MIT JOINT PROGRAM
SCIENCE POLICY
GLOBAL CHANGE

Report 343
August 2020

Challenges in Simulating Economic Effects of Climate Change on Global Agricultural Markets

John Reilly, Angelo Gurgel and Elodie Blanc

MIT Joint Program on the Science and Policy of Global Change combines cutting-edge scientific research with independent policy analysis to provide a solid foundation for the public and private decisions needed to mitigate and adapt to unavoidable global environmental changes. Being data-driven, the Joint Program uses extensive Earth system and economic data and models to produce quantitative analysis and predictions of the risks of climate change and the challenges of limiting human influence on the environment—essential knowledge for the international dialogue toward a global response to climate change.

To this end, the Joint Program brings together an interdisciplinary group from two established MIT research centers: the **Center for Global Change Science (CGCS)** and the **Center for Energy and Environmental Policy Research (CEEPR)**. These two centers—along with collaborators from the Marine Biology Laboratory (MBL) at Woods Hole and short- and long-term visitors—provide the united vision needed to solve global challenges.

At the heart of much of the program's work lies MIT's Integrated Global System Model. Through this integrated model, the program seeks to discover new interactions among natural and human climate system components; objectively assess uncertainty in economic and climate projections; critically and quantitatively analyze environmental management and policy proposals; understand complex connections among the many forces that will shape our future; and improve methods to model, monitor and verify greenhouse gas emissions and climatic impacts.

This report is intended to communicate research results and improve public understanding of global environment and energy challenges, thereby contributing to informed debate about climate change and the economic and social implications of policy alternatives.

—Ronald G. Prinn and John M. Reilly,
Joint Program Co-Directors

MIT Joint Program on the Science and Policy of Global Change

Massachusetts Institute of Technology
77 Massachusetts Ave., E19-411
Cambridge MA 02139-4307 (USA)

T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/

Challenges in Simulating Economic Effects of Climate Change on Global Agricultural Markets

John Reilly[1], Angelo Gurgel[2], Elodie Blanc[1]

Abstract: Previous studies on the impacts of climate change on agriculture have the following shortcomings: a) most focus only on a few major crops (maize, wheat, rice or soybeans); b) site-level and global gridded crop models (GGCMs) provide very different impacts of climate effects on crops; c) effects of climate change on livestock are well documented, but rarely quantified; d) there are several elements, causal relations and feedbacks among biophysical, environmental and socioeconomic aspects usually not taken into account in these studies. The goal of this paper is to investigate at the global level how alternative assumptions about these four aspects may affect agricultural markets, food supply, consumer well-being and environmental metrics. To that end, the study simulates changes in crop yield and livestock productivity in a large-scale socio-economic model of the global economy with detailed representation of the agriculture sector, the MIT EPPA-Agriculture model. The economic model considers many complex socio-economic relationships and feedbacks, such as changes in management and land-use allocation, shifts in demand for food as prices and incomes change, and changing patterns of global trade. The climate shocks considered were median agricultural productivity changes taken from several site-level crop models revised by IPPC and several GGCMs. We find global welfare impacts several times larger when climate impacts all crops and all livestock. At the regional level, food budget impacts are 10% to 25% in many developing countries, which may challenge food security. Most of the results are due to the role of land area expansion as a major source of adaptation. Climate impacts from site-level crop models revised by the IPCC generate most challenging socio-economic outcomes, while median climate impacts from GGCMs on yield were positive for major crops. However, due to the wide range of impacts from these two types of models, caution is warranted in comparing those median effects. Our conclusions indicate that the agricultural research community should expand efforts to estimate climate impacts on many more crops and livestock. Also, careful comparison of the GGCMs and traditional site-level models are needed to understand their major differences and implications for agricultural systems and food markets.

1. INTRODUCTION 2
2. MATERIAL AND METHODS 3
  2.1 THE EPPA-AGRICULTURE MODEL 3
  2.2 SCENARIOS 6
3. RESULTS 8
  3.1 SOCIO-ECONOMIC METRICS 8
  3.2 AGRICULTURE SECTOR METRICS 12
  3.3 ENVIRONMENTAL METRICS 16
4. CONCLUSIONS 20
5. REFERENCES 21
APPENDIX 24

1 Joint Program on the Science and Policy of Global Change, Massachusetts Institute of Technology, Cambridge, MA.

2 Corresponding author (Email: gurgel@mit.edu).

1. Introduction

Studies dating as far back as the 1980's already investigated the effect of climate change on agriculture, a sector highly exposed to the weather, as recently reviewed by Blanc and Reilly (2017). In the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the most comprehensive compilation and review of studies on climate impacts on food production and food security, Porter *et al.* (2014) find that climate change has already impacted agricultural and food production, affecting regional supply and markets, and may potentially harm food security in the future. The main conclusions highlight that crop yields react negatively to high daytime temperatures and a 2ºC increase in temperature has an overall negative impact on yields, although it may be beneficial in some specific locations. CO_2 fertilization increases yields, but tropospheric ozone damages them. Adaptation may reduce climate impacts or even improve yields, but its effectiveness is highly variable (Porter *et al.*, 2014).

Rosenzweig *et al.* (2014) discuss the several approaches used in the last two decades or more to investigate climate impacts on agricultural productivity: statistical analyses, biophysical process-based models, and agro-ecosystem models. Recent statistical analyses of historical data have focused on different approaches for estimating the direct effects of climate on crops, including a debate on whether panel data with fixed effects (Blanc and Schlenker, 2017), taking advantage of cross-section evidence (Mendelsohn and Massetti, 2017), or crop and economic simulation models (Antle & Stöckle, 2017) offer better insights. The "Ricardian" approach developed over more than 20 years, Mendelsohn and Massetti (2017) claim, represents a more complete estimate of impacts on agriculture, by including adaptations such as shifting to different cropping practices or crops, from crops to livestock or vice-versa, or among different types of livestock operations. In contrast, the panel data approach has largely been applied to specific crops, and captures largely the response of the crop to weather, leaving it to further analysis to understand whether different practices, or other crops might mitigate some of these weather effects. To the extent that the IPCC comprehensively evaluated agriculture climate studies (Porter *et al.*, 2014), the dominant approach to estimate impacts has been to use agronomic crop models, often linked to economic simulation models of farm operations or markets, as discussed by Antle & Stöckle (2017). Rosenzweig *et al.* (2014) discusses in more details agro-ecosystem models and site-based crop models considering detailed biophysical processes. They differ in terms of approaches, structure, assumptions, inputs and outputs, capturing in different ways and with more or less accuracy the stresses from biological and environmental sources, such as CO_2, oxygen, water, temperature, or macro- and micro-nutrients effects on crop yields and growth. Site-based crop models consider the complexity of crop, soil, atmosphere and management components interactions at field level. Agro-ecosystem models deal with larger spatial scale simulations of the carbon and nitrogen dynamics, energy, soil and water balance. The agro-ecological zone models simulate agricultural potentials at regional and global scales. All three approaches can be used to build GGCMs, but the site-based crop models are predominantly used for detailed studies of climate impacts at local and regional levels, as those reviewed in the IPCC's Fifth Assessment Report (Porter *et al.*, 2014).

This healthy debate around methods has, however, left some glaring oversights in much of the studies when it comes to understanding the full risks related to the effects of climate on agriculture. One oversight is that most studies have focused on estimating yield impacts on a few major crops, usually maize, wheat, rice or soybeans, whereas the Food and Agriculture Organization of the United Nations (FAO) publishes data on production of over 170 crops. And while the literature documents extensively the adverse effects of heat on livestock productivity, there have been no attempt to turn these various regional negative factors into a comprehensive set of impacts for livestock production at the global level. All told, global production of maize, wheat, rice, and soybeans was worth about 800 billion US dollars in 2016 but that amounted to only about 17% of the total value of all agricultural crop and livestock products (FAO, 2019). While it is beyond this study to estimate separate yield effects for the ~170 other crops grown in various parts of the world and various livestock, we can test the sensitivity of excluding impacts on other crops and livestock by extending impacts we have for the main crops to these other agricultural commodities.

A second issue is that site-level crop models require highly detailed local data. Once calibrated to the site conditions and management practices, these models can replicate crop yields quite well. However, the data requirements mean that a relatively few sites are used to calibrate the regional model, raising questions about the representativeness of those sites for the entire region. Global gridded crop models (GGCMs) simulate potential crop yields in every latitude-longitude grid, even far outside the area where the crop is currently grown, but assume static soil properties and/or management practices (Müller *et al.* 2017). Site-level crops models and GGCMs provide a very different picture of climate effects on crops (Müller *et al.* 2017). How do results from such different methods alter estimates of the climate impacts on the agricultural system?

Other aspects, besides alternative crop modeling approaches, can add uncertainties about future climate impacts on agriculture. The potential effects of heat on livestock are well documented, but rarely quantified. Rojas-Downing *et al.* (2017) provide an extensive discussion. These range from effects on pasture and forage, to direct effects on animal productivity and health, to more indirect effects on pathogens and disease vectors through changing changes in precipitation and temperature. Regarding the direct effects, higher temperatures increase morbidity and death rates in all livestock. Heat stress leads to a reduction in body size, carcass weight, and fat thickness in ruminants. In the poultry industry, low production results especially at temperatures higher than 30°C. Milk production in dairy cattle, sheep, and goats is reduced by higher temperatures and greater humidity, with the percentage loss higher among higher producing cattle. Rojas-Downing *et al.* (2017) review studies that indicate a current loss in the US of about $1.7 to $2.4 billion due to heat stress in the dairy and beef industry. Overall they conclude that climate change will negatively affect the livestock sector. Summer *et al.* (2019) similarly discuss effects of heat on milk and meat production, showing declines in milk production of about 3 to 23% as the temperature humidity index rises beyond 72°F and 80°F respectively, for high producing dairy cows, and slightly less (0 to 20%) for low producing cows. The difficulty in arriving at quantification is that effects can vary by breed and by management approach, and adaptive measures such as mist cooling, shade, and fans can offset some of these losses, but at extra cost.

To go beyond impacts on crop yields and livestock productivity, there are several elements, causal relations and feedbacks among biophysical, environmental and socioeconomic aspects that need to be considered. Such complexity brings many uncertainties to these projections, as discussed in Gornall *et al.* (2010). We attempt to consider many of the complex socio-economic relationships and feedbacks by using estimates of agricultural productivity changes within a large-scale model of the global economy with newly added detail on the agriculture sector. The model allows for changing management (substitution of other inputs as land productivity changes) as an adaptation response, in particular, for the global and regional extent of crop and pasture land to change. It also simulates changing demand for food as food prices and incomes change, along with changing patterns of global trade in food. Other studies have used similar models (e.g. Nelson, *et al.*, 2014) although few consider changes in crop and pasture land area as a response to changing productivity shocks.

There are many other sources of uncertainty in projections of climate impacts on agriculture and food supply, besides the aforementioned ones (crop coverage, crop model type, impacts on livestock, and socioeconomic aspects). Our focus on the four questions (or glaring omissions) is not to answer decidedly how big these omitted effects are, but rather to attract the attention of the agriculture-climate research community in an effort to prioritize these research gaps.

2. Material and methods

To be able to represent the impact of changing yields on agricultural and food markets taking into account land use changes, we improve an existing socioeconomic model of the global economy with an explicit characterization of multiple markets for primary factors (land, fossil fuel resources, labor, capital), energy, agricultural, food, industrial goods and services, and all relationships among such markets, including international trade. We describe the main features of the model in the next sections highlighting the further sectoral resolution in this version compared to earlier versions of the model.

2.1 The EPPA-Agriculture Model

The MIT Emissions Prediction and Policy Analysis (EPPA) model, version 6, is a recursive-dynamic multi-regional and multi-sectorial computable general equilibrium (CGE) model of the world economy (Chen *et al.* 2015). The underlying economic data in EPPA is sourced from the Global Trade Analysis Project Version 8 (GTAP 8) database, benchmarked for the year 2007 (Narayanan *et al.*, 2012). The GTAP dataset provides the base information on social accounting matrices and the input-output structure for regional economies, including bilateral trade flows, and a representation of energy markets in physical units (Hertel 1997; Narayanan, Aguiar, and McDougall 2012). In the original version of EPPA6, the GTAP data is organized into 18 regions and 14 sectors (**Figure 1**).

Here we expand the sectoral representation to 28 sectors, improving the detailing of agricultural and livestock sectors and commodities. **Table 1** shows the sectoral aggregation. The conventional version of EPPA contains just three aggregated land intensive sectors: crops, livestock and forests, while the EPPA-Agriculture model breaks them in eight different crop sectors and three livestock sectors. We also disaggregate energy intensive sectors and others representing building materials and construction sectors, to develop further investigation on possible implications for land use of greater use of forestry products in construction as substitutes for steel, cement, and other energy intensive construction materials.

We also parameterize a range of energy 'backstop technologies' not identified in the base year data, either because they were not deployed or only at relatively low levels but could be deployed in the future under different price or policy conditions (**Table 2**). These include some bio-based energy technologies that, if developed, compete for land used for conventional agricultural crops. The backstop technologies are represented in a similar fashion as in earlier EPPA versions (see Chen *et al.*, 2015). Table 2 also presents the several primary factors inputs explicitly represented in EPPA-Agriculture. Among them are both depletable and renewable natural capital inputs, as well as produced

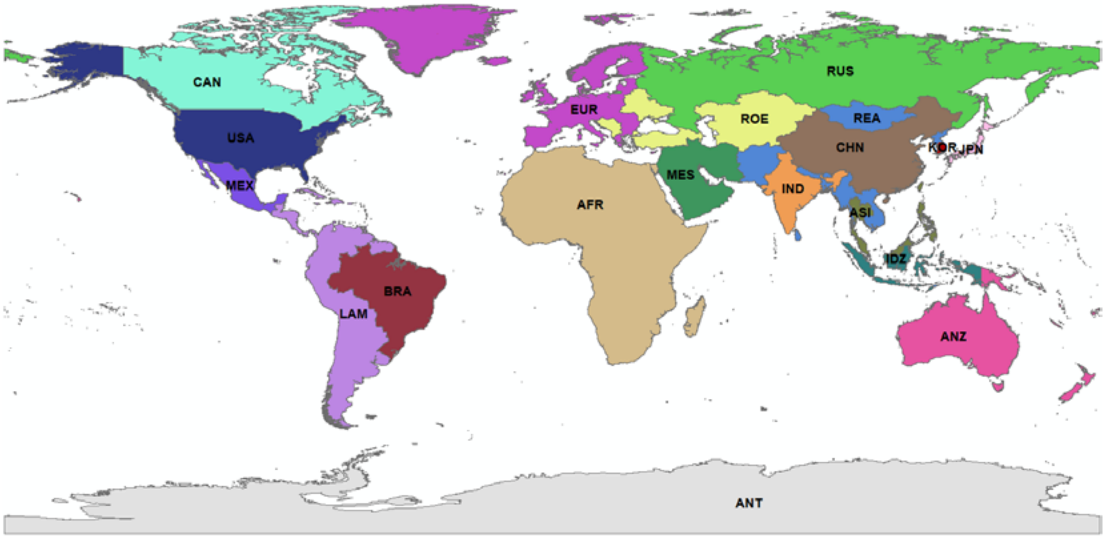

Figure 1. Regions in EPPA-Agriculture model.

Table 1. Sectors in EPPA-Agriculture.

Sector	Sector	Sector	Sector
Rice	Other crops	Coal	Non-Ferrous Metals
Maize[1]	Bovine Cattle[6]	Crude Oil	Other Energy-intensive Industries
Soybean[2]	Poultry and Pork[7]	Refined Oil	Other Industries
Wheat	Other Livestock[8]	Gas	Construction
Sugar Crops[3]	Forestry	Electricity	Other Services
Vegetables & Fruits[4]	Wood Products	Non-Metallic Minerals	Transport
Fiber plants[5]	Food Products	Iron & Steel	Ownership of dwellings

[1]Maize and Other Cereals; [2]Oil Seeds; [3]Sugar Cane and Sugar Beet; [4]Vegetables, Fruits and Nuts; [5]Fiber-based plants; [6]Bovine Cattle, Sheep, Goats, Horses; [7]Swine, Poultry, Other Animals; [8]Other Animal Prod. (Milk, Wool, Fish).

Table 2. Backstop sectors and Primary Factor Inputs in EPPA-Agriculture.

Backstop Technology	Primary Factor Inputs	
First Generation Biofuels	Depletable Natural Capital	Conventional Oil Resources
Second Generation Biofuels		Shale Oil
Oil Shale		Conventional Gas Resources
Synthetic Gas From Coal		Unconventional Gas Resources
Hydrogen		Coal Resources
Advanced Nuclear		Natural Forest
IGCC w/ CCS		Natural Grasslands
NGCC	Renewable Natural Capital	Solar Resources
NGCC w/ CCS		Wind Resources
Wind		Hydro Resources
Bio-Electricity	Produced Capital	Conventional Capital (Bldgs & Mach.)
Wind Power Combined with Bio-Electricity		Cropland
Wind Power Combined with Gas-Fired Power		Pasture and Grazing Land
Solar Generation		Managed Forest Land*
	Labor	

*Managed forest land includes planted forest and secondary vegetation regrowth.

capital and labor. Among produced capital, EPPA treats cropland, pastures, and managed forest land as "produced" from natural capital of forest areas and grasslands.

Household transportation including purchased commercial and own-supplied transport (personal automobile) is also represented in EPPA, requiring additional data to disaggregate household vehicle use within the GTAP data. Chen *et al.* (2015, 2017) describe the details of disaggregation and parameterization of transport and electric power generation, which takes into account bottom-up engineering analysis of costs, fuel use, and conversion efficiency.

EPPA also incorporates data on greenhouse gases (GHG) (CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6) and conventional air pollutant emissions (SO_2, NOx, black carbon, organic carbon, NH_3, CO, VOC), based on data from the International Energy Agency (IEA, 2012) in the case of CO_2 emissions from energy consumption, Boden *et al.* (2010) for CO_2 emissions related to cement production, the Emissions Database for Global Atmospheric Research (EDGAR) Version 4.2 (European Commission, 2013) and Bond *et al.* (2007) in the case of non-CO_2 GHGs and conventional air pollutants.

The base year of EPPA is 2007. The model simulates historical economic trajectories recursively for the year 2010 and 2015, and then projects future economic pathways at 5-year intervals from 2015 to 2100. Economic development through 2020 is benchmarked to historical data and short-term GDP projections of the IMF. The model is formulated using the mixed complementary problems (MCP) approach (TF Rutherford 1995; Ferris and Pang 1997), and solved using the MPSGE subsystem in GAMS programming language (TF Rutherford 1999).

Future projections in EPPA are driven by economic growth resulting from savings and investment, and exogenously specified productivity improvement in labor, capital, land, and energy. GDP and income growth through time increase demand for goods and services, including fuels and food. Higher cost grades of depletable resources are accessed as lower cost stocks are depleted. Sectors using renewable resources, such as land in the case of agriculture, compete for the available flow of services from them, generating rents. Backstop and advanced technologies may become cost competitive as regular energy sources become more expensive. These various economic drivers, combined with imposed policies, such as constraints on GHG emissions, determine the economic trajectories over time and across scenarios. Chen *et al.* (2015) provides a detailed description of the dynamics in EPPA6.

Explicit modeling of land-use that maintains consistent supplemental physical accounts of land is a unique feature in EPPA. The approach considers five broad land use categories: cropland, pasture, forest, natural forest and natural grass. We combine and reconcile several world scale data sources to build the land use change approach in EPPA-Agriculture. We use the "GTAP8 Land Use and Land Cover Database" (Baldos and Hertel 2012), separately covering cropland, pasture, built-up, forest land and a single category including all others land types by agro-ecological zones (AEZs) and 134 countries or regions of the world. The GTAP8 land use data itself is built from FAOSTAT production data as well as cropland and pasture data from Ramankutty (2012). To complement these data for other land use categories in EPPA-Agriculture, we use data produced by the Terrestrial Ecosystem Model (TEM) (Felzer *et al.* 2004), using historical land use transitions from Hurtt, Frolking, and Fearon (2006). **Table A1** in the Appendix presents the land cover data for each EPPA region in 2007, measured in million hectares (Mha).

We represent land and the transformation of natural lands (natural forest and natural grass) into managed land types (crop, pasture, and managed forest) in physical terms. Details of the approach can be found in Gurgel *et al.* (2016). The model considers that land improvements (draining, tilling, fertilization, fencing) can convert pastureland to cropland, or forestland can be harvested, cleared and ultimately used as pastureland or cropland. If investment in cropland is not maintained, the land can then go back to a less intensely managed use (pasture, or forest) or be abandoned completely and return to "natural" grass or forest land.

The land use transformation approach used in EPPA is well suited to longer term analysis where demand for some land uses could expand substantially. It also explicitly represents conversion costs associated with preparing the soil, spreading seeds and managing the creation of a new agricultural system. In this regard, it is a better alternative than the more common Constant Elasticity of Transformation (CET) approach often used in CGE models. The CET function makes large transformations of land difficult because the function tends to preserve input shares (Gurgel, *et al.*, 2007). The CET approach also does not explicitly account for conversion costs. In addition, Schmitz *et al.* (2014) point out the lack of direct relationship to area in physical units, since land enters the CET function in value terms. As a result, there is no guarantee of consistent update of the supplemental physical accounts. Finally, as the CET elasticities are symmetric to all changes, the ease of conversion from agricultural to forest land is the same as from forest to agriculture, which implicitly assumes the same "costs" and constraints on conversion in both directions.

In the case of conversion of natural forests, EPPA also accounts for the production of timber products similarly to a forest harvest on managed forest land. Natural areas transformation to agricultural areas are calibrated to mimic a land supply response, based on rates of conversion observed over the last two decades. This last feature captures a variety of factors that may slow land conversion, including increasing costs associated with larger deforestation in a single period and institutional costs (such as limits on deforestation, public pressures for conservation, or establishment of conservation easements or land trusts).

We assume conversion costs from one land use category to another as equal to the difference in value of these types, assuring "zero profit" conditions in the MCP equilibrium approach. One issue that arises for the current valuation of natural forest and grassland that is not currently used. However, for it to appear in the CGE framework it must have an economic value. We develop a "non-use value" for these land areas using data from Sohngen *et al.* (2009) and Sohngen (2007). This approach assumes that, at the margin, the cost of access to remote timber land must equal the value of the standing timber stock plus that of future harvests as the forest regrows. The net present value of the land and timber is calculated using an optimal timber harvest model for each region of the world and for different timber types. Setting the access costs to this value establishes the equilibrium condition that observed current income flow (i.e. rent and returns) from currently non-accessible land is zero because the timber there now and in the future can only be obtained by bearing costs to access it equal to its discounted present value. From these data, we calculate the value of an average standing stock of timber for each of regions and the separate value of the land based on the discounted present value of future timber harvests.

The value of natural forest and natural grass areas are considered in the model as part of the initial endowment of households in each region. These areas may be converted to other uses or conserved in their natural state. The reservation value of natural lands enters each regional representative agent welfare function with an elasticity of substitution with other consumption goods and services. Hence, the value the agent derives from natural land itself, is a deterrent to conversion. Thus, if for example current timber demand rises and puts pressure to harvest more land, it creates a partly offsetting demand to conserve forest area because, implicitly, the agent sees it as more valuable in the future. In the recursive dynamic structure of EPPA, introducing the natural forest value into the representative agent's welfare function approximates this behavior.

With the disaggregation of crop sectors, cropland becomes an input in the production of each separate crop sector listed in Table 1. Similarly, pasture land is used in each livestock sector. Managed Forest areas are only used for the production of managed and harvested forests. The land allocation of crop and pasture to the agricultural and livestock sectors is done by CET functions with elasticity equal to one, which is the common approach in all models dealing with broad land categories being allocated to alternative final uses.

Some other features regarding land use changes in EPPA relate to technological change affecting land productivity and specification of food and agricultural demand. EPPA assumes that land is subject to an exogenous productivity improvement of 1% per year for each land type, reflecting assessments of potential productivity improvements showing similar historical crop yields growth albeit with variations among regions, crops and time. (Reilly and Fuglie 1998; Gitiaux, Reilly, and Paltsev 2011; Ray *et al.* 2013). Besides exogenous yield changes, land can be partially substituted by inputs and other primary factors in the agricultural production functions as relative prices change over time.

Regarding the demand for agricultural, livestock, forestry and food products, most of the output of primary land use sectors end up as inputs in the food, energy, and other sectors of the economy. Food and agriculture production, and hence the amount of land used, is strongly influenced by the growth in population and incomes. Most studies find that, as income grows, the expenditure shares on food will decrease although food consumption levels may increase (Zhou *et al.* 2012; Haque 2006), which suggests an income elasticity of less than unity. It is considered in EPPA by introducing a Stone-Geary preference system following the approach presented in Markusen (2006), as described by Chen *et al.* (2015).

2.2 Scenarios

Our goal is to give an indicative quantitative answer to the caveats and questions we identified in Section 1. Our strategy is to compare results through 2050 from the EPPA-Agriculture model for which climate change impact on the agriculture sector is represented using estimates from traditional site level crop model studies as summarized by the IPCC, to results from GGCMs. We then compare those results to simulations assuming average impacts on crops not covered in these studies. Finally, we extend these impacts to pasture and livestock productivity. While it seems unlikely that other crops and livestock will be affected in the same way as the four major crops often studied, we intend this to be a sensitivity analysis helping to establish the priority the research community might place on producing climate impacts on a more comprehensive set of agricultural commodities. We also compare the climate effects scenarios against a baseline, business as usual (BAU), scenario assuming no climate change. We can then quantify the effects by region using several metrics that broadly include the overall socio-economic effects, effects on the agriculture sector itself, and the broader environmental effects associated with adapting to climate change.

Comparing conventional crop model results to GGCMs'

Based on results reported in Porter *et al.* (2014), we develop median crop response to climate by 2050 for each EPPA region for four main crops. The number of studies conducted vary by region, with relatively few produced in some regions. We estimate two ranges for each crop: one for northern temperate regions; and a separate range for tropical and southern Hemisphere regions. We then apply the relevant range to the median estimates for each EPPA region. While it would be ideal to show separate ranges for each EPPA region, the lack of enough estimates for some regions could make it appear that there was little uncertainty for some regions and crops only because there were just a couple of studies. The crop model results reported by Porter *et al* (2014) span a variety of different crop models and different climate scenarios. The estimates are medians and ranges across both climate scenarios produced by different climate models and across yields generated by different crop models.

Blanc (2017a; 2017b) has developed statistically estimated emulators of the major GGCMs. Two models, pDSSAT and GEPIC, are field-scale models applied at the global scale level, while the three others, LPJ-GUESS, LPJmL and PEGASUS, are global ecosystem models integrating field-scale crop model mechanisms and parameters (Müller *et al.* 2017). These models estimate crop yields at a fine resolution globally by considering the detailed effect of weather (monthly, daily, or even hourly) on crop growth (Bassu *et al.* 2014). Similar to the IPPC results, these models are largely limited to four major crops: rice, maize, soybean and wheat (RMSW). The emulators for the five GGCMs were used to simulate yields under nine climate scenarios, providing a total of 45 separate simulations for each crop and grid cell. Inputs from the nine climate change scenarios were obtained from the Massachusetts Institute of Technology Integrated Global System Modeling (MIT IGSM) framework using a pattern scaling method (Schlosser *et al.*, 2012) under GHG emissions scenarios consistent with the Paris climate negotiations (COP21) (Outlook 2015; Outlook, 2016). The pattern-scaling method uses global scale simulations of the MIT IGSM to estimate the effect of uncertainty in climate sensitivity, ocean heat uptake, and aerosol forcing on latitudinal climate change combined with longitudinal patterns from major general circulation models simulations available through Climate Model Intercomparison Projects (CMIPs). The nine climate scenarios include a high, median, and low climate response to GHG forcing, and three different climate model patterns. We estimate the mean of 45 crop responses simulations for each region for the 2050s (using the 5 year average for the 2047–2052).

The central tendency from the IPCC site level crops models is for negative effects on yields for nearly all crops and all regions (**Figure 2**) while the central tendencies for the emulated GGCMs results are mostly positive for all regions and all crops (**Figure 3**). We have plotted all crop yield results for both the IPCC and emulated GGCMs using the same y-axis scale to better show differences. Immediately this shows that the yield range for the IPCC estimates, while often showing a range of 15 to 20 percentage points from high to low, is much narrower than for the emulated GGCMs. The GGCM range is especially wide for rice, and more in line with the IPCC range for maize and wheat, with the exception for a few regions. Each approach has strengths and weaknesses. The site-level crop models typically are calibrated to represent current yields quite well at the sites where they are applied, and are typically simulated at highly resolved time steps. They may better capture the response of crops to extremes. However, if spatial variation smooths out the response of crops over a wide region, the limited number of sites typically simulated may not capture this smoothing, or the sites may not be broadly representative of the large regions they are used to represent. The GGCMs are simulated in every land grid cell. For our comparisons we have used results only for grids in which the crops are actually grown. These may then be more representative of a large region and may smooth out local variability. However, given the range of crop cultivars and management practices and limited data, the GGCM results are generally not calibrated closely to current yields, and with generally coarser time steps may not capture well weather extremes.

Extending impacts to all crops

As noted earlier, RMSW are important crops, but account for only 17% of value of global agriculture production. The FAO tracks more than 170 crops, and many of these are important food sources. We extend impacts to other crops by applying the simple average impacts of the four main crops in each region to all other crops represented in EPPA. Although it is a simplistic assumption, it avoids an outcome where production is simply shifted to crops that were left unaffected only because no yield estimates were available. By assuming all crop production is being affected by climate, we investigate how results may be biased by only simulating impacts on some crops. We identify such scenarios by "crop".

Extending impacts to livestock

The livestock sector will be affected by changes in climate. Livestock productivity will be directed affected by changes in climate but also indirectly affected by changes in the price and availability of livestock feed. However, the literature is very scarce on the potential climate change impacts on livestock production and pastures. Given the lack of information regarding these impacts, we consider one more subset of scenarios with climate impacts on all crops, pasture yields and livestock productivity.

In summary, we simulate three subsets of scenarios: (i) climate impacts only on *RMSW* yields; (ii) climate impacts on yields of all crops (*Crops*); and (iii) climate impacts on all crops and pasture yields and livestock productivity (*Crops & Livestock*). Each of these scenarios extend either the *IPPC RMSW* impacts or the *GGCM RMSW* impacts to the other commodities. The exception is that if the average crop yield impact is positive, we do not assume direct effect on livestock productivity, only on pasture yields. **Table 3** lists all seven scenarios, included the six different climate impact scenarios and the *BAU* case.

While we show ranges for base crop yields, we focus our analysis on the median estimates for both for the *IPCC RMSW* responses and the *GGCM RMSW* responses. As noted above, Figures 2 and 3 presents the changes in yields in each scenario in 2050. There is considerable variability in the median impacts among crops and among regions for each crop. The range of impact for both the *IPCC* and *GGCM* sets of impacts are quite wide, with the range often including both increases and decreases in yields. The median *GGCM* results are positive for crops in all regions. In contrast, the median *IPCC* impact is negative for nearly all crops and all regions, with the exception being small increases in soybean yields in a couple of regions

We linearly interpolate yield changes from zero in 2020 to the 2050 median yield impacts for both *IPCC* and emulated *GGCM* scenarios when implemented in EPPA-Agriculture. Yield impacts on crops are applied in the model as a shock on land use productivity, and productivity impacts on livestock activities are applied as shocks in their total factor productivity.

Table 3. Scenarios simulated in EPPA-Agriculture.

Scenario	Climate Impact
BAU	No climate impacts.
IPCC-RMSW	Median regional impacts for rice, maize, soybean, and wheat as reported in the IPCC (Porter *et al.*, 2014).
GGCM-RMSW	Median impacts for rice, maize, soybean, and wheat from 5 emulated GGCMs x 9 climate scenarios spanning climate uncertainties and varied spatial patterns.
IPCC-Crops	Average regional impacts for RMSW extended to all crops.
GGCM-Crops	Average regional GGCM impacts for RMSW extended to all crops.
GGCM-Crops & Livestock	Average regional GGCM impacts for RMSW extended to all crops and livestock.
IPCC-Crops & Livestock	Average regional IPCC impacts for RMSW extended to all crops and livestock.

3. Results

Given the complex interactions among regions through trade, and within the agricultural sector in terms of food consumption, crops, livestock, land use change, and land use emissions, we identify several metrics we use to quantify the potential economic importance of some of the major oversights we have seen in evaluating agricultural risks from climate change. These included metrics that cover (i) broader socio-economic impacts, (ii) agriculture sector impacts, and (ii) environmental implications of climate change, acting through impacts on agriculture.

3.1 Socio-economic metrics

The change in macroeconomic welfare measured as equivalent variation—the change in the total value of all goods consumed by households—is the broadest economic indicator (or synthesis) of all effects and adjustments in the human activities needed to accommodate the impacts of climate changes on crop yields. For example, demand for food is relatively price inelastic and so given, for example, yield declines, demand will adjust downward by less than the yield loss. To meet the still relatively high demand, resources will be diverted from other parts of the economy to increase food supplies. Our measure of welfare includes reductions in consumption of other goods because of the diversion of resources toward agriculture. Another useful socio-economic metric is the effect on the household budget share for food. Here we compare the aggregate welfare changes at the global and regional level, and how the food budget share changes for the representative agent in each region.

Global aggregate welfare impacts are six to 13 times larger in the *Crops & Livestock* scenarios compared with the *RMSW* scenarios and two to three times larger in the *Crops* scenarios compared with the *RMSW* scenarios (**Figure 4**). The *RMSW* scenarios, by covering only a fraction of all agricultural products, will obviously underestimate the total welfare impact on the economy (unless the impact on omitted commodities was of opposite sign on the impact on *RMSW* crops). However, the effect of the omission is magnified by the fact that allowing some commodities to be unaffected by climate change, allows a further avenue of adaptation—simply shifting away from negatively affected crops toward commodities left unaffected in the *IPCC* scenarios, or toward positively affected commodities from those left unaffected in the *GGCM* scenarios. By construction, the yield shocks are similar across all commodities, and so when all are affected, there is essentially little avenue to shift toward commodities with less impact, completely shutting off that mode of adaptation. Obviously, this may be extreme as the climate responses are likely to vary among different agricultural commodities. However, it often appears to be the case, that a family of crop models applied to different crops give somewhat similar yield changes, with greater

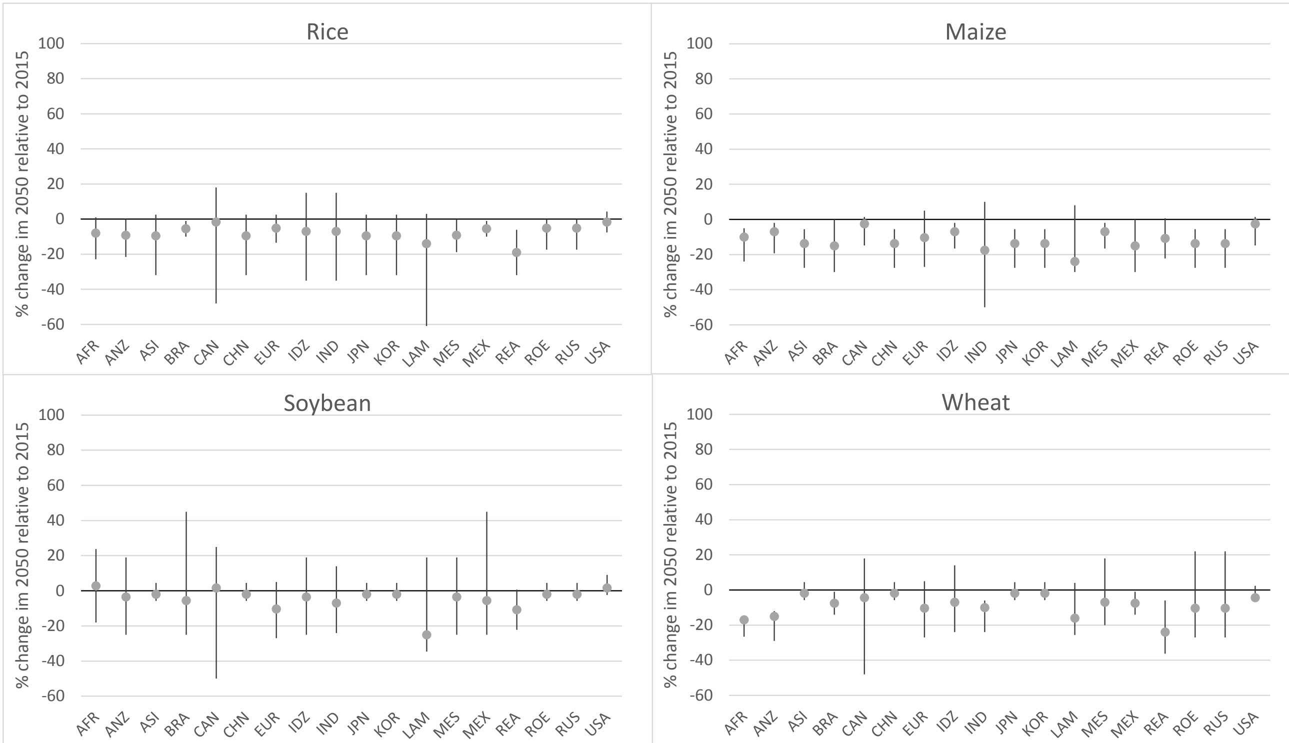

Figure 2. Range of climate Impacts on Yields by 2050, IPCC.

Source: Author´s compilation based on Porter et al (2014).

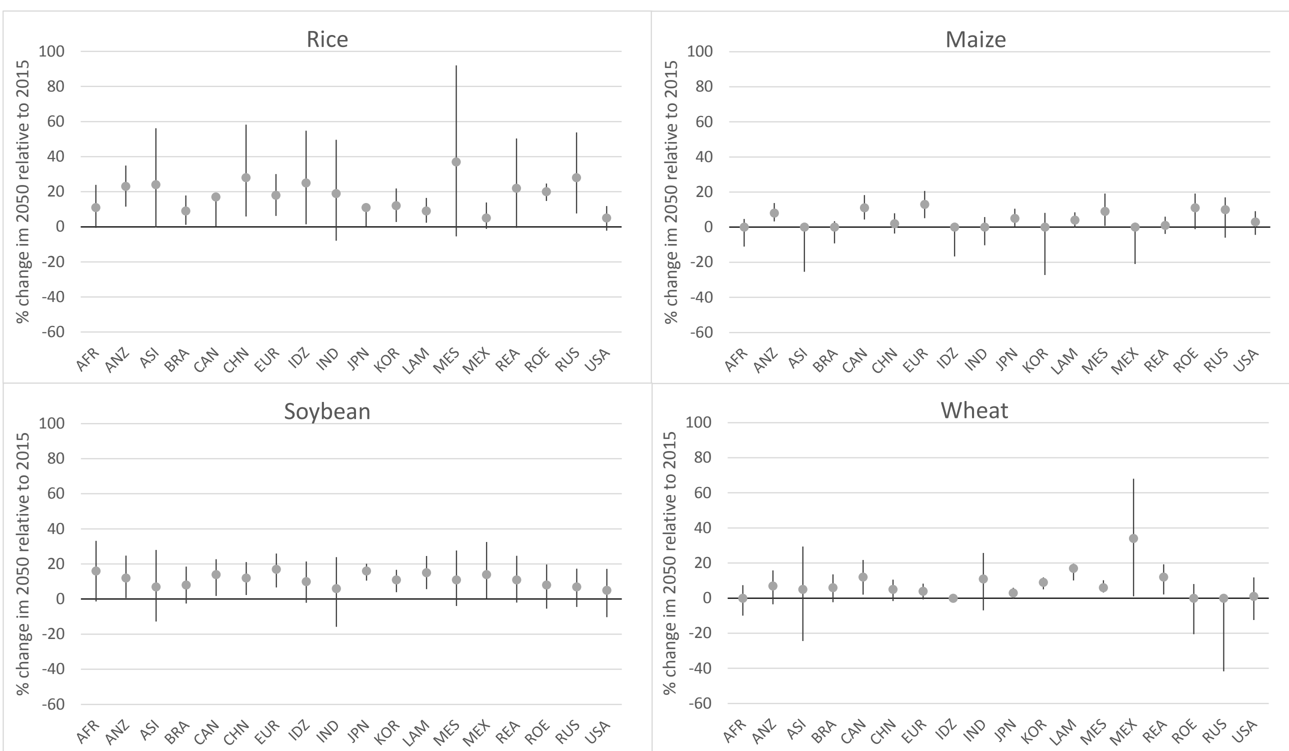

Figure 3. Range of climate Impacts on Yields by 2050, GGCMs.

Source: Author´s estimation using five crop emulators based on Blanc (2017a, 2017b).

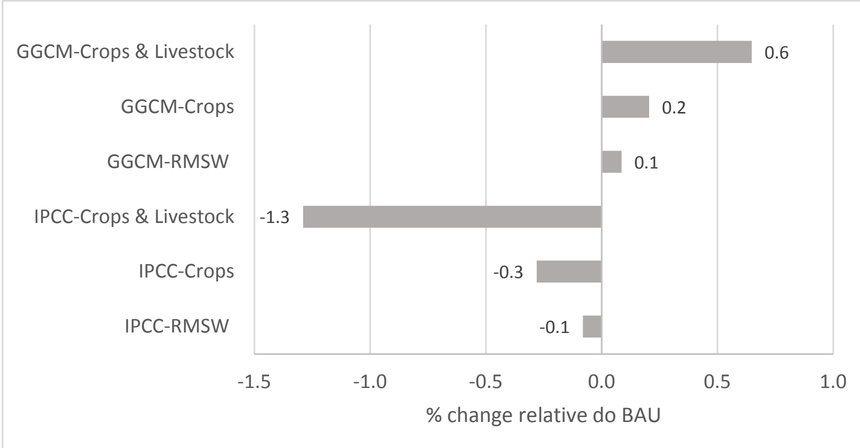

Figure 4. Global change in welfare in 2050 relative to *BAU*.

Table 4. Regional changes in welfare in 2050 relative to *BAU*.

	IPCC-RMSW	IPCC-Crops	IPCC-Crops & Livestock	GGCM-RMSW	GGCM-Crops	GGCM-Crops & Livestock
AFR	*-0.1*	*-0.1*	*-2.1*	**0.1**	**0.0**	**0.5**
ANZ	**0.0**	**0.1**	**0.3**	*-0.1*	*-0.1*	*-0.2*
ASI	*-0.1*	*-0.2*	*-0.9*	**0.2**	**0.2**	**0.4**
BRA	**0.0**	**0.0**	**0.1**	*-0.2*	*-0.2*	*-0.3*
CAN	**0.1**	**0.1**	**0.6**	*-0.1*	*-0.1*	*-0.2*
CHN	*-0.3*	*-0.6*	*-4.7*	**0.4**	**0.8**	**3.4**
EUR	**0.0**	**0.0**	**0.0**	*0.0*	*0.0*	*-0.1*
IDZ	*-0.6*	*-0.9*	*-3.5*	**1.2**	**1.4**	**2.6**
IND	*-0.1*	*-2.3*	*-4.3*	**0.3**	**1.2**	**1.9**
JPN	*0.0*	**0.0**	**0.2**	**0.0**	**0.0**	*-0.1*
KOR	*-0.1*	**0.0**	*-0.2*	**0.0**	**0.0**	**0.1**
LAM	*-0.4*	*-0.6*	*-2.4*	**0.0**	**0.1**	**0.1**
MES	*-0.2*	*-0.4*	*-1.5*	**0.1**	**0.4**	**0.9**
MEX	*0.0*	*-0.1*	*-0.3*	**0.0**	**0.0**	**0.1**
REA	*-0.7*	*-1.6*	*-14.7*	**0.4**	**0.9**	**4.9**
ROE	**0.0**	**0.1**	*-0.4*	*0.0*	*-0.1*	*0.0*
RUS	*0.0*	*-0.1*	*-0.7*	**0.0**	**0.1**	**0.3**
USA	**0.0**	**0.0**	**0.2**	*0.0*	*0.0*	*-0.1*

variation in estimated impact coming from apply different families of crop models, or different climate scenarios. The comparison between the "site-level family" of crop models in the *IPCC* scenarios and the "GGCM family" in the *GGCM* scenarios illustrate this tendency. Hence, if we are able to construct a full set of impacts for all commodities using a standard approach, it seems more likely that there would be less variation in impact among commodities then we might get by randomly selecting from a large range. If, for example, half of the estimates came from GGCM-based estimates, and half came from IPCC-reviewed site level estimate, they might well completely cancel each other out. But that seems a misapplication of fundamental differences in models to a scenario of how climate change might actually affect agriculture.

Welfare deviations in 2050 relative to *BAU* for each EPPA region are often much stronger than global welfare changes, with losses relative to BAU in red/italic and gains in blue/bold (**Table 4**). The *IPCC* scenarios show many more regions with negative impacts, and a very large (-14.7%) impact for Rest of East Asia (REA) in the *Crops & Livestock* scenario, and quite large impacts (3.5 to near 5%) in India, China, and Indonesia, some of the most populated places in world, with relatively little option to expand cropland.

The REA region has the most negative direct impacts on yields, consistent with the fact that it has the strongest aggregate economic effect. But many other factors work to result in a large net impact on a region. For example, in the *GGCM* scenarios, we see both losses and gains among regions even though the direct effects on yield are positive in all regions. This reflects changing terms of trade among regions. Notably, major agricultural exporters including ANZ, CAN, BRA, and to a lesser extent EUR and USA are among the negatively affected regions while importing regions are more likely to gain. These terms of trade effects also are operating in the *IPCC* scenarios, generating gains for many agricultural exporting regions and aggravating losses in importing regions.

Our second socio-economic metric is the change from BAU in the food budget share for the representative household in each region (**Figure 5**). For the *RMSW* and *Crops* scenarios the change in budget shares are relatively small, generally less than a couple of percent. Also notable, is that the direction of budget share change is the same across all regions, higher in the *IPCC* scenarios and lower in the *GGCM* scenarios, unlike the aggregate welfare changes. This reflects the fact that yield changes are negative almost everywhere in the *IPCC* scenarios and positive in the *GGCM* scenarios, and food price changes are further tied together because of food and agriculture trade. The aggregate welfare changes differed because of terms of trade changes, but those primarily affect agricultural producers and so do not show up in consumer food budget shares.

While the *RMSW* and *Crops* scenarios show small budget share effects, the *Crops & Livestock* scenarios show quite large effects, especially for the negative shocks in the *IPCC Crops & Livestock*. There are few reasons for the "undampened" effect on household food budgets. First, with all food items rising in price there is less ability to substitute than in cases where the price of some items did not rise because there was no direct climate effect on them. Second, while there can be substantial substitution among food items, overall food is relatively price inelastic, and so the result is that relatively more income is spent on food, reducing spending on non-food items. Third, the commodity cost of livestock products in final goods is much higher than the commodity cost of crops, where there is generally more value added. If 90% of the final food cost is value-added, then the consumer sees only 10% of the commodity price shock. Whereas, in livestock, 70% of the final food cost may be the commodity cost, and so the consumer will see most of the commodity cost shock.

Value-added differences in food consumption between richer and poorer countries also explain why we see bigger impacts in poorer countries. In the USA, CAN, EUR,

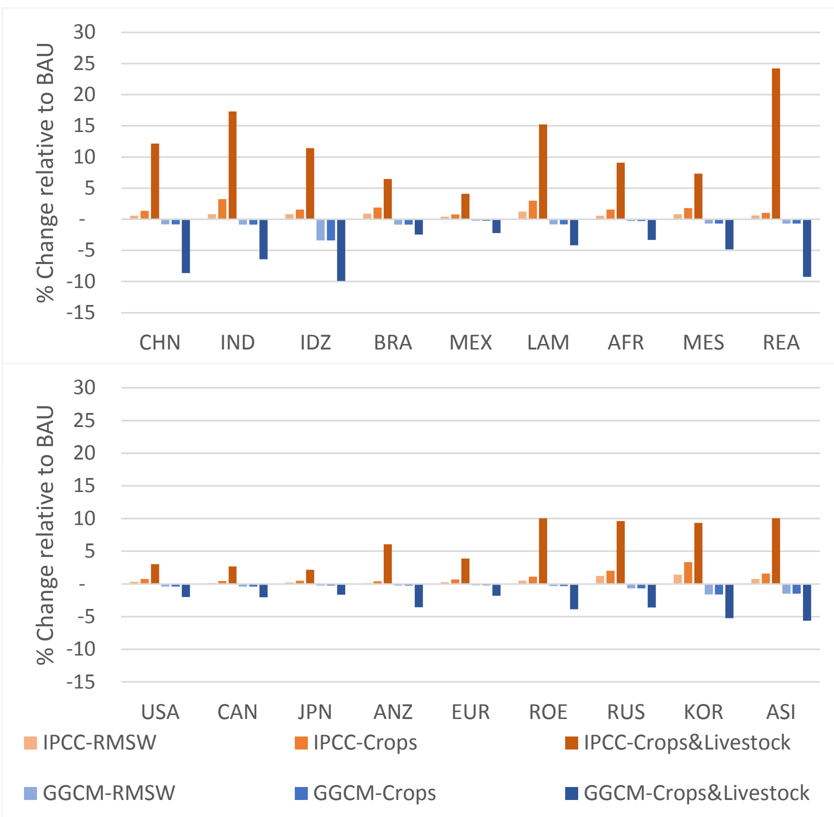

Figure 5. Change in food budget share in 2050 relative to BAU.

and JPN, even in the *IPCC Crops & Livestock* scenario, the impact on the household budget share is well under 5%. This reflects the purchase of more prepared foods, with higher valued added, and a large portion of the food budget spent eating out, where the commodity cost of food is dwarfed by labor and other valued added costs, sectors that are not modeled as directly affected by climate change in our simulations.

While we see this difference among countries characterized by different income levels, if we were able to model households of different income levels within a region we would likely see some of these effects amplified for the poorest households, and we would see households within the wealthier countries affected even more. Poor households would benefit under *GGCM* scenarios. However, the effects in the *IPCC Crops & Livestock* scenario are worrisome. A bigger share of low income households' budget is spent on food, and so it would mean, in percentage terms, cutting back much more on other goods than in wealthier households. And, finally, these scenarios are constructed to represent an average yield effect across several years meant to represent 2050. Any one year could be much worse (or much better). While wealthy households have more flexibility, by borrowing or temporarily tapping into savings, to balance out such swings, poorer households are generally less able to balance out.

3.2 Agriculture Sector Metrics

Our agriculture sector metrics include changes in commodity production and commodity prices. The initial yield and productivity shocks we have used to represent climate change effects are generally moderated by adaptation responses to the initial yield shocks. For a negative yield shock, adaptation may include substitution of other inputs to make up for the yield loss, expansion of land devoted to the crop, strategic storage, and reduction in use, with the reverse changes if there is a positive yield shock. There may also be shifts of supply among regions to those less negatively or more positively affected, and among crops and livestock, again to those commodities less negatively or more positively affected.

As expected, crop and livestock outputs are higher under positive climate impacts in the *GGCM* scenario than in BAU scenario, and lower under *IPCC* scenarios by 2050 (**Figure 6**). When climate impacts are imposed only on *RMSW* crops, agriculture outputs deviate less than 1% from the BAU projections in 2050. When all crops suffer yield impacts (*Crop Only* scenarios), outputs deviate at most 1.5% from BAU. However, when all crops and livestock are affected by climate change, some crop and livestock outputs decrease more than 5%. Global output of processed food falls just over 2% under the worst scenario.

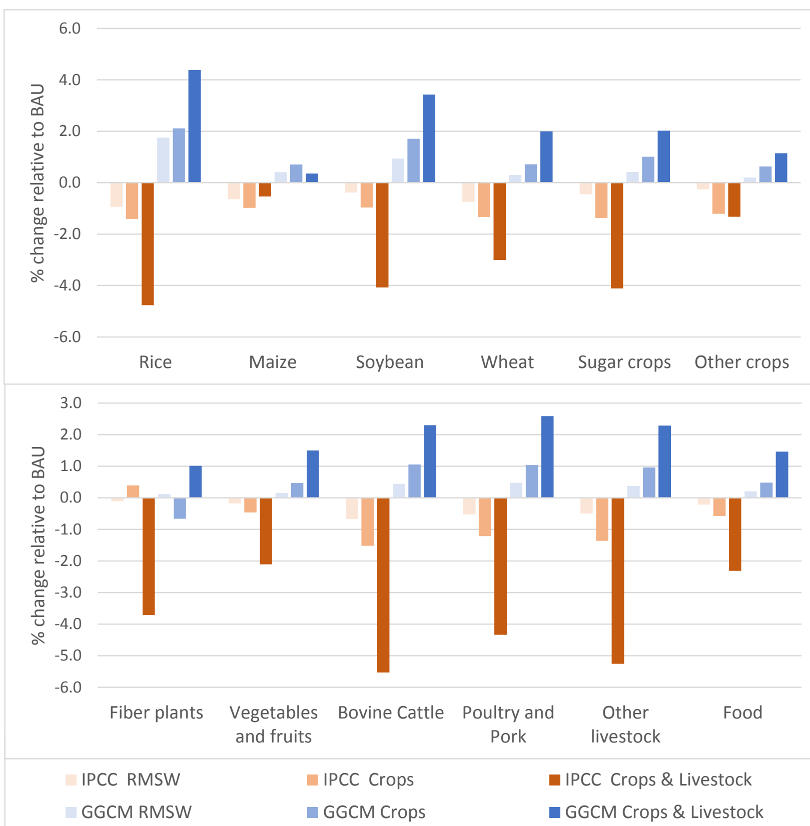

Figure 6. Global change in output index in 2050 relative to BAU.

The supply changes are generally much smaller in percentage terms than the initial yield shocks. For comparison, yield shocks in the *IPCC* scenarios are mostly in the range of -5 to 14% for rice, -7 to -24% for maize, -2 to -11% for soybean, and -7 to -17% for wheat, with a few outlier cases among regions that were outside these ranges. In the *IPCC RMSW* scenario, the output impact is on the order of one-tenth the yield shock. It is slightly larger, about one-seventh the yield impact in the *IPPC Crops* scenario. But in the *IPCC Crops & Livestock* scenario it is on order one-half the yield shock. We also see lower output in the non-impacted commodities in the *IPCC RMSW* and *IPCC Crops & Livestock* scenarios. As we will see in the following section, a main channel of adaptation is expansion of area devoted to the impacted commodities. When all commodities are directly negatively affected by climate change then they are all competing to expand area devoted to their production to make up for lost yield, so there is less scope for economic adaptation than when only a few crops are directly affected. The situation is reversed in the *GGCM* scenarios where increasing yields reduces pressure on crop and pasture land.

At the regional level, changes in agriculture and livestock outputs can be much stronger than at the global level. For regions with initial yield shocks greater than the global average, the shocks are amplified in terms of output because production shifts to other regions not as severely affected. And, symmetrically, the yield shocks in regions with smaller direct impacts are dampened in terms of output. Differential relative effects comparative advantage in crop production around the world. This is shown for selected important agriculture regions differentially affected by climate change including Latin America[1], Africa, China, and the USA (**Figure 7**). Output changes for soybean in Africa, as an example, reflects a slightly beneficial effect of climate on this crop in the region, whereas all other regions are estimated to have a yield decline under the *IPCC* scenarios. While the positive yield shock to the African region was only 2%, the output increase is as much as 10%. In contrast, under the *GGCM* positive and average climate impact scenarios, RMSW crops yields increase less than the average increase in yields in other regions. It leads to a decrease in the output of most of these crops in Africa under such scenarios, although modest in size. Livestock output is little affected except in the *Crop & Livestock* scenarios.

All crops in China increase output under *GGCM* scenarios (Figure 7), which is due to yield changes in China that are generally better than the average yield changes in other regions. In the *IPCC* scenario, the yield impacts are negative but somewhat less negative than the average for other regions, and hence, in general, the output impacts are smaller than the global average, with soybean output increasing because the median yield estimate showed virtually no effect of climate change, better than most other regions. As a result, soybean output in China is actually up on the order of 3–5% in the *IPCC* scenario. Output changes are higher when all crop and livestock sectors have their yields impacted by climate changes. With the *Crop & Livestock* scenarios, livestock sectors are affected much, with output decreases under *IPCC* scenario and increases under *GGCM* scenario. And exception is Cattle sector output, which decreases when climate impacts are positive. This is a result of the fact that China's yields on crops fare better than other regions, so more production shifts to China, taking over pasture land and leading to a reduction in the cattle sector output.

The Latin America region, responsible today for a large share of major crops and meat products in the world, experiences increase in output under *GGCM* scenarios, except for maize (Figure 7). Especially in the case of wheat, the Latin America region fares better than other regions (most due to favorable impacts in Mexico in Fig. 3), and we see a particularly large increase in wheat output. In contrast, the *IPCC* scenario generally imposes higher damages on crop yields in the Latin America region than in the rest of the world, and thus output declines are generally larger than for the global result. The *Crops* and *Crops & Livestock* scenarios amplify the effect we see in the *RMSW* scenarios. In summary, the Latin America region gains comparative advantage in agriculture under the *GGCM* scenarios, and loses it under *IPCC* scenario.

The USA results are almost directly the reverse of the results for the Latin America region. While yield changes are positive for the *GGCM* scenarios, they are less so than for other regions. We thus see a loss of comparative advantage for the US in these scenarios. Conversely, yields are less negatively affected in the US in the *IPCC* scenarios than in most other regions of the world, and we thus see a gain in comparative advantage, and less decrease in output than for the global average.

Global price indices for crop, livestock and food sectors vary from the *BAU* as supply and demand adjust under climate impacts on yields over the period 2015 to 2050 (**Figure 8**).[2] For most crops, prices are reduced from *BAU* prices under the *GGCM* scenarios and increased under the more negative *IPCC* scenarios. Under the *BAU* scenario, EPPA-Agriculture shows crop prices to be generally fairly

1 Here Latin America includes all countries in the region (EPPA regions LAM, BRA and MEX).

2 We calculate the Walsh price index by the formula:

$$P_W^t(p^0, p^t, q^0, q^t) = \sum_{i=1}^{n} p_i^t \sqrt{q_i^0 q_i^t} \Big/ \sum_{j=1}^{n} p_j^0 \sqrt{q_j^0 q_j^t}$$

where P_W is the Walsh price index as a function of prices p and quantities q at time 0 and time t. n represents the goods and services in the economy. In our case, we apply the index to each agriculture product and take n as the regions in EPPA. Other price indices (Laspeyres, Paasche, Fisher and Marshall-Edgeworth) give very similar results.

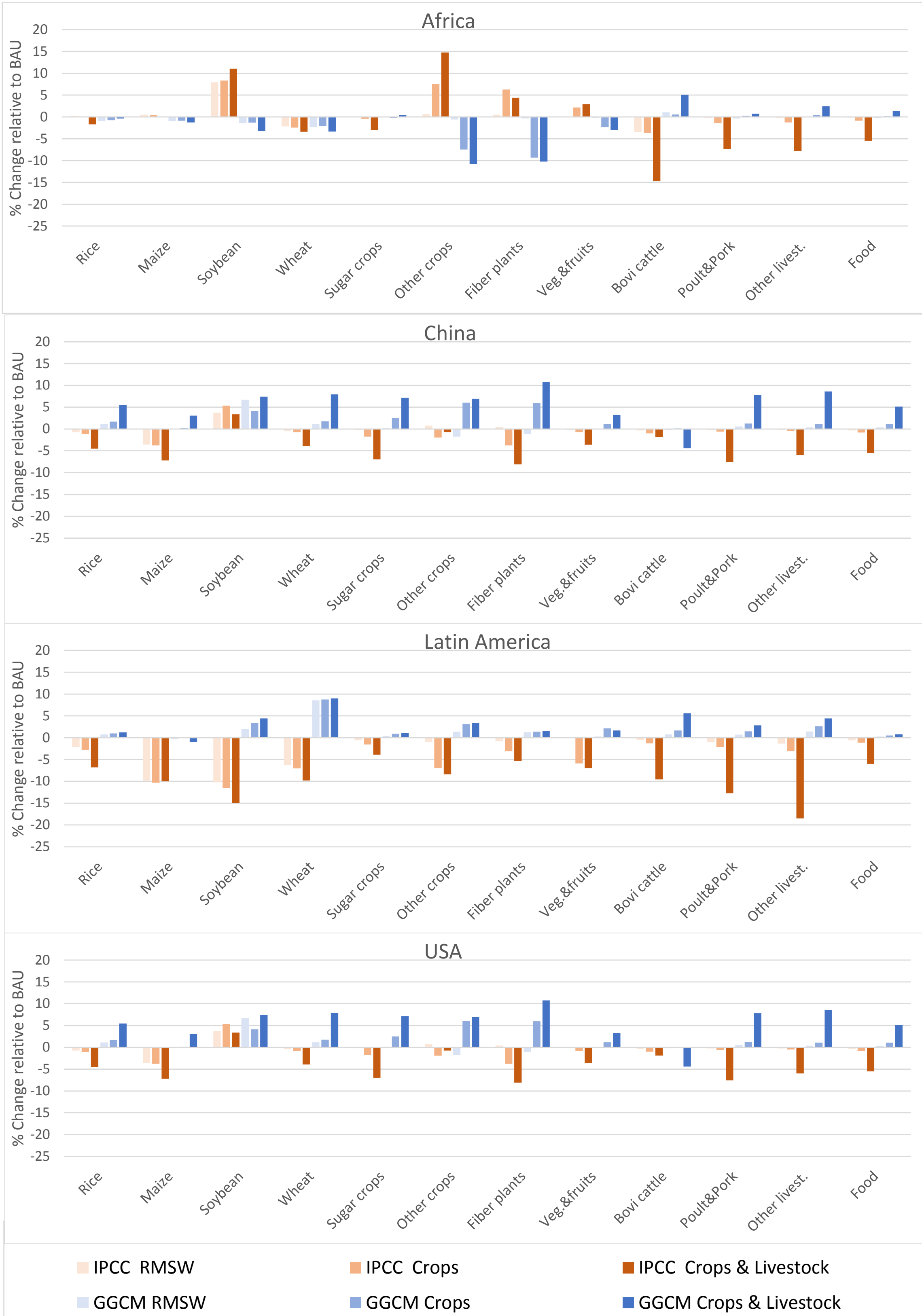

Figure 7. Change in regional output index in 2050 relative to BAU, selected regions.

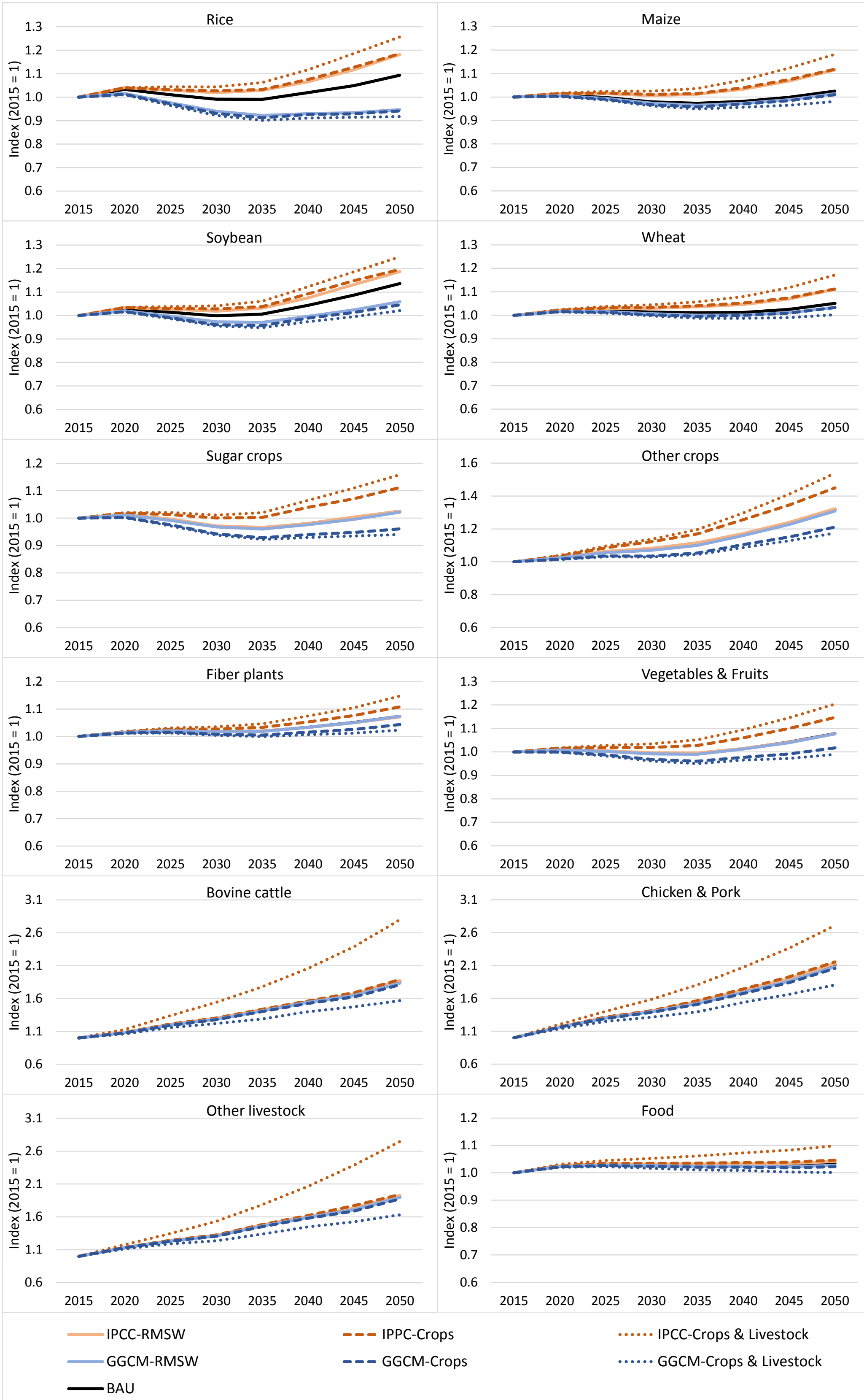

Figure 8. Global price indexes for crops, livestock and food sectors.

stable over the projection period, with the exception being *Other Crops*, where prices increase by about 30%. Under the *IPCC* scenarios, crop prices tend to increase above the *BAU*, rising in the range of 10 to 30% increase by 2050 from their 2015 levels. The *Other Crop* price index rises higher, by as much as 50% above 2015 levels, reflecting the greater increase in the *BAU*. The *GGCM* scenarios show prices 10 to 15% less than the *BAU* for most crop sectors by the middle of the century under the *IPCC* scenario and considering all crops and livestock products get impacted by climate, but in the case of other crops it may increase by 50% compared to 2015 price levels.

Under the *BAU* scenario, EPPA-Agriculture shows livestock sector prices to rise substantially, nearly doubling or more than doubling in the case of the chicken and pork sector. The differential effect reflects a higher income elasticity for meat, and with incomes rising across the world this implies more rapidly growing demand for livestock products. We do not see much impact on the *BAU* livestock product prices under the *RMSW* and *Crops* scenarios. However, on top of the steep rises in the *BAU*, we see substantial additional increases in the *IPCC Crops & Livestock* scenario, as much as a 270% increase above 2015 prices, an order 60% above the *BAU* price levels. When all crops and livestock yields are impacted by climate, changes in prices are higher for both crops and livestock sectors than in scenarios where only the major crops or all crops suffer yield impacts. These results reinforce the importance of land use changes as a mitigation strategy in agriculture and livestock. In the *GGCM Crop and Livestock* scenario we see some decline, from *BAU*, in both crop and livestock sector prices.

3.3 Environmental Metrics

To evaluate environmental impacts, we look at changes in land use and in CO_2 emissions from land. Bringing more land under cultivation or for use as pasture, in response to broadly negative impacts on crop and livestock can be an important adaptation response to make up for lost yields, but further encroachment on agriculture into natural lands may threaten biodiversity, and the deforestation and disruption of natural lands generally leads to release of carbon from the soils and vegetation as it decays or is burned.

Under the *BAU* scenario, with no climate impacts in yields, we project an increase of pasture and cropland, fairly stable amounts of land in managed forests, and nearly equal decreases in natural grassland and natural forests (**Figure 9**). The additional 80 Mha of cropland added between 2015 and 2040, while a substantial area, represents only a 5% increase from the current 1.6 Gha. Cropland areas level off after 2040. Pasture areas expanding by 119 Mha by 2050, and increase of about 6%. Such increase in cultivated areas are due to population growth and changing diets toward richer protein aliments. Natural forest and natural grass are the two main sources for these expansions, decreasing their amount by slightly more than 100 Mha each, about 3% and 7%, respectively.

At the regional level, the cropland expansion is more intense in Africa and Latin America, while pasture areas are projected to increase more in Asia, Latin America, the US and Canada[3] (**Figure 10**). Losses of Natural Forest and Natural Grass are almost entirely in Africa, Latin America and Asia. These land use trajectories through time in the *BAU* scenario ignore any possible climate impact on

3 The regions shown in Figure 3 and others follow further aggregation of EPPA-Agriculture original regions. Asia comprises EPPA regions JPN, RUS, ASI, KOR, IDZ, IND, MES and REA. Latin America: MEX, BRA and LAM. Europe: EUR and ROE. Oceania is the EPPA region ANZ, Canada and US comprises USA and CAN, Africa is the AFR region and China is CHN region.

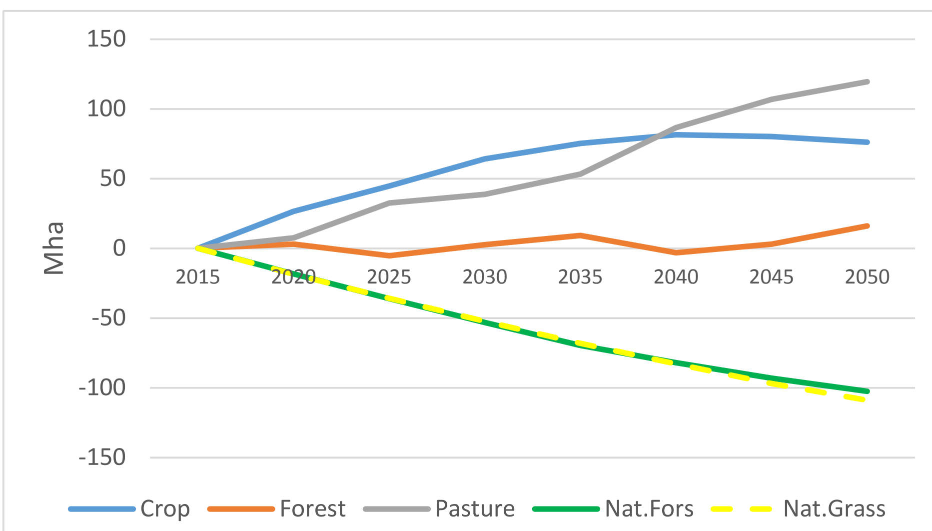

Figure 9. Global land use changes in the BAU scenario from 2015 to 2050 (Mha).

yields. As such, they are the starting point to understand the consequences of alternative shocks on crop yields due to climate impacts in the model projections.

For all *IPCC* and *GGCM* scenarios, the main land use changes from *BAU* are among managed land use types, with very little change in natural grass land and natural forest (**Figure 11**). For the *IPCC RMSW* and *Crops* scenarios, land in crops increase by about 40 and 100 Mha, respectively, above the increase in the *BAU*. The total increase from 2015 in the *IPCC Crops* scenario is more than double the increase under the *BAU*. Much of this increase in both the *RMSW* and *Crops* scenarios is at the expense of pasture land, and secondarily, managed forest. In the *IPCC Crops & Livestock* scenario there is a large increase in pasture land, a small increase in cropland, and these increases are almost entirely at the expense of managed forest. For the *GGCM* scenarios, all of these changes are reversed—less cropland is needed, leading to an increase in pasture, and secondarily managed forests in the *RMSW* and *Crops* scenarios—not surprisingly given that yields are generally increasing. In the *Crops & Livestock* scenario, both pasture and cropland decrease, and we see more land in managed forests. The relatively minor changes in natural forest and natural grass areas reflects calibration of the land transformation functions to observed land supply elasticities.

Some lessons can be taken from Figure 11. First, future land use trajectories depend, as expected, on the overall sign of yield impact. Second, failure to include productivity impacts across all commodities can give a misleading picture of land use change. And third, our results suggest that further land

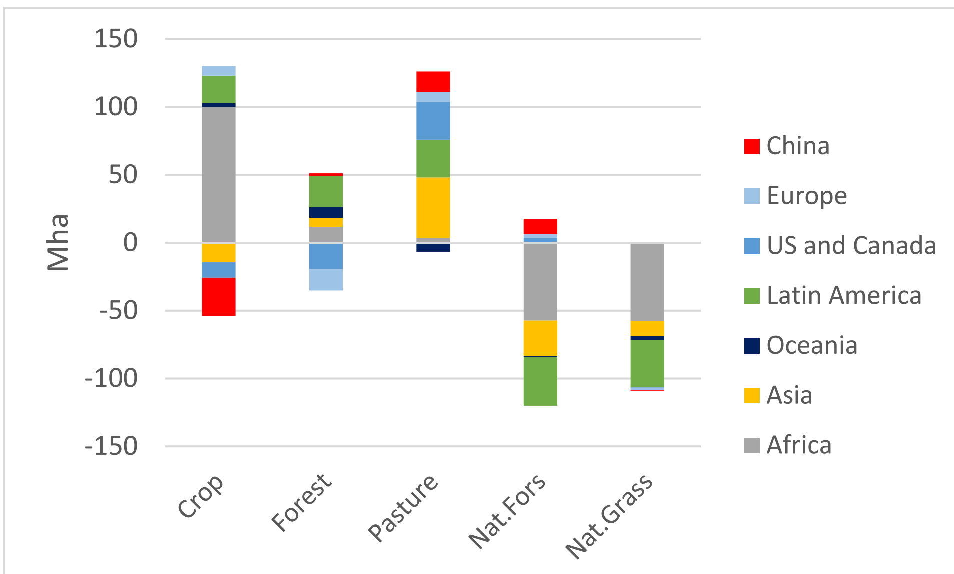

Figure 10. Regional cumulative (2015 to 2050) land use changes in the BAU scenario (Mha).

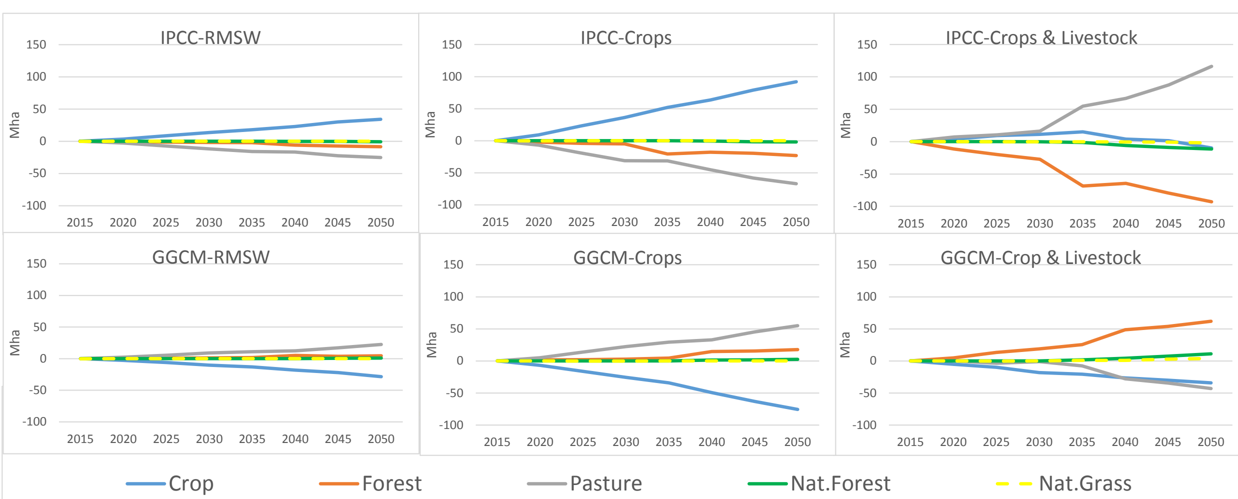

Figure 11. Land use changes in the impact scenarios relative to BAU, 2015 to 2050 (Mha).

use change due to climate change impacts, at least given the magnitude of impact seen in these median scenarios, is mainly through a reallocation of existing managed land areas, with small additional impact on natural areas.

The same basic information, plotted as total (*BAU* + climate scenario) cumulative effect on land use reinforces the lessons described in the previous paragraph (**Figure 12**). More apparent in the figure are the impacts on natural lands, where the largest impacts are comparing the *Crops & Livestock* scenarios to the *BAU*. In the *IPCC Crops & Livestock* scenario there is an additional loss of 14 Mha of natural lands. On the other hand, the generally positive impacts in the *GGCM Crops & Livestock* scenario avoids about 14 Mha of natural land conversion.

The regional land use changes play out fairly similarly to the results we saw at the global level, where impacts of the *IPCC* and *GGCM* scenarios on land use are close to the mirror image of one another, and the *Crops & Livestock* scenario reversing the land use change effect of *RMSW* and *Crops* scenarios (**Figure 13**). The largest land use changes are in

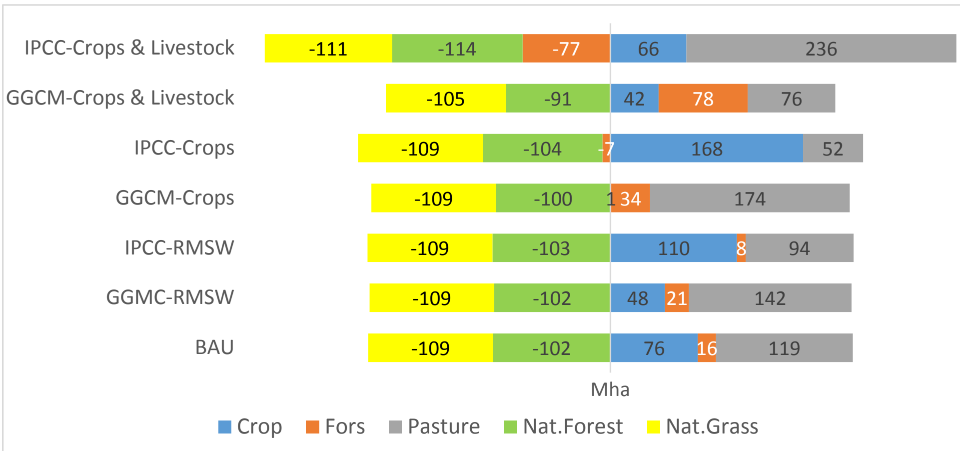

Figure 12. Land use changes in the impact scenarios relative to BAU, 2015 to 2050 (Mha).

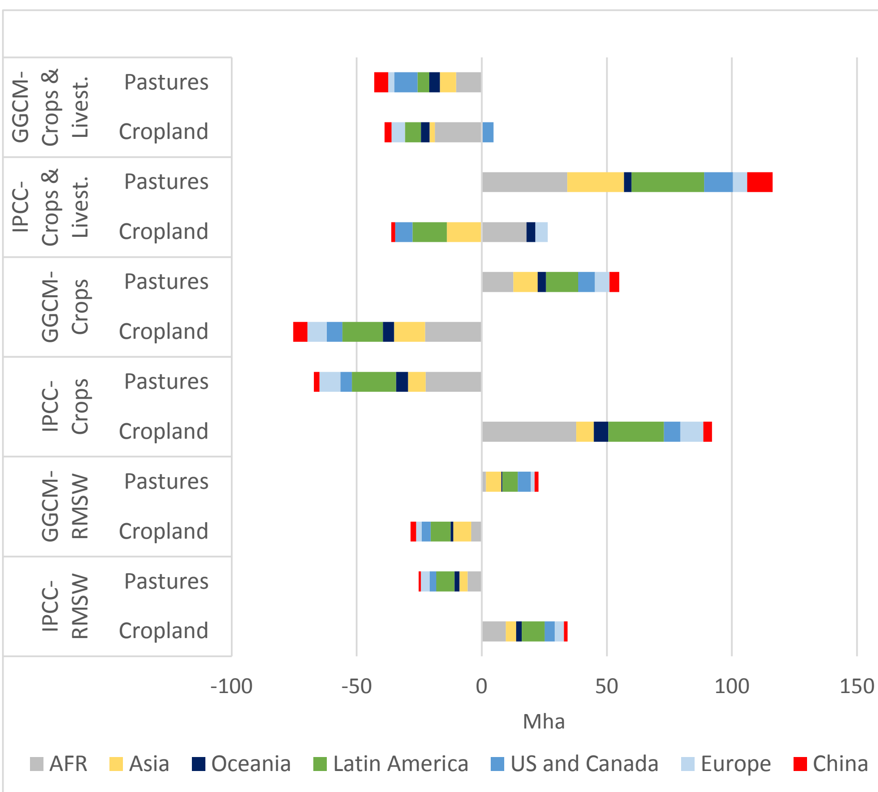

Figure 13. Changes in cropland and pastureland use by 2050 compared to BAU (Mha).

Africa and Latin America—by total land area they are the 2nd and 3rd largest of aggregate regions we plot. The largest region is Asia, which also shows substantial land use change, but less than Africa and Latin America. However, a large portion of the land area in the Asia is forest in Russia, and much of this is remote, largely inaccessible land in Siberia. So to some degree the magnitudes of land use change we see among regions reflects the relative size of these regions.

EPPA-Agriculture includes estimates of carbon storage in different land types that vary regionally. As a result, conversion of land from one land use category to another will lead to a change in total carbon storage on land (vegetation plus soils), with greater storage implying carbon sequestration and less storage implying greater emissions of carbon to the atmosphere. A conversion to cropland from pasture generally leads to more carbon storage on cropland as, according to our estimates, carbon stocks on cropland are higher than that on pasture land. However, a conversion from natural forest or managed forest to cropland results in less carbon storage. In general, we see the somewhat surprising result that the *IPCC RMSW and Crops* scenarios, with negative yields, lead to lower net CO_2 emissions (lower emissions from pasture and less in the carbon sink loss) (**Figure 14**). This is because most of the new cropland is converted from pasture, and higher levels of management (fertilizer, etc.) lead to more carbon on the new cropland than it would have with pasture. Conversely, in the *GGCM RMSW and Crops* scenarios, less cropland leads to more pasture and hence higher net CO_2 emissions. The *IPCC Crops & Livestock* scenario leads to much more pasture, with little change in cropland, and most of the new pasture coming from managed forest land (as shown previously in Figure 11). The loss of carbon in what was managed forest is attributed to its new use as pasture in Figure 14. The *GGCM Crops & Livestock* scenario has a fairly large increase in managed forest, coming from pasture and that shows up as a reduction in emissions from pasture, relative to the *BAU*.

This land emissions impacts of climate change are fairly complex, and depend on the specific land transitions. While one might expect the need for more cropland to lead to deforestation and greater emissions, if that cropland instead is created from pasture then the net result can be lower emissions. On the other hand, if we fail to consider that livestock may also be directly affected by climate, and those effects are generally negative, then that may instead shift land toward pasture, leading to an increase in emissions. This emphasizes the need for a comprehensive assessment of impacts of climate change on all agricultural commodities if the goal is to understand the broader implications of climate change for the sector.

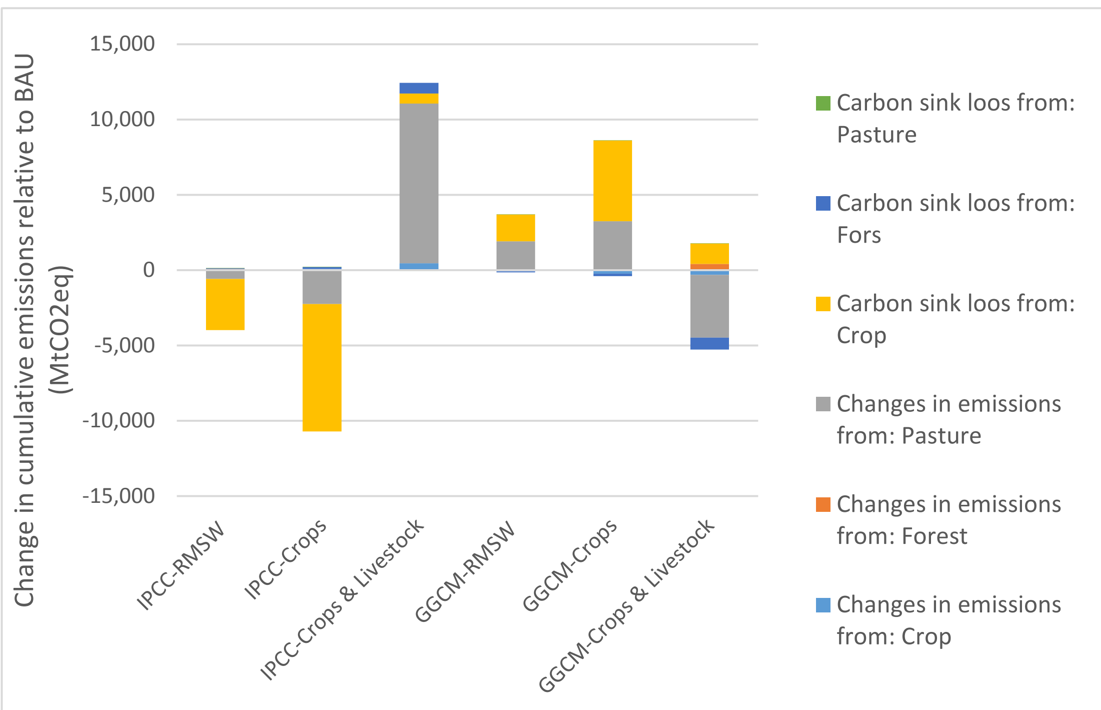

Figure 14. Cumulative (2020 to 2050) differences from BAU in emissions from land use

Note: we attribute emissions to the land use type to which the land was converted—e.g. losses from conversion of natural forest and grassland are accounted with the new land use.

4. Conclusions

We noted at the outset some glaring oversights in the literature in understanding the full impacts of climate change on agriculture. While there has been considerable research aimed at estimating climate impacts on crops over the last 30 years, much of the focus has been on a few major crops that are certainly important but only account for about 17% of the current value of agricultural production. Rice, maize, soybean, and wheat, the primary focus of most studies, are four very important crops, but there are over 170 different crops worldwide that contribute to food and fiber supply. Moreover, livestock production is an important component of agriculture. There is well-documented research on the negative effects of heat on livestock productivity in terms of weight gain and milk production with estimates that heat waves already lead to significant loss in the livestock sector, but these studies have not been combined with specific climate scenarios and scaled up to provide regional estimates for the entire world. Because agricultural markets are international, and shocks in one region of the world, or one set of commodities, reverberate through these markets only focusing on a few crops can be highly misleading. Understanding the overall risks to food supply, consumer well-being, agricultural markets, and the environmental implications of climate change through its effect on agriculture, require consideration of all of these interconnected commodities and all regions of the world. An obvious example of where a partial analysis can go wrong is that all the agricultural commodities compete at the margin for available land. If all or most commodities are negatively affected then a major avenue of adaptation—expanding area for a commodity—is much more limited than if we assume other commodities are not directly affected. There have been some studies over the years that have included other crops such as cotton, potato, and tomato but these have been limited to a few regions, and there is little or no note of them in the IPCC review of climate of the work in terms of understanding the full risks related to effects of climate on agriculture.

Another glaring limitation of many of the crop modeling exercises is that the complexity of the models and the required data make large scale simulation of these models expensive. The result has been that these site-level crop models are typically run at relatively few sites over a country-sized region. As a result, it is unclear whether the few sites are truly representative of the entire region to which they are scaled up. The southern border of northern temperate cropping areas may be very severely negatively affected, while the crop productivity may increase on the norther border of the cropping region and expand further north, no longer limited as much by cold weather. Capturing the gradient of these impacts across an entire region would require a relatively dense network of crop modeling sites. Stepping into this gap, are a relatively new set of globally gridded crop models, that estimate crop yield in every land grid, often at a .5×.5 latitude-longitude resolution. The results across available models that have been developed for rice, maize, soybean, and wheat show considerable variability. However, a median estimate for this new class of models is a generally positive effect on crop productivity on currently crop land in all regions of the world, when aggregated to a set of world regions. This is almost the complete reverse of median results, largely from site level crop models, reviewed by the IPCC. Except for a few crops in a few regions, those estimates suggest a negative impact on crop productivity in almost all regions.

While it was beyond the scope of this research to try to fill in productivity shocks for all crops and livestock for the entire world, we made a simple assumption to test how only focusing on the few crops for which we had estimates might be leading to a biased picture of the risks of climate to agriculture. Our simple assumption was to extend the average impacts we had for a region for rice, maize, soybean, and wheat, first to all crops, and then to all crops and all livestock commodities. This is really meant only to be a sensitivity analysis. With a diversity of crops and livestock types, we might expect some differential productivity shocks. And, if we were very fortunate, and negative effects on some commodities were cancelled by positive effects on others, then they might completely balance out. However, that seems unlikely. We evaluated these sensitivities using broad socio-economic metrics (economy-wide welfare change, effect on the representative agent's food budget), agriculture sector metrics (commodity output and prices), and environmental metrics (land use and CO_2 emissions from land use change). We found that omitting impacts on large set of commodities could potentially lead to a severe underestimate of climate impacts on economies and household food budgets. Some key findings:

1. Global aggregate welfare impacts were six to 13 times larger when we included direct climate impacts all crops and all livestock compared with scenarios where just rice, maize, soybean, and wheat were affected. Including all direct climate effects on all crops led to welfare impacts two to three times larger. We trace the reason for the more-than-proportional increase in the welfare impact to the fact that expansion of land area devoted to a commodity's production is a major source of adaptation. When all commodities are directly affected, that avenue of adaptation is limited.
2. Food budget impacts are on the order of 3% or less when only crops are directly affected by climate change, but the impact is 10 to 25% in many developing country regions when all crops and all livestock commodities are directly affected by climate change. The disproportionate jump in the budget effect can be traced to several factors. More

limited ability to adapt through land expansion, less ability to substitute among food commodities, and the fact that there is less value added in livestock products, as a proportion of final consumer cost, and so more of the commodity price increase shows up in the consumer budget, and even more so for those regions with lower incomes. This jump would seem to change the outcome from a minor annoyance to a major threat to food security.

3. Commodity output impacts at the global level were generally less than the direct impacts on yields, and food is generally price inelastic, leading to rising prices that create incentives to production growth. Regional impacts on output were more dependent on the yield change in the region relative to the average effect across the world, with production shifting toward those with a less negative or more positive impact, and away from those regions more severely, or less positively affected. Thus, the output effect could be amplified in a region if its yield was more severely affected than the global average. Including all crops and livestock amplified the effects on commodity prices, especial in livestock products affected indirectly through the price of feed and directly by its effect on livestock productivity.
4. Land use change and CO_2 emissions showed some of the most complex and surprising effects, with the direction of impact changing as we included direct impacts on all crops and livestock compared with simulations where we included direct effects only on crops. When only crops were directly affected we found that generally negative yield effects lead to lower net land use carbon emissions because crops expanded onto pasture, and with more intense management carbon stocks on the new cropland increased. But when these shocks were expanded to all crops and livestock, pasture increased, leading to increases in net carbon emissions to the atmosphere.
5. Taking the median of set runs of emulated GGCMs, we found positive yield effects across rice, maize, soybean, and wheat, and these provided generally improved overall welfare gains, lower household food budgets, increased commodity output, lower commodity prices, but possibly increased CO_2 emissions from land use. Similarly to results from site level crop models reviewed in the IPCC, there were a wide range of impacts from GGCMs, so caution is warranted in comparing those median effects.

While this analysis must be considered largely as a sensitivity analysis, and by construction may have exaggerated some of the conclusions—perhaps rice, maize, soybean, and wheat yields could all be negative in a region with other crops mostly positive, offsetting rather than amplifying impacts—the conclusions we reach at least indicate that (i) the agricultural research community needs to place a high priority on expanding efforts to estimate climate impacts on many more crops, and to include impacts on livestock; (ii) careful comparison of the GGCMs and traditional site level models are needed to try and resolve why, taken as a two distinct approaches, at least at median response, one arrives at such a different conclusion.

Acknowledgments

Reilly and Blanc were supported under funding from the Department of Energy, Office of Science under DEFG0294ER61937. Gurgel was supported by the Brazilian Council for Scientific and Technological Development – CNPQ (processes 312975/2017-1 and 449951/2014-6). The authors also gratefully acknowledge financial support for Integrated Global Systems Model (IGSM) development by other government, industry and foundation sponsors of the MIT Joint Program on the Science and Policy of Global Change. For a complete list of sponsors and U.S. government funding sources, please visit http://globalchange.mit.edu/sponsors/all.

5. References

Alexandratos, N. and J. Bruinsma (2012): World Agriculture towards 2030/2050: The 2012 Revision. ESA Working Paper No. 12-03, Agricultural Development Economics Division (ESA), Food and Agriculture Organization of the United Nations (FAO), Rome, Italy, 147 pp.

Antle, J.M. and C.O. Stöckle (2017): Climate Impacts on Agriculture: Insights from Agronomic-Economic Analysis. *Review of Environmental Economics and Policy*, 11(2): 299–318.

Baldos, U.L.C. and T.W. Hertel (2012): Development of a GTAP 8 Land Use and Land Cover Data Base for Years 2004 and 2007. GTAP *Research Memorandum 23*, September (https://www.gtap.agecon.purdue.edu/resources/download/6048.pdf).

Bassu, S., N. Brisson, J.L. Durand, K. Boote, J. Lizaso, J.W. Jones, C. Rosenzweig, *et al.* (2014): How Do Various Maize Crop Models Vary in Their Responses to Climate Change Factors? *Global Change Biology*, 20(7): 2301–2320 (https://doi.org/10.1111/gcb.12520).

Blanc, E. (2017): Statistical Emulators of Maize, Rice, Soybean and Wheat Yields from Global Gridded Crop Models. *Agricultural and Forest Meteorology*, 236(617): 145–161 (https://doi.org/10.1016/j.agrformet.2016.12.022).

Blanc, E. and J. Reilly (2017): Approaches to Assessing Climate Change Impacts on Agriculture: An Overview of the Debate. *Environmental Economics and Policy*, 11(2): 247–257 (https://doi.org/10.1093/reep/rex011).

Blanc, E. and W. Schlenker (2017): The Use of Panel Models in Assessments of Climate Impacts on Agriculture. *Review of Environmental Economics and Policy*, 11(2): 258–279 (https://doi.org/10.1093/reep/rex016).

Boden, T.A., G. Marland and R.J. Andres (2010): Global, Regional, and National Fossil-Fuel CO_2 Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., USA.

Bond, T.C., E. Bhardwaj, R. Dong, R. Jogani, S. Jung, C. Roden, D.G. Streets and N.M. Trautmann (2007): Historical Emissions of Black and Organic Carbon Aerosol from Energy-Related Combustion, 1850–2000. *Global Biogeochemical Cycles*, 21(2): 1–16 (https://doi.org/10.1029/2006GB002840).

Chen, Y.-H.H., S. Paltsev, J. Reilly, J. Morris, V. Karplus, A. Gurgel, P. Kishimoto N. Winchester, É. Blanc and M. Babiker (2017): The MIT Economic Projection and Policy Analysis (EPPA) Model: Version 5. MIT-JPSPGC *Technical Note 16*, March (https://globalchange.mit.edu/sites/default/files/MITJPSPGC_TechNote16.pdf).

Chen, Y.-H.H, S. Paltsev, J.M. Reilly, J.F. Morris and M.H. Babiker (2015): The MIT EPPA6 Model: Economic Growth, Energy Use, and Food Consumption. MIT JPSPGC *Report 278*, March, 43 p. (https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt278.pdf).

FAO (2019): Animal Production (http://www.fao.org/animal-production/en/).

Felzer, B., D. Kicklighter, J. Melillo and C. Wang (2004): Effects of Ozone on Net Primary Production and Carbon Sequestration in the Conterminous United States Using a Biogeochemistry Model. *Tellus B*, 56(3): 230–248 (https://doi.org/10.1111/j.1600-0889.2004.00097.x).

Ferris, M.C. and J.S. Pang (1997): Engineering and Economic Applications of Complementarity Problems. *SIAM Review*, 39(4): 669–713 (http://epubs.siam.org/doi/abs/10.1137/S0036144595285963).

Gitiaux, X., J.M. Reilly and S. Paltsev (2011): Future Yield Growth: What Evidence from Historical Data? MIT JPSPGC *Report 199*, May, 26 p. (https://globalchange.mit.edu/sites/default/files/MITJPSPGC_Rpt199.pdf).

Gornall, J., R. Betts, E. Burke, R. Clark, J. Camp, K. Willett and A. Wiltshire (2010): Implications of Climate Change for Agricultural Productivity in the Early Twenty-First Century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554): 2973–2989 (https://doi.org/10.1098/rstb.2010.0158).

Gurgel, A., Y.-H.H. Chen, S. Paltsev and J. Reilly (2016): CGE Models: Linking Natural Resources to the CGE Framework. In: *World Scientific Reference on Natural Resources and Environmental Policy in the Era of Global Change*, *Vol. 3. Computable General Equilibrium Models, A*. Dinar *et al.* (eds.), World Scientific Publishing: Hackensack, U.S., Chapter 3, pp. 57–98 (https://www.worldscientific.com/worldscibooks/10.1142/9747).

Gurgel, A., J.M. Reilly and S. Paltsev (2007): Potential Land Use Implications of a Global Biofuels Industry. *Journal of Agricultural & Food Industrial Organization*, 5: 1–34 (Article 9).

Haque, M.O. (2006): *Income Elasticity and Economic Development: Methods and Applications*. Springer Dordrecht: New York, U.S., 258 p.

Hertel, T.W. (1997): *Global Trade Analysis: Modeling and Applications*. Cambridge University Press: Cambridge, 379 p.

Hurtt, G.C., S. Frolking and M.G. Fearon (2006): The Underpinnings of Land-use History: Three Centuries of Global Gridded Land-use Transitions, Wood-harvest Activity, and Resulting Secondary Lands. *Global Change Biology*, 12(7): 1208–1229 (https://doi.org/10.1111/j.1365-2486.2006.01150.x).

Markusen, J. (2006): Extension of the Simple Model. Boulder: University of Colorado, 31 p. (http://spot.colorado.edu/~markusen/teaching_files/applied_general_equilibrium/GAMS/ch2.pdf).

Mendelsohn, R.O. and E. Massetti (2017): The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence. *Review of Environmental Economics and Policy*, 11(2): 280–298 (https://doi-org.libproxy.mit.edu/10.1093/reep/rex017).

Müller, C., J. Elliott, J. Chryssanthacopoulos, A. Arneth, J. Balkovic, P. Ciais, D. Deryng, *et al.* (2017): Global Gridded Crop Model Evaluation: Benchmarking, Skills, Deficiencies and Implications. *Geoscientific Model Development*, 10(4): 1403–22 (https://doi.org/10.5194/gmd-10-1403-2017).

Narayanan, B. G., A. Aguiar and R. McDougall (eds.) (2012): Global Trade, Assistance, and Production: The GTAP 8 Data Base. Center for Global Trade Analysis, Purdue University (https://www.gtap.agecon.purdue.edu/databases/v8/v8_doco.asp).

Nelson, G.C., D. van der Mensbrugghe, H. Ahammad, E. Blanc, K. Calvin, T. Hasegawa, P. Havlik, E. Heyhoe, P. Kyle, H. Lotze-Campen, M. von Lampe, D.M. d'Croz, H. van Meijl, C. Müller, J. Reilly, R. Robertson, R.D. Sands, C. Schmitz, A. Tabeau, K. Takahashi, H. Valin and D. Willenbockel (2014): Agriculture and climate change in global scenarios: why don't the models agree? *Agricultural Economics*, 45(1): 85–101 (http://dx.doi.org/10.1111/agec.12091).

Porter, J.R., L. Xie, A.J. Challinor, K. Cochrane, S.M. Howden, M.M. Iqbal, D.B. Lobell and M.I. Travasso (2014): Food security and food production systems. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.* Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 485–533.

Ramankutty, N. (2012): Global Cropland and Pasture Data: 1700–2007. LUGE (Land Use and the Global Environment) Laboratory, Department of Geography, McGill University, Montreal, Quebec, Canada.

Ray, D.K., N.D. Mueller, P.C. West and J.A. Foley (2013): Yield Trends Are Insufficient to Double Global Crop Production by 2050. *PloS One*, 8(6): e66428. (https://doi.org/10.1371/journal.pone.0066428).

Reilly, J.M. and K.O. Fuglie (1998): Future Yield Growth in Field Crops: What Evidence Exists? *Soil and Tillage Research*, 47(3–4):275–290 (http://www.sciencedirect.com/science/article/pii/S0167198798001160).

Rojas-Downing, M. Melissa, A. P. Nejadhashemi, T. Harrigan and S. A. Woznicki (2017): Climate Change and Livestock: Impacts, Adaptation, and Mitigation. *Climate Risk Management*, 16: 145–63 (https://doi.org/10.1016/j.crm.2017.02.001).

Rosenzweig, C., J. Elliott, D. Deryng, A.C. Ruane, C. Müller, A. Arneth, K.J. Boote, *et al.* (2014): Assessing Agricultural Risks of Climate Change in the 21st Century in a Global Gridded Crop Model Intercomparison. *Proceedings of the National Academy of Sciences*, 111(9): 3268–73 (https://doi.org/10.1073/pnas.1222463110).

Rutherford, T. (2002): Lecture Notes on Constant Elasticity Functions. University of Colorado. (http://www.gamsworld.org/mpsge/debreu/ces.pdf).

Rutherford, T.F. (1995): Extension of GAMS for Complementarity Problems Arising in Applied Economic Analysis. *Journal of Economic Dynamics and Control*, 19(8): 1299–1324 (http://www.sciencedirect.com/science/article/pii/0165188994008312).

Rutherford, T.F. (1999): Applied General Equilibrium Modeling with MPSGE as a GAMS Subsystem: An Overview of the Modeling Framework and Syntax. *Computational Economics*, 14: 1–46 (http://link.springer.com/article/10.1023/A:1008655831209).

Schmitz, C., H. van Meijl, P. Kyle, G.C. Nelson, S. Fujimori, A. Gurgel, P. Havlik, *et al.* (2014): Land-Use Change Trajectories up to 2050: Insights from a Global Agro-Economic Model Comparison. *Agricultural Economics*, 45(1): 69–84.

Summer, A., I. Lora, P. Formaggioni and F. Gottardo (2019): Impact of Heat Stress on Milk and Meat Production. *Animal Frontiers*, 9(1): 39–46 (https://doi.org/10.1093/af/vfy026).

Sutton, J.D. and A.J. Webb (1988): Trade Policies and the Use and Value of Natural Resources. Food and Agriculture Organization of the United Nations (http://agris.fao.org/agris-search/search.do?recordID=US8844785).

Zhou, Z., W. Tian, J. Wang, H. Liu and L. Cao (2012): Food Consumption Trends in China. Report. Australian Government Department of Agriculture, Fisheries and Forestry, Canberra, ACT, Australia.

Appendix

Table A1. Land cover (Mha) by EPPA regions in the base year.

	Cropland	Pasture	Managed Forest	Natural Grass	Natural Forest	TOTAL
USA	164.48	81.82	78.45	166.56	227.89	719.20
CAN	49.99	15.29	34.62	-	312.85	412.75
MEX	26.15	41.52	22.84	39.04	44.01	173.55
JPN	4.65	0.62	4.80	-	20.15	30.22
ANZ	45.03	232.89	19.32	159.02	116.72	572.98
EUR	119.88	67.42	77.50	46.84	70.52	382.16
ROE	87.77	168.96	17.95	101.05	25.28	401.01
RUS	123.37	20.17	69.55	71.93	741.78	1,026.79
ASI	37.05	2.59	6.96	-	37.58	84.17
CHN	121.74	199.85	35.98	192.99	160.09	710.64
IND	169.20	2.86	36.99	7.56	31.55	248.16
BRA	75.64	109.75	61.24	86.26	442.18	775.06
AFR	251.40	527.69	178.19	376.43	469.93	1,803.65
MES	35.87	130.05	6.08	106.27	8.06	286.33
LAM	77.50	176.50	70.33	103.13	313.61	741.07
REA	81.86	84.71	20.17	70.40	86.00	343.15
KOR	1.78	0.06	0.84	-	5.40	8.08
IDZ	42.00	11.00	10.76	-	85.73	149.49
TOTAL	1,515.35	1,873.73	752.57	1,527.48	3,199.32	8,868.44

Source: Baldos and Hertel *et al.* (2012), FAOSTAT, and Felzer *et al.* (2004), here summarized by EPPA regions.

Joint Program Report Series - Recent Articles

For limited quantities, Joint Program Reports are available free of charge. Contact the Joint Program Office to order.
Complete list: http://globalchange.mit.edu/publications

343. Challenges in Simulating Economic Effects of Climate Change on Global Agricultural Markets. *Reilly et al., Aug 2020*

342. The Changing Nature of Hydroclimatic Risks across South Africa. *Schlosser et al., Aug 2020*

341. Emulation of Community Land Model Version 5 (CLM5) to Quantify Sensitivity of Soil Moisture to Uncertain Parameters. *Gao et al., Feb 2020*

340. Can a growing world be fed when the climate is changing? *Dietz and Lanz, Feb 2020*

339. MIT Scenarios for Assessing Climate-Related Financial Risk. *Landry et al., Dec 2019*

338. Deep Decarbonization of the U.S. Electricity Sector: Is There a Role for Nuclear Power? *Tapia-Ahumada et al., Sep 2019*

337. Health Co-Benefits of Sub-National Renewable Energy Policy in the U.S. *Dimanchev et al., Jun 2019*

336. Did the shale gas boom reduce US CO_2 emissions? *Chen et al., Apr 2019*

335. Designing Successful Greenhouse Gas Emission Reduction Policies: A Primer for Policymakers – The Perfect or the Good? *Phillips & Reilly, Feb 2019*

334. Implications of Updating the Input-output Database of a Computable General Equilibrium Model on Emissions Mitigation Policy Analyses. *Hong et al., Feb 2019*

333. Statistical Emulators of Irrigated Crop Yields and Irrigation Water Requirements. *Blanc, Aug 2018*

332. Turkish Energy Sector Development and the Paris Agreement Goals: A CGE Model Assessment. *Kat et al., Jul 2018*

331. The economic and emissions benefits of engineered wood products in a low-carbon future. *Winchester & Reilly, Jun 2018*

330. Meeting the Goals of the Paris Agreement: Temperature Implications of the Shell Sky Scenario. *Paltsev et al., Mar 2018*

329. Next Steps in Tax Reform. *Jacoby et al., Mar 2018*

328. The Economic, Energy, and Emissions Impacts of Climate Policy in South Korea. *Winchester & Reilly, Mar 2018*

327. Evaluating India's climate targets: the implications of economy-wide and sector specific policies. *Singh et al., Mar 2018*

326. MIT Climate Resilience Planning: Flood Vulnerability Study. *Strzepek et al., Mar 2018*

325. Description and Evaluation of the MIT Earth System Model (MESM). *Sokolov et al., Feb 2018*

324. Finding Itself in the Post-Paris World: Russia in the New Global Energy Landscape. *Makarov et al., Dec 2017*

323. The Economic Projection and Policy Analysis Model for Taiwan: A Global Computable General Equilibrium Analysis. *Chai et al., Nov 2017*

322. Mid-Western U.S. Heavy Summer-Precipitation in Regional and Global Climate Models: The Impact on Model Skill and Consensus Through an Analogue Lens. *Gao & Schlosser, Oct 2017*

321. New data for representing irrigated agriculture in economy-wide models. *Ledvina et al., Oct 2017*

320. Probabilistic projections of the future climate for the world and the continental USA. *Sokolov et al., Sep 2017*

319. Estimating the potential of U.S. urban infrastructure albedo enhancement as climate mitigation in the face of climate variability. *Xu et al., Sep 2017*

318. A Win-Win Solution to Abate Aviation CO_2 emissions. *Winchester, Aug 2017*

317. Application of the Analogue Method to Modeling Heat Waves: A Case Study With Power Transformers. *Gao et al., Aug 2017*

316. The Revenue Implications of a Carbon Tax. *Yuan et al., Jul 2017*

315. The Future Water Risks Under Global Change in Southern and Eastern Asia: Implications of Mitigation. *Gao et al., Jul 2017*

314. Modeling the Income Dependence of Household Energy Consumption and its Implications for Climate Policy in China. *Caron et al., Jul 2017*

313. Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture. *Lanz et al., Jun 2017*

312. Can Tariffs be Used to Enforce Paris Climate Commitments? *Winchester, Jun 2017*

311. A Review of and Perspectives on Global Change Modeling for Northern Eurasia. *Monier et al., May 2017*

310. The Future of Coal in China. *Zhang et al., Apr 2017*

309. Climate Stabilization at 2°C and Net Zero Carbon Emissions. *Sokolov et al., Mar 2017*

308. Transparency in the Paris Agreement. *Jacoby et al., Feb 2017*

307. Economic Projection with Non-homothetic Preferences: The Performance and Application of a CDE Demand System. *Chen, Dec 2016*

MIT Joint Program on the Science and Policy of Global Change

Massachusetts Institute of Technology
77 Massachusetts Ave., E19-411
Cambridge MA 02139-4307 (USA)

T (617) 253-7492 **F** (617) 253-9845
globalchange@mit.edu
http://globalchange.mit.edu/