Climate change and its impact on global agriculture in 2050: Intercomparison across global economic models[1]

Gerald C. Nelson (International Food Policy Research Institute, IFPRI)

Dominique van der Mensbrugghe (Food & Agriculture Organization of the United Nations, FAO)

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Abstract

Agriculture is unique among economic sectors in the nature of impacts from climate change. The production activity that transforms inputs into agricultural outputs involves direct use of weather inputs (temperature and precipitation). Previous studies of the impacts of climate change on agriculture have reported substantial differences in outcomes of key variables such as prices, production, and trade. These divergent outcomes arise from differences in model inputs and model specification. The goal of this paper is to review climate change results and underlying determinants from a model comparison exercise with 10 of the leading global economic models that include significant representation of agriculture. By providing common productivity drivers that include climate change effects, differences in model outcomes are reduced. All models show higher prices in 2050 because of negative productivity shocks from climate change. The magnitude of the price increases, and the adaptation responses, differ significantly across the various models. Substantial differences exist in the structural parameters affecting demand, area, and yield, and should be a topic for future research.

Keywords: computable general equilibrium, partial equilibrium, climate change, agriculture

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The climate change drivers were provided as part of the ISI-MIP model comparison project (www.isi-mip.org). We acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 1 of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. The socioeconomic drivers were developed for the Shared Socio-economic Pathways (SSP) as part of a new set of IPCC scenarios for analyses of climate impacts, adaptation, and mitigation and are available at the SSP data portal https://secure.iiasa.ac.at/web-apps/ene/SspDb.
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JEL Codes: C63, C68, D58, Q11, Q54

Introduction

Agriculture is unique among economic sectors in the nature of impacts from climate change. The production activity that transforms inputs into agricultural outputs involves direct use of weather inputs (solar radiation, temperature and precipitation). Climate change alters these inputs and therefore has a direct, biophysical effect on agricultural productivity. Disentangling the consequences of these productivity effects from the larger set of drivers of change, including income, population, and productivity investments of the private sector, is crucial to formulating agricultural policies and programs that provide for sustainable food security.

Previous studies of the impacts of climate change on agriculture have reported substantial differences in outcomes of key variables such as prices, production, and trade. These divergent outcomes arise from differences in model inputs and model specification. The goal of this paper is to review climate change results and underlying determinants from a model comparison exercise with 10 of the leading global economic models that include significant representation of agriculture. It is part of a larger study undertaken by the AgMIP global economic modeling group to explore the underlying determinants of differences in model outputs (See von Lampe & Willenbockel et al, 2013 for an overview of the study). The goal of the study was *not* to generate plausible scenarios. Rather it was to compare model performance along three substantive axes – socioeconomic pathways, climate change pathways, and bioenergy pathways. Each of the 9 scenarios provides scenario specific results as well as comparisons to a reference scenario, described briefly below. This paper examines results from the four scenarios that vary climate-change-related drivers.

Climate change in long-term scenarios for agriculture: key results in the literature

A summary of the literature on the effects of climate change on agriculture is of transition from relative optimism to significant pessimism. In part the transition reflects gradual improvements in data availability and improvements in modeling, both biophysical and socioeconomic. But it also includes inherent differences in underlying assumptions about adaptation implicit in the choice of modeling technique. The conventional wisdom is that models that rely heavily on biophysical, process-based modeling are more pessimistic about climate change effects, even when they attempt to incorporate adaptive behavior, while models that use more flexible economic functional forms or statistical techniques (general equilibrium or statistical models) are less pessimistic. The underlying assumption seems to be that process-based models are unable to capture as much of the adaptive responses to climate change that other modelling approaches can do.

Studies in the early 1990s (e.g., Tobey, Reilly, and Kane 1992 and Reilly, Hohmann, and Kane 1994) concluded that agricultural impacts of climate change would in some cases be positive, and in other cases would be manageable globally in part because negative yield effects in temperate grain-producing regions would be buffered by interregional adjustments in production and consumption and corresponding trade flows.

A widely cited 2004 publication (Parry et al. 2004) based its conclusions on more complex modeling of both climate and agriculture, using the IPCC's third assessment results. This report was still relatively sanguine about global food production, but with more caveats than the earlier papers: "The combined model and scenario experiments demonstrate that the world, for the most part, appears to be able to continue to feed itself under the SRES scenarios during the rest of this century. The explanation for this is that production in the developed countries generally benefits from climate change, compensating for declines projected for developing nations." (Parry et al. 2004, p. 66). The IPPC's Fourth Assessment Report (AR4) on impacts (IPCC et al. 2007) presents similar findings.

The early literature that suggests a sanguine future for agriculture, with international trade flows largely compensating for regional negative effects, was based on less sophisticated modeling of biophysical impacts of climate change on agriculture and use of very limited climate change results. It has only been since AR4's climate modeling results, released in the mid-2000s, that more detailed modeling has been possible.

Nelson et al. (2009) and Nelson et al. (2010) represent recent analyses that combine detailed biophysical modeling of individual crop response to climate change at high spatial resolution across the globe using climate data from AR4 with a highly disaggregated economic model of global agriculture. They report substantial declines in yields for some crops in key producing countries when only climate-specific biophysical effects are included (i.e., holding management practices, varieties, and production areas constant). Depending on assumptions about technical change exogenous to the model as well as population and income growth trajectories, and allowing for a range of adaptation responses, they report simulated price increases of over 100 percent between 2000 and 2050 for some crops with some climate change results. By way of contrast, van der Mensbrugghe et al. (2011) suggest declining real prices are a possibility.

The literature that relies completely on statistical methods is sometime referred to as Ricardian analysis after the seminal paper by Mendelsohn, Nordhaus and Shaw (2009) based on cross section data for US agriculture in 1982. Essentially papers in this literature fit a multivariate regression with indirect measures of productivity such as land values or farm revenue on the left hand side and a variety of biophysical and socioeconomic variables on the right hand side. Mendelsohn, Nordhaus and Shaw (2009) claim that the modeling approaches that include biophysical process modeling suffer in that "None permits a full adjustment to changing environmental conditions by the farmer." Of course, any statistical approach can only capture effects that are included in the data used for the analysis. The unanswered question is whether out-of-sample projections, which any projection for climate effects in 2050 would be (see Lobell et al. 2008)—either of direct impacts such as changes in temperature or precipitation or of indirect impacts such as effects on pests and diseases—bear any resemblance to plausibility.

Method of analysis

To eliminate common sources of model output differences, three types of exogenous drivers were provided to each of the modeling teams – GDP, population, and agricultural productivity growth. Remaining output differences are then assumed due to model-specific choices such as functional form, structural parameters such as demand elasticities and area and yield responses to price changes, and aggregation issues. A reference scenario, called S1, is based on the GDP and population values from the Shared Socioeconomic Pathway 2 (SSP2) developed for IPCC 5th assessment report inputs (AR5_. See van Vuuren et al. (2012) and Kriegler et al. (2012) for a discussion of SSPs.[2] In SSP2, global population by 2050 reaches 9.3 billion, an increase of 35 percent relative to 2010. Global GDP is assumed to triple between 2010 and 2050. Exogenous agricultural productivity changes were provided from the IMPACT modeling suite (Rosegrant and IMPACT Development Team 2012).

To assess differences in climate change modeling, data from four climate change scenarios were used (S3-S6, see Table 1) based on the most extreme of the Representative Concentration Pathways (RCPs) developed for AR5, RCP 8.5 (see Moss et al. 2010 for a discussion of RCPs). This RCP has a radiative forcing of over 8.5 watts per square meter, with a CO_2 concentration of about 935 ppm in 2100 compared to a level in the early 21st century of about 370 ppm.[3] This RCP is used as an input into two general circulation models (GCMs) – Hadley and IPSL. The resulting climate outputs were bias-corrected and downscaled for the ISI-MIP model comparison project (http://www.pik-potsdam.de/research/climate-impacts-and-vulnerabilities/research/rd2-cross-cutting-activities/isi-mip).

The ISI-MIP climate data were then used as inputs into two crop growth models – the Lund-Potsdam-Jena model of the managed planetary land surface (LPJmL) (Bondeau et al. 2007) and the suite of crop models included in the Decision Support System for Agricultural Technology (DSSAT) software (Jones et al. 2003). Climate data for 2000 and 2050 were used to generate yields at ½ degree resolution (about 55.5 kilometers at the equator). The crop modeling assumed a limited CO_2 fertilization effect in 2050, using a CO_2 concentration level of 370 ppm in 2050, roughly the level in 2000. CO_2 fertilization is especially important for crops such as rice, oil seeds, and wheat that use the C3 photosynthetic pathway and can partially offset the negative effects of higher temperatures and precipitation. The combination of the most extreme RCP outputs with an assumed low CO_2 concentration level in 2050 means that the negative productivity effects are at the upper end of what is plausible by 2050.

The process of transforming crop model data to inputs for economic modeling involved three challenges – deriving yield effects for crops not included in the crop models, aggregating from high resolution spatial crop model outputs to lower resolution country or regional units of the economic models, and determining yield effects over time. See Mueller and Robertson, 2013 for a detailed discussion of the how these issues were managed.

The end result is scenarios S3-S6 with climate change productivity effects for each crop[4], conditioned by the SSP2 socioeconomic pathway, on the set of outputs reported by all the models. Table 2 reports the exogenous yield increases for selected crops (coarse grains, oil seeds, rice, sugar, and wheat) and countries (Brazil, Canada, China, India, and the USA). In the scenario without climate change (S1), the exogenous productivity increases between 2005 and

[2] The SSP data are available for download at https://secure.iiasa.ac.at/web-apps/ene/SspDb).
[3] See the table "Global Radiative Forcing 1979-2010 (W m^{-2})" in http://www.esrl.noaa.gov/gmd/aggi/, accessed January 5, 2013
[4] MAgPIE does not use these exogenous productivity shifters. Instead it incorporates the outputs from the crop models directly.

2050 range from 12 percent for oilseeds in Canada to 132 percent for coarse grains in India. Across the countries included in Table 2, coarse grain increases are greatest and oilseeds the smallest.

Climate effects on biophysical productivity are almost uniformly negative, with the largest negative effects most often found on Brazilian and Indian crops. In a few cases, in the northern parts of the northern hemisphere (coarse grains in Canada (S4), rice in China (S5 and S6), and wheat in Canada (S4) and China (S3)), climate change results in increased yields over the no-climate change exogenous effects. The exception to this general rule is sugar, where climate change increases yields in Table 2 in S3 and S4 and in India in all scenarios.

One potential issue is that either the crop models or the GCMs might have a systematic bias in their climate change effects. To test this, we calculated the means of the scenarios that employed the same crop models (S3 and S4 use LPJmL; S5 and S6 use DSSAT) and differenced them. We followed the same procedure for the GCM scenarios (S3 and S5 use IPSL; S4 and S6 use Hadley). The crop model choice matters for coarse grains and wheat; the DSSAT climate change results are uniformly more negative than the LPJmL results. For oilseeds and rice, the crop model results differ but not in a common direction. For example, DSSAT results in India are less negative for oilseeds (+0.21 percent difference in annual growth rate relative to S1) but more negative for rice (-0.44). The climate models results do not appear to have any systematic bias and the differences are relatively small, except for Canadian coarse grains and wheat and Brazilian where the crop model results using the IPSL climate data show less negative yield consequences than with Hadley climate data.

Key results of the analysis

Each of the models used the exogenous productivity shocks to alter yield determinants. For the CGE models, the shocks were implemented as shifts in the land efficiency parameters of the sectoral production functions. For the partial equilibrium models, the shocks were additive shifters in a yield or supply equation (see Robinson, van Meijl and Willenbockel (2013) for more discussion on the differences between general and partial equilibrium modeling of productivity effects).

Conceptually, the exogenous yield shock reduces supply at the existing price. Area, yield and consumption all respond to equilibrate price at a new level. If the analysis is at the world level then net trade cannot change. But for individual countries, changes in trade are an additional response option to the yield shock. The model responses can be decomposed into their endogenous yield, area, and consumption changes with differences in model outcomes determined by their underlying specification of these endogenous changes.

We look individual at effects on prices, yields, area, and consumption and then relationships among these in the decomposition analysis.

Climate change and effects on price

We begin by examining the effects of climate change on prices. We use the producer price variable for comparison (see Willenbockel, Robinson and van Meijl 2013 for a discussion of the choice of price variable). We focus on five commodities/commodity groups, collectively called

CR5 – coarse grains (CGR) (mostly maize in most countries), rice (RIC), oil seeds (mostly soybeans) (OSD), sugar (about 80 percent is from sugar cane) (SUG) and wheat (WHT) – because these commodities make up the lion's share of global agricultural production, consumption, and trade.

The following discussion focuses on three key points drawn from Table 3 and Figure 1 – prices increase relative to the reference scenario across all models, there is significant variation by economic and crop model, and small variation by climate model. It is important to emphasize that these results are percent changes from the 2050 outcomes in each of the models for the reference scenario. There are also significant differences in 2005 to 2050 price changes, discussed in the overview paper (von Lampe and Willenbockel 2013).

Figure 1 provides a visual overview of the model results for the CR5 crops by scenario – a few models have price declines for a few crops in selected scenarios but price increases dominate. The GCAM and Envisage models generally have the smallest price increases; the MagPIE and GLOBIOM models the largest. The EPPA model does not generate crop specific price increases but for the AGR aggregate activity, EPPA price increases range from 1.3 to 4.6 percent over the AGR aggregate price in 2050 without climate change.

Higher prices but with significant variation by model, GCM and crop model

For the CR5 crop aggregate, all models report higher prices in 2050 with climate change than without (Table 3). The range of price increases for the CR5 aggregate is from 3.0 percent for S4 in GCAM to 78.9 percent for S4 in MagPIE. For all crops other than sugar, all models report a price increase; coarse grains – 1.9 percent to 118.1 percent, oilseeds – 4.4 percent to 89.0 percent, rice – 1.5 percent to 75.6 percent, and wheat – 2.1 percent to 71.0 percent. Several models report sugar price declines in 2050 with climate change in S3 and S4, the scenarios that use the LPJmL crop model. See Mueller and Robertson 2013 for a discussion of why the LPJmL sugar results in S3 and S4 are likely more appropriate than the DSSAT-derived results.

Crop and economic model effects

In general, the price effects from the crop models follow the differences in the climate change productivity shocks, with LPJmL-based results having smaller price increases than the DSSAT-based shocks.

GCM effects

For most models Hadley GCM results in higher prices for the CR5 aggregate. But the differences are quite small (-5.3 percent to 6.8 percent) except in MagPIE where the Hadley results are 8.8 percent to 61.1 percent greater than the IPSL results.

Yield effects

Changes in crop yields are a function of both exogenous and endogenous elements in all models except MagPIE, where there is no exogenous yield change component. The exogenous changes in the S1 scenario (see Table 2) arise from investments in productivity enhancing technologies and changes in information delivery systems that are not captured in the modeling. Climate change effects are added (or subtracted) from these exogenous effects. Then each of the models adds endogenous yield effects from price changes.

Figure 2 provides an overview perspective on the combined exogenous and endogenous effects of climate change on yields. A few key points are clear. While almost all models have yield reductions relative to S1, the magnitudes differ substantially by model. GTEM generally has the smallest negative effects; MagPIE has the largest number of positive effects. MAGNET, GCAM, and GLOBIOM generally have the largest negative effects across all commodities. Sugar yields are positively affected by climate change in several of the models in the S3 and S4 scenarios that use the LPJmL crop model results.

Table 4 provides a more detailed look at the global average yield effects for CR5 crops. The minimum values are relatively consistent across the crops, ranging from -17.1 percent for rice (AIM, S5) to -28.8 percent for coarse grains (MAGNET, S8). The maximum values differ dramatically. Rice yields in MagPIE for S5 increase 25.6 percent; wheat yields decline by 2.3 percent in GTEM.

The choice of crop model has a greater effect on yields than the choice of GCM. But the crop model differences are starker for some crops (e.g., coarse grains and sugar) than others.

Area effects

Figure 3 provides an overview of crop area change from climate change in 2050 relative to the reference scenario (with no climate change) in 2050. Almost all models show an increase in crop area over the S1 scenario. MAGNET has the largest crop area increases across the scenarios; MagPIE the smallest for all but S4 where GLOBIOM is the smallest.

Table 5 provides numerical results of the area changes for the individual CR5 crops. Coarse grains and wheat area increase in all the models for all the scenarios, with the largest increases in MAGNET, S6 – 35.4 percent for coarse grains and 27.4 percent for wheat. Oil seeds area increases in all scenarios for all models except MagPIE where it fall slightly in S5 and S6. Rice area decline in GLOBIOM in S3 and S4 and in MagPIE in S3 to S5. Sugar area is constant or declines in all models for S3 and S4, and MagPIE also has a sugar area decline in S5. The sugar results are driven by the dramatically different crop model assessment of climate change impacts on sugar productivity.

Decomposing area, yield and consumption responses by model

The yield shock from climate change causes endogenous adjustments in prices, consumption, area and yield. This section decomposes the results across models and reports some key findings.

The goal of the decomposition is to identify the relative importance of the three adjustment components in the model responses to a climate change shock. Start from the basic equation:

(1) $$PROD^R = AREA^R YILD^R$$

where *PROD* is output, *AREA* is area, *YILD* is yield and the superscript *R* stands for the reference variables. The direct impact is the application of the exogenous yield shock YI^X:

(2) $$PROD^D = AREA^R (YILD^R - YI^X)$$

where $PROD^D$ is the initial production effect from the climate change shock. We call $YEXO \equiv YILD^R - YI^X$ the exogenous yield after climate change.

Final output ($PROD^S$) is:

(3) $$PROD^S = AREA^S YILD^S = AREA^S (YEXO + YI^N) = AREA^S (YILD^R - YI^X + YI^N)$$

after area, yield and demand adjust to changing relative prices. The endogenous yield response YI^N is in response to the initial price change.[5]

The effect of the initial shock

(4) $$dPROD^D = PROD^R - PROD^D = AREA^R (YILD^R - YEXO) = AREA^R YI^X$$

is a positive number for a negative climate shock ($YILD^R > YEXO$). The final term shows that we are decomposing the exogenous shock (i.e. the exogenous difference in yields) as applied to the reference area.

The adjustments to the shock can be decomposed into three effects—changes in demand, changes in area, and changes in yields (relative to the shock). The following formula captures these adjustments:

[5] YI^N can take negative values (and does for some models) and YI^X can also take negative values (and does for some crop/region combinations under the various climate change scenarios), i.e. there can be positive climate shocks.

(5)
$$
\begin{aligned}
dPROD^{D} &= \underbrace{(PROD^{R} - PROD^{S})}_{\text{Demand effect}} \\
&+ \underbrace{(AREA^{S} - AREA^{R})\frac{YILD^{S} + YEXO}{2}}_{\text{Area effect}} \\
&+ \underbrace{(YILD^{S} - YEXO)\frac{AREA^{S} + AREA^{R}}{2}}_{\text{Yield effect}}
\end{aligned}
$$

The equation is applied at the global level where demand must equal supply. To do the decomposition at the regional level, the formula would need to take into account changes in trade. The first term is adaptation via changes in demand; the second is adaptation via area change; the third is adaptation via endogenous yield change. The area change is weighted by the average of the final yield and the shock yield, an average of the Laspeyres and Paasche volume indices. The yield change is weighted by the average of the initial and final area. The final term measures the change in output derived from the indirect yield changes. Note that the term ($YILD^S$ – $YEXO$) is equal to YI^N, i.e. the endogenous yield response.

Table 6 compiles the decomposition results for the world in 2050 under different aggregations of the underlying model simulations. Seven of the 10 models provided sufficient disaggregation to undertake the decomposition analysis. The overall average across all commodities suggests that area response contributes about 55 percent of the adjustment with roughly 22-24 percent each for demand and yield response.

The results are roughly the same for the individual climate change scenarios S3 to S6 but the scenarios based on the LPJmL crop model (S3 and S4) have somewhat larger area adaptations than the DSSAT-based results (S5 and S6).

The commodity-specific decompositions show greater differences. Wheat, for example, shows a much larger area contribution on average, and rice a much lower contribution.

The largest differences occur across models. The demand contribution varies from a low of 4 percent to a high of 49 percent, area response contribution varies from a low of 10 percent to a high of 109 percent, and yield adjustment contribution varies from a low of -19 percent to a high of 56 percent.

Figure 4 to Figure 6 below highlight the decomposition for seven models for four of the commodities (wheat, rice, coarse grains and oil seeds), pooled over the four climate shock scenarios. The figures suggest:

- Adaptation generally relies more on the supply-side than on the demand side, where the average contribution is 20 percent or less with the exception of GLOBIOM. There is some evidence of higher demand adjustment on average in the PE models compared to the GE models, as well as more variance in demand’s contribution to adjustment. One possible explanation is the supply chains in the GE models dampen the transmission of the farm level price impacts at the consumer level.

- There is a symmetric response between area and yield impacts—models with high area adjustments (AIM and MAGNET) have low yield responses, and vice versa for the remaining models.
- The spread across most models is wide—except for Envisage and FARM. This suggests some significant non-linearities in most of the models.
- The figures highlight some significant outliers—area response for MAGNET in S5 and S6 (mirrored in the yield response), and yield adjustment for rice in IMPACT for S5.
- Across the board, all models had very wide bands for the sugar sector (not shown), particularly for scenarios S3 and S4, because of the differences in the way that DSSAT and LPJmL model sugar responses to climate shocks.
- The choice of underlying structural parameters differ across the models. MAGNET, AIM, and GCAM modelers have chosen parameters that allow area expansion to be relatively easy. For the GE models, another factor that will impact the endogenous yield response is the degree of substitutability across factors. Models with relatively high factor substitution elasticities will see relative increases in labor and capital as land becomes dearer, thereby raising yields at the expense of land expansion. GLOBIOM demand parameters are the most responsive. Crop specific supply side parameters vary most in AIM, MAGNET, and GCAM. GCAM demand parameters vary most across the crops.

Concluding remarks

There is little disagreement now that climate change will have significant, and mostly negative, effects on agricultural productivity. The earlier disagreements in the economic community about its effects globally no longer exist for the modeling community represented in this exercise. Prices are a useful single indicator for the combined effects, including adaptation processes built into these models, and they almost universally increase in all the scenarios for all the models. That useful wide-ranging agreement, however, should be qualified by the observation that the magnitudes of the increases vary dramatically across the models and the sectors included.

A second point is that, at least for this set of crop models and climate models, the differences in results across the two crop models are larger than the difference across the two climate models.

A third point is that assumptions that are typically buried in technical reports can have significant effects on highly visible output measures. Even one so obvious an output as ‘price’ required extended consultations to reach a consensus on how best to compare these across the various model outputs. But after clarification of these technical issues, a decomposition of the adaptation responses suggests that modelers have made substantially different assumptions about demand, area, and yield structural parameters. Elaborating on the sources these differences, and assessing their relative importance, should be a high-priority research topic.

Finally, the data on which much of this analysis relies, from basic agricultural statistics to field data for crop model coefficients tuning is not adequate for the task at hand. Much better data, collected using 21st technologies would make it much easier to understand the nature of the challenges facing agriculture from climate change.

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Table 1. Climate change scenarios

Scenario identifier	General circulation model	Crop model
S1	None	None
S3	IPSL-CM5A-LR	LPJmL
S4	HadGEM2-ES	LPJmL
S5	IPSL-CM5A-LR	DSSAT
S6	HadGEM2-ES	DSSAT

Notes: LPJml – Lund-Potsdam-Jena managed Land Dynamic Global Vegetation and Water Balance Model, DSSAT – Decision Support System for Agricultural Technology.

Table 2. Exogenous annual yield increases, IMPACT model, 2005-2050 (percent per year)

Crop and commodity	S1	S3 – S1	S4 – S1	S5 – S1	S6 – S1	DSSAT-LPJmL	Hadley - IPSL
Coarse grains							
Brazil	2.23	-0.30	-0.15	-0.70	-0.68	-0.47	0.09
Canada	2.19	-0.11	**0.12**	-0.23	-0.20	-0.22	0.13
China	2.04	-0.13	-0.11	-0.53	-0.48	-0.39	0.04
India	2.32	-0.20	-0.28	-0.72	-0.70	-0.47	-0.03
USA	1.68	-0.31	-0.20	-0.64	-0.82	-0.48	-0.04
Oil seeds							
Brazil	1.23	-0.42	-0.39	-0.27	-0.27	0.14	0.02
Canada	1.12	-0.12	-0.01	-0.10	-0.23	-0.10	-0.01
China	1.50	-0.09	-0.13	-0.06	-0.04	0.06	-0.01
India	1.38	-0.37	-0.46	-0.20	-0.21	0.21	-0.05
USA	1.43	-0.24	-0.18	-0.18	-0.26	-0.01	-0.01
Rice							
Brazil	1.48	-0.30	-0.24	-0.12	-0.19	0.12	-0.01
China	1.43	-0.07	-0.06	**0.04**	**0.04**	0.11	0.01
India	1.79	-0.18	-0.23	-0.67	-0.61	-0.44	0.00
USA	1.44	-0.11	-0.09	-0.01	-0.10	0.04	-0.03
Sugar							
Brazil	1.71	**0.35**	**0.31**	-0.44	-0.40	1.71	0.35
Canada	1.69	**0.08**	**0.06**	**0.10**	-0.03	1.69	0.08
China	1.65	**0.09**	**0.08**	-0.28	-0.25	1.65	0.09
India	1.12	-0.14	-0.15	-0.54	-0.50	1.12	-0.14
USA	1.32	**0.02**	**0.01**	-0.23	-0.32	1.32	0.02
Wheat							
Brazil	2.03	-0.43	-0.36	-0.70	-0.46	-0.19	0.16
Canada	2.29	-0.09	**0.29**	-0.29	-0.05	-0.27	0.31
China	1.62	**0.03**	-0.01	-0.37	-0.31	-0.35	0.01
India	1.40	-0.20	-0.23	-0.58	-0.47	-0.31	0.04
USA	1.49	-0.20	-0.14	-0.18	-0.20	-0.02	0.02

Source: AgMIP Global Model Intercomparison Project.

Notes: Positive effects of climate change are indicated in bold. The productivity effects reported here are exogenous to the modeling environment but reported values can differ from model to model because of model-specific aggregation procedures. These aggregations are from the IMPACT model.

Table 3. The effects of climate change on world agricultural prices (percent change, S3-S6 results in 2050 relative to S1 results in 2050)

Model/scenario	Coarse grains	Oil seed	Rice	Sugar	Wheat	Weighted average of 5 crops
AIM						
S3	5.3	16.2	11.3	8.0	9.5	10.0
S4	5.1	15.0	13.0	10.5	10.2	9.1
S5	12.9	12.2	22.7	41.6	20.7	16.3
S6	16.0	13.8	21.0	36.6	16.9	16.3
DSSAT - LPJmL	*9.3*	*-2.5*	*9.7*	*29.9*	*9.0*	*6.7*
Hadley - IPSL	*1.4*	*0.2*	*0.0*	*-1.2*	*-1.6*	*-0.5*
ENVISAGE						
S3	2.7	9.7	4.5	0.7	2.5	4.1
S4	1.9	9.0	5.0	0.8	2.1	3.8
S5	7.2	4.8	6.0	7.5	4.2	5.7
S6	8.8	6.2	5.6	6.6	3.4	6.0
DSSAT - LPJmL	*5.7*	*-3.8*	*1.0*	*6.3*	*1.5*	*1.9*
Hadley - IPSL	*0.4*	*0.3*	*0.0*	*-0.4*	*-0.6*	*-0.1*
FARM						
S3	7.7	36.1	23.7	14.3	17.1	21.0
S4	8.2	51.6	31.8	20.1	23.7	28.8
S5	18.8	38.6	47.5	68.1	56.1	42.4
S6	19.0	34.4	38.9	52.2	38.9	34.5
DSSAT - LPJmL	*11.0*	*-7.4*	*15.4*	*42.9*	*27.1*	*13.5*
Hadley - IPSL	*0.3*	*5.6*	*-0.2*	*-5.0*	*-5.3*	*-0.1*
GTEM						
S3	6.2	17.7	7.9	1.9	7.7	8.8
S4	5.7	20.0	9.3	2.3	8.0	9.4
S5	14.3	13.3	9.1	9.4	19.3	12.8
S6	16.6	14.0	8.5	8.3	14.6	12.3
DSSAT - LPJmL	*9.5*	*-5.2*	*0.2*	*6.7*	*9.1*	*3.4*
Hadley - IPSL	*0.9*	*1.5*	*0.4*	*-0.3*	*-2.2*	*0.1*

MAGNET						
S3	17.2	34.5	17.7	0.2	15.9	18.9
S4	13.2	32.4	18.4	0.2	14.6	17.6
S5	35.1	27.7	19.1	9.3	33.9	26.7
S6	39.4	34.5	19.6	10.4	31.7	29.5
DSSAT - LPJmL	*22.1*	*-2.3*	*1.3*	*9.6*	*17.6*	*9.9*
Hadley - IPSL	*0.1*	*2.3*	*0.6*	*0.5*	*-1.7*	*0.7*
GCAM						
S3	3.7	7.8	2.7	-4.4	4.4	3.6
S4	2.5	7.4	2.7	-3.9	2.5	3.0
S5	9.7	4.8	1.5	13.1	3.1	6.2
S6	10.1	6.6	1.5	12.7	2.0	6.5
DSSAT - LPJmL	*6.8*	*-1.9*	*-1.2*	*17.1*	*-0.9*	*3.1*
Hadley - IPSL	*-0.4*	*0.7*	*0.0*	*0.0*	*-1.5*	*-0.1*
GLOBIOM						
S3	31.6	40.5	25.2	-8.4	25.7	29.9
S4	25.3	34.1	25.4	-6.9	27.5	26.3
S5	69.9	31.8	18.5	50.6	50.4	40.7
S6	88.7	51.8	16.3	41.2	37.7	50.0
DSSAT - LPJmL	*50.8*	*4.5*	*-7.9*	*53.5*	*17.5*	*17.2*
Hadley - IPSL	*6.2*	*6.8*	*-1.0*	*-3.9*	*-5.4*	*2.8*
IMPACT						
S3	8.0	3.5	23.2	-3.4	10.4	8.2
S4	9.6	4.9	32.4	-0.9	12.3	11.1
S5	18.8	4.4	12.1	24.0	22.7	12.3
S6	22.1	5.5	16.5	25.8	18.5	13.6
DSSAT - LPJmL	*11.7*	*0.7*	*-13.5*	*27.1*	*9.2*	*3.3*
Hadley - IPSL	*2.5*	*1.2*	*6.8*	*2.1*	*-1.1*	*2.1*
MAgPIE						
S3	28.9	6.2	12.4	-2.9	10.9	14.3
S4	118.1	89.0	67.8	7.1	71.0	78.9
S5	59.8	13.0	34.1	41.0	52.4	33.8
S6	92.8	42.1	75.6	48.6	69.4	59.7
DSSAT - LPJmL	*2.8*	*-20.0*	*14.7*	*42.6*	*20.0*	*0.2*
Hadley - IPSL	*61.1*	*56.0*	*48.4*	*8.8*	*38.5*	*45.3*

Table 4. The effects of climate change on global average yields of CR5 crops (S3-S6 results in 2050 relative to S1 results in 2050)

Model/ scenario	CGR	OSD	RIC	SUG	WHT	Weighted average of 5 crops
AIM						
S3	-10.8	-23.2	-12.6	1.3	-12.1	-15.0
S4	-10.0	-20.4	-13.1	0.2	-9.9	-13.5
S5	-22.4	-11.3	-17.1	-24.6	-16.2	-18.1
S6	-24.8	-14.3	-16.1	-23.7	-13.9	-19.3
DSSAT - LPJmL	-13.2	8.9	-3.7	-24.9	-4.0	-4.4
Hadley - IPSL	-0.8	-0.1	0.2	-0.1	2.2	0.1
ENVISAGE						
S3	-4.5	-10.9	-5.4	-1.1	-4.9	-6.2
S4	-3.7	-10.4	-5.9	-1.1	-4.5	-5.9
S5	-12.0	-5.5	-5.8	-14.3	-9.1	-8.6
S6	-13.6	-6.1	-5.4	-13.2	-7.3	-8.7
DSSAT - LPJmL	-8.7	4.9	0.1	-12.7	-3.5	-2.5
Hadley - IPSL	-0.4	-0.1	0.0	0.5	1.1	0.1
FARM						
S3	-7.7	-17.3	-8.6	2.8	-8.0	-10.3
S4	-6.6	-15.5	-9.5	2.1	-7.0	-9.4
S5	-16.0	-8.0	-9.9	-18.5	-13.5	-12.6
S6	-17.3	-9.9	-8.9	-17.1	-10.2	-12.7
DSSAT - LPJmL	-9.5	7.4	-0.4	-20.3	-4.3	-2.8
Hadley - IPSL	-0.1	-0.1	0.1	0.4	2.1	0.4
GTEM						
S3	-2.2	-10.2	-7.0	3.2	-4.0	-6.2
S4	-1.9	-10.0	-7.9	3.1	-2.3	-5.8
S5	-8.3	-3.3	-8.2	-14.1	-8.2	-7.5
S6	-9.3	-4.3	-7.6	-12.8	-5.7	-7.8
DSSAT - LPJmL	-6.8	6.4	-0.4	-16.7	-3.8	-1.7
Hadley - IPSL	-0.3	-0.4	-0.2	0.6	2.1	0.1
MAGNET						
S3	-12.0	-24.2	-13.0	4.7	-14.6	-14.7
S4	-9.0	-22.7	-14.0	3.7	-12.5	-13.1
S5	-25.2	-13.3	-13.4	-21.3	-25.4	-17.3
S6	-28.8	-16.9	-12.8	-21.7	-21.9	-18.7
DSSAT - LPJmL	-16.5	8.3	0.4	-25.7	-10.1	-4.1
Hadley - IPSL	-0.3	-1.1	-0.2	-0.7	2.8	0.1

GCAM						
S3	-11.8	-20.0	-12.7	13.6	-11.7	-11.5
S4	-7.0	-17.8	-13.5	11.8	-8.6	-8.9
S5	-23.7	-13.0	-7.7	-26.9	-11.3	-15.1
S6	-26.4	-18.6	-7.8	-25.4	-9.9	-17.1
DSSAT - LPJmL	-15.6	3.1	5.3	-38.8	-0.4	-5.9
Hadley - IPSL	1.1	-1.7	-0.5	-0.1	2.2	0.3
GLOBIOM						
S3	-7.3	-10.7	-9.5	12.7	-9.2	-6.5
S4	-6.3	-8.4	-7.6	7.5	-8.2	-5.2
S5	-13.3	-10.3	-4.1	-31.2	-9.4	-12.5
S6	-19.1	-15.7	-5.8	-28.2	-9.5	-15.4
DSSAT - LPJmL	-9.4	-3.4	3.6	-39.8	-0.8	-8.1
Hadley - IPSL	-2.4	-1.5	0.2	-1.1	0.5	-0.8
IMPACT						
S3	-9.6	-19.1	-3.1	7.7	-9.5	-6.8
S4	-9.2	-17.1	-5.9	5.2	-6.6	-6.8
S5	-20.8	-10.8	-6.5	-20.9	-13.1	-18.1
S6	-24.2	-14.0	-10.4	-20.1	-12.7	-19.7
DSSAT - LPJmL	-13.1	5.7	-3.9	-27.0	-4.8	-12.1
Hadley - IPSL	-1.5	-0.6	-3.3	-0.8	1.7	-0.8
MAgPIE						
S3	-2.4	-6.1	9.6	15.4	-16.3	-5.5
S4	-1.5	-4.8	6.2	15.9	-19.0	-6.3
S5	-11.7	3.4	25.6	13.6	-11.1	-4.6
S6	-10.8	8.3	19.8	-7.6	-8.0	-3.7
DSSAT - LPJmL	-9.3	11.3	14.8	-12.6	8.1	1.8
Hadley - IPSL	0.9	3.0	-4.5	-10.3	0.2	0.0

Source: AgMIP global economic model runs, January 2013.

Table 5. The effects of climate change on global area of CR5 crops (percent change, S3-S6 results in 2050 relative to S1 results in 2050)

Model/Scenario	Coarse grains	Oil seeds	Rice	Sugar	Wheat	Weighted average of 5 crops
AIM						
S3	12.1	25.7	10.5	-2.9	13.2	15.5
S4	11.1	21.7	10.8	-2.0	10.7	13.6
S5	28.1	9.9	15.7	26.8	17.3	19.2
S6	31.7	13.4	13.8	25.5	15.9	21.0
DSSAT - LPJmL	18.3	-12.1	4.1	28.5	4.7	5.5
Hadley - IPSL	1.3	-0.2	-0.8	-0.2	-1.9	-0.1
ENVISAGE						
S3	3.3	7.9	3.5	0.0	3.6	4.5
S4	2.5	7.2	3.9	0.0	3.0	4.1
S5	10.2	3.5	3.3	11.6	5.8	6.0
S6	12.0	4.3	3.0	10.6	4.5	6.3
DSSAT - LPJmL	8.2	-3.7	-0.5	11.1	1.9	1.8
Hadley - IPSL	0.5	0.1	0.1	-0.5	-1.0	0.0
FARM						
S3	8.2	19.0	8.6	-3.0	9.0	11.0
S4	6.7	16.3	9.5	-2.4	7.9	9.8
S5	16.7	7.6	9.9	21.9	16.5	13.2
S6	17.9	9.7	8.7	19.9	12.0	13.0
DSSAT - LPJmL	9.8	-9.0	0.2	23.6	5.8	2.7
Hadley - IPSL	-0.1	-0.3	-0.1	-0.7	-2.7	-0.7
GTEM						
S3	2.5	11.4	5.7	-3.5	3.7	5.7
S4	2.2	11.1	6.4	-3.3	1.9	5.3
S5	9.4	3.4	6.2	17.0	8.4	7.1
S6	10.5	4.4	5.6	14.8	5.6	7.1
DSSAT - LPJmL	7.6	-7.4	-0.2	19.3	4.2	1.6
Hadley - IPSL	0.4	0.4	0.1	-1.0	-2.3	-0.2
MAGNET						
S3	13.3	23.7	13.3	-1.7	15.5	16.4
S4	9.6	22.8	14.6	-0.4	14.1	14.8
S5	29.4	12.3	16.3	46.2	33.3	24.6
S6	35.4	17.0	15.1	45.5	27.4	26.3
DSSAT - LPJmL	21.0	-8.6	1.7	46.9	15.6	9.9
Hadley - IPSL	1.1	1.9	0.1	0.3	-3.7	0.0

GCAM						
S3	12.5	6.5	14.7	-11.4	12.7	10.2
S4	7.7	4.0	15.7	-10.1	9.3	7.3
S5	22.6	5.6	8.7	35.9	12.5	14.3
S6	26.3	8.7	9.0	33.2	11.6	16.2
DSSAT - LPJmL	14.4	1.9	-6.3	45.3	1.0	6.5
Hadley - IPSL	-0.6	0.3	0.6	-0.7	-2.1	-0.5
GLOBIOM						
S3	0.2	3.4	0.6	-13.3	6.3	1.7
S4	-0.4	1.1	-1.4	-9.2	4.8	0.4
S5	2.9	1.1	-4.5	27.5	5.8	2.5
S6	9.1	4.5	-2.8	23.0	5.7	5.7
DSSAT - LPJmL	6.1	0.5	-3.2	36.5	0.2	3.0
Hadley - IPSL	2.7	0.5	-0.2	-0.2	-0.8	0.9
IMPACT						
S3	5.1	12.9	2.0	-2.5	5.8	6.7
S4	5.7	11.5	3.3	-1.6	4.6	6.4
S5	13.4	5.8	3.6	6.6	8.5	8.6
S6	16.0	7.9	5.2	6.6	8.5	10.3
DSSAT - LPJmL	9.3	-5.3	1.8	8.6	3.4	2.9
Hadley - IPSL	1.6	0.4	1.5	0.5	-0.6	0.7
MAgPIE						
S3	2.4	6.3	-8.4	-13.3	19.3	5.9
S4	1.7	4.9	-5.9	-13.7	23.0	6.7
S5	13.1	-3.4	-20.0	-11.9	12.4	4.9
S6	12.3	-7.8	-16.1	8.2	8.2	4.0
DSSAT - LPJmL	10.7	-11.2	-10.9	11.7	-10.8	-1.9
Hadley - IPSL	-0.7	-3.0	3.2	9.9	-0.2	0.0

Source: AgMIP global economic model runs, January 2013.

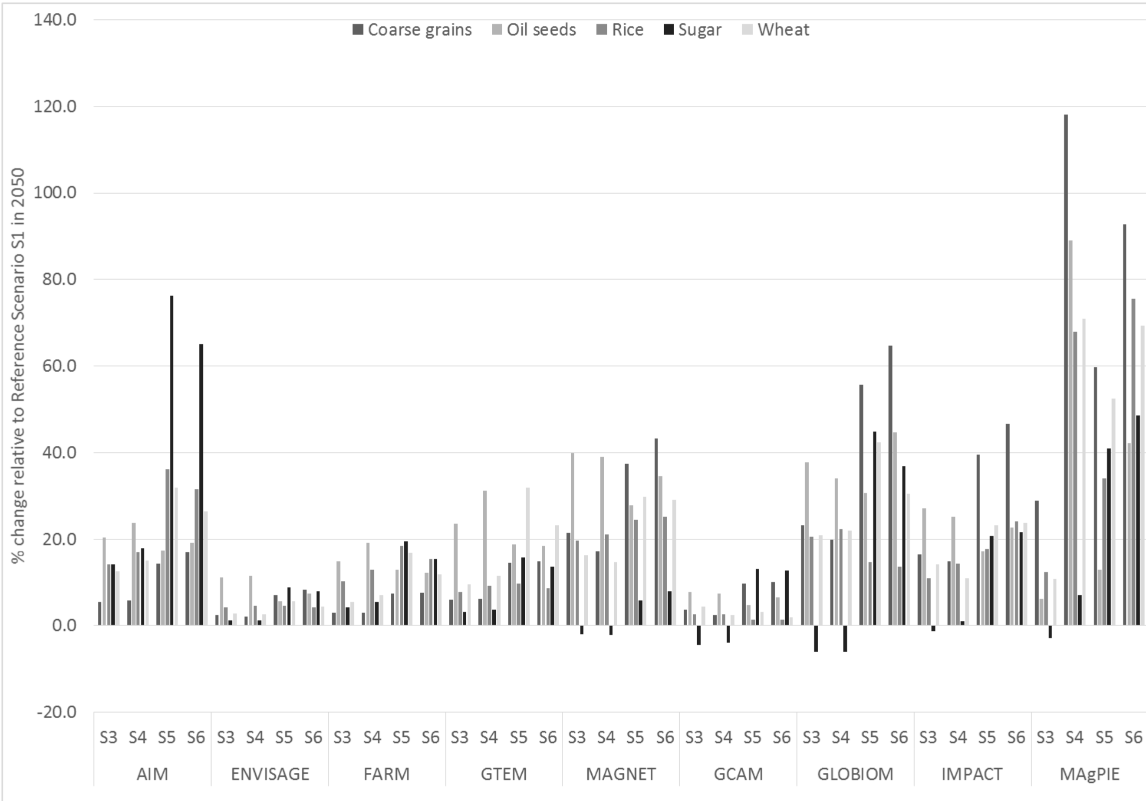
Table 6. Decomposition of adjustment to climate shock in 2050, percent

	Decomposition				Decomposition relative to average		
	Demand	**Area**	**Yield**		**Demand**	**Area**	**Yield**
Model-specific results							
AIM	12	73	15		-10	18	-9
ENVISAGE	17	28	56		-5	-27	32
FARM	4	57	40		-18	2	16
MAGNET	10	109	-19		-11	54	-43
GCAM	22	64	15		0	9	-9
GLOBIOM	49	10	40		28	-44	17
IMPACT	38	43	19		16	-12	-4
Scenario-specific results							
S3	21	58	21		0	3	-3
S4	21	57	22		-1	2	-2
S5	22	51	27		0	-4	4
S6	22	53	25		1	-2	1
Commodity-specific results							
Wheat	13	70	18		-9	15	-6
Rice	19	43	37		-2	-12	14
Coarse grains	20	58	22		-1	3	-1
Oil seeds	34	49	17		13	-6	-7
Average	22	55	24				

Source: AgMIP global economic model runs, January 2013.

Notes: The model-specific results are averaged across all scenarios and four crops – wheat, rice, coarse grains, and oil seeds – all equally weighted. In the scenario-specific and crop-specific results, results from all 7 models are weighted equally. In the crop-specific results all models and scenarios are weighted equally. The last three columns report the decomposition effects relative to the overall average.

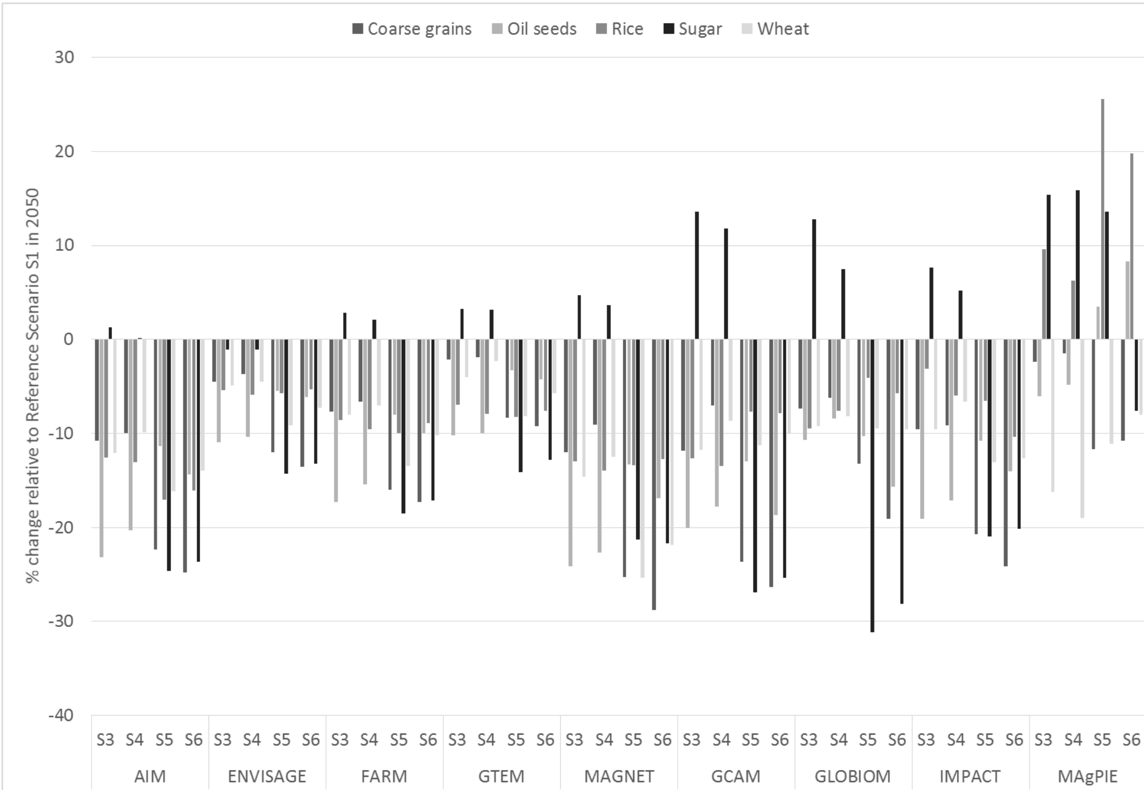
Figure 1. The effects of climate change on agricultural prices (S3-S6 results in 2050 relative to S1 results in 2050)



Note: Price comparisons based on producer price at the world level. See supplementary information for details.

Source: AgMIP global economic model runs, January 2013.

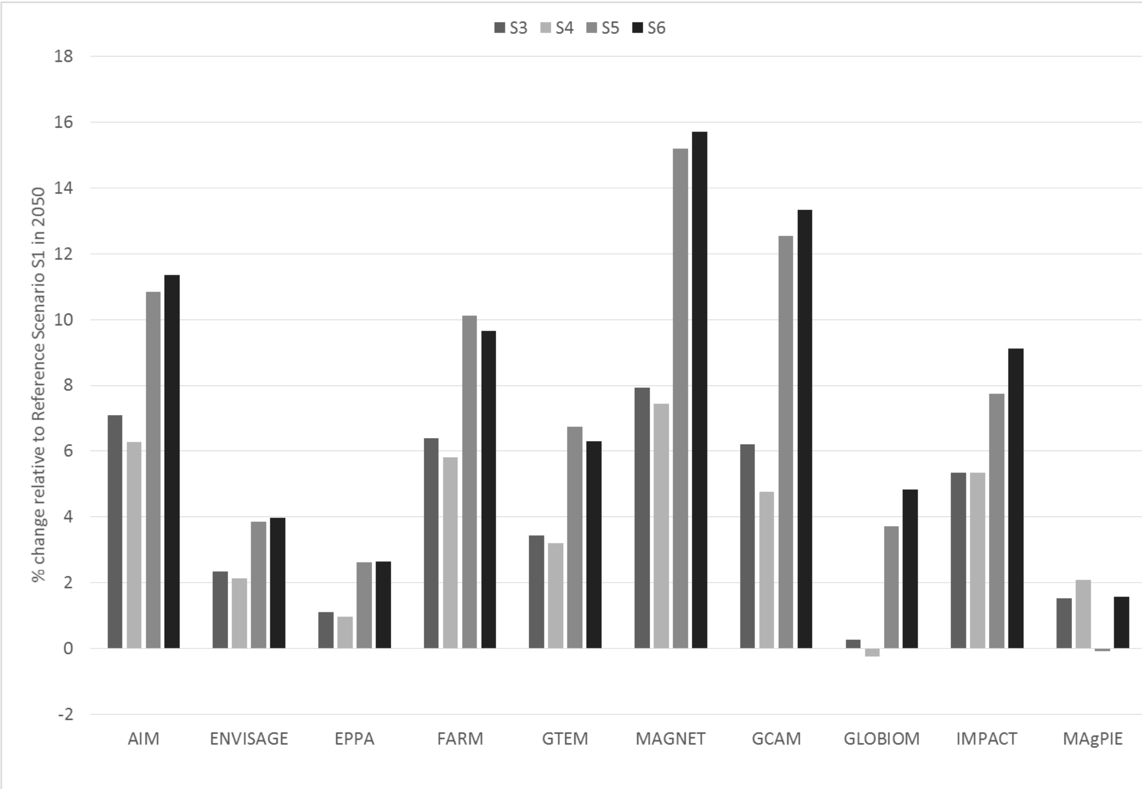
Figure 2. The effects of climate change on global average yields of CR5 crops (S3-S6 results in 2050 relative to S1 results in 2050)



Note: Area weighted yields at world level. See supplementary information for details.

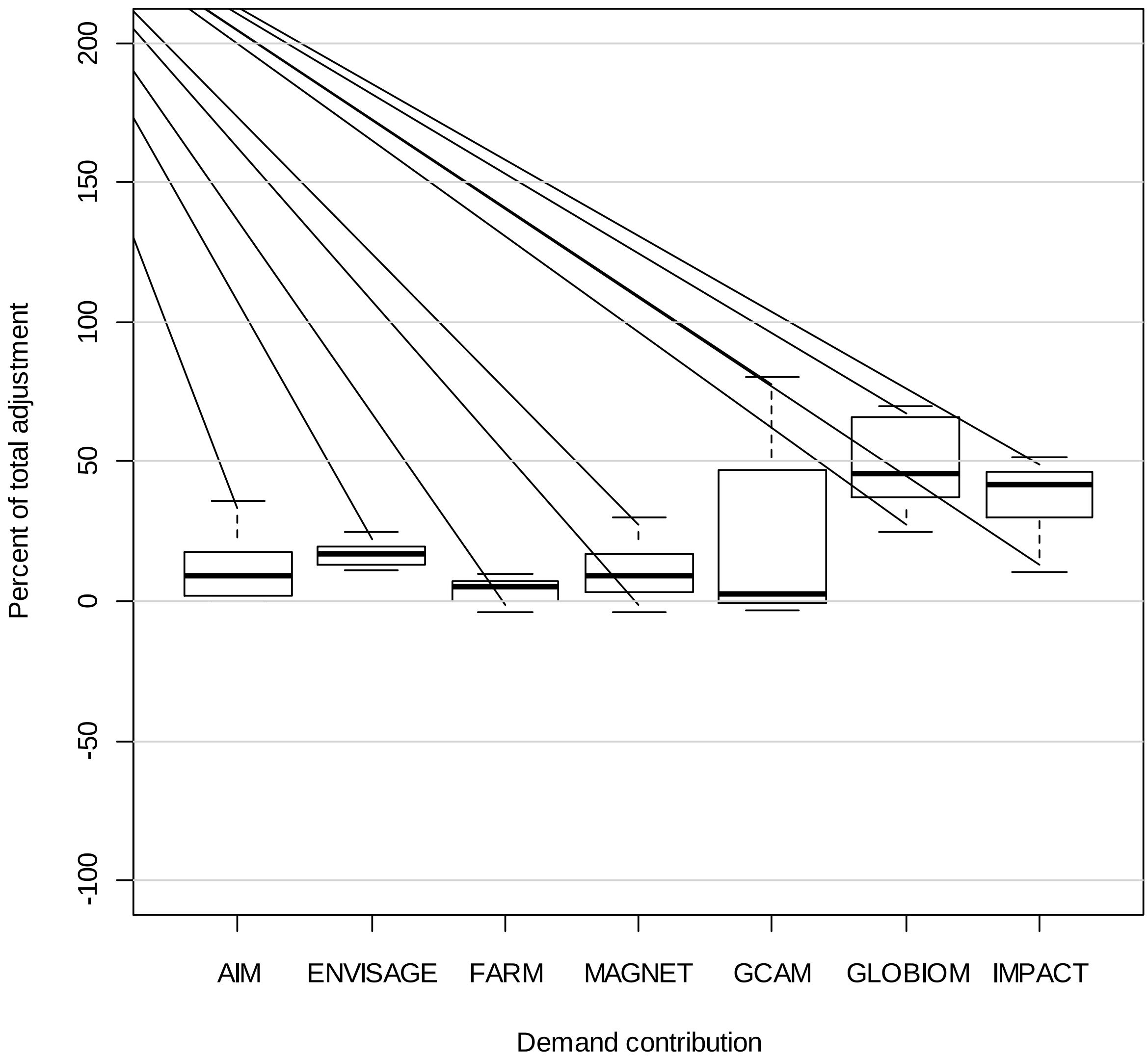
Source: AgMIP global economic model runs, January 2013.

Figure 3. The effects of climate change on global area of all crops (S3-S6 results in 2050 relative to S1 results in 2050)



Source: AgMIP global economic model runs, January 2013.

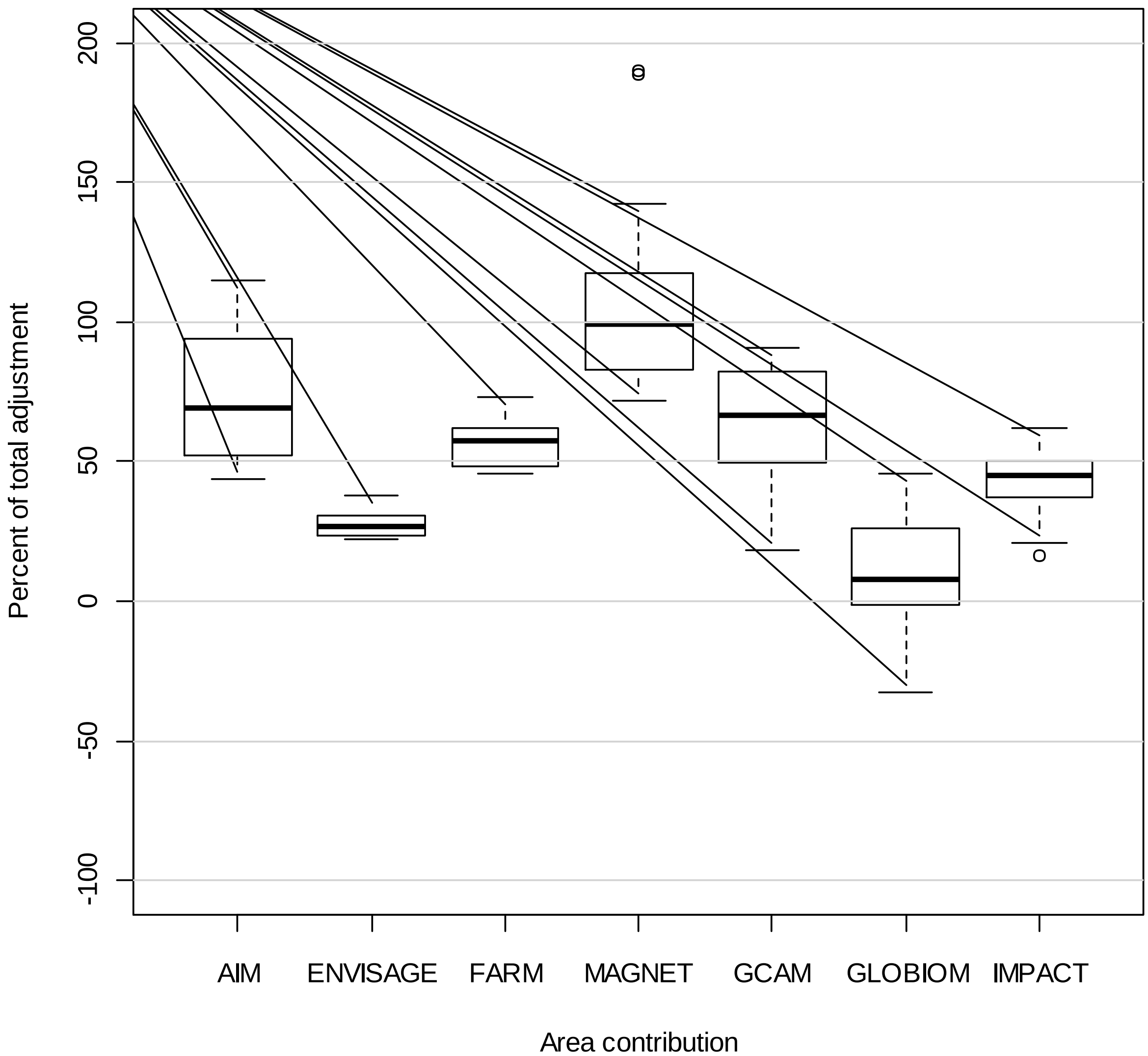
Figure 4. Demand contribution



Source: AgMIP global economic model runs, January 2013.

Note: Demand component of decomposition for seven models for four of the commodities (wheat, rice, coarse grains and oil seeds) pooled over the four climate shock scenarios, S3 to S6.

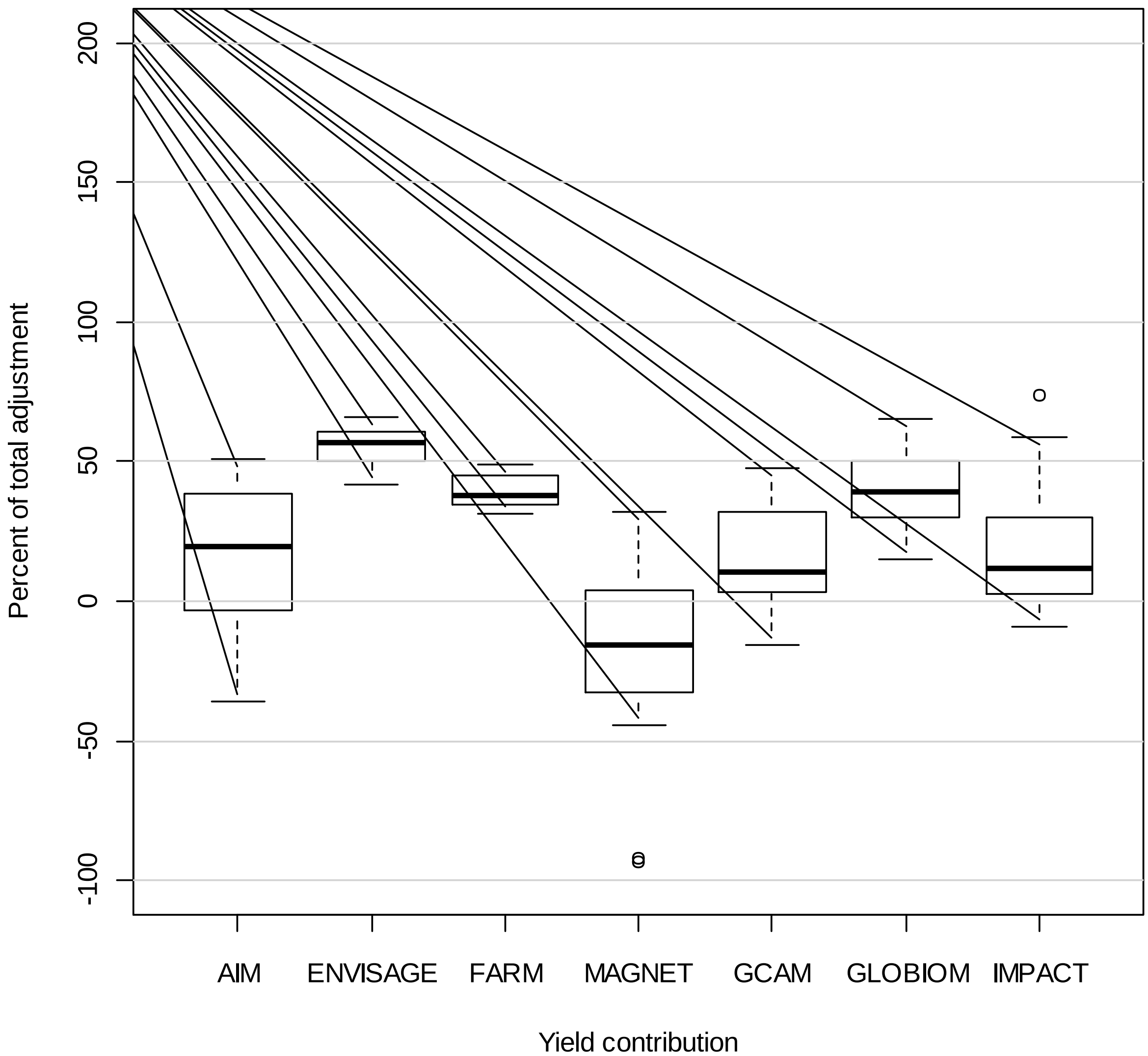
Figure 5. Area contribution



Source: AgMIP global economic model runs, January 2013.

Note: Area component of decomposition for seven models for four of the commodities (wheat, rice, coarse grains and oil seeds) pooled over the four climate shock scenarios, S3 to S6.

Figure 6. Yield contribution



Source: AgMIP global economic model runs, January 2013.

Note: Yield component of decomposition for seven models for four of the commodities (wheat, rice, coarse grains and oil seeds) pooled over the four climate shock scenarios, S3 to S6.