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Agriculture and climate change in global scenarios: why don't the models agree

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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, solar radiation available to the plant, and precipitation). Previous studies of the impacts of climate change on agriculture have reported substantial differences in outcomes such as prices, production, and trade arising from differences in model inputs and model specification. This article presents 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 harmonizing key drivers that include climate change effects, differences in model outcomes were reduced. The particular choice of climate change drivers for this comparison activity results in large and negative productivity effects. All models respond with higher prices. Producer behavior differs by model with some emphasizing area response and others yield response. Demand response is least important. The differences reflect both differences in model specification and perspectives on the future. The results from this study highlight the need to more fully compare the deep model parameters, to generate a call for a combination of econometric and validation studies to narrow the degree of uncertainty and variability in these parameters and to move to Monte Carlo type simulations to better map the contours of economic uncertainty.

JEL classifications: Q10, Q11, Q16, Q21, Q54, Q55

Keywords: Climate change impacts; Economic models of agriculture; Scenarios

1. Introduction

Agriculture is unique among economic sectors in the nature of impacts from climate change. Its production processes involve direct use of weather inputs (solar radiation available to the plant, temperature, and precipitation). Climate change

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

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alters the weather and therefore has a direct, biophysical effect on agricultural productivity. Disentangling the consequences of these productivity effects from the other 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. The goal of this article is to contribute to our understanding of the extent to which the differing results represent substantive differences of opinion about how the future might evolve as opposed to differences arising in modeling methodologies.

Previous studies of the impacts of climate change on agriculture have reported substantial differences in key outcomes such as prices, production, and trade, arising from differences in model inputs and model specification. This article presents climate change results from a model comparison exercise with 10 of the leading global economic models that include significant representation of agriculture. We use data from two climate models, two crop modeling suites, and ten global economic models. Each *crop* model uses a common set of climate drivers from the climate models. Each *economic* model uses a common set of socioeconomic drivers and agricultural productivity drivers including the crop model outputs. This comparison is part of a study undertaken by the AgMIP global economic modeling group to explore the underlying determinants of differences in model outputs (see von Lampe et al., 2014 for an overview of the study). This article examines results from the four scenarios that vary climate change-related drivers, comparing them to a reference scenario.

2. 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 has witnessed a 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 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.

Studies in the early 1990s (e.g., Tobey et al., 1992; Reilly et al., 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 IPCC's Fourth Assessment Report (AR4) on impacts (IPCC et al., 2007) presents similar findings.

The 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 limited smaller, older set of 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, 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 partial equilibrium 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% 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.

An early literature that looks at the effects of climate change on land rents that uses statistical methods is sometimes referred to as Ricardian analysis after the seminal paper by Mendelsohn et al. (1994) based on cross-section data for US agriculture in 1982. Papers in this literature essentially 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 et al. (1994) 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." The approach used in this article for combining biophysical and socioeconomic model addresses this concern. 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 using parameters estimated with this process, which any projection for climate effects in 2050 would be, are plausible. See Lobell and Burke (2008) and Lobell et al. (2013) for more recent statistical approaches to the effects of climate change on agriculture.

3. Methods

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 with and without the effects of climate change. Remaining output differences are then 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 methods.[1] A reference scenario, called S1, is based on the GDP and population values from the Shared Socioeconomic Pathway 2 (SSP2) developed for Intergovernmental Panel on Climate Change (IPCC) 5th assessment report (AR5).[2] In SSP2, global population by 2050 reaches 9.3 billion, an increase of 35% 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 et al., 2012). The reference scenario does not include any effects of climate change on agricultural productivity.

For the climate change scenarios, outputs from two GCMs[3] using the representative concentration pathway (RCP) 8.5 from IPCC's fifth assessment representative greenhouse gas concentration pathways, are used as inputs into two crop modeling suites[45] resulting in four scenarios (see Table 1).[6] Outputs from the crop models become inputs into 10 global economic models—six computable general equilibrium and four partial equilibrium economic models (see the Data Appendix for brief descriptions of these models). Remaining differences in economic model results are then due to model-specific choices such as functional form and parameters, supply and demand elasticities, calibration data sets, aggregation approaches, and optimization methods.

Although this activity was designed to compare model responses to a climate change shock rather than generate plausible estimates of the effects, it is useful to consider how plausible are the results reported here. There are three major drivers of climate change effects—the choice of RCP, CO_2 fertilization, and omitted effects of climate change—that influence the plausibility of the results. RCP 8.5 has a radiative forcing of over 8.5 watts per square meter by the end of this century, with a CO_2 concentration of about 540 ppm in 2050 compared to a level in the early 21st century of about 370 ppm.[7] The use of this RCP puts these results at the upper end of the effects from the RCPs. However, the GHG concentrations (as of early 2013) are closer to RCP 8.5 than the RCPs that result in lower concentrations.[8] Hence in choice of RCP these results seem plausible.

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 less precipitation. The crop models used a CO_2 concentration in 2050 that is equivalent to that in the early 21st century, approximately 370 ppm. This assumption of a constant CO_2 concentration throughout the period means that we do not capture the benefits of additional CO_2 for these crops and hence overstate the negative effects of climate change. Lobell and Gourdji (2012) suggest that, "A likely scenario in the near term is that warming will slow global yield growth by about 1.5% per decade while CO_2 increases will raise yields by roughly the same amount." However, this assessment was based on a qualitative assessment of results using earlier climate data and crop response modeling and before the recent increases in GHG concentrations and so could understate the effect of temperature.

Table 1
Key scenario elements

Scenario identifier	General circulation model	Greenhouse gas emissions pathway	Crop model	CO_2 atmospheric concentration assumed by the crop models
S1	None	None	None	350 ppm in all periods
S3	IPSL-CM5A-LR	RCP 8.5	LPJmL	350 ppm in all periods
S4	HadGEM2-ES	RCP 8.5	LPJmL	350 ppm in all periods
S5	IPSL-CM5A-LR	RCP 8.5	DSSAT	350 ppm in all periods
S6	HadGEM2-ES	RCP 8.5	DSSAT	350 ppm in all periods

Notes: LPJmL—Lund-Potsdam-Jena managed Land Dynamic Global Vegetation and Water Balance Model, DSSAT—Decision Support System for Agricultural Technology. All GCMs use the greenhouse gas emissions pathway RCP 8.5. The crop models assume CO_2 fertilization is constant at 370 ppm throughout the period of the analysis. Effects of increased ozone concentration, increased weather variability, and greater biotic stresses are not included.

[1] An additional source of difference can be the choice of base year and/or calibration data base.

[2] See van Vuuren et al. (2012) and Kriegler et al. (2012) for a discussion of SSPs. The SSP data are available for download at https://secure.iiasa.ac.at/web-apps/ene/SspDb.

[3] HadGEM2-ES (Jones et al., 2011) and IPSL-CM5A-LR (Dufresne et al., 2013).

[4] The Lund-Potsdam-Jena managed Land Dynamic Global Vegetation and Water Balance Model (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).

[5] The climate outputs from the GCMs were bias-corrected and downscaled as part of the ISI-MIP model comparison project (Hempel et al., 2013). Climate data for 2000 and 2050 were used to generate yields at 1/2 degree resolution (about 55.5 km at the equator) (Müller and Robertson, 2014).

[6] See Moss et al. (2010) for a discussion of RCPs.

[7] http://www.iiasa.ac.at/web-apps/tnt/RcpDb.

[8] The most recent data from NOAA's Earth System Research Laboratory (ftp://ftp.cmdl.noaa.gov/ccg/co2/trends/co2_annmean_gl.txt) shows no inflection in the rate of growth of CO_2 concentration. Simple OLS analysis, if anything, shows an acceleration over the last six years, notwithstanding the financial crisis. This would be consistent with a high radiative forcing trend such as RCP 8.5.

Finally, both the results considered in the Lobell and Gourdji paper, this analysis, and indeed the bulk of literature ignore three effects of climate change that are all negative—increasing tropospheric ozone, because the crop models do not include it (Ainsworth and McGrath, 2010), increasing biotic stresses from a range of pests that will thrive under higher temperatures and more CO_2, because there are no quantitative estimates of the changes in pest and disease incidence, and increasing variability in weather including more extreme events (because none of the economic models included here incorporate uncertainty)—all of which will reduce agricultural productivity. Hence, we conclude that, while from the point of view of temperature-driven impacts, the climate change shocks modeled reflect upper bound estimates from the fifth assessment activities of the IPCC on the climate change impacts on agriculture to 2050, the omission of other, largely negative factors, which will likely depress yields suggest that the productivity impacts may not be as extreme as they appear at first blush.

The process of transforming crop model data to inputs for economic modeling involved three issues—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 Müller and Robertson (2014) for a detailed discussion on how these issues were managed.

The end result is four scenarios, dubbed here: S3 to S6, with climate change productivity effects for each crop,[9] 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 or crop groups (coarse grains, oil seeds, rice, sugar, and wheat) and countries (Brazil, Canada, China, India, and the United States) used by all the modeling teams except MAgPIE. In the scenario without climate change (S1), the exogenous changes (in column 1 of Table 2) arise from investments in productivity-enhancing technologies and changes in information delivery systems that are not captured in the modeling. These values are taken from the IMPACT model's "intrinsic productivity growth rates" (Rosegrant et al., 2012). Between 2005 and 2050, these productivity increases range from 12% for oil seeds in Canada to 132% for coarse grains in India. Across the countries included in Table 2, coarse grain increases are greatest and oil seeds the smallest.

Climate change effects are added to (or subtracted from) these exogenous effects. The climate effects used in this analysis are almost uniformly negative for the countries reported, with the largest negative effects most often found for 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 the climate change effect is positive in S3 and S4 and in India in all scenarios.

Table 2
Examples of exogenous annual yield increases in the scenarios, 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

Notes: Positive effects of climate change under RCP 8.5 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. The values for S1 are taken from the IMPACT model (Rosegrant et al., 2012). See notes to Table 1 for the key elements of the scenarios.

Source: AgMIP Global Model Intercomparison Project.

One potential issue is whether either the crop models or the GCMs 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, sugar, and wheat; the DSSAT climate change results are uniformly more negative than the LPJmL results. For oil seeds and rice, the crop model results differ but not in a common direction. For example, DSSAT results in India are less negative for oil seeds (+0.21% difference in annual growth rate relative to S1) but more negative for rice (−0.44). The climate model results do

[9] MAgPIE does not use these exogenous productivity shifters. Instead it incorporates the outputs from the crop models directly.

not appear to have any systematic bias and the differences are relatively small, except for Canadian coarse grains and wheat, and Brazilian coarse grains, sugar, and wheat, where the crop model results using the IPSL climate data show less negative yield consequences than with Hadley climate data.

Each of the models used the exogenous productivity shocks to alter yield determinants. For the CGE models in this study, the shocks were implemented as shifts in the land efficiency parameters of the sectoral production functions.[10] For the partial equilibrium models, the shocks were additive shifters in a yield or supply equation (see Robinson et al., 2014 for more discussion on the differences between general and partial equilibrium modeling of productivity 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 (see Dietrich et al., 2013 for a discussion of how MAgPIE models yield change) and AIM and GCAM where there is no endogenous response of yields to price within any agricultural region but global average yield can respond as production shifts to more productive agro-ecological zones.

Conceptually, a negative 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.

The yield shock from climate change causes endogenous adjustments in prices, consumption, area, and yield. We decompose the effects of the climate change shock to identify the relative importance of the three adjustment components at the global level—consumption, area, and yield—in the model responses.[11] Start from the basic equilibrium equation:

$$Q^R \equiv A^R Y^R, \tag{1}$$

where Q is output, A is area, Y is yield, and the superscript R stands for the variables in the reference scenario (S1). Now introduce a productivity shock from climate change. The final yield change, ΔY^S, can be decomposed into exogenous (ΔY) and endogenous $\left(\Delta Y^N\right)$ components. The exogenous component consists of the climate shock. The endogenous component consists of management responses to price changes including changes in input use.

$$Y^S \equiv Y^R + \Delta Y + \Delta Y^N. \tag{2}$$

We expect a climate shock to be generally negative ($\Delta Y < 0$). The endogenous effect (ΔY^N), which is part of the adaptation to the shock, will partially offset the effect of the exogenous shock.

The direct impact is the application of the exogenous yield shock to the reference scenario yield Y^R:

$$Q^D = A^R(Y^R + \Delta Y), \tag{3}$$

where Q^D is the initial production effect from the climate change shock.

Final output after the shock (Q^S) is:

$$Q^S = A^S Y^S = A^S(Y^R + \Delta Y + \Delta Y^N) \tag{4}$$

after area, yield, and demand adjust to changing relative prices.

The effect of the initial shock on production

$$dQ^D = Q^R - Q^D = -A^R \Delta Y \tag{5}$$

is a positive number for a negative climate shock, that is, the direct effect of the shock leads to *declining output*. The final term shows that we are applying the exogenous shock (i.e., the exogenous difference in yields) just to the reference area.

The adjustments to the shock at the world level can be decomposed into three effects—changes in demand, changes in area, and changes in yields (relative to the shock).[12] The following formula captures these adjustments:

$$dQ^D = \underbrace{(Q^R - Q^S)}_{\text{Demand effect}} + \underbrace{(A^S - A^R)\frac{Y^S + Y^R}{2}}_{\text{Area effect}} + \underbrace{(Y^S - Y^R)\frac{A^S + A^R}{2}}_{\text{Yield effect}}. \tag{6}$$

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 reference yield and the final yield after the shock, an average of the Laspeyres and Paasche volume indices. The yield change is weighted by the average of the initial and final

[10] Labor productivity is generated by economy-wide estimates of labor productivity growth—with allowance for sector-specific deviations—and land productivity growth is calibrated exogenously to the yield growth assumptions derived from IFPRI's IMPACT model. The PE models do not have the option of including total factor productivity changes. There is anecdotal evidence of autonomous changes in farm practices that are not picked up by the GE models, but that could neutralize the impact of climate change on productivity of factors other than land in agriculture—for example, changes in the timing of planting and harvesting. The GE models pick up endogenous adaptation that is a result of changes in relative (efficient) prices; that is, the *de facto* rise in the price of land (in efficiency terms) leads to an increase in the demand for other inputs such as labor and capital; the degree of which is determined by the underlying factor substitution elasticities. Nonetheless, the question of how to implement exogenous factor productivity remains an open empirical issue that can be treated with additional sensitivity analysis (such as applying the shock to agricultural TFP) and through focused econometric research.

[11] To do the decomposition at a regional level, the formula would also need to take into account changes in trade.

[12] The decomposition focuses on global averages. The models—being multiregional—will also generate compositional effects that in some cases could reinforce the analysis and in others could compensate.

area. The final term measures the change in output derived from the indirect yield changes. Note that the term $(Y^S - Y^R - YX^S)$ is equal to ΔY^N, the endogenous yield response.

The previous discussion has emphasized the relative responses in consumption, area, and yield to the climate change shock. To understand the effect on prices, Hertel (2011, 2010) has derived a framework that can be used to quantify the links from shock through to price change, though with certain restrictions.

$$\Delta P = \frac{\Delta^D + \Delta^L - \Delta^Y}{\eta^D + \eta^E + \eta^I}. \qquad (7)$$

This equation links the change in prices to three exogenous factors and three partial price elasticities. The long-run shocks (in the numerator) include aggregate demand, Δ^D (population, income, biofuels, other), an exogenous land supply shift, Δ^L (urbanization, conservation, etc.), and exogenous yield changes ΔY. The key elasticities are the price elasticity of demand, η^D, the land supply (the area or extensification response) elasticity with respect to the agricultural price, η^E (essentially the land price elasticity adjusted for land's cost share), and the share adjusted substitution (yield or intensification response) elasticity of land with respect to the other inputs, η^I.

The first two elements in the numerator, that is, an increase in demand and an exogenous reduction in land supply, are likely to increase prices for given elasticities. The third element will lower prices—and thus it is the combination of the three that determines the sign of the price shift over the long run.

Given that we are assessing deviations from the baseline brought about by climate change, the numerator is only composed of changes to ΔY, that is, an exogenous change in yields. The climate change impact leads generally to a drop in yields and therefore the direction of the price change will in general be positive.

The size of the response to climate change will be determined by the sum of the elasticities, that is, the more responsiveness in the system, the less impact there will be on price changes for the same shock. As the responsiveness parameters become smaller, the price changes grow larger. To the extent the relation holds in aggregate, the price response coming from the different models should be a reflection of these elasticities, inherent either explicitly or implicitly in all of the models, whether they be PE or GE. In other words, there is no theoretical reason why we should observe any systemic differences between the two classes of models.

4. Key results: prices, yield, and area

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

4.1. Price effects

We begin by examining the effects of climate change on prices. We use the producer price variable for comparison (see von Lampe et al., 2014 for a discussion of the choice of price variable). We focus on five commodities/commodity groups, collectively called CR5—coarse grains (predominantly maize in most countries), rice, oil seeds (mostly soybeans), sugar (about 80% is from sugar cane), and wheat—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 Fig. 1—prices increase relative to the reference scenario across all models, there is significant variation by economic and crop model, and there is 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 et al., 2014).

Figure 1 provides a visual overview of the price results for the individual 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 from climate change and MAgPIE the largest. The EPPA model does not generate crop-specific price increases but for its aggregate agricultural activity, price increases range from 1.3% to 4.6% over the price in 2050 without climate change.

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% for S4 in GCAM to 78.9% for S4 in MAgPIE. For all crops other than sugar, all models report a price increase; for coarse grains from 1.9% to 118.1%, for oil seeds from 4.4% to 89.0%, for rice from 1.5% to 75.6%, and for wheat from 2.1% to 71.0%. Several models report sugar price declines in 2050 with climate change in S3 and S4, the scenarios that use the LPJmL crop model. See Müller and Robertson (2014) for a discussion of why the LPJmL sugar results in S3 and S4 are likely more appropriate than the DSSAT-derived results.

In general, the final 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. For most economic models, the Hadley GCM results in higher prices for the CR5 aggregate than the IPSL GCM results. But the differences due to the climate model are quite small (−5.3% to 6.8%), except in MAgPIE where the Hadley results are 8.8% to 61.1% greater than the IPSL results.

If we look at some of the outliers in the context of expression (7), several features distinguish themselves. MAgPIE, which has the largest price deviations, has fixed demand and thus the price elasticity of demand is 0, thereby magnifying the price impacts of a perturbation in yields. Similarly, AIM also tends to have rather high price deviations, and it has near zero land

Table 3
Scenario effects on world agricultural prices (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 five crops (CR5)
AIM						
S3	5.6	20.4	14.1	14.2	12.7	14.1
S4	5.8	23.8	17.1	18.0	15.1	16.7
S5	14.4	17.3	36.1	76.3	31.9	30.9
S6	17.1	19.1	31.5	65.1	26.4	28.6
DSSAT – LPJmL	10.1	−3.9	18.2	54.6	15.2	14.4
Hadley – IPSL	1.5	2.6	−0.8	−3.7	−1.5	0.1
ENVISAGE						
S3	2.5	11.1	4.2	1.2	2.8	4.2
S4	2.1	11.6	4.6	1.3	2.7	4.4
S5	7.1	5.7	4.7	8.9	5.6	6.3
S6	8.4	7.4	4.3	7.9	4.5	6.4
DSSAT – LPJmL	5.4	−4.8	0.1	7.2	2.3	2.1
Hadley – IPSL	0.4	1.1	0.0	−0.5	−0.6	0.1
FARM						
S3	3.1	14.9	10.2	4.2	5.6	8.0
S4	2.9	19.2	13.0	5.5	7.2	10.0
S5	7.5	12.9	18.4	19.5	16.8	14.2
S6	7.6	12.2	15.5	15.4	11.9	12.0
DSSAT – LPJmL	4.5	−4.5	5.4	12.6	7.9	4.1
Hadley – IPSL	0.0	1.8	−0.1	−1.4	−1.7	−0.1
GTEM						
S3	6.0	23.6	7.8	3.2	9.6	10.4
S4	6.2	31.2	9.2	3.8	11.6	12.8
S5	14.6	18.8	9.8	15.7	31.9	17.4
S6	14.9	18.4	8.7	13.6	23.2	15.2
DSSAT – LPJmL	8.7	−8.8	0.8	11.2	17.0	4.7
Hadley – IPSL	0.3	3.6	0.2	−0.7	−3.4	0.1
MAGNET						
S3	21.5	40.0	19.7	−2.0	16.2	14.6
S4	17.2	38.9	21.1	−2.1	14.7	13.9
S5	37.4	27.9	24.5	5.9	29.8	21.8
S6	43.2	34.5	25.1	8.1	29.0	24.6
DSSAT – LPJmL	20.9	−8.3	4.4	9.0	14.0	8.9
Hadley – IPSL	0.8	2.8	1.0	1.0	−1.2	1.0
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	23.2	37.8	20.5	−6.1	21.0	21.6
S4	19.8	34.0	22.4	−6.0	21.9	20.9
S5	55.7	30.7	14.8	44.9	42.4	35.6
S6	64.8	44.7	13.6	36.8	30.6	36.7
DSSAT – LPJmL	38.7	1.8	−7.3	46.9	15.0	14.9
Hadley – IPSL	2.8	5.1	0.4	−4.0	−5.5	0.2
IMPACT						
S3	16.5	27.1	11.0	−1.2	14.2	18.7
S4	14.9	25.1	14.4	1.1	11.0	17.8
S5	39.6	17.1	17.6	20.8	23.3	22.4
S6	46.7	22.7	24.0	21.6	23.7	27.3
DSSAT – LPJmL	27.5	−6.2	8.1	21.3	10.9	6.6
Hadley – IPSL	2.7	1.8	4.9	1.5	−1.4	2.0
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

Continued

Table 3
Continued

Source: AgMIP global economic model runs, February 2013. See notes to Table 1 for the key elements of the scenarios.

substitution elasticities, low demand response, and low input flexibility.[13]

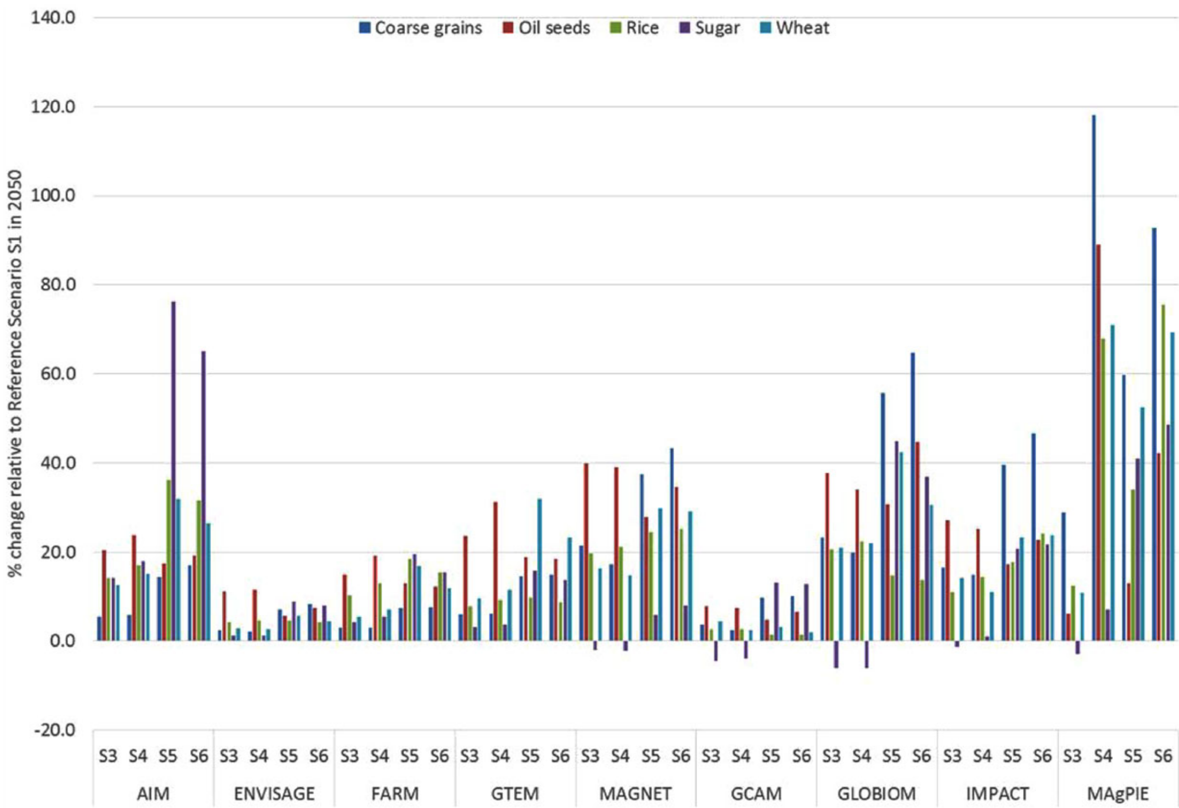
The results raise two related issues that require further research. Assuming the demand response is fairly similar across models, with the exception of MAgPIE, how different are the supply responses? (The latter include area response and substitutability with other factors [see Valin et al., 2014 for more details on the demand results].) Do these elasticities correspond to long-run responsiveness, or have they been calibrated to short- and medium-term responsiveness as hypothesized by Hertel (2011) who suggests that such models are overly influenced by the need to generate near-term forecasts (e.g., FAPRI, AgLink/Cosimo)?

4.2. Yield effects

Figure 2 provides an overview of the combined exogenous and endogenous effects of climate change on yields. 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% for rice (AIM, S5) to −28.8% for coarse grains (MAGNET, S8). The maximum values differ dramatically. Rice yields in MAgPIE for S5 increase 25.6%; wheat yields decline by 2.3% in GTEM.

[13] See Schmitz et al. (2014) on land use for further details.



Note: Price comparisons based on producer price at the world level. See Table 1 for a description of the scenarios. See the Data Appendix for details.
Source: AgMIP global economic model runs, February 2013.

Fig. 1. Scenario effects on agricultural prices (S3–S6 results in 2050 relative to S1 results in 2050).

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

4.3. Area effects

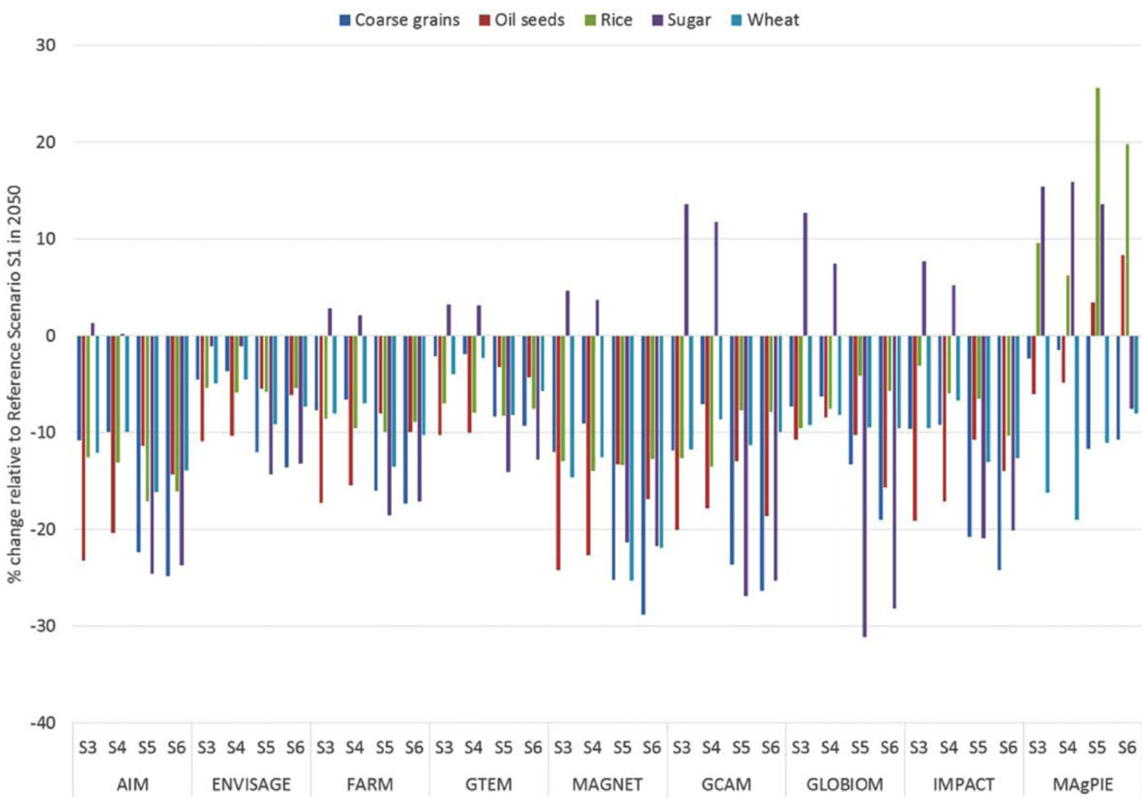
Figure 3 provides an overview of crop area change from climate change in 2050 relative to the reference scenario (with no climate change) in 2050. Almost all models show an increase in crop area over the S1 scenario. MAGNET has the largest crop area increases across the scenarios; MAgPIE the smallest 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% for coarse grains and 27.4% for wheat. Oil seed area increases in all scenarios for all models except MAgPIE where it falls slightly in S5 and S6. Rice area declines 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.

4.4. Decomposing area, yield, and consumption responses by model

Table 6 compiles the decomposition results for the world in 2050 under different aggregations of the underlying model simulations. Nine of the 10 models provided sufficient detail to undertake the decomposition analysis. Averaging across all scenarios, models, and commodities, area response contributes about 44% of the adjustment with roughly 17% from demand and 38% from yield. 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.

Since this decomposition is largely a reflection of the underlying model parameters, it is hardly surprising that the largest differences in results occur across economic models—as opposed to across scenarios. The demand contribution varies from



Note: Area weighted yields at world level. See notes to Table 1 for the key elements of the scenarios. See the Data Appendix for details.
Source: AgMIP global economic model runs, February 2013.

Fig. 2. Scenario effects on global average yields of CR5 crops (S3–S6 results in 2050 relative to S1 results in 2050).

a low of about 5% in FARM and GTEM to a high for IMPACT (39%) and GLOBIOM (49%). Area response is greatest in MAGNET (109%) and smallest in MAgPIE (−8%) where pasture and forest are not allowed to be converted to agriculture. The yield adjustment contribution varies from a low of −19% in MAGNET to a high of 108% in MAgPIE.[14]

The results in Table 6 can be used to back-out the implicit elasticities for each of the models based on expression (7).[15] There are some caveats. First, only the relative size of the elasticities can be derived, not the absolute values—this is consistent with the conclusions in Hertel (2011). Second, the derived supply-side elasticities are not the models' input elasticities, but the input elasticities adjusted for the land share in production. They also reflect *equilibrium* elasticities, that is, not just movements along supply and demand schedules, but also shifts in the schedules. Thus if the backed-out extensification (area change) elasticity is 1, the input elasticity is 1 times the land share, or 0.2 if the land share is 20%. Third, the derived elasticities are based on the suite of all four climate and crop model simulations and thus reflect an average. Fourth, the Hertel formulas hold for aggregate agricultural production. In this article, we are only assessing the impacts from a subset of global agriculture that accounts for about 70% of global agricultural area.

Table 7 shows the derived model elasticities. Note that they have been normalized to sum to 1 as the formulas only hold for relative elasticities and not absolute levels. As expected the MAgPIE demand elasticity is zero, since price does not affect demand in that model. The demand elasticities are also small for FARM (0.04), GTEM (0.06), MAGNET (0.10), and AIM (0.12). The partial equilibrium models other than MAgPIE all have relatively high demand elasticities.

The extensive margin (area) elasticities differ dramatically, from a low of −0.08 for MAgPIE (in part because the version of the model used for this exercise does not allow conversion of pasture and forest area to agriculture) to a high of 1.39 for MAGNET.

The intensive margin elasticities of AIM and MAGNET are negative, relatively low for IMPACT and zero for GCAM. AIM allows relatively low levels of substitution of other inputs for land and thus low levels of an intensification response when faced with a climate change yield shock. MAGNET's large area elasticities and low substitution elasticities result in compensating factor price effects that result in the estimated intensive

[14] The negative yield response in MAGNET is most likely a compositional effect reflecting a reallocation of agricultural production across modeled regions with different agricultural yields—for example, toward Sub-Saharan Africa and Latin America that have relatively high land supply elasticities in MAGNET.

[15] The formulas are summarized in the Data Appendix and the derivation of the formulas is available from the authors.

Table 4
Scenario effects on global average yields of CR5 crops (S3–S6 results in 2050 relative to S1 results in 2050)

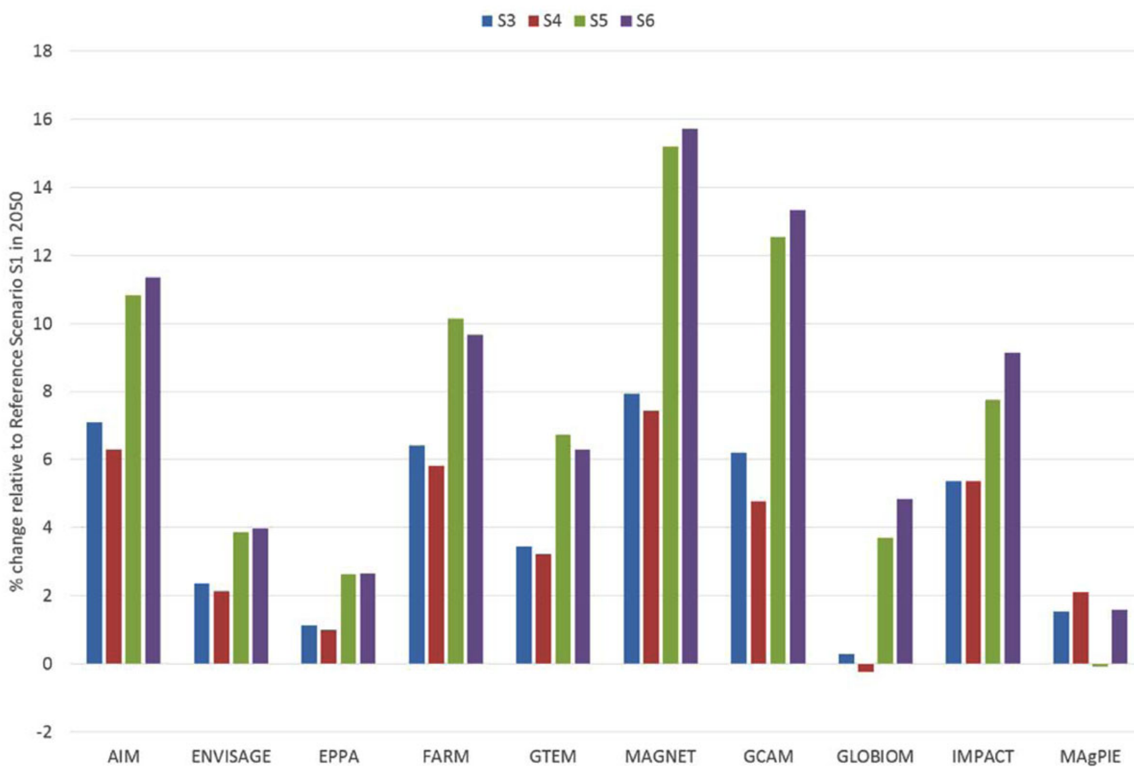
Model/scenario	Coarse grains	Oil seeds	Rice	Sugar	Wheat	Weighted average of five crops (CR5)
AIM						
S3	−10.8	−23.2	−12.6	1.3	−12.1	−15.0
S4	−10.0	−20.4	−13.1	0.2	−9.9	−13.5
S5	−22.4	−11.3	−17.1	−24.6	−16.2	−18.1
S6	−24.8	−14.3	−16.1	−23.7	−13.9	−19.3
DSSAT – LPJmL	−13.2	8.9	−3.7	−24.9	−4.0	−4.4
Hadley – 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

Continued

Table 4
Continued

Model/scenario	Coarse grains	Oil seeds	Rice	Sugar	Wheat	Weighted average of five crops (CR5)
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, February 2013. See notes to Table 1 for the key elements of the scenarios.



Source: AgMIP global economic model runs, February 2013. See notes to Table 1 for the key elements of the scenarios.

Fig. 3. Scenario effects on global area of all crops (S3–S6 results in 2050 relative to S1 results in 2050).

elasticity being negative. GTEM, ENVISAGE, and GLOBIOM are toward the other end of the supply response, with relatively low land extensification response and higher intensification response.

The fourth column shows the demand elasticity over the sum of the two supply elasticities. The higher this value, the greater the importance of demand adjustments to price. GLOBIOM and IMPACT have the highest ratios. FARM and MAGNET have the lowest ratios (other than MAgPIE, which explicitly does not allow demand price adjustments).

Combining these elasticities with the supply response suggests some of the following considerations for parameter evaluation in individual models (keeping in mind the caveats about the estimation approach noted earlier).

- Demand elasticities for GLOBIOM and IMPACT could be on the high side in the long run, with FARM perhaps underestimating the long-run demand elasticity.
- AIM, GCAM, and MAGNET may be underestimating the degree of input substitution and overestimating the degree of extensive response of land over the long run.
- GLOBIOM and MAgPIE may be underestimating the price responsiveness of land supply—though this may be the hardest to categorize over the long run as the regulatory

Table 5
Scenario effects 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 five crops (CR5)
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

Continued

Table 5
Continued

Model/Scenario	Coarse grains	Oil seeds	Rice	Sugar	Wheat	Weighted average of five crops (CR5)
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, February 2013. See notes to Table 1 for the key elements of the scenarios.

Table 6
Decomposition of adjustment to climate shock in 2050 (based on RCP 8.5 as interpreted by two GCMs, and constant CO_2 fertilization assumed in the crop models), percent

	Decomposition			Decomposition relative to average		
	Demand	Area	Yield	Demand	Area	Yield
Model-specific results						
AIM	12	73	15	−6	29	−23
ENVISAGE	17	28	56	−1	−17	18
FARM	4	57	40	−14	12	2
GTEM	6	25	69	−11	−20	31
MAGNET	10	109	−19	−7	64	−57
GCAM	22	64	15	4	19	−23
GLOBIOM	49	10	40	32	−34	2
IMPACT	38	43	19	20	−2	−19
MAgPIE	−1	−8	108	−18	−52	70
Scenario-specific results						
S3	17	53	30	0	9	−8
S4	17	49	34	−1	5	−4
S5	18	36	47	0	−9	9
S6	18	40	42	1	−4	4
Commodity-specific results						
Wheat	11	63	27	−7	18	−11
Rice	15	21	64	−2	−24	26
Coarse grains	17	54	30	−1	9	−8
Oil seeds	28	41	32	10	−4	−6
Average	17	44	38			

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 the nine models with sufficient detail 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.

Source: AgMIP global economic model runs, February 2013.

environment is likely to have a significant influence on land supply responsiveness.

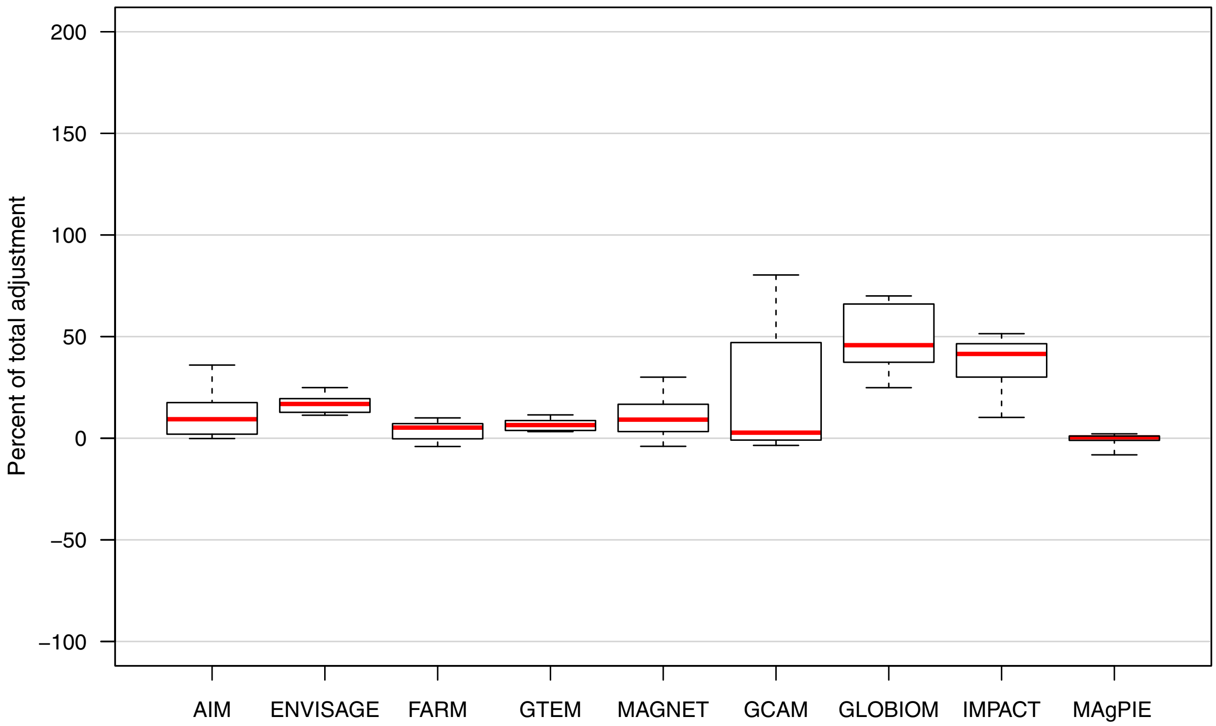
- FARM and ENVISAGE are highly responsive, with the latter probably overestimating both the demand responsiveness as well as the flexibility of the production system.

Preliminary analysis suggests that four of the seven models have chosen parameters that result in low supply and demand responsiveness and this is reflected in the relatively high price impacts.

Figures 4–6 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 reinforce conclusions drawn from the discussions above:

- Adaptation generally relies more on the supply side than on the demand side, where the average contribution is 20% or less with the exception of GLOBIOM, GCAM, and IMPACT. There is some evidence of higher demand adjustment on average in the PE models compared to the CGE models, as well as more variance in demand's contribution to adjustment (see Valin et al., 2014 for more details on the demand results). One possible explanation is the supply chains in the CGE models dampen the transmission of the farm level price impacts at the consumer level.



Notes: Demand component of decomposition for the nine models with sufficient disaggregation for four of the commodities (wheat, rice, coarse grains, and oil seeds) pooled over the four climate shock scenarios, S3 to S6. See Table 1 for a description of the scenarios. Boxes represent first and third quartiles and whiskers include all points up to two times the box width. The thick black line represents the median value.
Source: AgMIP global economic model runs, February 2013.

Fig. 4. Demand contribution to economic adaptation.

Table 7
Implicit aggregate model elasticities (normalized)

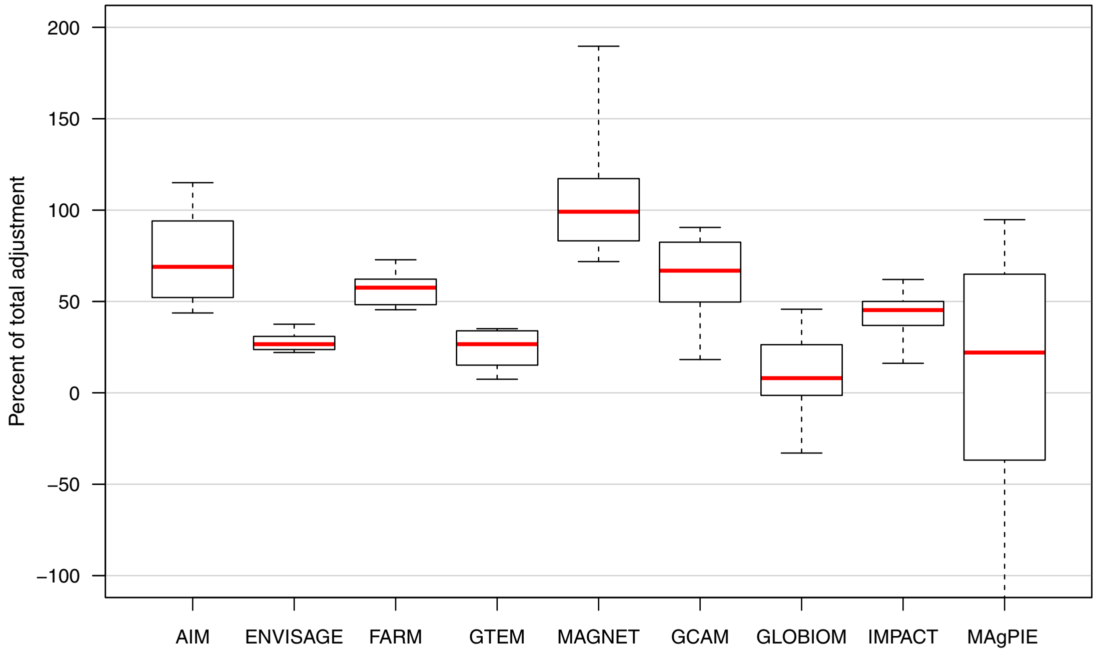
	Demand	Extensive	Intensive	Demand/supply
AIM	0.12	0.90	−0.02	0.14
ENVISAGE	0.17	0.32	0.51	0.20
FARM	0.04	0.67	0.29	0.04
GTEM	0.06	0.29	0.65	0.06
MAGNET	0.10	1.39	−0.49	0.11
GCAM	0.22	0.78	0.00	0.28
GLOBIOM	0.49	0.12	0.38	0.98
IMPACT	0.38	0.53	0.09	0.61
MAgPIE	−0.01	−0.08	1.09	−0.01
Average	0.17	0.53	0.30	0.21

Notes: The “Extensive” elasticities relate a price change to a change in area. The “Intensive” elasticities relate a price change to a change in yield. The fourth column shows the demand elasticity over the sum of the two supply elasticities.

- By definition, there is a symmetric response between area and yield adjustments—models with high area responses (AIM and MAGNET) have low yield responses, and vice versa for the remaining 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 CGE models, the choice of 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.

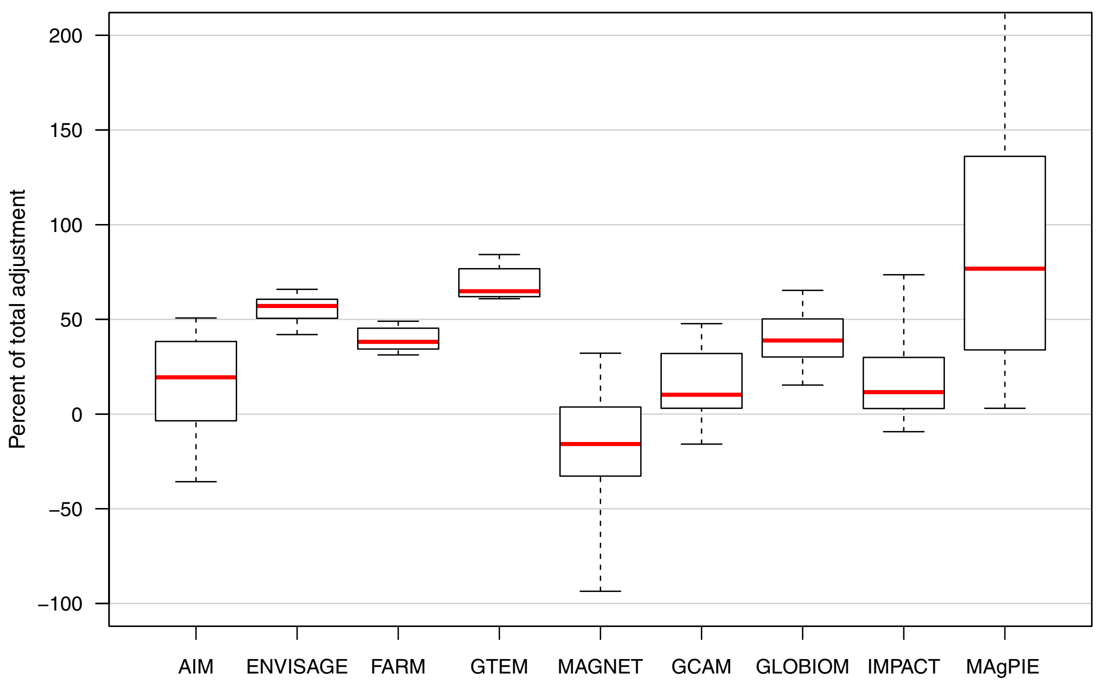
5. Concluding remarks

With harmonization of key drivers, model outputs are more consistent with each other than in earlier comparisons (see von Lampe et al., 2014). For the particular climate shock chosen, all models report higher prices for almost all commodities in all regions, with yields down, area up, and consumption somewhat reduced. But the relative size of the adjustments varies dramatically by model. These differences depend on both model structure and parameter choice. For model structure, the CGE models explicitly allow factor substitutability, which can sometimes result in significant yield response. But, in their effort



Notes: Area component of decomposition for nine models with sufficient disaggregation for four of the commodities (wheat, rice, coarse grains, and oil seeds) pooled over the four climate shock scenarios, S3 to S6. See Table 1 for a description of the scenarios. Boxes represent first and third quartiles and whiskers include all points up to two times the box width. The thick black line represents the median value.
Source: AgMIP global economic model runs, February 2013.

Fig. 5. Area contribution to economic adaptation.



Notes: Yield component of decomposition for nine models with sufficient disaggregation for four of the commodities (wheat, rice, coarse grains, and oil seeds) pooled over the four climate shock scenarios, S3 to S6. See Table 1 for a description of the scenarios. Boxes represent first and third quartiles and whiskers include all points up to two times the box width. The thick black line represents the median value.
Source: AgMIP global economic model runs, February 2013.

Fig. 6. Yield contribution to economic adaptation.

to track bilateral trade flows, these CGE models also use the Armington assumption (Armington, 1969), which can result in less responsive net trade depending on choice of Armington elasticities Within the PE models, GLOBIOM and MAgPIE explicitly optimize land use while the other PE models rely on reduced form specifications.

Examples of parameter choice decisions affecting outcomes include MAgPIE and GCAM's choice of wholly elastic price elasticities of demand and yield, and AIM, GCAM, and MAGNET choices of low values for the degree of input substitution and high values for degree of extensive response of land over the long run. All of the models rely on some plausible set of deep parameters (such as demand, land supply, and factor substitution elasticities, but it must be recognized that many of the parameters have limited econometric and/or validation studies to back them up with significant confidence at least not on the disaggregated level, both spatial and sectoral) that these models operate on. Moreover, to the extent parameters have been sourced from econometric studies, it is unclear to what extent they reflect medium-term relations rather than the long term. The results from this study highlight the need in a subsequent phase to more fully compare the deep model parameters and to generate a call for a combination of econometric and validation studies to narrow the degree of uncertainty and variability in these parameters and to move to Monte Carlo type simulations to better map the contours of the economic uncertainty.

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