 percent decrease in sorghum yield across Africa and 11 percent across South Asia. Changes in rainfall coupled with a rise in temperature may reduce the length of the growing period as determined by the duration of soil water availability. Therefore, in order to achieve higher and more stable yields, it will be critical to breed varieties that not only can better withstand drought conditions, but also can reach maturity within the period of water availability. For the Global Futures study, ICRISAT has worked to simulate the traits of a DT sorghum cultivar across Burkina Faso, Eritrea, Ethiopia, India, Mali, Nigeria, Sudan, and Tanzania (Figure 3.6).

Figure 3.6 Countries whose adoption of an alternative sorghum variety is simulated in this analysis



Source: Authors.
Note: Gray = drought tolerance adoption.

Using the CSM-CERES sorghum model and the alternative cultivar approach, ICRISAT assessed the potential benefits of altering crop life cycle, enhancing yield potential traits, and incorporating drought and heat tolerance in the commonly grown cultivar types at two sites each in India (cv. CSV 15 at both Akola and Indore) and Mali (cv. CSM 335 at Samanko and cv. CSM 63E at Cinzana) (Singh, Nedumaran, Traore, et al. 2014). Decreasing the crop life-cycle duration of cultivars by 10 percent decreased yields at all the sites under both current and future climates. In contrast, increasing the crop life-cycle duration by 10 percent increased yields by up to 12 percent at Akola, 9 percent at Indore, 8 percent at Samanko, and 33 percent at Cinzana. Enhancing yield potential traits (radiation use efficiency, relative leaf size, and partitioning of assimilates to the panicle each increased by 10 percent) in the longer-cycle cultivars increased the yields by 11 to 18 percent at Akola, 17 to 19 percent at Indore, 10 to 12 percent at Samanko, and 14 to 25 percent at Cinzana under the current and future climates of the sites. Except for the Samanko site, yield gains were larger with incorporated drought tolerance than with heat tolerance under the current climate. However, under future climates, yield gains were increased by incorporating heat tolerance at Akola, Samanko, and Cinzana, but not at Indore. Net benefit of incorporating both drought and heat tolerance in alternative cultivars was an increase in yield of up to 17 percent at Akola, 9 percent at Indore, 7 percent at Samanko, and 16 percent at Cinzana under climate change. The study concluded that different combinations of traits will be needed to increase and sustain productivity of sorghum in current and future climates at these target sites in India and West Africa.

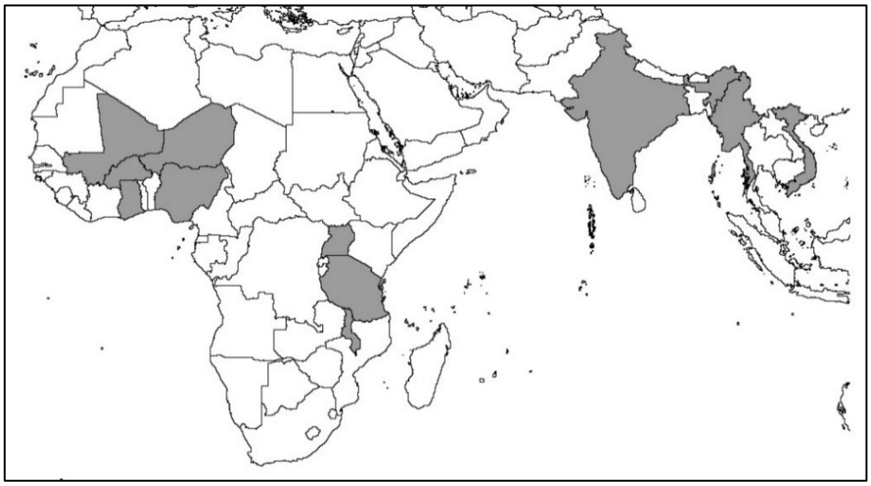
Groundnut

Rich in protein and edible oil, groundnut is central to the financial and nutritional well-being of hundreds of millions of farmers and consumers across the semiarid tropics. Besides protein and oil, groundnut seeds are a rich source of minerals, vitamins, and dietary fiber. The groundnut haulms are used as fodder for livestock. Groundnut is currently grown on about 21.8 million hectares worldwide. Global production totaled 38.6 million tons, 95 percent of which occurred in developing countries (FAO 201). Major producers include China, India, Myanmar, Nigeria, and the United States. Production is concentrated in Asia (50 percent of global area and 68 percent of global production) and Africa (46 percent of global area and 24 percent of global production). In India, groundnut is mostly grown in rainfed conditions (83 percent of total groundnut area), during the main rainy season; the remaining 17 percent of area is irrigated, especially after the end of the rainy season. While India has the largest area under groundnut (6.36 million hectares) in the world, its production (6.5 million tons) and productivity (1,022 kilograms per hectare) have remained low, the latter being well below the world average (Birthal et al. 2010, 92). In West Africa, Nigeria and Senegal are the largest producers of groundnut, and Mali and Niger are also important producers. In Mali, groundnut is grown on 0.29 million hectares with an average production and productivity of 0.26 million tons and 880 kilograms per hectare, respectively. In Niger, groundnut is grown over a larger area (0.44 million hectares) than in Mali, but with greater fluctuation in production due to the variable climate. Average production and productivity of groundnut in Niger are 0.21 million tons and 480 kilograms per hectare, respectively (mean of 2001 to 2010 production data reported in FAO 2012).

There are many region-specific abiotic and biotic stresses that limit groundnut productivity in Asia and Africa. The major diseases are early and late leaf spot, rust, and bacterial wilt (Nigam et al. 2006). The crop is highly susceptible to an aflatoxin caused by the fungus *Aspergillus flavus* (Nigam et al. 2006). Aflatoxins are extremely hazardous to human health and especially harmful to the physical and mental development of young children. Other major biotic stresses are sucking insect pests (aphids, thrips, and jassids) and foliar-feeding insect pests (groundnut leaf miner, red hairy caterpillar, and pod borers) (Nigam et al. 2006). Major abiotic stresses include drought, high temperature, and soil nutrient deficiencies. In both Asia and Africa, average temperature during the groundnut growing season is already close to or above the upper limit of the optimum temperature range (20 to 30 degrees Celsius) for groundnut growth. As climate change accelerates, increasing temperatures may affect growth and development of crops, thus impacting potential yields. A critical variable is the number of days a crop is exposed to supra-optimal temperatures at critical growth stages, that is, flowering, pollination, or grain filling (Prasad et al. 2003). In the semiarid tropical regions, the changes in rainfall coupled with a rise in temperature may reduce the length of the growing period and intensify droughts. Therefore, it will be important to breed DT cultivars and to match their maturity durations to the period of soil water availability for higher and more stable yields. For the Global Futures study, ICRISAT has worked to simulate the traits of DT groundnut cultivars, HT groundnut cultivars, and a drought- and heat-tolerant high-yielding cultivar (DHTY) across Burkina Faso, Ghana, India, Malawi, Mali, Myanmar, Niger, Nigeria, Tanzania, Uganda, and Vietnam (Figure 3.7).

Using the CROPGRO groundnut model, ICRISAT assessed the potential benefits of incorporating DT, HT, and yield-enhancing traits into the commonly grown cultivar types at two sites each in India (Anantapur and Junagadh) and West Africa (Samanko, Mali; and Sadore, Niger) (Singh, Nedumaran, Ntare, et al. 2014). Increasing crop maturity by 10 percent increased yields by up to 14 percent at Anantapur and 19 percent at Samanko, and sustained the yields at Sadore. However, at Junagadh, the current maturity of the cultivar holds well under future climate. Increasing yield potential of the crop by increasing its leaf photosynthesis rate, partitioning to pods, and seed-filling duration each by 10 percent increased pod yield by 9 to 14 percent over the baseline yields across the four sites. Under the current climates of Anantapur, Junagadh, and Sadore, the yield gains were larger with drought tolerance than heat tolerance. Under climate change, the yield gains from incorporating both drought and heat tolerance increased to 13 percent at Anantapur, 12 percent at Junagadh, and 31 percent at Sadore. At the Samanko site, the yield gains from drought or heat tolerance were negligible. Therefore, a combination of site-specific technologies will be needed to enhance and sustain groundnut productivity in the groundnut-growing regions in West Africa and South Asia.

Figure 3.7 Countries whose adoption of alternative groundnut varieties is simulated in this analysis



Source: Authors.
Note: Gray = drought tolerance, heat tolerance, and drought and heat tolerance plus high-yielding variety adoption.

Cassava

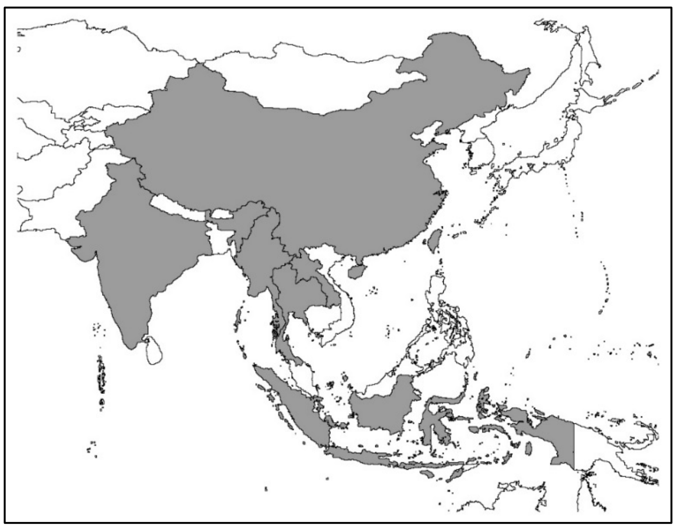
Cassava (*Manihot esculenta* Crantz) is a woody shrub native to the American tropics that produces a starchy tuberous root. It is the third most important staple crop in the tropics after rice and maize. Global production in 2010 was 240 million tons, with the five largest producers of cassava (Nigeria, Brazil, Thailand, Indonesia, and the Democratic Republic of Congo) accounting for more than 50 percent of total production (FAO 2012). Cassava's successful introduction to Africa in the 16th century was followed by its introduction to the Asian subcontinent and Southeast Asia in the 19th century. Cassava has traditionally been a crop of choice for poorer farmers on marginal lands, where its hardiness allows it to grow in soils with low fertility and moisture.

Biotic stresses are the cause of major losses in cassava production. The biggest reported losses due to plagues in Latin America and the Caribbean correspond to those caused by cassava bacterial blight. Both cassava mosaic disease (CMD) and cassava brown streak disease (CBSD) are present in most African countries and parts of Asia. CMD is the most severe and widespread, limiting production of the crop in Africa south of the Sahara. CMD produces a variety of foliar symptoms that include mosaic, mottling, misshapen and twisted leaflets, and an overall reduction in size of leaves and plants. CBSD is a damaging disease of cassava plants, and is especially troublesome in East Africa.

Cassava crops throughout the world are under attack by arthropod pests, causing huge losses to farmers in Asia, Latin America, and Africa. Major pests reported in cassava-producing countries include cassava green mites and white flies. The specific characteristics of cassava fuel the expansion of pests: vegetative reproduction, drought resistance, long life cycle, staggered planting dates, intercropping, and more recently, the lack of genetic diversity due to intensification, among others (Bellotti, Campo, and Hyman 2012). In Asia the most important pest is the mealybug (*P. manihoti*). Of the more than 15 varieties of mealybug attacking cassava in tropical countries, *Phenacoccus manihoti* and *P. herreni* are what have caused major losses in cassava production. In particular, *P. manihoti* began to spread through Africa in the 1970s, causing severe damage, threatening cassava cultivation in Africa.

In a combined effort of IITA, CIAT, and the CIBC (Commonwealth Institute of Biological Control), in 1980 scientists found in Paraguay a parasitoid of *P. manihoti*: *A. lopezi*. The *A. lopezi* is a tiny wasp that lays its eggs on the mealybug. As they grow inside the mealybug, the wasp larvae feed on the mealybug, killing it. This parasitoid has attacked and effectively controlled populations of mealybug in South America for centuries. It was successfully introduced in Africa along with three coccinellid predators. This strategy succeeded in reducing the mealybug losses from 80 percent down to 5 to 10 percent (Belloti, Campo, and Hyman 2012), while in controlled simulations the coccinellid predators reduced losses by 25 percent (Neuenschwander 2001). Recently, *A. lopezi* was introduced successfully in Thailand to contain the mealybug pest.

Figure 3.8 Countries whose adoption of alternative pest management practices for cassava is simulated in this analysis



Source: Authors.
Note: Gray = region where cassava mealybug and biological control scenarios were targeted.

The previous sections focused on the impact of promising new technologies that can help farmers adapt to the abiotic stresses of climate change; however, technologies that counteract the negative impact of biotic stresses such as pests and diseases are also very important. Cassava and the mealybug infestation is a particularly good example of a case where we can focus on the effects of biotic stresses and management practices. The pest management scenarios designed by CIAT use historical data on the effects of the appearance of mealybug in Africa, and the subsequent introduction of the *A. lopezi* wasp to South and Southeast Asian cassava production. The cassava-mealybug scenarios were framed with an initial scenario representing an untreated infestation of the mealybug in the entire target area (this scenario is simply referred to as "mealybug"). Three biological control scenarios were then specified, which reflect each country's capacity to reduce damages and approach baseline yields (Figure 3.8):

1. CBIOL1: Thailand, being the world leader in cassava production technology, is assumed to aggressively treat the infestation in the first treatment scenario. China also follows Thailand's adoption of the biological controls.
2. CBIOL2: The remaining countries in the region begin to adopt the control treatment but with less efficacy than Thailand and China.
3. CBIOL3: All targeted countries implement the biological controls effectively and approach the preinfestation baseline yields.

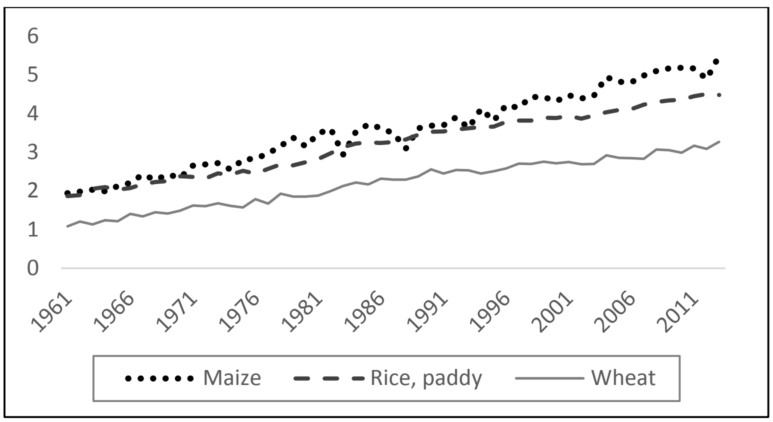
4. HOW WILL YIELDS, PRODUCTION, AND PRICES CHANGE?

The yield changes simulated through the crop models (as described in Section 3) represent the biophysical productivity–enhancing potential of the new varieties under specific conditions of soil and climate. In reality, a host of other factors influence actual yields. By aggregating the biophysical yield changes from the pixel to the food production unit (FPU) level, and using these data as an input into the IMPACT model, we are able to simulate impacts that reflect the combination of biophysical effects as well as interactions with prices and other economic variables.

Yields in IMPACT

The links between results from the crop models (biophysical) and the IMPACT multimarket model (economic) involve four different mechanisms. First, the IMPACT model assumes underlying improvements in yields over time. These trends are based initially on historical productivity growth rates (see Figure 4.1) and are adjusted to reflect expert opinion on future changes in input levels, investments in agriculture, and biological limits. These long-run trends, or intrinsic productivity growth rates (IPRs), represent the effects of expected increases in inputs, as well as improvements in management practices. These IPRs are exogenous to the IMPACT model and are treated as part of its input data (that is, they are not solved within the IMPACT multimarket model).

Figure 4.1 Global average yields (tons per hectare) of maize, rice and wheat, 1961 to 2012



Source: FAO (2014).

Second, the IMPACT model includes the simulation of potential adoption of specific new technologies (for example, agricultural practices) or new varieties such as those described in Section 3. The biophysical yield changes calculated through crop models can be used as “shifters” on top of the IPRs. Where positive impacts on production systems are seen, we can estimate the potential pool of adopters of the new technology in each FPU. The adoption of the technology in IMPACT is further specified by an adoption pathway, which is represented as a logistic function, determining the rate of adoption.

Third, given these adoption functions, the effect of the new technologies on average FPU yields will be affected by climate shocks that vary over time. These climate shocks change both temperature and water availability. The new crop varieties will vary in their yield reactions to these changes. IMPACT captures the effect of changes in water availability through the linked water models (water basin management and water stress models). DSSAT provides estimates on the effects of temperature changes on yields. These two inputs are combined, resulting in the total impact of climate change and adoption of new crop varieties on average yields by crop and region, which are then passed to the IMPACT multimarket model.

Fourth, the IMPACT multimarket model includes an endogenous link between yields and changes in output prices. The underlying assumption is that farmers will respond to changes in prices by varying the use of inputs, such as fertilizer, chemicals, and labor, which will in turn change yields. If the price of a crop falls, there is less incentive to allocate resources to that crop, and its yield will fall as a result. The first three mechanisms involve technology and climate, and are essentially independent of prices. We will denote these as “climate and technology” effects below. The fourth mechanism involves markets and prices, and we will denote it as “market” effects.

Table 4.1 shows climate and technology effects and market effects that change productivity in 2050 compared with 2005, without climate change (NoCC) and under a dry climate scenario (CC).[9] Columns 1 and 2 show climate and technology increases that reflect only the effects of IPRs (that is, the contribution of new technology adoption is not included). They also do not include the effect of prices, which would be expected to change as production rises. Changes in productivity range across the selected crops and regions of adoption from 15 percent to 224 percent in the absence of climate change and from -2.7 percent to 177 percent under the climate change scenario (both relative to 2005 yields). Increases are largest in the case of DT sorghum and wheat, and smallest for the region where HT wheat is simulated (South Asia). Interpreting the impact of climate and changing technologies should be done with care because in some cases, especially for wheat in temperate regions, the modeling shows that climate change may actually be beneficial in terms of yields compared with a no-climate-change scenario.

Table 4.1 Impact of productivity growth on baseline yields, percent change between 2005 and 2050

			Climate and technology impacts on yields (% change)		Market impacts on yields (% change)	
Crop	**Region**	**Water regime**	**NoCC (1)**	**CC (2)**	**NoCC (3)**	**CC (4)**
Maize	M1	Irrigated	68.25	60.44	48.73	46.15
		Rainfed	55.76	46.72	36.46	32.44
	M2	Irrigated	85.64	46.25	65.99	33.57
		Rainfed	123.54	74.02	96.30	56.03
Wheat	W1	Irrigated	153.21	177.43	141.07	164.25
		Rainfed	89.14	102.17	78.95	91.34
	W2	Irrigated	103.91	90.61	97.54	85.03
		Rainfed	86.34	86.40	81.06	81.24
	W3	Irrigated	34.77	15.73	19.01	2.31
		Rainfed	15.20	-2.67	0.75	-14.70
Rice	R1	Irrigated	50.31	26.80	38.42	18.86
		Rainfed	42.87	25.14	29.09	15.36
Potatoes	P1	Irrigated	56.64	53.58	38.46	38.17
		Rainfed	16.09	15.51	3.05	4.34
Sorghum	S1	Irrigated	224.02	123.40	197.09	107.73
		Rainfed	88.37	70.63	72.08	57.89
Groundnut	G1	Irrigated	31.34	17.67	16.53	6.85
		Rainfed	30.70	18.82	16.52	8.30
Cassava	C1	Irrigated	101.56	89.71	81.85	75.45
		Rainfed	33.18	15.57	22.31	8.72

Source: Authors.

Notes: Numbers are percent change in baseline yields between 2005 and 2050 under assumed constant climate (NoCC) or under climate change (CC). Detailed numbers by country can be found in Appendix D. Values are averaged across all countries in the region of adoption. Countries belonging to each region as well as improved variety adopted in each region are described in Table 2.1.

[9] This scenario is modeled by the GFDL-ESM2M GCM using a RCP of 8.5.

As yields rise, we expect that prices will change, and that this in turn will influence farmers' incentives to increase input use or improve management practices. Other things being equal, increased production would be expected to lead to lower prices, which would in turn reduce incentives and consequently market impacts relative to the climate and technology effects alone. Analyzing this combination of effects is a key contribution that the Global Futures project makes by linking biophysical and economic impacts on yield changes. The climate and technology impacts and the market impacts on yields are presented in columns 3 and 4, respectively, of Table 4.1. They range across the selected crops from -0.75 percent to 197 percent in the absence of climate change and from -14.7 percent to 164 percent under the climate change scenario (both relative to 2005 yields). Gains are more modest relative to the exogenous case, but still double or more relative to 2005 in the case of wheat and sorghum, while increasing more slowly or even declining in the region where HT wheat is tested (South Asia).

Impacts of New Technologies

In this study we are interested in the impact of promising new technologies that would help farmers adapt to climate change and mitigate its impacts by improving the drought tolerance and heat tolerance of selected crops, as well as technologies to counteract the negative impact of pests, such as mealybug on cassava. The scenarios involve adoption of new technologies only in targeted regions, as identified in Table 2.1. Table 4.2 shows the global shares of production for all the crops in the targeted regions, across the various simulated technologies, in 2005 and 2050, under NoCC and CC. The simulated crops/regions represent 20 to 40 percent of global production in most cases, but less than 10 percent in the case of maize. This means that while the new technologies may have significant effects on yields in areas where they are adopted, their impact on global prices is expected to be modest.

The tables in the following sections include the results of the technology scenarios described in Section 3. All scenarios were run under the same dry climate scenario modeled using GFDL-ESM2M and RCP 8.5. The scenario results have been aggregated at the regional level (see Table 2.1 for reference). Appendixes D and E present all of the country-level results.

Table 4.2 Shares of global production represented by the target regions for the various crops

		NoCC		CC	
Crop	**Region**	**2005**	**2050**	**2005**	**2050**
Maize	M1 + M2	5.50	5.48	5.50	5.71
Wheat	W1 + W2 + W3	22.98	22.66	22.98	24.46
Rice	R1	34.64	34.53	34.64	37.43
Potatoes	P1	32.77	40.46	32.77	39.63
Sorghum	S1	43.69	40.22	43.69	42.68
Groundnut	G1	34.66	35.52	34.66	35.14
Cassava	C1	27.58	18.72	27.58	18.56

Source: Authors.

Note: CC = climate change; NoCC = assumed constant climate. The share of global production is obtained by summing the global share of production in each of the countries where the new crop variety is being simulated (see Table 2.1).

Yield Changes without Market Effects

This section explores the results of adoption of the agriculture technologies described in Section 3. First we examine yields changes resulting from the adoption of the new crop varieties (DT, HT, DTHT, and DHTY), followed by the yield effects of the biological control scenarios for cassava. All of the exogenous yields presented in this section include climate change shocks and IPRs. The complete list of adoption rates for each crop in each country and for each technology is in Appendix C.

Table 4.3 shows the exogenous yield effects for the different promising varieties. The numbers reflect the percent difference in yields between the scenario in which the new variety is adopted and the baseline in 2050 before market effects are considered (that is, column 2 in Table 4.1). The values are aggregated at the regional level (that is, at the level of each region included in the simulations; the regions of interest differ crop by crop). Detailed results by country are presented in Appendix D.

Table 4.3 Change in regional crop yields (percent difference from 2050 climate change baseline without the new technologies)

	DT		HT		DTHT		DHTY	
Crop	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**
Maize	31.81	32.02	111.88	44.46				
Wheat	0.21	5.78	5.66	-	10.20	9.57		
Rice	0.70	1.01						
Potatoes	1.65	6.20	5.67	3.74	15.26	9.90		
Sorghum	1.95	5.21						
Groundnut	0.30	5.74	11.87	7.35			26.99	26.24

Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. Values are percent change in yield between technology and base in 2050 under climate change. Drought tolerance is implemented only under rainfed conditions. Blank cells are those without any scenario input. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

In general, the HT varieties outperform the DT varieties. This is unsurprising due to the high increases in temperature that are expected more uniformly globally under the climate change scenario, compared with the greater variation in regional precipitation. It should also be noted that the benefits of both traits are underestimated by excluding extreme events. Extreme water stress and heat stress is important not only in terms of general trends (greater temperatures, less rainfall), but also in the timing of extreme weather events (extreme temperatures during flowering, or drought during filling stages). This exclusion likely underestimates the benefits of drought tolerance even more than heat tolerance, because we can observe large and uniform temperature increases from the climate model but are unable to observe the interannual variation of precipitation that would occur under a drought. Therefore, we are testing the DT trait under general water scarcity instead of under drought conditions. (See Appendix A for more detailed description of methodology used in this study.) Nevertheless, in regions where the precipitation under climate change decreases significantly, the DT varieties begin to increase yields similarly to HT varieties, especially under rainfed conditions. For example, in Turkey and Iran, which would experience substantial rainfall decreases (Figure 2.3), and where DT wheat was implemented, the yield increases for rainfed wheat are nearly 6 percent, comparable to the gains the HT wheat made in irrigated areas of South Asia.

Where combined-trait varieties were tested, these technologies demonstrated significant improvements over the adoption of single-trait varieties, which suggests that the benefits of these traits are additive if not multiplicative when combined. Potatoes are a particularly good example of this stacking of traits, because both DT and HT were implemented in the same region individually, before being combined. In the case of rainfed potatoes we observe gains of more than 6 percent for DT and less than 4 percent for HT, with nearly a 10 percent gain when DT and HT traits are combined. When water constraints are further reduced through irrigation, the gains of these combined traits are even more impressive—almost 3 times greater than for HT alone and nearly 10 times greater than for DT alone.

Groundnut further illustrates the benefits of stacking beneficial traits, with the DHTY variety not only improving drought and heat tolerance but also enhancing yields. The improvements observed using this variety more than double to quadruple the improvements observed from only DT and HT varieties.

The cassava biological control scenarios were designed differently from the new varieties scenarios, in that the objective of this technology is not to increase the yield potential of cassava, but instead to reduce the negative effect of the infestation scenario ("Mealybug"). The question isn't so much the effectiveness of the technology, which has been proven, but the level of adoption. The greater the level of adoption, the closer the yield reductions are to zero, or to pre-infestation levels (Table 4.4).

Table 4.4 Change in regional cassava yields (percent difference from 2050 climate change baseline without the new technologies)

Scenario	Irrigated	Rainfed
Mealybug	-12.18	-11.17
CBIOL1	-12.18	-6.26
CBIOL2	-4.79	-2.93
CBIOL3	-1.64	-1.51

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

In general, these technologies show significant adaptive capabilities, with many of the adopting regions mitigating or counteracting the negative climate effects observed. For example, in Table 4.5, the M2 region suffers significant yield declines (greater than 20 percent) due to climate but is able to more than overcome these negative effects with the adoption of the HT maize variety (yield increases of 40+ and 110+ percent). Of the technologies tested, only the sorghum and rice technologies failed to significantly bridge the productivity gap created by climate change.

It is important to note that the regional results can hide a large degree of variability at the country level (see Appendixes D and E for complete country results). For example, the benefits of DT rice are fairly insignificant in many of the countries within the region of adoption, with most of the productivity gains in the region being observed in Sri Lanka and India, where rice yields improve by 3.5 and 1 percent, respectively. DT sorghum is another technology that shows significant variation of benefits across countries, with much larger improvements observed in Eritrea, Ethiopia, and India than those observed in Tanzania. In the case of cassava, the largest decrease in exogenous cassava yields due to mealybug occurs in Vietnam under irrigated conditions, which are almost double the negative effects observed in the rest of the region.

Table 4.5 Comparing climate shocks with the improvements under new technologies

			% change in 2050 yields	
Crop	**Region**	**Water regime**	**CC (1)**	**CC with new technologies (2)**
Maize	M1	Irrigated	-4.64	**31.81**
		Rainfed	-5.80	**32.02**
	M2	Irrigated	-21.22	**111.88**
		Rainfed	-22.15	**44.46**
Wheat	W1	Irrigated	9.57	0.21
		Rainfed	6.89	5.78
	W2	Irrigated	-6.52	5.66
		Rainfed	0.03	-
	W3	Irrigated	-14.13	10.02
		Rainfed	-15.51	9.57
Rice	R1	Irrigated	-15.64	0.70
		Rainfed	-12.41	1.01
Potatoes	P1	Irrigated	-1.95	**1.65 to 15.26**
		Rainfed	-0.50	**3.74 to 9.90**
Sorghum	S1	Irrigated	-31.05	1.95
		Rainfed	-9.42	5.21
Groundnut	G1	Irrigated	-10.41	**0.30 to 26.99**
		Rainfed	-9.09	**5.74 to 26.24**

Source: Authors.

Notes: Column 1 values are calculated by comparing columns 1 and 2 in Table 4.1. Column 2 summarizes the yield effects from the technologies analyzed in Tables 4.3 and 4.4. Ranges in bold highlight the technologies that fully overcome the effects of climate change in the climate change (CC) scenario.

Yield Changes with Market Effects

The effect on exogenous yields after adoption of the different improved varieties can be significant in some countries, and the added productivity from improved varieties leads to price decreases compared with the baseline scenario. Because adoption of the new technologies is simulated only in target regions, however, the impacts on global prices are moderate (Table 4.6). The largest impact is observed when a DHTY groundnut variety is adopted, which is not surprising considering the significant increases in productivity of this variety (Table 4.3) and the large share of global production (more than 30 percent) of the region of adoption (Table 4.2).

We expect that cassava yield changes (exemplified by the exogenous changes in Table 4.4) will also trigger price changes that will in turn influence farmers' decisions to adopt new technologies or management practices. The pest infestation scenario ("Mealybug" scenario) shows a strong effect on global cassava prices, with price increases greater than 3 percent compared with the baseline (Table 4.7). The first treatment scenario (CBIOL1) significantly reduces the price increase, demonstrating the importance of Thailand to the cassava world market. Each of the final two treatment scenarios decreases the previous price increases by about 50 percent, such that in the last scenario (CBIOL3) the price is only 0.4 percent higher than the base price, which indicates that the treatment sequence has brought the mealybug pest to a level of control very close to the preinfestation baseline scenario.

Table 4.6 Change in world commodity prices (percent difference from 2050 climate change baseline without the new technologies)

Crop	DT	HT	DTHT	DHTY
Maize	-0.76	-0.64		
Wheat	-0.13	-0.13	-0.14	
Rice	-0.04			
Potatoes	-0.11	-0.04	-0.22	
Sorghum	-3.21			
Groundnut	-1.18	-1.64		-4.99

Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. By definition these are world prices; therefore only these global results are available. Blank cells are those without any scenario input. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

Table 4.7 Change in world cassava prices (percent difference from 2050 climate change baseline without the new technologies)

Scenario	Price
Mealybug	3.12
CBIOL1	2.17
CBIOL2	0.93
CBIOL3	0.41

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

The IMPACT model is a dynamic multimarket model in which supply and demand respond to world prices. The price changes shown in Tables 4.6 and 4.7 have endogenous effects on yields because they affect the choices (for example regarding inputs such as fertilizer) made by farmers, as well as consumers. Importantly, these price changes affect both farmers who adopt the new technologies and those who do not. Tables 4.8 and 4.9 show the changes in final IMPACT yields (or endogenous yields), including the market effects embodied by the price changes in Tables 4.6 and 4.7.

The effects of prices serve to reduce the effects of the climate and technology (or exogenous) yield improvements. By reducing the adverse impacts of climate change, the new technologies increase production and thus reduce prices relative to what would otherwise have been realized. Lower prices in turn dampen incentives to farmers. Farmers who adopt the new technologies still benefit from doing so, but less than they would have done if prices had not declined. Farmers who do not adopt the new technologies typically suffer because prices fall, but without the mitigating improvement in crop yields. Results for HT rainfed wheat and irrigated cassava under CBIOL1 illustrate this point. In areas where the new technology or management practices were not implemented, farmers face lower prices (due to increased productivity elsewhere) without any offsetting exogenous improvements on yield (from new technology), ending with lower final endogenous yields.

Table 4.8 Change in crop yields with market effects (percent difference from 2050 climate change baseline without the new technologies)

	DT		HT		DTHT		DHTY	
Crop	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**
Maize	10.53	23.85	27.51	13.49				
Wheat	0.05	1.99	0.92	-	4.53	2.84		
Rice	0.03	0.23						
Potatoes	0.34	0.4	1.56	0.12	3.14	0.43		
Sorghum	-0.03	6.59						
Groundnut	0.15	3.7	7.07	4.06			15.62	13.77

Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. Values are average across countries. Blank cells are those without any scenario input. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

Table 4.9 Change in cassava yields with market effects (percent difference from 2050 climate change baseline without the new technologies)

Scenario	Irrigated	Rainfed
Mealybug	-11.93	-10.91
CBIOL1	-12.00	-6.07
CBIOL2	-4.71	-2.84
CBIOL3	-1.60	-1.47

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

The general story illustrated in the previous section continues to hold, with HT varieties generally outperforming DT varieties, and combined-trait varieties demonstrating greater impacts, not only on prices but also on endogenous yields. The scale of the dampening effects of prices is largely based on the size of the price decreases (Table 4.6). The largest difference between endogenous yield increases (13 to 16 percent, Table 4.8) and exogenous yield increases (26 to 27 percent, Table 4.6) occurs for DHTY groundnut, where prices decline by nearly 5 percent due to technology adoption. DT sorghum, where the second largest price decline is observed (greater than 3 percent), similarly has a large difference between exogenous and endogenous yield gains.

The biological control scenarios show the dampening effects in the opposite direction. Diminished production due to mealybug infestation leads to higher prices, incentivizing farmers to apply more inputs into their production, thereby mitigating somewhat the negative exogenous yields seen in Table 4.4.

As was the case in Section 4.3, the regional results can hide significant variation at the country level. The observed variation in endogenous yields at the country level are primarily driven by the variation in the exogenous yield benefits observed in Section 4.3 and the country-level adoption pathways (Appendix C). For example, DT maize is adopted in 12 countries under rainfed conditions, whereas it is only adopted in 4 countries under irrigated conditions. Therefore, much of the change observed between Table 4.3 and Table 4.8 for irrigated DT maize is driven by Ethiopia, the largest irrigated maize producer in the region. The endogenous yields in Table 4.8 illustrate the aggregate market responses to world prices in the targeted regions.

Changes in Area, Production, and Trade

Crop production in IMPACT is determined by the interaction of crop areas and their respective productivity. Farmers respond to price changes not only by changing the inputs they apply to their crops but also by selecting what crops they choose the cultivate. Where productivity grows, there is a reduced incentive to expand agricultural production to new areas; hence increased endogenous yields for, say, DT rice and HT wheat result in a reduction, albeit modest, of the area cultivated under either of these two crops in 2050 (compared with a base in which the new varieties are not adopted). On the other hand, an increase in prices provides farmers with an incentive to expand harvested area, as would happen in the cassava biological control scenarios. On balance, these modeled scenarios show that the overall incentive is to reduce harvested area given the impacts of climate change and alternative technologies. Table 4.10 illustrates the changes in crop areas due to the adoption of new varieties. The largest declines in harvested area occur where the largest price declines are observed (DHTY groundnut and DT sorghum).

Table 4.10 Change in harvested area (percent difference from 2050 climate change baseline without the new technologies in modeled regions)

	DT		HT		DTHT		DHTY	
Crop	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed	Irrigated	Rainfed
Maize	-0.15	-0.20	-0.17	-0.30				
Wheat	-0.02	-0.03	-0.04	-0.09	-0.18	-0.08		
Rice	-0.01	-0.01						
Potatoes	-0.02	-0.04	-0.01	-0.01	-0.05	-0.08		
Sorghum	-0.35	-1.01						
Groundnut	-0.22	-0.61	-0.30	-0.83			-0.96	-2.61

Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. Values are average across countries. Blank cells are those without any scenario input. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

With the relatively small changes in harvested area observed above, it is unsurprising that changes in crop production (shown in Table 4.11) mirror the scenario results for endogenous yields observed in Table 4.8, with slightly smaller changes in production reflecting the changes in cropped area.

In the case of cassava, decreasing productivity and increasing prices give farmers an incentive to expand cultivated area. Table 4.12 illustrates this relationship clearly, with the greatest area expansion occurring in the full infestation scenario, where the greatest price increases and yield declines are observed.

Increased production is not automatically consumed locally; countries can and do export. Understanding how changes in production affect a county's relationship to global markets is valuable in determining their vulnerability to global price shocks. Ultimately adoption of new technologies should make adopting countries more competitive globally, allowing for greater involvement in world markets and potentially reducing reliance on imports.

Table 4.11 Change in production (percent difference from 2050 climate change baseline without the new technologies)

	DT		HT		DTHT		DHTY	
Crop	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**
Maize	10.33	23.6	27.3	13.14				
Wheat	0.04	1.97	0.87		4.35	2.76		
Rice	0.03	0.23						
Potatoes	0.32	0.36	1.55	0.11	3.1	0.36		
Sorghum	-0.41	5.35						
Groundnut	-0.14	3.07	6.66	3.19			14.24	10.79

Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. Values are average across countries. Blank cells are those without any scenario input. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

Table 4.12 Change in cassava area and production (percent difference from 2050 climate change baseline without the new technologies)

Scenario	**Area**		**Production**	
	Irrigated	**Rainfed**	**Irrigated**	**Rainfed**
Mealybug	0.32	0.52	-11.77	-10.21
CBIOL1	0.23	0.37	-11.94	-6.15
CBIOL2	0.10	0.16	-4.67	-2.79
CBIOL3	0.04	0.07	-1.57	-1.37

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

Figures 4.2 and 4.3 summarize changes in the ratio of net trade over national production in the targeted regions. This ratio is a useful way of analyzing changes in commodity trade for a couple of reasons. First, it allows us to identify when countries or regions change from being importers (negative net trade) to being exporters (positive net trade). DHTY groundnut is an example of a technology whose adoption causes a region to switch from being an importing region to being an exporting region. Second, this ratio allows us to observe changes in trade while controlling for changes in production. If demand increases at the same rate as production, we would expect to see no change in the ratio, and we could say that all additional production is being consumed in the region. If, on the other hand, the ratio increases, it means that the additional production displaces imports or is exported, which contributes to improved terms of trade.[10]

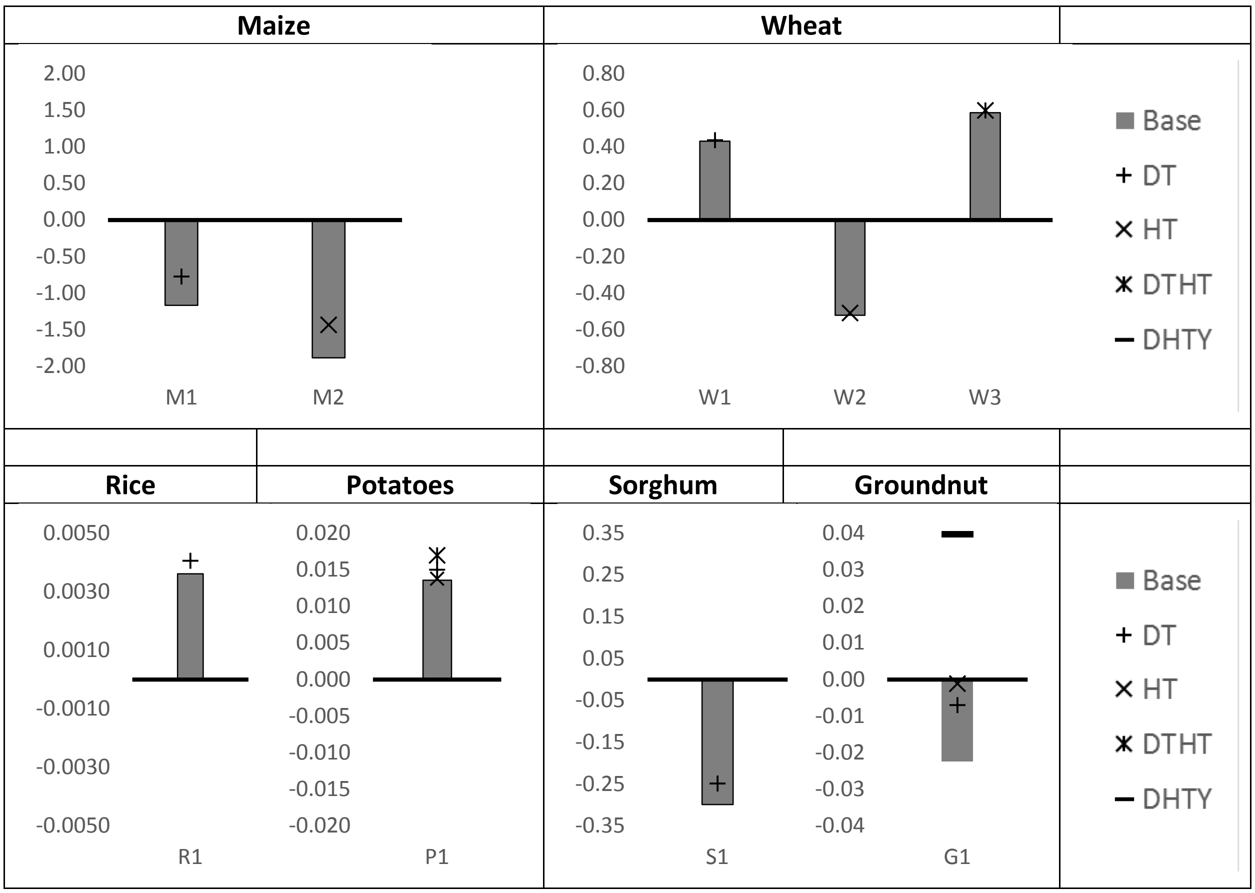
In all cases, the adoption of new varieties has a positive effect on the ratio of trade over production. As should be expected, the technologies with the largest effects on production have the largest effects on trade. As mentioned previously, the DHTY groundnut scenario actually causes the

[10] If the ratio of net trade to production were to decline, this would mean that demand in the region for the commodity is outpacing the increase in production. While no example of this occurs in the scenarios examined, such a hypothetical situation could occur if price decreases for a commodity lead to a large increase in regional demand.

region to go from being a small importing region (importing an additional 2 percent of its production to satisfy regional demand) to being a slight exporter (exporting an excess 4 percent of production). Regions highly dependent on imports of staple crops, like both maize regions (M1 and M2), reduce their vulnerability to global price shocks by reducing their imports as a share of production. The M2 region, for example, goes from importing almost twice its regional production to importing less than 1.5 times its production. Regions that are already exporting the targeted crops, such as DT wheat in W1, DTHT wheat in W2, and DT potatoes in P1, see an increase in their exports even as their production increases due to the adoption of new technologies.

The trade ratio for the cassava scenarios demonstrates a story similar to that of the previous sections. The uncontrolled infestation has a drastic effect, nearly doubling the share of imports with respect to production, with each increase in adoption of the mealybug control more closely approximating preinfestation levels.

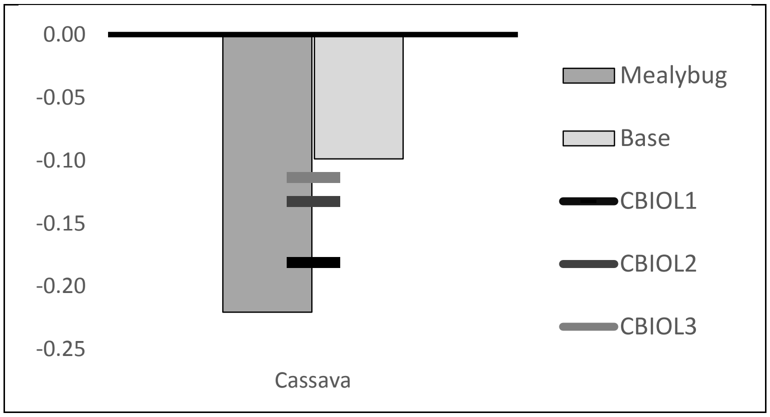
Figure 4.2 Change in commodity trade ratios (net trade over national production, percent difference from 2050 climate change baseline without the new technologies)



Source: Authors.

Notes: DHTY = drought and heat tolerant, high yield; DT = drought tolerant; DTHT = drought tolerant, heat tolerant; HT = heat tolerant. Refer to Table 2.1 for details of the regions where the various combinations of crop and "technology" (drought tolerance, heat tolerance, and so on) are simulated.

Figure 4.3 Change in the cassava trade ratio (net trade over national production, percent difference from 2050 climate change baseline without the new technologies)



Source: Authors.

Notes: The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

5. SUMMARY AND CONCLUSION

Climate change is already reducing crop yields in some parts of the world through changes in average temperatures, shifting precipitation patterns, and extreme events such as heat waves, droughts, and floods (Knox et al. 2012; Porter et al. 2014). Without adaptation, these impacts are projected to worsen with time. In this context, the long-term goal of the CGIAR Global Futures and Strategic Foresight (GFSF) program is to support decisionmaking in the agricultural sector by evaluating promising agricultural technologies and practices that support agricultural adaptation through improvements in productivity. At its core, the program evaluates technologies and practices through a system of linked economic, water, and crop simulation models.

In this study, the IMPACT system of models was used to assess the productivity-enhancing potential of new technologies selected by CGIAR centers for their high adaptive value. GFSF team members at CIMMYT, CIP, ICRISAT, and IRRI identified drought- and heat-tolerance traits in maize, wheat, potatoes, groundnut, sorghum, and rice as priorities. CIAT identified biotic stresses as the priority for cassava, focusing on mealybug control in Southeast Asia.

Summary of Results

In all cases analyzed in this report, the technologies led to improved production under both the NoCC and GFDL climate scenarios. In general the HT traits performed better than the DT traits, although in regions under greater water scarcity the DT traits approached the yield gains from the HT varieties. In the analyzed scenarios, the combined-trait varieties clearly performed better than the single-trait varieties. Given that climate change scenarios generally increase both water and heat stress, these results suggest that more work should be focused on integrating these traits to ensure more robust adaptation.

Productivity gains from adopting the analyzed technologies were relatively small when compared with the overall effects of socioeconomic change and general productivity improvements (IPRs) over the entire projection period (column 1, Table 4.1). Nevertheless, they were comparable in scale to the effects of climate observed under the GFDL RCP 8.5 climate scenario (Table 4.5). Additionally, the productivity gains observed in all of the technologies improved the regions' terms of trade (Figures 4.2 and 4.3). For importing regions, the share of imports compared with production declined, making the domestic supply of these commodities less reliant on global supply. For exporting regions, increased productivity led primarily to greater exports, making the agriculture sector relatively more competitive in global markets. These changes suggest that all of the adopting regions would be less vulnerable to global price shocks under these scenarios.

IMPACT is a global multimarket model, in which changes in domestic yields and areas respond to changes in aggregate global production and demand through equilibrium world prices. Scenarios with limited changes in world prices will see limited changes in areas, yields, trade, and food security. The global consequences of the different technology scenarios vary by crop and technology, in large part due to the total share of global production and the rate of adoption in the region. For example, the potato technologies analyzed show beneficial yield effects but have limited global impacts (world prices decrease by .04 to .22 percent) due to low adoption rates at the national level (Appendix D) despite the P1 region's producing a significant share of global production (Table 4.2). This is in contrast to the groundnut technologies, which caused world groundnut prices to decline by 1 to 5 percent due to the G1 region's relatively higher adoption rates coupled with its significant share of global production. It should be noted that scenarios with larger world price changes like the groundnut scenario will have more diffused benefits, whereas the benefits of a technology with limited price effects will likely be captured primarily by the adopting producers.

Reflections on Methodology

Due to the uncertain nature of projecting economic, social, political, and physical changes over many decades, it is necessary to test potential policies and alternative technologies across a wide set of climatic and economic conditions. The current study has chosen a relatively limited set of conditions to verify the response of the potential technologies to a drier and hotter global climate (SSP2 under two climates: NoCC and GFDL RCP 8.5). In the future, this methodology of linked models should be used to test the robustness of potential technologies by performing long-run analyses of scenarios that combine a range of different climatic and economic characteristics (for example, how do DT varieties perform under wetter conditions?).

As mentioned earlier, the current representation of climate change fails to capture interannual variability, which does not allow testing of the technologies under the extreme climate events that they are designed to mitigate. This lack of variability limits the potential of this methodology to assess the effects of any technology that is primarily risk reducing as opposed to yield enhancing. Future research should look at ways of adapting the current methodology to include climate variability, not only by increasing the number of climate scenarios (represented by RCPs and GCMs), but also by developing methods to represent the effects of weather variability at more refined time scales; the timing of extreme events is important because weather sensitivity varies across different stages of plant development.

The current methodology relies greatly on crop models to capture changes in crop productivity. These tools are powerful, and they allow the development of highly localized and specific scenarios that better capture the local effects of climate and soils. However, these models have weaknesses, which may limit the scenarios and technologies that can be easily tested. The highly detailed nature of these models requires detailed inputs as well as assumptions describing cultivar characteristics, management practices, and soil properties. Crop models do not incorporate economic drivers and therefore require assumptions on how the initial conditions could change over time. In many cases, these assumptions (nitrogen application, for example) may have larger effects than the technologies we are analyzing. Additionally, crop models currently do not capture changes in quality (appearance, taste, and so on) or nutritional composition. To test quality-enhancing technologies, we would need greater nutritional composition information out of the crop models as well as a more detailed food demand system in the multimarket model.

The global benefits of the potential technologies are sensitive to assumptions on adoption rates. Therefore it will also be necessary to test the technologies under a broader range of adoption pathways. This type of sensitivity testing has already been done to a limited extent in the cassava scenarios, but it would need to be extended to include greater variation in maximum adoptions, speed of adoption, and starting and ending dates of adoption for all of the technologies studied.[11]

There is a natural inclination to try to identify the technologies that provide the largest benefit. This methodology can be a potential tool in doing this type of analysis and research priority setting. However, scenario design will play a critical role in how satisfactorily these technologies can be compared and assessed in terms of their benefit. How we compare the benefits of a technology adopted in one region and crop under different adoption assumptions with its adoption in another region and crop is not straightforward. To facilitate this type of analysis it is necessary to control scenario design to limit the number of differences across the dimensions we are interested in. This is important because we need not only to quantify the differences in the scenario results but also to understand the root drivers of these differences. Trying to prioritize research across the range of regions and crops that this study has examined, for example, would be very difficult. The scenarios have greatly varying assumptions on adoption rates, with the regions selected often varying significantly in terms of expected climate effects (wheat in Argentina versus India for example) as well as economic conditions. Additionally, detailed analysis of the potential costs of developing, diffusing, and implementing the agricultural technologies would be needed. The current study has focused only on the benefit side of potential technologies, and

[11] These adoption pathways should also be tied back to the scenarios' socioeconomic assumptions to ensure they are logical and consistent with the overall scenario.

comparable work on technology costs and how they relate to adoption would be necessary for any prioritization of investments.

Next Steps

Experts agree that sustainable food security is a broad goal; to achieve it will require a combination of increases in agricultural productivity, reduction of waste and losses, more sustainable consumption patterns, and better food distribution worldwide (Garnett et al. 2013; Smith 2013). Productivity scenarios like the ones analyzed in this study can be useful policy tools to identify technologies that would impact global food production. The methodology developed for the Global Futures program provides a flexible framework to test and compare different production technologies in crop models as well as economic models. Additional traits can be identified and tested, such as C4 rice or crop varieties that have longer or shorter maturation periods, in addition to those examined here.

As our understanding of the possible adverse and positive impacts of climate change improves over time, scientists have started to better understand and address resulting changes in biotic stresses on crops. However, the magnitude of what we still do not know is troubling. We expect that a changing climate will affect the geographical range and distribution of pests, diseases, and weeds (Gornall et al. 2010; Paulson et al 2009; Deutsch et al 2008). New pests can emerge as a result of changes in complex ecological conditions: climate may affect crops' natural defenses, the interaction between these defenses and pests' life cycles, and the interaction between those and specific agricultural practices and technologies. Biotic stresses will need to be taken into consideration in the design of alternative climatic futures, to allow the testing of policy interventions that would make sense in response to changes in pests' prevalence or composition. These types of questions may be better approached, at least initially, in a more stylized way without the direct use of crop models, in much the same manner as was done for the cassava mealybug scenarios.

Improving productivity is only one area that needs to be examined. There may be large benefits from technologies and policies that do not focus exclusively on production, but instead consider access to and consumption of quality food. Scenarios that examine shifts in diet as a result of changes in sociodemographics, policy, and consumer preferences are also an important component of achieving food security globally. Scenarios focusing on questions revolving around food demand and utilization should extend beyond "overconsumption" in rich countries and should address complementary investments in infrastructure, education, and improved trade.

Continued improvement of the modeling system for long-term scenario analysis is a key component of the Global Futures and Strategic Foresight program. The current study has done much to advance the integration of crop, water, and economic models. The continued and strengthened involvement of experts and colleagues across the CGIAR network (and beyond) will be needed to ensure that the selected scenarios capture the most pressing concerns and questions, and the most promising solutions.

APPENDIX A: SUPPLEMENTARY METHODOLOGY

The DSSAT Suite of Crop Models

Crop Models

As a decision support tool, crop systems models have been showing potential at various levels of decision-making, from household (for example, irrigation scheduling in farmers' fields) to global (for example, identifying the potential breadbasket areas). Crop models mathematically describe the growth of a crop and its interaction with soils, climate, and management practices. Most modern crop models can quantify, on a daily basis, various biological processes of a crop (for example, the amount of solar energy transformed into biomass; water and nutrient requirements, supply, and stresses; and growth stages) as well as physical processes around the crop (for example, soil water runoff, soil carbon sequestration, and nitrogen leaching).

Since the early 1970s, various crop models have been developed by agricultural scientists based on improved knowledge of plant photosynthesis and respiration processes. Models range from generic and simple to specific and complex. Some models use response functions (for example, yield as a function of rainfall and nutrients) at their core, while others use sets of differential equations to describe the complexity of different processes and their interactions. There is no final and universal crop model—rather, crop models are selected based on the type of research question posed.

DSSAT Crop Systems Model

The DSSAT, or Decision Support System for Agrotechnology Transfer, is one of the most popular crop modeling software packages in the world. DSSAT is actually a suite of single crop models with access to the same crop, soil, and weather databases. The models integrate the effects of crop systems components and management options, to simulate the states of all the components of the cropping system and their interaction. DSSAT crop models provide a framework for users to understand how the overall cropping system and its components function throughout cropping season(s), on a day-to-day basis. Users are expected to provide at least a minimum set of data that are essential to run the crop model for each geographical location. The minimum dataset includes the following:

1. Site daily weather data for the duration of the growing season
2. Site soil data
3. Management and observed data from an experiment

Given the availability of the input dataset, DSSAT users can simulate single-season or multiseasonal outcomes of the crop management decisions for different crops at any location in the world.

DSSAT is one of the principal products developed by the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project supported by the US Agency for International Development from 1983 to 1993. It has subsequently continued to be developed through collaboration among scientists from multiple universities and international agricultural research institutes, and scientists associated with the International Consortium for Agricultural Systems Applications (ICASA).

Currently, DSSAT is a commercial open-source application, which provides source code to registered users. Adopting a modular modeling approach, many parts of crop models can be plugged in or removed by users as necessary. The main engine of DSSAT is written in the FORTRAN 90 programming language, originally compiled in a PC environment. With minimal changes in the source code, DSSAT can be also compiled and executed in any other operating system with a FORTRAN compiler.

The IMPACT Global Agriculture Simulation Model

Basic Multimarket Methodology

The multimarket trade model is a system of equations offering a methodology for analyzing baseline and alternative scenarios for global food demand, supply, trade, income, and population. The multimarket submodule encompasses 159 geopolitical regions and 154 hydrological basins in the world. The intersection of these two geographical layers creates 320 food production units (FPUs). IMPACT models 62 main agricultural commodities produced in the world. Within each region, supply, demand, and prices for agricultural commodities are determined. All regions are linked through trade. Supply and demand functions incorporate elasticities to approximate the underlying production and demand. World agricultural commodity prices are determined annually at levels that clear international markets.

Crop Production

Domestic crop production at the FPU level is determined by area and yield response functions separately for irrigated and rainfed cultivation. Harvested area is specified as a response to the crop's own price, the prices of other competing crops, the projected rate of exogenous (nonprice) growth trends in harvested area, and the climate stress. The projected exogenous trend in harvested area captures changes in area resulting from factors other than direct crop price effects, such as expansion through population pressure and contraction from soil degradation or conversion of land to nonagricultural uses. Assumptions for exogenous trends are determined by a combination of historical changes in land use and expert judgment on potential future regional dynamics.

Commodity yield is a function of the commodity prices, the prices of inputs, climate stress, and a projected nonprice exogenous trend factor. The trend factors, also called intrinsic productivity growth rates (IPRs), reflect productivity growth driven by technology improvements, including crop management research, conventional plant breeding, wide-crossing and hybridization breeding, and biotechnology and transgenic breeding. Other sources of growth considered include private-sector agricultural research and development, agricultural extension and education, markets, infrastructure, and irrigation. Annual production of a commodity in a country is then estimated as the product of its area and yield (Rosegrant and IMPACT Development Team 2012). The IPRs are specified as exogenous in the IMPACT model. We assume that these underlying trends vary by crop and region, and that they will decline somewhat over the next 50 years as the pace of technological improvements in developed countries slows, and as developing countries "catch up" to yields in developed countries.

Supply elasticities are broken out by area and yield elasticities. Crop area elasticities simulate the supply response to changes in own-commodity and competing-commodity prices. Own-price area elasticities of supply for most products in developing countries are approximately two-thirds of those in the developed countries, reflecting the difficulties that producers in developing countries face in access to markets, information, and technology. Crop yield elasticities simulate the supply response of cropping intensity with respect to changes in crop prices, the cost of labor, and the cost of inputs. The absolute values of yield elasticities with respect to own price, capital, and labor add up to the crop price elasticity.

Demand

Domestic demand for a commodity is the sum of its demand for food, feed, biofuels, crush, and other uses. Food demand is a function of the price of the commodity and the prices of other competing commodities, per capita income, and total population. Per capita income and population increase annually according to region-specific population and income growth rates. Population statistics and growth rates are drawn from IIASA projections. Regional income growth is based on the OECD projections. Feed demand is a derived demand determined by the changes in livestock production, feed ratios, and own- and cross-price effects of feed. The equation also incorporates a technology parameter that indicates improvements in feeding efficiencies. Demand for feedstock for biofuels production is derived from the implied demand among various alternatives for the development of ethanol and biodiesel. The crush demand for oilseeds for processing into oils is derived from the prices of the oil and meal by-product, the oilseed commodity, and the oil- and meal-processing ratios. The demand for other uses is estimated as a proportion of food and feed demand.

The IMPACT demand elasticities are originally based on USDA elasticities and adjusted to represent a synthesis of average, aggregate elasticities for each region, given the income level and distribution of urban and rural population (USDA 1998). Over time the elasticities are adjusted to accommodate the gradual shift in demand from staples to high-value commodities like meat, especially in developing countries, based on expert opinion. This assumption is based on expected economic growth, increased urbanization, and continued commercialization of the agricultural sector.

Prices

Prices are endogenous in the system of equations for food, and are calibrated to year 2005 commodity prices (OECD-AMAD 2010). Domestic prices are a function of world prices, adjusted by the effect of price policies and expressed in terms of the producer subsidy equivalent (PSE), the consumer subsidy equivalent (CSE), and the marketing margin (MI). PSEs and CSEs measure the implicit level of taxation or subsidy borne by producers or consumers relative to world prices and account for the wedge between domestic and world prices. PSEs and CSEs are based on OECD estimates and are adjusted by expert judgment to reflect regional trade dynamics (OECD 2000). MI reflects other factors such as transport and marketing costs of getting goods to market and is based on expert opinion on the quality and availability of transportation, communication, and market infrastructure. In the model, PSEs, CSEs, and MIs are expressed as percentages of the world price. To calculate producer prices, the world price is reduced by the MI value and increased by the PSE value. Consumer prices are obtained by adding the MI value to the world price and reducing it by the CSE. The MI of the intermediate prices is smaller because wholesale instead of retail prices are used, but intermediate prices (reflecting feed prices) are otherwise calculated in the same way as consumer prices.

International Linkage and Trade

Regional production and demand are linked to world markets through trade. Commodity trade by region is a function of domestic production, domestic demand, and stock change. Regions with positive trade are net exporters, while those with negative values are net importers. This specification does not permit a separate identification of both importing and exporting regions of a particular commodity.

Algorithm for Solving the Equilibrium Condition

The systems of equations for IMPACT are written in the General Algebraic Modeling System (GAMS) programming language (GAMS Development Corporation 2012). The solution of these equations is achieved by the PathNLP solver. This procedure minimizes the sum of net trade at the international level and seeks a world market price for a commodity that satisfies the market-clearing condition.

The world price (PW) of a commodity is the equilibrating mechanism such that when an exogenous shock is introduced in the model, PW will adjust and each adjustment is passed back to the effective producer (PS) and consumer (PD) prices via the price transmission equations.

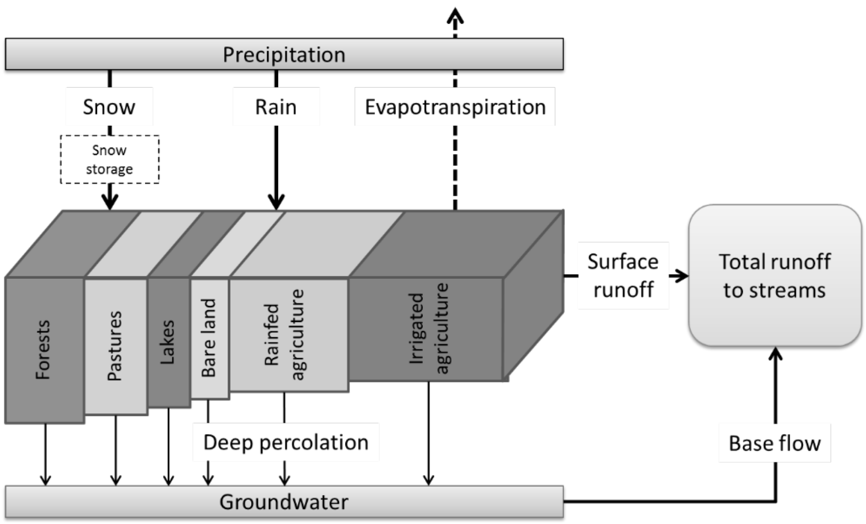
Changes in domestic prices subsequently affect commodity supply and demand, necessitating their iterative readjustments until world supply and demand balance and world net trade again equals zero.

IMPACT Water Simulation Models

IMPACT Global Hydrology Model

As described in the schematic of Figure A.1, the IGHM hydrological model is a semi-distributed parsimonious model. It simulates monthly soil moisture balance, evapotranspiration, and runoff generation on each 0.5 degree latitude by 0.5 degree longitude grid cell spanning the global land surface except the Antarctic. Gridded output of hydrological fluxes—namely effective rainfall, evapotranspiration, and runoff—are spatially aggregated to FPUs within the river basin and weighted by grid cell area.

Figure A.1 IMPACT Global Hydrology Model



Source: Authors.

The most important climatic drivers for water availability are precipitation and evaporative demand determined by net radiation at ground level, atmospheric humidity, wind speed, and temperature. In IGHM, the Priestley-Taylor equation (Priestley and Taylor 1972) is used to calculate potential evapotranspiration (PET). Soil moisture balance is simulated for each grid cell using a single-layer water bucket. To represent subgrid variability of soil water-holding capacity, we assume it spatially varies within each grid cell, following a parabolic distribution function.

Actual evapotranspiration is determined jointly by the PET and the relative soil moisture state in a grid cell. The generated runoff is divided into a surface runoff component and a deep percolation component using a partitioning factor. The base flow is linearly related to storage of the groundwater reservoir. The total runoff to the streams in a month is the sum of surface runoff and base flow.

IMPACT Water Basin Simulation Model

Water Demand

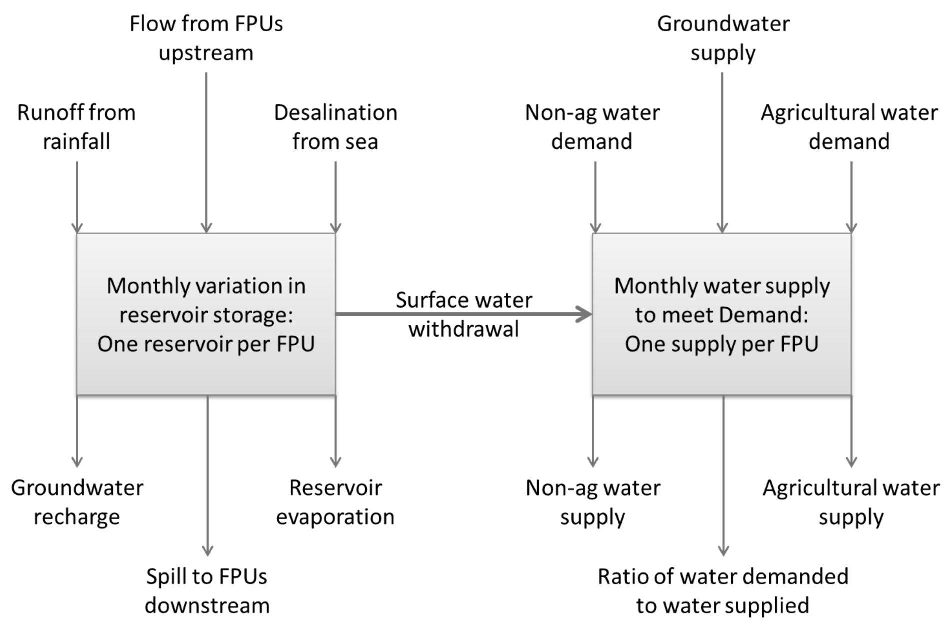
The water demand module calculates water demand for crops, industry, households, and livestock at the FPU level. Irrigation water demand is assessed as the portion of crop water requirement not satisfied by precipitation or soil moisture based on hydrologic and agronomic characteristics. Crop demand is calculated for each crop using evapotranspiration and effective rainfall from IGHM. It relies on the FAO crop coefficient approach (Allen et al. 1998) to calculate actual water demand for each crop for every month. The IMPACT model solves for the allocation of land to different crops, depending on output and input prices and agricultural technology. Total irrigation demand in the FPU is calculated given this cropping pattern and after taking into account the basin efficiency of the irrigation system.

Industrial water demand is modeled as a nonlinear function of GDP per capita and technology change. Future domestic water demands are based on projections of population and income growth. In each region or basin, income elasticities of demand for domestic water use are synthesized based on the literature and available estimates (de Fraiture 2007). These elasticities of demand measure the propensity to consume water with respect to increases in per capita income. The elasticities also capture both direct income effects and conservation of domestic water use through technological and management change. Livestock water demand is proportional to the number of animals raised as calculated by the multimarket model.

Water Supply

The IMPACT Water Basin Simulation Model (IWSM) is a water basin management model. For FPUs where there is water storage capacity (for example, dams), the model specifies a single reservoir that summarizes all water storage capacity and then manages that reservoir to maximize the ratio of water available to total water demand. IWSM uses the runoff calculated by IGHM, climatic data, and the water demands presented above to allocate available water to different uses. The schematic in Figure A.2 provides an overview of the model. In each FPU, IWSM solves for a balance between the change in the amount of water stored in the reservoirs, the entering water flows (runoff from precipitation, water from nontraditional sources like desalination, and inflows from FPUs situated upstream), the exiting water flows (groundwater recharge from the stream, evaporation from the reservoirs, outflows to the FPU downstream or the ocean), and the water withdrawn for human use (surface water depletion).

Figure A.2 The IMPACT Water Basin Simulation Model



Source: Authors.

Note: FPU = food production unit.

Surface water depletion, added to the pumped groundwater (which is limited by the monthly capacity of tube wells and other pumps) is used to meet the various water demands. The model solves by maximizing the ratio of water supplied to water demanded over a year in all FPUs. Solving for water demand and supply in all FPUs simultaneously, IWSM assumes that linked water basins are operated cooperatively, optimally allocating water between upstream and downstream demanders (qualified by imposing constraints on water delivery to downstream demanders). The model is parameterized to use available storage to smooth the distribution of water over months in order to avoid dramatic swings in monthly water delivery, if possible.

Following standard practice, IWSM incorporates the basic rule that nonagricultural water demands have priority over agricultural water demands. Any shortage in water supply is absorbed by agriculture first. If the shortage is larger than irrigation water demand, then livestock, domestic, and industrial supplies are reduced proportionally.

IMPACT Crop Water Allocation and Stress Model

The Water Allocation and Stress module (ICWASM) then allocates water among crops in an area, given the economic value of the crop. We use the FAO Ky approach (Doorenbos, Kassam, and Bentvelsen 1979) to measure water stress using a monthly approach to include seasonality of water stress. Because optimizing total value of production given fixed prices leads to a tendency for specializing in high-value crops, we include a measure of risk aversion for farmers in the objective function, which preserves a diversified production structure even in case of a drought. The stress model produces a measure of yield stress for every crop—both irrigated and rainfed—in each of the FPUs where that crop is grown. The yield stress for the base year is recorded and the model defines the yield shock for subsequent years as the ratio of that year's yield stress to the base-year yield stress. This method allows for a consistent modeling framework while making sure that the base-year yields from the multimarket model dataset are preserved.

Linking the IMPACT Water and Multimarket Models

The IMPACT model is solved dynamically (refer to Figure 2.1 in the main text of the report). First, the IMPACT multimarket model is solved for the current year assuming exogenous trends on various parameters, yielding projected production, prices, and allocation of land to crops. For this first run, expected water stress is set to the average of the previous four years, which sets harvest expectations for the allocation of land to different crops.

The water demand module then calculates water demand for crops, industry, households, and livestock. Agricultural and nonagricultural water demands are then calculated as outlined above. IWSM (Figure A.2) uses these water demands, along with river flows provided by IGHM (Figure A.1), to provide the monthly repartition of water among FPUs given the objective function described above.

ICWASM then allocates water among crops in an area, given the economic value of the crop. The stress model produces a measure of water stress on yield for every crop—both irrigated and rainfed—in each of the FPUs, which is then multiplied by the temperature stress obtained from DSSAT.

Finally, the new yield shocks are calculated and applied to the IMPACT multimarket model, which is solved a second time for the final equilibrium, but now assuming that the allocation of land to crops is fixed, since farmers cannot change their decisions after planting. This solution yields all economic variables, including quantities and prices of outputs and inputs, and all trade flows. The model then moves to the next year, updates various parameters on trend, and starts the process again.

Crop Modeling: Climate, Planting Period, and Soil Type Input Data

Climate data must ultimately drive the crop models. Monthly means were obtained at 0.5-arc-degree spatial resolution for four climate models through ISI-MIP for two time periods representing an interval around 2005 and 2055. These were used to apply a delta-method approach to the baseline/historical data from the FutureClim dataset (Jones, Thornton, and Heinke 2010), resulting in an internally consistent set of future conditions that are directly comparable to a common baseline. Daily weather realizations for 40 years were generated based on those monthly means.

Because crops must be planted at a particular time, rules were developed to identify reasonably appropriate planting months under climate change conditions. Within the designated planting month, the crop model is run for the 40 years of simulated weather with the planting date being on the first of the month, and another 40 times using the same weather but planting in the middle of the month. The resulting 80 yields are pooled to determine the overall average yields. This was done to reflect the observation that even in very similar locations, not all planting takes place simultaneously. Since no rule is going to be perfect, this process is repeated for the month prior to and the month after the target planting month. The final yield is taken as the highest of those three individual monthly average yields.

The remaining parameters can be thought of as two types: those likely to be different in each location and those defined once and applied in the same way in every location. We have already encountered the first example of site-specific data in the climate, weather, and planting month bundle. The soil type will also be different from location to location. We follow a generic soil profile approach known as HC27 (HarvestChoice 2010), whereby 27 soil profiles are generated ({sandy, loamy, clay} × {shallow, medium, deep} × {low, medium, high organic carbon}). Applying some simple rules to the Harmonized World Soil Data allowed us to choose which profile is most appropriate for each location. Another important spatially distributed input is the fertilizer application rate. In practice, this is defined at the country level with different values for rainfed and irrigated situations.

Linking DSSAT Crop Model Results to the IMPACT Model

Process-based crop simulation models can be used to explore the effect of various technologies/practices and climates on the mechanics of crop production. For instance, the models can simulate how yields may respond to varietal choice, soil management practices (for example residue retention, tillage depth), and length of growth period. The next level of assessment performed in this study is to consider these biophysical processes in conjunction with economic factors. Process-based crop models can simulate accurately the growth of particular crops, but provide no insight into the availability of a variety or technology and how farmers respond to medium- to long-term incentives. They are mechanical biophysical models containing no economic factors or inputs. The challenge is then to take both management and climate change effects simulated in crop models and incorporate them into economic models alongside price effects, general technological progress, and assumptions on adaptive behavior on the part of producers. The approach we use at IFPRI is to feed into IMPACT the responses of selected crops to climate, soil, and nutrients simulated by DSSAT. The yield simulations in DSSAT are performed on a geographic grid, whereas IMPACT operates on a regional basis (FPUs). Therefore, the first challenge is to transform the detailed gridded crop modeling results into a form compatible with that of the economic model. This transformation is accomplished using area-weighted average yields. The relative importance of each pixel is judged by the physical area allocated to the crop of interest by the Spatial Production Allocation Model (SPAM) (You, Wood, and Wood-Sichra 2006; You et al. 2014). The SPAM areas are summed in the FPU to determine a total crop area. Next, the SPAM areas are multiplied (pixel by pixel) by the DSSAT simulated yields, providing pixel-level production information. These are summed in the FPU to obtain the total simulated production. Based on these, the area-weighted average yield is just total production divided by total area. These yields are computed for all combinations of cases. These yields are then transferred to IMPACT and used to construct the “shifters” that are used in the simulations to reflect the climate change shock and the effects of technology adoption. All crop model results are applied in IMPACT using a delta method, meaning the changes in yields (deltas) observed in the crop models’ simulated yields are applied to the IMPACT yields.

We use this approach because it allows 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. Modeling technology adoption adds complexity to the traditional delta method used for climate change in that it adds choice. Farmers can’t choose whether or not climate change will happen; however, they can choose whether they will implement a new technology. This choice is influenced by biophysical (whether the new technology is better in a given farmer's field), economic (access to technology, cost of adoption, and so on), and individual (level of risk aversion) factors. To try to capture some of this complexity in the technology scenarios, we divide each FPU into two parts based on the biophysical potential of the new technology:

1. Nonadopters: The share of the FPU where no new technology adoption occurs (new technology does not improve crop yields), and the baseline technology continues to be used[12]
2. Potential adopters: The share of the FPU where adopting the new technology could be beneficial due to increased crop yields[13]

From DSSAT, we get the crop yields for nonadopters (baseline technology only) and for potential adopters (under the baseline and under the new technology). Even when the technology is beneficial compared with the baseline, not all potential adopters will adopt a new technology, because of economic and individual factors. Using the technology adoption curves in IMPACT, which represent the economic and individual preferences, we can calculate what share of the potential area of adoption is actually implementing the new technology at a given time *t*. The nonadopters have no additional effect from the technology because they remain with the baseline technology, whereas the potential adopters who adopt gain the benefit of the new technology, which is calculated as $TechDelta_t = \frac{TechYield_t}{BaselineYield_t}$, where *t* is the time period. This delta is applied as a yield multiplier in IMPACT in the following way:

$$Yield = YieldInt * CCShock * WaterModelShock * TechDelta * PriceEffect,$$

where *YieldInt* represents the intrinsic productivity growth rates (IPRs), *CCShock* is the climate shocks from the DSSAT model, *WaterModelShock* comes from the Water Model portion of IMPACT, and *PriceEffect* is the endogenous price effect simulated in IMPACT on the basis of the exogenous yields (the exogenous yields can be represented with the same equation, without the price effect component).

Climate change effects on crop production enter into IMPACT by altering both crop area and yield. Yields are altered through the intrinsic yield growth as well as the water availability coefficient for irrigated crops. The effects of climate change on productivity are obtained by calculating location-specific yields for each of the crops modeled with DSSAT for the climate scenarios in 2000 and 2050 (as described above). They are then converted to growth rates at the FPU level, which are used to shift the yield portion of the supply relationships for that FPU.

Positive-Only Impacts for Adoption Scenarios

Implementation of the chosen improved varieties in DSSAT results in pixels with both lower and higher yields. We assume that farmers implement the alternative varieties over many years only if yields are higher than under the "older" varieties. Thus, we include adoption of improved varieties only if the yield change from the reference case is positive. Otherwise, the baseline yields are used. This is why, as explained above, an FPU may have a share of adopters and one of nonadopters.

How Yields Can Be Changed in the IMPACT Model

The IMPACT model includes four ways for changes in yields to be achieved. At its base, the model assumes underlying improvements in yields over time that continue trends observed over the past 50–60 years (refer to Figure 4.1 in the main text). These long-run trends, or IPRs, are intended to reflect the expected increases in inputs as well as improvements in management practices, particularly in developing

[12] See also the section "Positive-Only Impacts for Adoption Scenarios," below.

[13] $Maximum\ Potential\ FPU\ Adoption = \frac{Area\ of\ Potential\ Adoption}{Total\ Area}$.

countries, where there is considerable scope to narrow the gap in yields compared with developed countries. These IPRs are exogenous to the model because they are part of the input data that go into the model, not a solution of the model itself. The IPRs are specified as exogenous in the IMPACT model. We assume that these underlying trends vary by crop and region, and that they will decline somewhat over the next 50 years as the pace of technological improvements in developed countries slows, and as developing countries "catch up" to yields in developed countries.

Second, the IMPACT model also includes a short-run (annual), endogenous response of yields to changes in output prices. These yield response functions specify the change in yield as a constant elasticity function of the change in output price, with elasticity parameters that can vary by crop and region. The underlying assumption is that farmers will respond to changes in prices by varying the use of inputs, including inputs such as fertilizer, chemicals, and labor that will, in turn, change yields.

Third, the IMPACT model includes the possibility of introducing new technologies such as varieties that are tolerant of drought, heat, or both. These are included as new crop- and region-specific "activities" in the model. We discussed the nature of these alternative crop varieties in Section 3 above; their impacts are described in more detail below. We assume (as part of the technology adoption scenarios) that the share of production that originates from using the new activities increases over time, following a logistic adoption function. Given these adoption functions, the effect of the new activities on average yields is exogenous in the multimarket model, but yields will be affected by climate shocks that vary over time (that is, different crop varieties will vary in their yield reaction to climate shocks).

Fourth, climate change is assumed to affect yields through two mechanisms. The first mechanism is through the effects of changes in temperature and "weather" due to climate change on the yields of rainfed and irrigated crops, as calculated from the solution of a crop simulation model (DSSAT) for different climate change scenarios. These crop simulations vary by crop type and include different treatments of new alternative crops. The DSSAT model is run with detailed time, geographic, and crop disaggregation for different climate change scenarios that are "downscaled" to include weather variation over small geographic areas. This analysis generates changes in average yields due to climate change, which are then averaged to generate yield shocks by crop and region (FPU) in the IMPACT model. These long-run climate scenario yield shocks are assumed to follow simple trends over time.

The second mechanism by which climate change affects yields is through variation in water availability for agriculture from year to year under different climate scenarios. This mechanism is modeled through the use of the IMPACT water models, which include a global hydrology model that determines runoff to the river basins (FPUs) included in the IMPACT model, and water basin management models for each FPU that allocate available water to competing uses, including irrigation. The water available for irrigation is then allocated to crops and, when water supply is less than demanded by crop, a "water stress" model computes the impact of the water shortage on crop yields (accounting for differences in impacts on alternative versus existing varieties). These yield shocks are then passed to the IMPACT model, affecting year-to-year crop yields.

APPENDIX B: IMPACT OF INTRINSIC PRODUCTIVITY GROWTH RATES ON BASELINE YIELDS

Table B.1 Impact of intrinsic productivity growth rates on baseline yields (percent change between 2050 and 2005)

		NoCC		CC	
Crop	**Country**	***Irrigated***	***Rainfed***	***Irrigated***	***Rainfed***
Maize	Angola	63.49	80.35	68.64	86.03
	Bangladesh	53.94	53.91	-3.31	-3.34
	Benin	189.88	92.18	198.06	116.12
	Ethiopia	25.28	15.8	34.2	23.6
	Ghana	100.4	74.4	109.81	111.97
	India	64.36	107.55	34.84	65.93
	Kenya	-31.26	-20.69	-30	-19.23
	Malawi	-33.41	-14.25	-39.87	-22.57
	Mali	104.08	69.37	109.17	73.22
	Mozambique	110.35	59.18	-7.31	32.73
	Nepal	53.32	22.87	17.56	-5.16
	Pakistan	68.08		33.9	
	Tanzania	-40.29	-31.32	-63.11	-58.04
	Uganda	78.16	96.18	89.78	108.97
	Zambia	38.98	55.5	45.09	62.33
	Zimbabwe	466.44	258.62	386.92	208.59
Wheat	Argentina	75.49	77.49	101.93	80.26
	India	9.14	0.75	-6.04	-14.7
	Iran	176.57	174.87	203.73	196.11
	Pakistan	49.29		27.93	
	South Africa	104.27	124.31	79.87	93.09
	Turkey	29.45	54.91	40.1	65.09
Rice	Bangladesh	40.08	43.36	34.03	36.92
	Cambodia	53.45	16.23	43.29	8.58
	India	34.84	9.57	10.23	-11.56
	Lao Republic	58.77	20.31	53.21	14.93
	Nepal	72.3	46.49	62.47	41.36
	Sri Lanka	89.18	71.53	79.38	26.35
	Thailand	46.01	46.99	35.72	35.21
Potatoes	Bangladesh	64.25	22.84	57.51	16.24
	China	39.53	4.83	42.4	6.73
	India	27.86	-8.02	30.37	-8.36
	Kyrgyzstan	67.58	67.43	78.46	72.59
	Nepal	46.21	18.21	48.56	21.84
	Pakistan	34.98		24.76	
	Tajikistan	45.38	16.4	-45.39	-56.74
	Uzbekistan	59.77	18.93	62.72	20.68
	Vietnam	23.63	-0.82	25.46	-1.32

Table B.1 Continued

		NoCC		CC	
Crop	**Country**	**Irrigated**	**Rainfed**	**Irrigated**	**Rainfed**
Sorghum	Burkina Faso	55.81	71.31	57.36	72.82
	Eritrea	-8.02	1.17	-7.50	1.75
	Ethiopia	75.13	87.19	99.40	112.74
	India	73.63	61.85	30.58	32.76
	Mali	139.33	176.39	121.87	153.97
	Nigeria		85.72		75.60
	Sudan	223.85	33.21	116.91	4.83
	Tanzania	24.85	38.41	26.14	39.87
Groundnut	Burkina Faso		82.15		16.53
	Ghana	-0.82	9.21	3.55	14.02
	India	2.33	0.17	-13.22	-16.33
	Malawi	17.81	18.5	18.42	19.11
	Mali	52.69	26.95	56.73	29.02
	Myanmar	23.1	16.07	25.36	18.2
	Niger	71.29	7.87	64.34	4.32
	Nigeria	38.28	33.74	36.33	30.87
	Tanzania	257.24	-10.8	264.13	-8.55
	Uganda	161.09	2.2	178.95	9.19
	Vietnam	30.81	5.98	16.10	-5.69

Source: Authors.

Notes: CC = climate change; NoCC = assumed constant climate.

APPENDIX C: ADOPTION RATES FOR EACH CROP, BY TECHNOLOGY AND COUNTRY

Table C.1 Adoption rates for each crop, by technology and country

Crop	Technology	Country	Start year	End year	Max adoption	Irrigated max adoption	Rainfed max adoption	Median year
Maize	Drought tolerance	Angola	2013	2050	30%		29.90%	2021
Maize	Drought tolerance	Benin	2013	2050	30%		29.78%	2021
Maize	Drought tolerance	Ethiopia	2013	2050	30%	30.00%	30.00%	2021
Maize	Drought tolerance	Ghana	2013	2050	30%		22.72%	2021
Maize	Drought tolerance	Kenya	2013	2050	30%		30.00%	2021
Maize	Drought tolerance	Malawi	2013	2050	30%	30.00%	30.00%	2021
Maize	Drought tolerance	Mali	2013	2050	30%		29.53%	2021
Maize	Drought tolerance	Mozambique	2013	2050	30%	27.41%	29.55%	2021
Maize	Drought tolerance	Tanzania	2013	2050	30%	30.00%	30.00%	2021
Maize	Drought tolerance	Uganda	2013	2050	30%		30.00%	2021
Maize	Drought tolerance	Zambia	2013	2050	30%		30.00%	2021
Maize	Drought tolerance	Zimbabwe	2013	2050	30%	30.00%	30.00%	2021
Maize	Heat tolerance	Bangladesh	2017	2032	30%	30.00%		2022
Maize	Heat tolerance	India	2017	2032	30%	30.00%	30.00%	2022
Maize	Heat tolerance	Nepal	2017	2032	30%	30.00%	30.00%	2022
Maize	Heat tolerance	Pakistan	2017	2032	30%	30.00%		2022
Wheat	Drought tolerance	Iran	2015	2050	35%	32.14%	33.50%	2023
Wheat	Drought tolerance	Turkey	2015	2050	35%	35.00%	35.00%	2023
Wheat	Heat tolerance	India	2020	2050	30%	29.35%		2028
Wheat	Heat tolerance	Pakistan	2020	2050	30%	30.00%		2028
Wheat	Drought and heat tolerance with high yield	Argentina	2022	2050	30%	29.35%	30.00%	2027
Wheat	Drought and heat tolerance with high yield	South Africa	2022	2050	30%	28.10%	30.00%	2027

Table C.1 Continued

Crop	Technology	Country	Start year	End year	Max adoption	Irrigated max adoption	Rainfed max adoption	Median year
Rice	Drought tolerance	Bangladesh	2015	2040	25%	0.13%	25.00%	2030
Rice	Drought tolerance	Cambodia	2015	2040	21%	12.50%	21.00%	2030
Rice	Drought tolerance	India	2015	2040	35%	21.81%	35.00%	2030
Rice	Drought tolerance	Lao Republic	2015	2040	16%	0.38%	16.00%	2030
Rice	Drought tolerance	Nepal	2015	2040	16%		16.00%	2030
Rice	Drought tolerance	Sri Lanka	2015	2040	40%	10.54%	40.00%	2030
Rice	Drought tolerance	Thailand	2015	2040	40%	1.85%	32.94%	2030
Potatoes	Drought tolerance	Bangladesh	2024	2034	4%	4.00%	4.00%	2029
Potatoes	Drought tolerance	China	2024	2034	4%		3.91%	2029
Potatoes	Drought tolerance	India	2024	2034	10%		10.00%	2029
Potatoes	Drought tolerance	Kyrgyzstan	2024	2034	20%	20.00%	20.00%	2029
Potatoes	Drought tolerance	Nepal	2024	2034	20%		20.00%	2029
Potatoes	Drought tolerance	Pakistan	2024	2034	10%	10.00%		2029
Potatoes	Drought tolerance	Tajikistan	2024	2034	30%	30.00%		2029
Potatoes	Drought tolerance	Uzbekistan	2024	2034	40%		40.00%	2029
Potatoes	Drought tolerance	Vietnam	2024	2034	20%		20.00%	2029
Potatoes	Heat tolerance	Bangladesh	2024	2034	4%		4.00%	2029
Potatoes	Heat tolerance	China	2024	2034	4%		3.10%	2029
Potatoes	Heat tolerance	India	2024	2034	10%		9.93%	2029
Potatoes	Heat tolerance	Kyrgyzstan	2024	2034	20%	20.00%	20.00%	2029
Potatoes	Heat tolerance	Nepal	2024	2034	20%		20.00%	2029
Potatoes	Heat tolerance	Pakistan	2024	2034	10%			2029
Potatoes	Heat tolerance	Tajikistan	2024	2034	40%	22.93%		2029
Potatoes	Heat tolerance	Uzbekistan	2024	2034	30%		30.00%	2029
Potatoes	Heat tolerance	Vietnam	2024	2034	20%		7.69%	2029

Table C.1 Continued

Crop	Technology	Country	Start year	End year	Max adoption	Irrigated max adoption	Rainfed max adoption	Median year
Potatoes	Drought and heat tolerance	Bangladesh	2024	2034	4%	4.00%	4.00%	2029
Potatoes	Drought and heat tolerance	China	2024	2034	4%		3.10%	2029
Potatoes	Drought and heat tolerance	India	2024	2034	10%		10.00%	2029
Potatoes	Drought and heat tolerance	Kyrgyzstan	2024	2034	20%	20.00%	20.00%	2029
Potatoes	Drought and heat tolerance	Nepal	2024	2034	20%		20.00%	2029
Potatoes	Drought and heat tolerance	Pakistan	2024	2034	10%	10.00%		2029
Potatoes	Drought and heat tolerance	Tajikistan	2024	2034	40%	40.00%		2029
Potatoes	Drought and heat tolerance	Uzbekistan	2024	2034	30%		30.00%	2029
Potatoes	Drought and heat tolerance	Vietnam	2024	2034	20%		10.93%	2029
Sorghum	Drought tolerance	Burkina Faso	2023	2037	20%		20.00%	2030
Sorghum	Drought tolerance	Eritrea	2023	2035	40%		40.00%	2029
Sorghum	Drought tolerance	Ethiopia	2023	2035	40%	40.00%	40.00%	2029
Sorghum	Drought tolerance	India	2023	2032	80%	80.00%	80.00%	2028
Sorghum	Drought tolerance	Mali	2023	2035	50%	48.60%	50.00%	2029
Sorghum	Drought tolerance	Nigeria	2023	2035	60%		60.00%	2029
Sorghum	Drought tolerance	Sudan	2023	2038	20%	19.53%	20.00%	2033
Sorghum	Drought tolerance	Tanzania	2023	2035	40%		40.00%	2029
Groundnut	Drought tolerance	Burkina Faso	2024	2040	40%		40.00%	2033
Groundnut	Drought tolerance	Ghana	2024	2040	40%		40.00%	2033
Groundnut	Drought tolerance	India	2024	2035	60%	54.94%	60.00%	2030
Groundnut	Drought tolerance	Malawi	2024	2040	60%		60.00%	2033
Groundnut	Drought tolerance	Mali	2024	2040	50%		50.00%	2033
Groundnut	Drought tolerance	Myanmar	2024	2035	40%		40.00%	2030
Groundnut	Drought tolerance	Niger	2024	2040	40%		40.00%	2033
Groundnut	Drought tolerance	Nigeria	2024	2040	60%		60.00%	2033
Groundnut	Drought tolerance	Tanzania	2024	2040	40%		40.00%	2033
Groundnut	Drought tolerance	Uganda	2024	2040	60%		60.00%	2033
Groundnut	Drought tolerance	Vietnam	2024	2035	50%	45.91%	50.00%	2030

Table C.1 Continued

Crop	Technology	Country	Start year	End year	Max adoption	Irrigated max adoption	Rainfed max adoption	Median year
Groundnut	Heat tolerance	Burkina Faso	2024	2040	40%		40.00%	2033
Groundnut	Heat tolerance	Ghana	2024	2040	40%		40.00%	2033
Groundnut	Heat tolerance	India	2024	2035	60%	60.00%	60.00%	2030
Groundnut	Heat tolerance	Malawi	2024	2040	60%		60.00%	2033
Groundnut	Heat tolerance	Mali	2024	2040	50%		50.00%	2033
Groundnut	Heat tolerance	Myanmar	2024	2035	40%		39.62%	2030
Groundnut	Heat tolerance	Niger	2024	2040	40%		40.00%	2033
Groundnut	Heat tolerance	Nigeria	2024	2040	60%		60.00%	2033
Groundnut	Heat tolerance	Tanzania	2024	2040	40%		40.00%	2033
Groundnut	Heat tolerance	Uganda	2024	2040	60%		60.00%	2033
Groundnut	Heat tolerance	Vietnam	2024	2035	50%	50.00%	50.00%	2030
Groundnut	Drought and heat tolerance	Burkina Faso	2024	2040	40%		40.00%	2033
Groundnut	Drought and heat tolerance	Ghana	2024	2040	40%		40.00%	2033
Groundnut	Drought and heat tolerance	India	2024	2035	60%	60.00%	60.00%	2030
Groundnut	Drought and heat tolerance	Malawi	2024	2040	60%		60.00%	2033
Groundnut	Drought and heat tolerance	Mali	2024	2040	50%		50.00%	2033
Groundnut	Drought and heat tolerance	Myanmar	2024	2035	40%		40.00%	2030
Groundnut	Drought and heat tolerance	Niger	2024	2040	40%		40.00%	2033
Groundnut	Drought and heat tolerance	Nigeria	2024	2040	60%		60.00%	2033
Groundnut	Drought and heat tolerance	Tanzania	2024	2040	40%		40.00%	2033
Groundnut	Drought and heat tolerance	Uganda	2024	2040	60%		60.00%	2033
Groundnut	Drought and heat tolerance	Vietnam	2024	2035	50%	50.00%	50.00%	2030

Source: Authors.

APPENDIX D: EXOGENOUS AND ENDOGENOUS COUNTRY-LEVEL RESULTS: TECHNOLOGY ADOPTION SCENARIOS

Table D.1 Exogenous yield change (percent) from technology adoption compared with base (2050 climate change)

Crop	Technology	Country	Irrigated	Rainfed
Maize	Drought tolerance	Angola	0.00	11.72
		Benin	0.00	10.87
		Ethiopia	37.13	5.50
		Ghana	0.00	7.84
		Kenya	0.00	113.61
		Mali	0.00	7.38
		Mozambique	13.68	43.20
		Malawi	3.22	3.12
		Tanzania	126.08	114.50
		Uganda	0.00	64.98
		Zambia	0.00	18.66
		Zimbabwe	1.25	3.22
	Heat tolerance	Bangladesh	142.90	0.00
		India	43.67	41.47
		Nepal	44.76	80.67
		Pakistan	178.34	0.00
Wheat	Drought tolerance	Iran	0.21	7.24
		Turkey	0.25	5.16
	Heat tolerance	India	4.13	0.00
		Pakistan	9.13	0.00
	Heat tolerance with drought tolerance	Argentina	0.37	9.38
		South Africa	13.61	11.69
Rice	Drought tolerance	Bangladesh	0.02	0.59
		India	0.95	1.59
		Cambodia	0.02	0.72
		Lao Republic	0.01	0.63
		Sri Lanka	0.01	3.54
		Nepal	0.00	0.46
		Thailand	0.01	0.93
Potatoes	Drought tolerance	Bangladesh	0.57	18.24
		China	0.00	4.79
		India	0.00	10.75
		Kyrgyzstan	5.36	8.75
		Nepal	0.00	9.73
		Pakistan	1.47	0.00
		Tajikistan	0.91	0.00
		Uzbekistan	0.00	15.43
		Vietnam	0.00	9.12

Table D.1 Exogenous yield change (percent) from technology adoption compared with base (2050 climate change)

Crop	Technology	Country	Irrigated	Rainfed
Potatoes	Heat tolerance	Bangladesh	0.00	0.40
		China	0.00	4.81
		India	0.00	0.80
		Kyrgyzstan	6.31	1.09
		Nepal	0.00	2.08
		Tajikistan	0.42	0.00
		Uzbekistan	0.00	0.78
		Vietnam	0.00	7.26
	Heat tolerance with drought tolerance	Bangladesh	1.14	17.81
		China	0.00	9.17
		India	0.00	11.31
		Kyrgyzstan	71.69	9.70
		Nepal	0.00	10.53
		Pakistan	1.47	0.00
		Tajikistan	46.27	0.00
		Uzbekistan	0.00	15.78
		Vietnam	0.00	14.51
Sorghum	Drought tolerance	Burkina Faso	0.00	3.27
		Eritrea	0.00	144.06
		Ethiopia	4.65	1.83
		India	0.17	2.14
		Mali	0.74	1.31
		Nigeria	0.00	0.82
		Sudan	1.89	2.80
		Tanzania	0.00	110.10
Groundnut	Drought tolerance	Burkina Faso	0.00	6.43
		Ghana	0.00	20.67
		India	0.31	4.49
		Mali	0.00	16.55
		Myanmar	0.00	0.99
		Malawi	0.00	10.39
		Niger	0.00	9.31
		Nigeria	0.00	4.11
		Tanzania	0.00	9.99
		Uganda	0.00	4.99
		Vietnam	0.07	1.87

Table D.1 Continued

Crop	Technology	Country	Irrigated	Rainfed
Groundnut	Heat tolerance	Burkina Faso	0.00	12.14
		Ghana	0.00	23.24
		India	11.96	8.19
		Mali	0.00	9.86
		Myanmar	0.00	4.31
		Malawi	0.00	0.54
		Niger	0.00	22.82
		Nigeria	0.00	5.64
		Tanzania	0.00	0.95
		Uganda	0.00	1.36
		Vietnam	9.04	6.35
	Drought and heat tolerance with high yield	Burkina Faso	0.00	33.21
		Ghana	0.00	44.86
		India	27.15	27.14
		Mali	0.00	42.99
		Myanmar	0.00	18.39
		Malawi	0.00	26.51
		Niger	0.00	50.03
		Nigeria	0.00	22.81
		Tanzania	0.00	25.88
		Uganda	0.00	19.94
		Vietnam	22.10	21.21

Source: Authors.

Table D.2 Endogenous average yield changes (percent difference of technology from base) when price feedbacks are included (2050 climate change)

Crop	Technology	Country	Irrigated	Rainfed
Maize	Drought tolerance	Angola		8.10
		Benin		3.10
		Ethiopia	10.72	1.54
		Ghana		1.64
		Kenya		112.07
		Mali		2.08
		Mozambique	0.27	30.76
		Malawi	0.81	0.78
		Tanzania	75.62	69.02
		Uganda		62.42
		Zambia		15.00
		Zimbabwe	0.23	0.82

Table D.2 Continued

Crop	Technology	Country	Irrigated	Rainfed
Maize	Heat tolerance	Bangladesh	42.71	
		India	13.29	12.50
		Nepal	13.32	24.08
		Pakistan	52.67	
Wheat	Drought tolerance	Iran	0.05	2.43
		Turkey	0.07	1.79
	Heat tolerance	India	1.07	
		Pakistan	0.47	
	Heat tolerance with drought tolerance	Argentina	0.14	2.80
		South Africa	5.32	3.54
Rice	Drought tolerance	Bangladesh	-0.01	0.14
		India	0.05	0.54
		Cambodia	0.00	0.15
		Lao Republic	0.00	0.10
		Sri Lanka	0.00	1.44
		Nepal		0.07
		Thailand	0.00	0.32
Potatoes	Drought tolerance	Bangladesh	-0.01	0.70
		China		0.16
		India		1.04
		Kyrgyzstan	1.53	1.72
		Nepal		1.92
		Pakistan	0.18	
		Tajikistan	0.24	
		Uzbekistan		6.14
		Vietnam		1.80
	Heat tolerance	Bangladesh		0.00
		China		0.12
		India		0.06
		Kyrgyzstan	1.73	0.21
		Nepal		0.41
		Pakistan	0.08	
		Tajikistan		0.22
		Uzbekistan		0.60
		Vietnam	-0.02	0.65

Table D.2 Continued

Crop	Technology	Country	Irrigated	Rainfed
Potatoes	Heat tolerance with drought tolerance	Bangladesh		0.20
		China		1.06
		India	14.72	1.88
		Kyrgyzstan		2.05
		Nepal	0.15	
		Pakistan	18.43	
		Tajikistan		4.67
		Uzbekistan		1.55
		Vietnam		4.07
Sorghum	Drought tolerance	Burkina Faso		151.53
		Eritrea	1.18	0.31
		Ethiopia	-0.27	1.30
		India	-0.06	0.22
		Mali		0.14
		Nigeria	-0.42	0.13
		Sudan		118.00
		Tanzania	-0.01	0.70
Groundnut	Drought tolerance	Burkina Faso		2.41
		Ghana		16.91
		India	0.16	2.55
		Mali		8.11
		Myanmar		0.29
		Malawi		6.04
		Niger		3.58
		Nigeria		2.35
		Tanzania		3.80
		Uganda		2.79
		Vietnam	-0.09	0.81
	Heat tolerance	Burkina Faso		4.59
		Ghana		17.87
		India	7.14	4.81
		Mali		4.70
		Myanmar		1.57
		Malawi		0.05
		Niger		8.89
		Nigeria		3.20
		Tanzania		0.11
		Uganda		0.55
		Vietnam	4.24	3.00

Table D.2 Continued

Crop	Technology	Country	Irrigated	Rainfed
Groundnut	Drought tolerance with high yield	Burkina Faso		12.46
		Ghana		25.96
		India	15.75	15.70
		Mali		20.67
		Myanmar		6.86
		Malawi		14.96
		Niger		19.23
		Nigeria		13.07
		Tanzania		9.45
		Uganda		11.03
		Vietnam	10.38	10.03

Source: Authors.

Table D.3 Endogenous changes in production between technology and base by crop, technology, and country, 2050 climate change

Crop	Technology	Country	Irrigated	Rainfed
Maize	Drought tolerance	Angola		7.86
		Benin		2.93
		Ethiopia	10.5	1.36
		Ghana		1.46
		Kenya		111.69
		Mali		1.89
		Mozambique	0.12	30.44
		Malawi	0.64	0.57
		Tanzania	75.29	68.7
		Uganda		62.06
		Zambia		14.76
		Zimbabwe	0.12	0.64
	Heat tolerance	Bangladesh	42.62	
		India	13.08	12.14
		Nepal	13.19	23.88
		Pakistan	52.45	
Wheat	Drought tolerance	Iran	0.04	2.41
		Turkey	0.05	1.76
	Heat tolerance	India	1.03	
		Pakistan	0.41	
	Heat tolerance with drought tolerance	Argentina	0.09	2.73
		South Africa	5.12	3.24

Table D.3 Continued

Crop	Technology	Country	Irrigated	Rainfed
Rice	Drought tolerance	Bangladesh	-0.01	0.14
		India	0.04	0.51
		Cambodia	0	0.14
		Lao Republic	0	0.09
		Sri Lanka	-0.01	1.42
		Nepal		0.06
		Thailand	-0.01	0.31
Potatoes	Drought tolerance	Bangladesh	-0.03	0.65
		China		0.12
		India		0.99
		Kyrgyzstan	1.51	1.68
		Nepal		1.88
		Pakistan	0.16	
		Tajikistan	0.22	
		Uzbekistan		6.11
		Vietnam		1.76
	Heat tolerance	Bangladesh		-0.01
		China		0.11
		India		0.04
		Kyrgyzstan	1.72	0.18
		Nepal		0.39
		Tajikistan	0.08	
		Uzbekistan		0.21
		Vietnam		0.59
	Heat tolerance with drought tolerance	Bangladesh	-0.06	0.56
		China		0.13
		India		0.96
		Kyrgyzstan	14.68	1.8
		Nepal		1.97
		Pakistan	0.11	
		Tajikistan	18.39	
		Uzbekistan		4.6
		Vietnam		1.48
Sorghum	Drought tolerance	Burkina Faso		3.15
		Eritrea		149.7
		Ethiopia	0.52	-0.82
		India	-0.95	0.13
		Mali	-0.71	-0.75
		Nigeria		-1.18
		Sudan	-0.68	-0.39
		Tanzania		114.3

Table D.3 Continued

Crop	Technology	Country	Irrigated	Rainfed
Groundnut	Drought tolerance	Burkina Faso		1.86
		Ghana		16.38
		India	-0.13	2.01
		Mali		7.57
		Myanmar		-0.21
		Malawi		5.27
		Niger		2.98
		Nigeria		1.64
		Tanzania		2.96
		Uganda		1.95
		Vietnam	-0.35	0.32
	Heat tolerance	Burkina Faso		3.83
		Ghana		17.01
		India	6.73	4.15
		Mali		4.02
		Myanmar		0.88
		Malawi		-0.97
		Niger		8.07
		Nigeria		2.2
		Tanzania		-1.02
		Uganda		-0.6
		Vietnam	3.86	2.34
	Drought and heat tolerance with high yield	Burkina Faso		9.92
		Ghana		22.34
		India	14.37	13.38
		Mali		18.2
		Myanmar		4.64
		Malawi		11.48
		Niger		16.38
		Nigeria		9.73
		Tanzania		5.68
		Uganda		7.17
		Vietnam	9.13	7.86

Source: Authors.

Table D.4 Endogenous changes in harvested area between technology and base by crop, technology, and country, 2050 climate change

Crop	Technology	Country	Irrigated	Rainfed
Maize	Drought tolerance	Angola	-0.15	-0.23
		Benin	-0.10	-0.16
		Ethiopia	-0.20	-0.18
		Ghana	-0.10	-0.18
		Kenya	-0.11	-0.18
		Mali	-0.10	-0.19
		Mozambique	-0.15	-0.24
		Malawi	-0.17	-0.21
		Tanzania	-0.19	-0.19
		Uganda	-0.11	-0.22
		Zambia	-0.11	-0.21
		Zimbabwe	-0.11	-0.18
	Heat tolerance	Bangladesh	-0.06	-0.13
		India	-0.18	-0.32
		Nepal	-0.11	-0.16
		Pakistan	-0.14	
Wheat	Drought tolerance	Iran	-0.02	-0.03
		Turkey	-0.02	-0.03
	Heat tolerance	India	-0.04	-0.09
		Pakistan	-0.06	
	Heat tolerance with drought tolerance	Argentina	-0.04	-0.07
		South Africa	-0.19	-0.29
Rice	Drought tolerance	Bangladesh	0.00	-0.01
		India	-0.01	-0.03
		Cambodia	0.00	0.00
		Lao Republic	0.00	0.00
		Sri Lanka	0.00	-0.01
		Nepal	0.00	-0.01
		Thailand	0.00	-0.01
Potatoes	Drought tolerance	Bangladesh	-0.02	-0.04
		China	-0.02	-0.04
		India	-0.03	-0.05
		Kyrgyzstan	-0.02	-0.04
		Nepal	-0.02	-0.04
		Pakistan	-0.02	
		Tajikistan	-0.02	-0.03
		Uzbekistan	-0.02	-0.03
		Vietnam	-0.02	-0.04

Table D.4 Continued

Crop	Technology	Country	Irrigated	Rainfed
Potatoes	Heat tolerance	Bangladesh	-0.01	-0.02
		China	-0.01	-0.01
		India	-0.01	-0.02
		Kyrgyzstan	-0.01	-0.02
		Nepal	-0.01	-0.02
		Pakistan	-0.01	
		Tajikistan	-0.01	-0.01
		Uzbekistan	-0.01	-0.01
		Vietnam	-0.01	-0.01
	Heat tolerance with drought tolerance	Bangladesh	-0.04	-0.08
		China	-0.04	-0.07
		India	-0.05	-0.10
		Kyrgyzstan	-0.04	-0.07
		Nepal	-0.04	-0.08
		Pakistan	-0.04	
		Tajikistan	-0.03	-0.06
		Uzbekistan	-0.03	-0.06
		Vietnam	-0.04	-0.07
Sorghum	Drought tolerance	Burkina Faso	-0.55	-0.88
		Eritrea	-0.16	-0.73
		Ethiopia	-0.66	-1.12
		India	-0.68	-1.16
		Mali	-0.64	-0.96
		Nigeria		-1.32
		Sudan	-0.26	-0.53
		Tanzania	-0.89	-1.70
Groundnut	Drought tolerance	Burkina Faso		-0.53
		Ghana	0.16	-0.45
		India	-0.29	-0.53
		Mali	-0.29	-0.50
		Myanmar	-0.25	-0.50
		Malawi	-0.35	-0.73
		Niger	-0.28	-0.57
		Nigeria	-0.12	-0.70
		Tanzania	-0.41	-0.81
		Uganda	-0.41	-0.81
		Vietnam	-0.26	-0.48

Table D.4 Continued

Crop	Technology	Country	Irrigated	Rainfed
Groundnut	Heat tolerance	Burkina Faso		-0.73
		Ghana	0.07	-0.73
		India	-0.38	-0.64
		Mali	-0.41	-0.65
		Myanmar	-0.34	-0.68
		Malawi	-0.49	-1.02
		Niger	-0.36	-0.76
		Nigeria	-0.13	-0.97
		Tanzania	-0.57	-1.13
		Uganda	-0.57	-1.14
		Vietnam	-0.37	-0.64
	Drought and heat tolerance with high yield	Burkina Faso		-2.26
		Ghana	-0.73	-2.88
		India	-1.19	-2.01
		Mali	-1.27	-2.05
		Myanmar	-1.05	-2.08
		Malawi	-1.43	-3.03
		Niger	-1.17	-2.39
		Nigeria	-0.30	-2.96
		Tanzania	-1.77	-3.45
		Uganda	-1.76	-3.48
		Vietnam	-1.13	-1.98

Source: Authors.

Table D.5 Endogenous changes in trade as a ratio of net trade over national production—by crop, technology, and country, 2050 climate change

Crop	Technology	Country	Trade Index
Maize	Drought tolerance	Angola	-0.63
		Benin	0.13
		Ethiopia	-0.93
		Ghana	-1.07
		Kenya	-0.64
		Mali	-0.97
		Mozambique	-0.46
		Malawi	-3.57
		Tanzania	-3.08
		Uganda	-0.35
		Zambia	-1.04
		Zimbabwe	0.49
	Heat tolerance	Bangladesh	-0.67
		India	-1.41
		Nepal	-0.81
		Pakistan	0.26

Table D.5 Continued

Crop	Technology	Country	Trade Index
Wheat	Drought tolerance	Argentina	0.75
		South Africa	-0.36
	Heat tolerance	Iran	0.54
		Turkey	0.19
	Heat tolerance with drought tolerance	India	-0.22
		Pakistan	-0.39
Rice	Drought tolerance	Bangladesh	0.07
		India	0.04
		Cambodia	0.10
		Lao Republic	0.26
		Sri Lanka	0.44
		Nepal	-0.21
		Thailand	0.48
Potatoes	Drought tolerance	Bangladesh	-0.43
		China	0.06
		India	-0.02
		Kyrgyzstan	0.53
		Nepal	-0.58
		Pakistan	-0.28
		Tajikistan	0.10
		Uzbekistan	0.26
		Vietnam	-0.22
	Heat tolerance	Bangladesh	-0.43
		China	0.06
		India	-0.02
		Kyrgyzstan	0.48
		Nepal	-0.58
		Pakistan	-0.28
		Tajikistan	-0.04
		Uzbekistan	0.27
		Vietnam	-0.22
	Heat tolerance with drought tolerance	Bangladesh	-0.43
		China	0.06
		India	-0.02
		Kyrgyzstan	0.48
		Nepal	-0.60
		Pakistan	-0.28
		Tajikistan	-0.05
		Uzbekistan	0.26
		Vietnam	-0.23

Table D.5 Continued

Crop	Technology	Country	Trade Index
Sorghum	Drought tolerance	Burkina Faso	-0.11
		Eritrea	0.07
		Ethiopia	-0.02
		India	-0.18
		Mali	0.31
		Nigeria	-0.63
		Sudan	0.07
		Tanzania	0.49
Groundnut	Drought tolerance	Burkina Faso	0.43
		Ghana	0.27
		India	0.17
		Mali	0.20
		Myanmar	0.32
		Malawi	-0.17
		Niger	-0.67
		Nigeria	-0.26
		Tanzania	-0.10
		Uganda	0.03
		Vietnam	0.37
	Heat tolerance	Burkina Faso	0.40
		Ghana	0.26
		India	0.10
		Mali	0.15
		Myanmar	0.30
		Malawi	-0.23
		Niger	-0.77
		Nigeria	-0.29
		Tanzania	-0.12
		Uganda	-0.01
		Vietnam	0.33
	Drought and heat tolerance with high yield	Burkina Faso	0.40
		Ghana	0.26
		India	0.11
		Mali	0.11
		Myanmar	0.31
		Malawi	-0.29
		Niger	-0.76
		Nigeria	-0.29
		Tanzania	-0.15
		Uganda	-0.03
		Vietnam	0.34

Source: Authors.

APPENDIX E: EXOGENOUS AND ENDOGENOUS COUNTRY-LEVEL RESULTS: CASSAVA SCENARIOS

Table E.1 Exogenous average yield change (percent difference) from mealybug scenario and technology adoption scenarios compared with baseline (2050—GFDL)

Scenario	Country	Irrigated	Rainfed
Mealybug	China		-1.66
	India		-8.56
	Indonesia	-13.20	-13.23
	Lao Republic		-13.87
	Myanmar		-11.16
	Thailand		-15.99
	Vietnam	-11.49	-11.65
CBIOL1	China		-1.66
	India		-8.56
	Indonesia	-13.20	-13.23
	Lao Republic		-13.87
	Myanmar		-11.16
	Thailand		-2.26
	Vietnam	-11.49	-11.65
CBIOL2	China		-0.59
	India		-3.32
	Indonesia	-5.22	-5.23
	Lao Republic		-5.53
	Myanmar		-4.36
	Thailand		-2.26
	Vietnam	-4.50	-4.57
CBIOL3	China		-0.20
	India		-1.08
	Indonesia	-1.77	-1.77
	Lao Republic		-1.87
	Myanmar		-1.47
	Thailand		-2.26
	Vietnam	-1.55	-1.58

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

Table E.2 Endogenous average yield change (percent difference) from mealybug scenario and technology adoption scenarios compared with baseline (2050, GFDL)

Scenario	Country	Irrigated	Rainfed
Mealybug	China		-1.36
	India		-8.37
	Indonesia	-12.91	-12.94
	Lao Republic		-13.60
	Myanmar		-10.94
	Thailand		-15.71
	Vietnam	-11.27	-11.43
CBIOL1	China		-1.45
	India		-8.42
	Indonesia	-13.00	-13.03
	Lao Republic		-13.68
	Myanmar		-11.01
	Thailand		-2.03
	Vietnam	-11.34	-11.49
CBIOL2	China		-0.50
	India		-3.25
	Indonesia	-5.12	-5.14
	Lao Republic		-5.44
	Myanmar		-4.29
	Thailand		-2.16
	Vietnam	-4.43	-4.50
CBIOL3	China		-0.16
	India		-1.06
	Indonesia	-1.72	-1.73
	Lao Republic		-1.83
	Myanmar		-1.44
	Thailand		-2.22
	Vietnam	-1.52	-1.54

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. Price feedback is included. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

Table E.3 Endogenous changes in production (percent difference) compared with baseline (2050, GFDL)

Scenario	Country	Irrigated	Rainfed
Mealybug	China		-0.88
	India		-7.93
	Indonesia	-12.51	-12.15
	Lao Republic		-13.19
	Myanmar		-10.51
	Thailand		-15.26
	Vietnam	-11.06	-11.01
CBIOL1	China		-1.12
	India		-8.12
	Indonesia	-12.72	-12.48
	Lao Republic		-13.39
	Myanmar		-10.70
	Thailand		-1.67
	Vietnam	-11.19	-11.20
CBIOL2	China		-0.35
	India		-3.11
	Indonesia	-4.99	-4.88
	Lao Republic		-5.30
	Myanmar		-4.15
	Thailand		-2.00
	Vietnam	-4.36	-4.36
CBIOL3	China		-0.09
	India		-0.99
	Indonesia	-1.66	-1.61
	Lao Republic		-1.77
	Myanmar		-1.38
	Thailand		-2.15
	Vietnam	-1.49	-1.48

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. Price feedback is included. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

Table E.4 Endogenous percent change in harvested area compared with base (2050, GFDL climate change scenario)

Scenario	Country	Irrigated	Rainfed
Mealybug	China		0.49
	India		0.48
	Indonesia	0.45	0.91
	Lao Republic		0.49
	Myanmar		0.49
	Thailand		0.53
	Vietnam	0.24	0.48
CBIOL1	China		0.34
	India		0.34
	Indonesia	0.32	0.63
	Lao Republic		0.34
	Myanmar		0.34
	Thailand		0.37
	Vietnam	0.17	0.33
CBIOL2	China		0.15
	India		0.14
	Indonesia	0.14	0.27
	Lao Republic		0.15
	Myanmar		0.15
	Thailand		0.16
	Vietnam	0.07	0.14
CBIOL3	China		0.06
	India		0.06
	Indonesia	0.06	0.12
	Lao Republic		0.06
	Myanmar		0.07
	Thailand		0.07
	Vietnam	0.03	0.06

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. Price feedback is included. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

Table E.5 Endogenous effect of scenarios on trade—ratio of net trade over national production (2050, GFDL climate change scenario)

Scenario	Country	2050
Mealybug	China	-3.66
	India	-0.33
	Indonesia	-0.10
	Lao Republic	-0.98
	Myanmar	0.03
	Thailand	0.47
	Vietnam	0.66
CBIOL1	China	-3.68
	India	-0.34
	Indonesia	-0.10
	Lao Republic	-0.99
	Myanmar	0.03
	Thailand	0.54
	Vietnam	0.66
CBIOL2	China	-3.65
	India	-0.27
	Indonesia	-0.01
	Lao Republic	-0.82
	Myanmar	0.09
	Thailand	0.54
	Vietnam	0.68
CBIOL3	China	-3.65
	India	-0.24
	Indonesia	0.02
	Lao Republic	-0.76
	Myanmar	0.12
	Thailand	0.53
	Vietnam	0.69

Source: Authors.

Notes: The values in the table indicate the percent change compared with the baseline. The baseline represents an ideal case in which cassava has not been exposed to the mealybug pest. Price feedback is included. The scenarios are as follows: Mealybug = Untreated pest infestation. CBIOL1 = Mealybug wasps are applied only in Thailand. CBIOL2 = Mealybug wasps are applied in all countries, but less completely than in Thailand. CBIOL3 = Mealybug treatment applied completely in all targeted countries.

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