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Climate change effects on agriculture: Economic responses to biophysical shocks

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Abstract

Agricultural production is sensitive to weather and thus directly affected by climate change. Plausible estimates of these climate change impacts require combined use of climate, crop, and economic models. Results from previous studies vary substantially due to differences in models, scenarios, and data. This paper is part of a collective effort to systematically integrate these three types of models. We focus on the economic component of the assessment, investigating how nine global economic models of agriculture represent endogenous responses to seven standardized climate change scenarios produced by two climate and five crop models. These responses include adjustments in yields, area, consumption, and international trade.

We apply biophysical shocks derived from the IPCC's Representative Concentration Pathway that result in end-of-century radiative forcing of 8.5 watts per square meter. The mean biophysical yield effect with no incremental CO_2 fertilization is a 17 percent reduction globally by 2050 relative to a scenario with unchanging climate. Endogenous economic responses reduce yield loss to 11 percent, increase area of major crops by 12 percent, and reduce consumption by 2 percent. Agricultural production, cropland area, trade, and prices show the greatest degree of variability in response to climate change, and consumption the lowest. The sources of these differences includes model structure and specification; in particular, model assumptions about ease of land use conversion, intensification, and trade. This study identifies where models disagree on the relative responses to climate shocks and highlights research activities needed to improve the representation of agricultural adaptation responses to climate change.

Keywords: climate change impacts | agriculture | model intercomparison | climate change adaptation | integrated assessment

Significance statement (98 words)

Plausible estimates of climate change impacts on agriculture require integrated use of climate, crop, and economic models. We investigate the contribution of economic models to uncertainty in this impact chain. In the nine economic models included, the direction of management intensity, area, consumption, and international trade responses to harmonized crop yield shocks from climate change are similar. But the magnitudes differ significantly. The differences depend on model structure, in particular the specification of endogenous yield effects, land use change and propensity to trade. These results highlight where future research on modeling climate change impacts on agriculture should focus.

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Introduction

Climate change alters weather conditions and thus has direct, biophysical effects on agricultural production. Assessing the ultimate consequences of these effects after producers and consumers respond requires detailed assessments at every step in the impact chain from climate through to crop and economic modeling.

Comparisons of results from studies that have attempted such model integration in the past show substantial differences in effects on key economic variables. Studies in the early 1990s found that climate change would have limited agricultural impacts globally, but with varying effects across regions (1–3). Adaptation and carbon dioxide (CO_2) fertilization effects were the two largest sources of variation in the results. New simulation approaches emerged in the mid-2000s, with gridded representation of yield impacts and more comprehensive coverage of variability in climate model projections (4, 5). However, these studies still relied on a single crop model and a single economic model. The number of economic models used for these types of analysis has remained relatively limited, and there has been no attempt to compare their behavior systematically. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (6) renewed the call to "enhance crop model inter-comparison" and noted that "economic, trade and technological assumptions used in many of the integrated assessment models to project food security under climate change were poorly tested against observed data" (p.285).

This paper is part of a collective effort (7) to make progress in this direction by systematically integrating results from the three types of models – climate, crop, and economic – to assess how agriculture responds to climate change. The modeling chain is portrayed in Fig. 1. General circulation models use a representative (greenhouse gas) concentration pathway (RCP) to produce data on changes in climate variables such as temperature and precipitation. Process-based models of crop growth use the climate results as inputs to simulate biophysical yield effects, and these, in turn, become inputs into economic models. The economic models then simulate the responses of key economic variables to the changes in biophysical crop yields.

This paper focuses on the endogenous responses of the economic models. Conceptually, the initial effect of climate change that reduces yields (given existing practices) is a leftward shift of the supply curve, reducing production and raising prices. Consumers respond by reducing consumption of more expensive crops and shifting to other goods. Producers respond by changing farm-level management practices and increasing the amount of acreage under these crops. Global reallocation of production and consumption through international trade further alters climate change impacts on global agriculture. The economic models represented in this paper all capture these general effects but have large differences in the relative contribution of these response options. The models represent a diversity of approaches to describing human-nature interactions, with five computable general equilibrium (CGE) models covering the full economy and four partial equilibrium (PE) models specialized in agriculture, including two grid-cell-based optimization models (see Table S1 for more details).

Results from seven scenarios on biophysical crop yield changes under climate change (described in Table S2) are compared across the nine economic models used in the exercise. These scenarios are based on a combination of five different crop models and two general circulation models (GCMs). In the economic models, the climate change effects on agricultural productivity are added to a reference scenario that harmonizes socioeconomic and exogenous agricultural productivity drivers; other drivers and parameter choices remain specific to each model. All climate change scenarios use the same RCP (RCP 8.5), which is the most extreme of the emissions pathway scenarios developed for the IPCC's Fifth Assessment Report. The crop models use a constant CO_2 level equal to that of the early 2000s.

The standardization of model outputs allows us to compare the effects of the exogenous climate change shock on yields (YEXO) arising from differences in crop model outputs for four crop aggregates – coarse grains, oil seeds, wheat, and rice – which collectively account for about 70 percent of global crop harvested area. The differences in the endogenous responses in the economic models are measured through changes in 2050 in final yields (YTOT), crop area (AREA), net imports relative to production in the reference scenario (TRSH), and consumption (CONS) that accompany the market price effects (PRICE) of the climate shock.

Results

Endogenous responses in the economic models distribute the effects of climate change. Together with the assumption of no incremental yield effects from CO_2 fertilization, the mean biophysical effect of the climate change shock on yields (YEXO) of the four crop groups and 13 regions of the globe is a 17 percent decline. The distribution of the biophysical yield shocks (standard deviation (SD) of ± 13 percent) arises from both the heterogeneous impacts of climate change over crops and geography, and the diversity of modeling approaches in the GCM and crop models (8).

Fig. 2 provides an overview of how the initial shock at the crop and the regional level propagates through the response options in the economic modeling. The economic models transfer the shock effect to the response variables. Producers respond to the price increase associated with the shock both by intensifying management practices (the final yield change (YTOT) is a mean decline of 11 percent) and by altering the area devoted to these crops (AREA), resulting in a mean area increase of 11 percent. The combined yield decline and area increase result in a mean decline in production of only 2 percent. Consumption (CONS) also declines only slightly (mean decline of 3 percent). Changes in trade shares cancel out across regions but the share of global trade in world production increases by 1 percent on average (see Fig. S1 for world aggregated effects). Finally, average producer prices (PRICE) increase by 20 percent. The direction of responses described above are common to all models, as can be seen in the correlation matrix (Table S3). However, the magnitude of responses varies significantly across models, crops, and regions (see Fig. S2, Fig. S3 and S4).

More heterogeneous responses in production than consumption. The second interesting pattern of model responses is the change in variance of the shock across geography, crops, and scenarios along the modeling chain, displayed as box plots in Fig. 2. Economic adjustment occurs through the endogenous PRICE variable, which has variation comparable to variables AREA, PROD, and TRSH. Variation in the initial productivity shock YEXO (SD of 13 percent) is similar to that of equilibrium yield YTOT (SD of 17 percent). Variability values for agricultural area (AREA), production (PROD) and trade share (TRSH) are similar in size (SD of 25 to 26 percent) and substantially larger than those for yields. Consumption (CONS, SD of 6 percent) has the smallest variation of all variables in Fig. 2.

Model-specific results (Fig. S2) show notable differences in shock propagation from YEXO through yield and area responses to PROD, a point to which we return below. Part of these differences can be explained by model-specific differences in regional impacts. This can be seen by comparing Fig. 2 with Fig. S1 and S5 in SI that display world aggregates for the complete sample and by model. Consumption responds little because food demand globally is less sensitive to price changes than other variables. This effect is particularly visible when comparing the correlation of PRICE and CONS to the correlations of PRICE and other endogenous responses in the models (see Table S4 and Fig S6 in SI). The large variability in trade and area responses is the result of varying assumptions about trade flexibility and ease of land conversion in the models.

Analysis of variance (Table 1) allows us to investigate the individual contributions of a number of sources of variation for the seven response variables described above. Specifically, the variables' responses are assessed for effects by economic model (n=9), crop type (n=4), region (n=13), and scenario (n=7), which we further decompose by GCM (n=2) and crop model (n=5). The sum of squared error (Sum Sq.) column in Table 1 displays the magnitude of total variance attributed to each source, with the remaining variance allocated to residuals. The mean squared error (Mean Sq.) column adjusts for the number of items in each group and provides an indication of the relative contribution of sources.

Variability in the exogenous productivity shock YEXO is primarily due to crop model and region. The only contribution from the economic models is due to differences in model-specific product and regional differences in how the shock is implemented. Final yield YTOT demonstrates the transition toward variation contributed by economic models, which is now the grouping with the largest contribution to variation. This pattern continues in agricultural area (AREA) and production (PROD), with large contributions from models to variability. Consumption (CONS) is an interesting variable, again with economic models as the largest contributor to variability, but with very low contributions from other groupings, and it has the smallest total sum of squared errors of all economic variables. For TRSH, only the region is a significant source of variability because in other dimensions net imports sum to zero. Model-specific responses for scenarios and variables are available in Figs. S7-S16.

Distribution of responses across models. More in-depth analysis of model responses is required to understand the origins of heterogeneity introduced along the chain of variables. For this purpose, Fig. 3 graphs univariate regression lines of response variables of each model against the initial shock (YEXO). The slope coefficient reflects the local response and can be roughly interpreted as an elasticity. A value of 1 indicates that a change in the climate shock generates an equivalent percentage change in the response variable; for yields, this means there is no endogenous response at the regional level. An intercept that differs from zero indicates that a local change arises from effects elsewhere via price effects transmitted through international trade. Table 2 reports regression results by individual model and by model type (general or partial equilibrium). One additional variable is added to the regression analysis to isolate the pure endogenous yield response (YENDO) (see the Methods section for more details).

Yield response varies by model with four different patterns. Four models (AIM, GCAM, IMPACT and MAGNET) appear relatively unresponsive in terms of productivity management, with the YTOT slope coefficient close to 1 (little or no significant endogenous yield response YENDO to climate change). Three other models (ENVISAGE, FARM, and GTEM) show a significant management response to regional shocks but responses are mainly local (large negative slope value for YENDO and intercept close to 0). These models compensate the most through intensification in regions where yields are most severely affected. The final yield reduction is reduced on average to 65 percent of the initial shock for ENVISAGE and 32 percent for GTEM. A third pattern, represented by the MAgPIE model, is characterized by a strong response in all regions independent of the magnitude of the impact. This model displays a slope on YTOT close to 1 with a positive intercept. Finally, the yield response in the GLOBIOM model is unique. Unlike all the other models, its slope on final yield is greater than one. This is due to a reallocation effect both through international trade, which is highly responsive in this model, and through intra-region spatial allocation of the most fertile lands to least severely hit crops with more severely affected ones being shifted to marginal lands, hence further exacerbating the climate change effect.

Area responses differ substantially by model. Five models show an inverse relationship (as productivity declines AREA increases) of moderate (ENVISAGE, GTEM) to relatively high magnitude (AIM, FARM, and MAgPIE). For these models, the intercept is zero, suggesting international price transmission does not affect area. MAGNET and IMPACT have the same inverse relationship but also show some price transmission effects (significant intercept dummies). Two models (GLOBIOM and GCAM) have a positive relationship between productivity and area indicating strong reallocation patterns across regions. For these two models, regions that are most affected by climate change decrease cultivated area and replace less profitable production with imports from more favorable areas. This reallocation pattern is also evident in the PROD regression, with slope much greater than 1 for these two models and a positive intercept. For these two models, production increases in regions with a small climate shock but in regions and crops where the negative effects are larger, production decreases, and imports grow.

Trade responses to the productivity shock are implicit in the intercept responses discussed above. The TRSH regression coefficients reinforce the observations above. GCAM and GLOBIOM are the most trade-responsive models. They reallocate a significant share of production across regions and are less dependent on local yield and area responses. IMPACT and MAGNET show an intermediate level of trade responsiveness, resulting in a PROD slope close to one. Finally, AIM, ENVISAGE, GTEM, FARM and MAgPIE are the least trade–responsive. This result is not unexpected as AIM, ENVISAGE, GTEM and FARM are CGE models that rely on the Armington assumption (9) that generally results in less responsiveness to international price changes. The model-type results of Table 2 confirm this smaller trade response characteristic of CGEs (see Table S6 for regression results on model type effects). MAgPIE also shows this pattern due to restrictive trade assumptions with self-sufficiency constraints.

Consumption responses are relatively small and differ little across the models. Two models (GCAM and MAgPIE) do not include endogenous consumption change. For the seven other models, endogenous consumption responses are smaller than for other variables. GLOBIOM has the strongest effect (0.26 slope), followed by IMPACT, MAGNET and ENVISAGE. Hence, across the models included here, at least three quarters of climate change responses occur through land use change, management intensity, and trade adaptation.

Discussion

This paper offers for the first time a systematic comparison of responses of the food system to climate change across a large set of global economic models. The same economic behaviors are represented in the models and their results are qualitatively similar. With a negative productivity effect from climate change, prices increase and trigger more intensive management practices, area expansion, reallocation through international trade and reduced consumption. However, the relative magnitude of these responses varies widely across the models, reflecting differences in model structure and parameterization. The distribution and magnitude of these effects are of crucial importance because of their effects on human well-being.

Our analysis shows that all models transfer a large part of the climate change shock to production-side and trade responses. An important implication of this is that analyses that limit climate change impact to biophysical effects alone significantly underestimate our capacity to respond. However, the models disagree on whether area or yield responses will be most important locally, and on the role of exploiting international comparative advantage. And while the average consumption effect is relatively small, the price increases caused by the inelastic nature of global demand are likely to significantly increase food costs for the poor, with especially negative effects for the poor in rural areas who will also see reduced income from production side effects.

Model specification and parameterization. Both model structure and parameter choice affect the results. Parameter choice is the most obvious way in which modeling teams represent their perspectives about the future. For example, on the demand side how quickly will other Asian countries follow Japan in reducing rice consumption as incomes rise (represented as declining income elasticities)? On the supply side, how easy is it to switch from wheat to maize in Canada or Russia if temperatures rise? How much tropical forest can be converted to agricultural land and how easy is that conversion? The CGE models all have their roots in the GTAP database and the CGE optimizing approach (10) and so have similar model specifications but parameterization choices result in very different outcomes. For instance, ENVISAGE and FARM absorb on average one-third of the climate shock through intensification but for GTEM it is as much as two-thirds. AIM and MAGNET parameterization results in most of the response taking place in area expansion.

Model specification choices can also influence the results. For example, in the case of trade, some models (e.g., GLOBIOM, GCAM, and IMPACT) rely on an integrated world market representation which could overstate the degree of trade response (11), whereas others use trade-restrictive specifications such as the Armington assumption in CGE models (12) and the self-sufficiency constraints of MAgPIE. With respect to land, both GLOBIOM and MAgPIE have a full representation of land use and allocate it through an optimization process with high spatial resolution whereas, for instance, the IMPACT model only considers cropland and assumes it can be expanded as needed without constraint. On the CGE side, land representation also varies strongly, from the simplified structure of substitution found in GTEM or ENVISAGE that does not consider land expansion into forest to MAGNET that relies on a land supply curve calibrated on a biophysical model (13). Finally, endogenous yield adjustments can differ widely between a CGE which represents substitution with factors such as capital and labor; a bottom-up model like GLOBIOM that explicitly represents switches between different management systems and the relocation of production between different grid-cell locations (14); and for instance MAgPIE that features an endogenous mechanisms of public and private investments in agricultural productivity (15).

From comparison to improvement. This model comparison exercise has not only enhanced understanding of the different economic responses of agriculture to climate change; it has also created a systematic process for improvement of model input data, integration with other models, and sharing of modeling insights.

A first set of envisioned improvements is more detailed assessment and, as appropriate, harmonization of specific types of model parameters and drivers. For instance, price and income elasticities are all currently sourced from different datasets with little assessment of their appropriateness for long-term scenarios. While progress was made toward a standardized language with respect to scenario assumptions such as macro-economic drivers, exogenous productivity paths and behavioral parameters, further efforts on protocol development and simulation experiments are needed to effectively compare model behavior. Finally, harmonization of some base data would also be beneficial, but this appears especially challenging, with CGE models relying on different versions of the GTAP data base and partial equilibrium models aligned with FAOSTAT data but with different starting years. Still, some diversity in model approaches will and should remain because of the inherent uncertainty about the future of demand, trade, technological progress, and other processes (16).

Model integration under a common protocol of data exchange also constitutes a great potential for future improvement of models and overall assessments. This study has compared the results from 63 climate, crop and economic model combinations, with standardized procedures allowing full tracing of modeling assumptions on choice of RCP, GCM, and level of CO_2 fertilization. Further harmonization with more detailed geographical scales and products would also allow improvements in future analysis and systematize the distinction of management systems and spatially explicit analyses.

Finally, this exercise has focused on improving the model integration process. But it has omitted some potential large biophysical effects of climate change, including CO_2 fertilization effects on crops and weeds, plant nutrient management choices, ozone damage, extreme events, or biotic stresses. And it has ignored the potential for policy and program responses around the world to facilitate or hinder adaption to these challenges. Attention to these topics should be high on the agenda for future research across the modeling chain. The collective experience gained in this first exercise of model integration and comparison will help to improve current estimates, and to refine the contribution of economic models to the full chain uncertainty.

Methods

Climate data. Climate model inputs were provided by the HadGEM2-ES (17) and IPSL-CM5A-LR (18) GCMs using the Representative Concentration Pathway (RCP) 8.5, the most extreme of the RCPs developed for the IPCC's 5th Assessment Report (19). This RCP has a radiative forcing of approximately 8.5 watts per square meter by 2100. Its CO_2 concentration in 2050 is 540 ppm (see http://www.iiasa.ac.at/web-apps/tnt/RcpDb). The resulting climate outputs were bias-corrected and downscaled for the ISI-MIP model comparison project (20).

Crop models. The ISI-MIP climate data were used as inputs into five crop growth models as part of a global gridded crop modeling exercise (21). Climate data for 2000 and 2050 were used to generate yields at ½ degree resolution (about 55.5 kilometers at the equator). The crop models results used are all based on a constant CO_2 atmospheric concentration assumption, eliminating any fertilization effect from the additional CO_2 emitted during the period from 2000 to 2050. The combination of the most extreme RCP with the assumption of limited CO_2 fertilization effects in 2050 means that the negative productivity effects are at the upper end of *direct* yield effects from climate change by 2050. However, they do not include the deleterious effects of increased ozone concentrations, biotic stresses from a range of pests and diseases that will thrive under higher temperatures and more CO_2, and the likelihood of increased occurrence of extreme events. The process of transforming crop model data to inputs for economic modeling involves 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 SI Text for more technical discussion of the process.

Baseline in economic models. All models were run with GDP and population values from Shared Socioeconomic Pathway 2 (SSP2, (22, 23)). In SSP2, global population reaches 9.3 billion by 2050, an increase of 35 percent relative to 2010, and global gross domestic product (GDP) triples. The SSP data are available at https://secure.iiasa.ac.at/web-apps/ene/SspDb). Exogenous agricultural productivity changes from research and extension efforts were also aligned across models using IMPACT modeling suite estimates (24), except for MAgPIE which represent this effect through its own endogenous yield response (11). IMPACT values are based on expert opinion about potential biological yield gains for crops in individual countries based on historical yield gains and expectations about future private and public sector research and extension efforts. Table S7 reports the resulting yield changes between 2005 and 2050 for selected crops in selected countries. These estimate do not include crop-model-based climate change effects or economic model yield responses to changes in input or output prices.

Economic responses to climate shocks. Each of the global economic models used the exogenous productivity shocks as yield determinants (YEXO). For the computable general equilibrium economic 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.

The variables YEXO, YTOT, AREA, CONS, and PRICE were reported by each model for the same set of regions (see Table S8) and the four following crop aggregates: wheat, coarse grain, rice and oilseeds. These variables are calculated as percent change for a climate change scenario relative to the reference scenario. Trade share TRSH is defined as the 2050 difference in net imports between climate change scenarios and reference scenario, divided by 2050 production in the reference scenario. For TRSH world aggregate, only positive net flows are accounted to obtain the share of production traded. Two additional variables are used in the main text or the SI to isolate the endogenous yield response YENDO and supply response PENDO. The formulas are YENDO = (1+YTOT)/(1+YEXO)-1 and PENDO = (1+PROD)/(1+YEXO)-1=(1+AREA)*(1+YENDO)-1. The price variable chosen for this comparison (PRICE) is the average producer price weighted by production volumes, and deflated by the GDP price index.

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Table 1. Partition of the sum of squares and analysis of variance for the different variables.

		YEXO			YTOT			AREA			PROD			TRSH			CONS			PRICE		
Variable	Df	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.	Sum Sq.	Mean Sq.	Sgn.
Econ. model	8	0.11	0.01		10.64	1.33	***	9.98	1.25	***	1.80	0.22	***	0.63	0.08		1.75	0.22	***	35.71	4.46	***
Climate model	1	0.12	0.12	**	0.18	0.18	**	0.29	0.29	*	0.01	0.01		0.07	0.07		0.02	0.02	*	0.90	0.90	***
Crop model	4	3.26	0.82	***	1.67	0.42	***	1.87	0.47	***	0.67	0.17	*	0.27	0.07		0.12	0.03	***	9.69	2.42	***
Product	3	0.34	0.11	***	0.96	0.32	***	1.57	0.52	***	0.38	0.13	.	0.49	0.16	.	0.24	0.08	***	0.89	0.30	***
Region	12	9.53	0.79	***	7.35	0.61	***	7.49	0.62	***	13.06	1.09	***	5.54	0.46	***	1.17	0.10	***	16.01	1.33	***
Residuals	2862	36.09	0.01		58.87	0.02		157.60	0.06		164.84	0.06		194.94	0.07		8.23	0.00		105.90	0.04	

The point (.), single asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10%, 5%, 1% and 0.1% levels, respectively.

Table 2. Regressions of economic responses to climate change shock (YEXO) by model.

Model		YTOT	YENDO[†]	AREA	PROD	TRSH	CONS	XPRP
AIM	Int	0.004 **	-0.001	0.001	0.047 ***	-0.038 ***	0.011*	-0.006
	Slope	0.923 ***	-0.143***	-1.140 ***	0.293 ***	-0.216 ***	0.122***	-0.931 ***
ENVISAGE	Int	0.044 ***	0.020***	0.032 ***	0.084 ***	-0.063 ***	0.020***	-0.003
	Slope	0.654 ***	-0.679***	-0.195 ***	0.537 ***	-0.331 ***	0.205***	-0.384 ***
FARM	Int	0.018 ***	0.001	0.018 *	0.055 ***	-0.063 ***	0.005	-0.011
	Slope	0.717 ***	-0.513***	-0.694 ***	0.262 ***	-0.239 ***	0.055*	-0.788 ***
GCAM	Int	-0.002	-0.002	0.315 ***	0.283 ***	-0.333 ***	-0.030***	0.035 ***
	Slope	0.998 ***	0.003	0.978 ***	1.863 ***	-1.871 ***	0.015	-0.095 ***
GLOBIOM	Int	0.098 ***	0.114***	0.119 **	0.189 ***	-0.242 ***	-0.028***	0.137 ***
	Slope	1.277 ***	0.339***	0.382 .	1.436 ***	-1.11 ***	0.253***	-1.272 ***
GTEM	Int	-0.009	-0.055***	0.010	0.007 ***	-0.063 ***	0.014*	-0.010
	Slope	0.318 ***	-1.192***	-0.336 ***	0.375 ***	-0.261 ***	0.127***	-0.738 ***
IMPACT	Int	0.010 .	0.005	0.053 ***	0.070 ***	-0.115 ***	-0.044***	0.176 ***
	Slope	0.881 ***	-0.201***	-0.210 ***	0.802 ***	-0.573 ***	0.137***	-0.490 ***
MAGNET	Int	-0.017 ***	-0.015**	0.132 ***	0.133 ***	-0.138 ***	-0.005	0.073 ***
	Slope	0.960 ***	-0.021	-0.440 ***	0.916 ***	-0.707 ***	0.176***	-1.462 ***
MAgPIE	Int	0.179 ***	0.181***	-0.068 *	0.011	-0.012	-0.004*	0.204 ***
	Slope	0.910 ***	-0.459***	-0.720 ***	0.123	-0.113	0.000	-0.676 ***
All models	Int	0.036 ***	0.022***	0.058 ***	0.090 ***	-0.108 ***	-0.011***	0.068 ***
	Slope	0.862 ***	-0.330***	-0.330 ***	0.649 ***	-0.538 ***	0.102***	-0.738 ***

The point (.), single asterisk (*), double asterisk (**), and triple asterisk (***) indicate significance at the 10%, 5%, 1% and 0.1% levels, respectively. Summary statistics for the different regressions are available in Table S5. [†] YENDO measure the yield endogenous response and is defined from the YTOT column as: YENDO = (1+YTOT)/(1+YEXO)-1.

Figure Legends

Fig. 1. The impact modeling chain from climate through to crop and economic effects. Abbreviations: Temp = Temperature; Prec = Precipitation; Cons= Consumption.

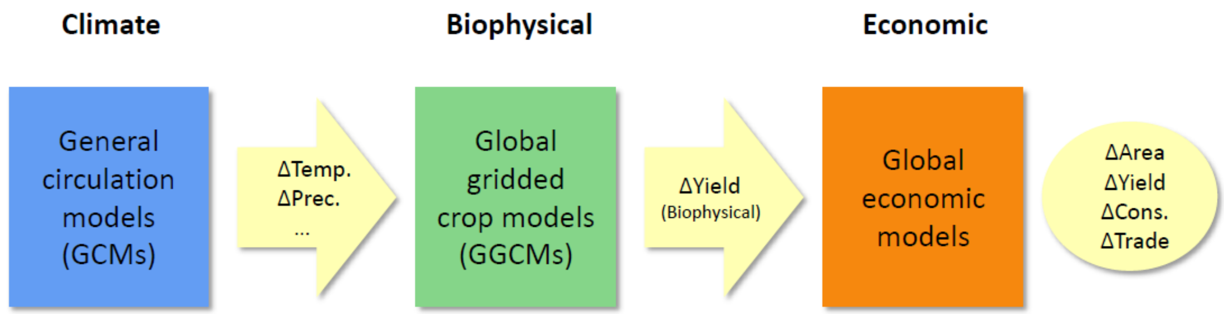
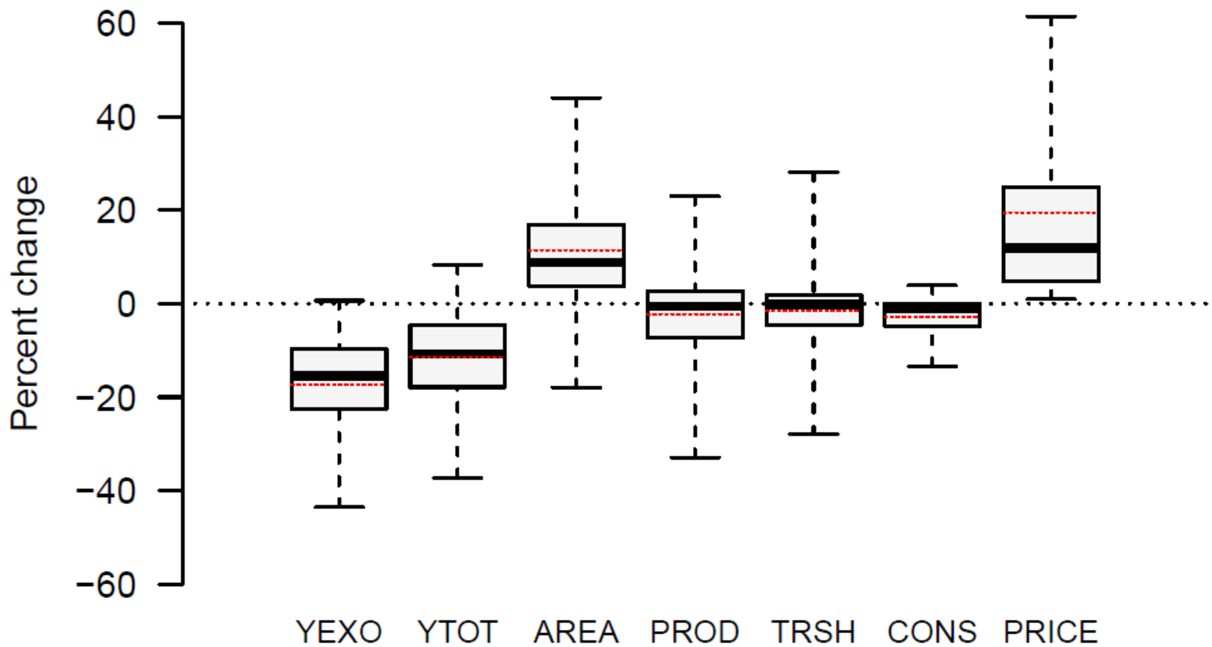


Fig. 2. Variability of key crop and economic model results across crop aggregates (n=4), models (n=9), scenarios (n=7) and regions (n=13). Box and whiskers plots for key crop and economic model results. The variables YEXO, YTOT, AREA, PROD, CONS, and PRICE are reported as percent change for a climate change scenario relative to the reference scenario (with constant climate) in 2050. TRSH is the change in net imports relative to reference scenario production in 2050. Total n is not equal to the full product of dimensions because region-crop pairs without production and consumption in the baseline of a model are not represented for that model. Boxes represent first and third quartiles and whiskers show 5-95 percent intervals of results. The thick black line represents the median and the thin red dotted line the mean value.



	YEXO	YTOT	AREA	PROD	TRSH	CONS	PRICE
n	2891	2891	2891	2891	2891	2891	2891
Mean	−0.17	−0.11	0.11	−0.02	−0.01	−0.03	0.2
SD	(0.13)	(0.17)	(0.25)	(0.25)	(0.26)	(0.06)	(0.24)

Fig. 3. Economic responses of model variables against YEXO, by model. Grey circles represent the PROD results on y-axis versus YEXO input on the x-axis, obtained in each model for the 13 regions, four crops, and seven scenarios of the analysis. The different lines represent results of univariate regressions for each variable against YEXO. The thick blue line corresponds to the regression on the grey circles; points for other variables are not displayed.