Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison

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Here we present the results from an intercomparison of multiple global gridded crop models (GGCMs) within the framework of the Agricultural Model Intercomparison and Improvement Project and the Inter-Sectoral Impacts Model Intercomparison Project. Results indicate strong negative effects of climate change, especially at higher levels of warming and at low latitudes; models that include explicit nitrogen stress project more severe impacts. Across seven GGCMs, five global climate models, and four representative concentration pathways, model agreement on direction of yield changes is found in many major agricultural regions at both low and high latitudes; however, reducing uncertainty in sign of response in mid-latitude regions remains a challenge. Uncertainties related to the representation of carbon dioxide, nitrogen, and high temperature effects demonstrated here show that further research is urgently needed to better understand effects of climate change on agricultural production and to devise targeted adaptation strategies.

food security | AgMIP | ISI-MIP | climate impacts | agriculture

The magnitude, rate, and pattern of climate change impacts on agricultural productivity have been studied for approximately two decades. To evaluate these impacts, researchers use biophysical process-based models (e.g., refs. 1–5), agro-ecosystem models (e.g., ref. 6), and statistical analyses of historical data (e.g., refs. 7 and 8). Although these and other methods have been widely used to forecast potential impacts of climate change on future agricultural productivity, the protocols used in previous assessments have varied to such an extent that they constrain cross-study syntheses and limit the ability to devise relevant adaptation options (9, 10). In this project we have brought together seven global gridded crop models (GGCMs) for a coordinated set of simulations of global crop yields under evolving climate conditions.

This GGCM intercomparison was coordinated by the Agricultural Model Intercomparison and Improvement Project (AgMIP; 11) as part of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP; 12). In order to facilitate analyses across models and sectors, all global models are driven with consistent bias-corrected climate forcings derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (13). The objectives are to (*i*) establish the range of uncertainties of climate change impacts on crop productivity worldwide, (*ii*) determine key differences in current approaches used by crop modeling groups in global analyses, and (*iii*) propose improvements in GGCMs and in the methodologies for future intercomparisons to produce more reliable assessments.

We examine the basic patterns of response to climate across crops, latitudes, time periods, regional temperatures, and atmospheric carbon dioxide concentrations [CO_2]. In anticipation of the wider scientific community using these model outputs and the expanded application of GGCMs, we introduce these models and present guidelines for their practical application. Related studies in this special issue focus on crop water demand and the freshwater supply for irrigation (14), the application of the crop model results as part of wider intersectoral analyses (15), and the integration of crop-climate impact assessments with agro-economic models (16).

1. Global Gridded Crop Models

Details of the seven global crop models used in this study are provided in *SI Appendix*, Tables S1–S6. These include the Environmental Policy Integrated Climate Model [EPIC (17–20); originally the Erosion Productivity Impact Calculator (17)], the Geographic Information System (GIS)-based Environmental Policy Integrated Climate Model (GEPIC; 18–21), the Global AgroEcological Zone Model in the Integrated Model to Assess the Global Environment (GAEZ-IMAGE; 22, 23), the Lund-Potsdam-Jena managed Land Dynamic Global Vegetation and Water Balance Model (LPJmL; 24–26), the Lund-Potsdam-Jena

Significance

Agriculture is arguably the sector most affected by climate change, but assessments differ and are thus difficult to compare. We provide a globally consistent, protocol-based, multimodel climate change assessment for major crops with explicit characterization of uncertainty. Results with multimodel agreement indicate strong negative effects from climate change, especially at higher levels of warming and at low latitudes where developing countries are concentrated. Simulations that consider explicit nitrogen stress result in much more severe impacts from climate change, with implications for adaptation planning.

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General Ecosystem Simulator with Managed Land (LPJ-GUESS; 24, 27, 28), the parallel Decision Support System for Agro-technology Transfer [pDSSAT; 29, 30; using the Crop Environment Resource Synthesis (CERES) models for maize, wheat, and rice and the Crop Template approach (CROPGRO) for soybean], and the Predicting Ecosystem Goods And Services Using Scenarios model (PEGASUS; 31).

These models differ in regard to model type, inclusion and parameterization of soil and crop processes, management inputs, and outputs. These dissimilarities must be taken into account in interpreting the results of the intercomparison and in the use of results in other analyses (*SI Appendix*, Table S1). Examples include the biological and environmental stresses affecting crops in each model and the treatment of how increasing [CO_2] affects plant growth and yield. GAEZ-IMAGE, LPJ-GUESS, and LPJmL focus on water and temperature responses, whereas the other four models also consider stresses related to nitrogen deficiency and severe heat during various stages of development. In addition to these, pDSSAT considers oxygen stress, PEGASUS considers phosphorus and potassium stresses, and EPIC and GEPIC both consider oxygen, phosphorus, bulk density, and aluminum stresses.

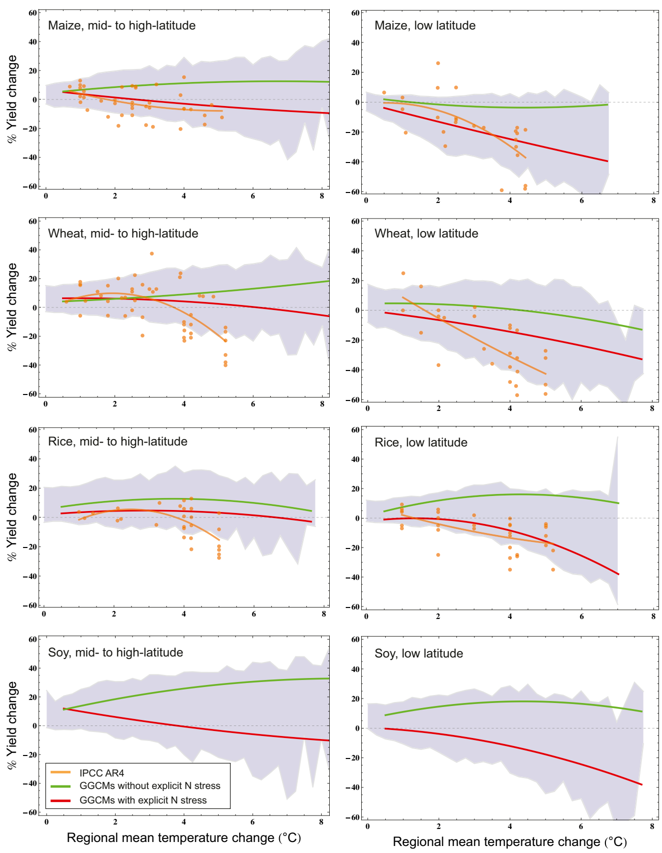

Fig. 1. Mean relative yield change (%) from reference period (1980–2010) compared to local mean temperature change (°C) in 20 top food-producing regions for each crop and latitudinal band. Results shown for the 7 GGCMs (6 for rice) for all GCM combinations of RCP8.5 compared to results from IPCC AR4 (represented as orange dots and quadratic fit; 36). Quadratic least-squares fits are used to estimate the general response for the GGCMs with explicit nitrogen stress (EPIC, GEPIC, pDSSAT, and PEGASUS; red line) and for those without (GAEZ-IMAGE, LPJ-GUESS, and LPJmL; green line). The 15–85% range of all models for each ¼°C band is represented in gray. Limits of local temperature changes reflect differences in projected warming in current areas of cultivation.

2. Comparison with Intergovernmental Panel on Climate Change Fourth Assessment Report Results

A relevant question is to what extent findings of this substantial effort of coordinated GGCM modeling are different from what was reported in the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4; 32) (Fig. 1). Crop modeling results in the IPCC AR4 showed that small beneficial impacts on rainfed crop yields may be found in mid- and high-latitude regions with moderate-to-medium local increases in temperature (1–3 °C) along with associated [CO_2] increase and rainfall changes (figure 5.2 in ref. 32; reproduced as orange dots and quadratic fit in Fig. 1). In low-latitude regions, even moderate temperature increases (1 to 2 °C) were found to have negative yield impacts for major cereals, because the climate of many tropical agricultural regions is already quite close to the high-temperature thresholds for suitable production of these cereals (33, 34). Furthermore, increases in tropical temperatures can lead to greater evaporative demand and thus water stress on crops.

We find that general patterns of the GGCM results are similar, especially among those models that simulate nitrogen stress on crops and include fertilizer application rates based on observational databases (red line in Fig. 1). GGCMs without nitrogen stress tend to be more optimistic in yield response (green line in Fig. 1). The 15–85% range of all GGCM results (indicated by the shaded envelope) suggests that climate impacts on tropical croplands are generally more negative than the mid- and high-latitude impacts. There is considerable variation in response within these broader latitudinal bands, with mid- and high-latitude crop yields spanning both positive and negative responses, especially at high levels of temperature change (which are also associated with higher [CO_2]). The GGCM results generally display a wider range of uncertainty compared to the AR4 results, reflecting the much broader geographical coverage, projected temperature, and diversity of crop models represented in the current study.

3. GGCM Structural Differences

A major source of uncertainties in projected climate impacts across the globe is the result of variations in GGCM approaches, assumptions, and structures. Documentation of these differences is fundamental to at least partially constraining them and to improving analyses of ensemble crop projections.

3.1 Model Types. The seven GGCMs may be grouped into three types according to their original purpose, structure, and processes: site-based crop models (EPIC, GEPIC, and pDSSAT), agro-ecosystem models (LPJ-GUESS, LPJmL, and PEGASUS), and agro-ecological zone models (GAEZ-IMAGE) (*SI Appendix*, Fig. S1). A critical question is whether two models from the same lineage, such as EPIC and GEPIC, and LPJ-GUESS and LPJmL are truly independent. For instance, in the case of EPIC and GEPIC, the same model version is used (0810), but with different parameterizations and assumptions about soil and management input data that are reflected in the variations in their results.

Site-based models were developed to simulate processes at the field scale, and include dynamic interactions among crop, soil, atmosphere, and management components (2, 20, 30). These models are often calibrated and validated with data from agronomic field experiments. The versions of the site-based models used in this study have been developed to run simulations on global grids, as has been done using DSSAT (29, 35–37).

Agro-ecosystem models were primarily developed to simulate carbon and nitrogen dynamics, surface energy balance, and soil water balance. The LPJmL and LPJ-GUESS models are dynamic global vegetation models that simulate the full global carbon and water cycles. Vegetation dynamics and agricultural modules were originally introduced to improve the simulations of these cycles. PEGASUS is a simple global vegetation model designed to test how agroecosystems respond to climate change and to evaluate potential benefits of various farming adaptation options at the global scale.

The agro-ecological zone methodology (used here by GAEZ-IMAGE) was developed to assess agricultural resources and potential at regional and global scales and has been embedded into integrated assessment models for global environmental change (6, 23).

3.2 Model Processes. Crop processes simulated in all or some of the GGCMs include leaf area development, light interception and utilization, yield formation, crop phenology, root distribution responsiveness to water availability at soil depth, water and heat stress, soil–crop–atmosphere water cycle dynamics, evapotranspiration, soil carbon and nitrogen cycling, and the effect of [CO_2] (*SI Appendix*, Table S1). All of the GGCMs explicitly simulate the effects of temperature and water on crop growth; fewer models simulate, for example, the effects of specific heat stress at critical stages of crop development or the effects of water-logging on root function. GGCMs differ as to their simulation of some processes in individual crops, such as which models simulate rice phenology as sensitive to day length as well as temperature.

Thus the GGCMs vary in their interactive responses to increasing [CO_2], rising temperature, and changes in water availability, which are the core characteristics of projected climate changes in agricultural regions around the world (32). How the GGCMs handle these factors and their interactions with nutrient availability (especially N) has significant impacts on the results (41).

This GGCM intercomparison focuses on long-term yield levels affected by inputs (climate, [CO_2], water, nutrients) rather than on short-term shocks. The effects of pests and diseases are not included explicitly; pest vulnerability may be implicitly included through calibration to observed yields in some of the models. LPJmL and PEGASUS, for instance, reflect the level of farming intensification and technological inputs (such as the use of pesticides). However this method does not allow for estimation of how the effects of pests and diseases may change under changing climate conditions, an important area for future model development.

Climate change influences on short-term temperature extremes, monsoon dynamics, and the frequency and intensity of precipitation may also play a substantial role in the nature of future agricultural impacts. GCMs do not fully resolve these features, and the representation of corresponding stresses remains an active area of GGCM development.

3.3 Model Inputs. A key contrast among the GGCMs is in nutrient response in regard to underlying soil properties and to nutrients applied (nitrogen, phosphorus, and potassium), amount, and timing. Disparities in the resulting nutrient stress may affect the sensitivity of yields to climate change because climate stresses and benefits may also interact with (or be overwhelmed by) nutrient stresses. Alternate approaches in the GGCMs' fertilization and nutrient schemes therefore need to be taken into account in interpreting crop yield responses to [CO_2] and other variables.

GGCM differences in the simulation of water availability and the application of irrigation also have a direct effect on climate sensitivity in irrigated regions. While the GGCMs deviate in how water availability is determined, the effects of these deviations were reduced by testing two irrigation scenarios: 1) no irrigation, and 2) full irrigation (assuming water is available to fully irrigate crops) (see *SI Appendix*). In GEPIC, full irrigation was set as a complete elimination of water stress of crops. In other GGCMs, full irrigation does not necessarily eliminate water stress completely, as irrigation events are triggered by model-specific soil moisture thresholds (rainfed and irrigated production responses are shown in Fig. S5). In some cases, the ability of the crop plant to transpire water may not be sufficient to satisfy the atmospheric demand (i.e., stomata may close despite full irrigation).

3.4 Model Procedures. An important disparity in GGCM outputs is whether the models calculate actual or potential yields as the primary output. The GAEZ-IMAGE and LPJ-GUESS results represent potential yields, unlimited by nutrient or management constraints and without calibration of growth parameters to reproduce historical yields. They are best suited to studies that are designed to advance scientific understanding of the plant-atmosphere processes being represented and their sensitivity to climatic stresses, rather than for economic forecasts or sensitivity to soil edaphic conditions. LPJmL is similar to LPJ-GUESS in that nitrogen stress is not explicitly represented; however, growth parameters in the model are calibrated so that simulations over the historical period reproduce realistic average yield patterns (see *SI Appendix* for details). GEPIC, PEGASUS, and pDSSAT used historical patterns of fertilizer application rates, while EPIC used standardized low-, moderate-, and high-input management systems with thresholds that trigger fertilizer and irrigation automatically. All four of these models explicitly represent nitrogen stress. The issue of actual vs. potential yields is further complicated by the presence of numerous other "yield gap" factors, including variations in cultivars and farmer management, as well as soil characteristics, pests, diseases, and weeds (38).

4. Current and Future Yield Simulations

4.1 Simulation of Current Crop Yields. The seven GGCMs largely reproduce relative patterns of current crop yields (39) at multinational regional scales but are dissimilar in the levels of their base yields (maize: Fig. 2; wheat, rice, and soybean results in *SI Appendix*, Figs. S2–S4). PEGASUS displayed the largest regional variation in simulated yields, whereas GAEZ-IMAGE displayed the least. Each model has regions where crop yield simulations vary markedly from the patterns observed in the reference period.

LPJmL and LPJ-GUESS vary in reproducing current maize yields, even though they both have a common base model, as do EPIC and GEPIC. Each of these two GGCM pairs vary in parameter settings, assumptions, inputs (e.g., management, fertilizer), processes (e.g., carbon allocation), and model procedures

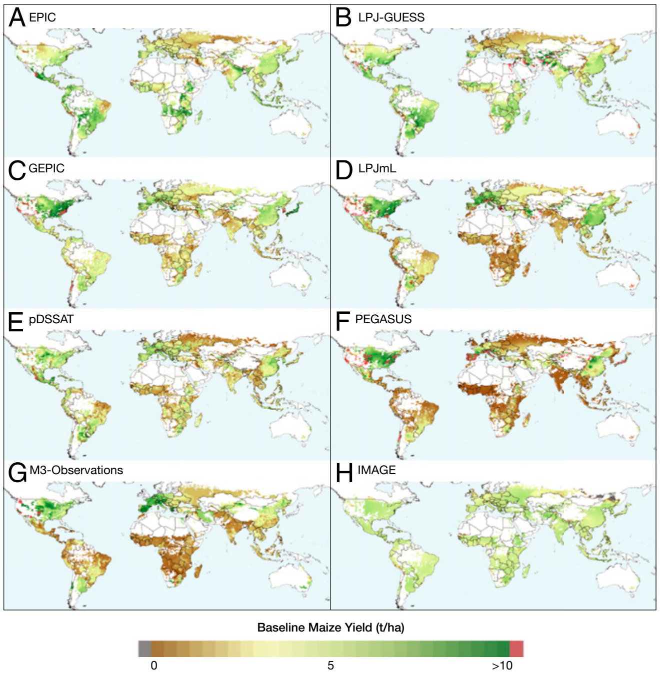

Fig. 2. Average reference period (1980–2010) GGCM maize yield (*A*–*F*, *H*), rescaled to a common global average to make the spatial patterns more apparent, and historical yield M3 observation set (*G*) (39). Note that because some models are calibrated and others are not and because some models simulate potential rather than actual yields, it is not advisable to compare the absolute yields in the ensemble with observations.

(e.g., calibration) that are reflected in the wide variations in their results (*SI Appendix*).

4.2 Global Relative Yield Changes by Crop. Despite the differences among models in their assumed inputs and simulations of absolute yields, relative yield changes provide a more consistent set of results for comparison across models and with previously reported climate change impact results. When taken as a multi-GGCM and multi-GCM ensemble, global results for relative changes in the major crops under representative concentration pathway 8.5 (RCP8.5; 42) with CO_2 effects show broad agreement with results and regional patterns seen in previous studies (Fig. 3, *Upper*).

End-of-century (2070–2099) maize yield changes with CO_2 effects for RCP8.5 show substantial impacts and broad agreement among GGCMs, at least as to the sign of the effect. Results for maize and wheat indicate high-latitude increases and low-latitude decreases with general agreement among models. However, the quality, depth, and hydraulic properties of soils for agricultural production at high latitudes merit further investigation. Results for rice and soybean are consistent in the mid- and high-latitude regions showing yield increases, but show less agreement among models in the tropical regions where median changes are small. Generally, the tropics are subject to more severe (or less beneficial) climate change impacts whereby CO_2 fertilization does not compensate for increases in water demand and shortening of already-short growing periods for annual C_3 crops.

When the results are grouped by GGCMs with and without explicit nitrogen fertilization (*Lower Left* and *Lower Right* in Fig. 3; red and green lines in Fig. 1), results are substantially more negative with explicit nitrogen fertilization than without. The GGCMs with explicit nitrogen fertilization may capture enhanced dynamics of crop growth and yield interactions with CO_2 fertilization; experiments show lower CO_2 enhancement of yield under nitrogen limitation (41). Further work is needed to understand how these interactions affect the GGCM results and identify how variations in crop model parameter values also affect simulated yields (e.g., ref. 43).

4.3 Sensitivity of Yield Response to CO_2. Projections of global relative yield changes under RCP8.5 differ substantially among GGCMs but also between simulations with and without CO_2 effects for maize, wheat, rice, and soybean (Fig. 4). By the end of the 21st century, most GGCMs show a range of approximately ± 10% yield change across the five GCM scenarios when CO_2 effects are included (GCMs cause nearly double that range for PEGASUS and only half that range for GAEZ-IMAGE). Relative global average model response to climate is more similar and much more negative across tropical and midlatitude bands once CO_2 effects are removed, indicating that crop model parameterization of CO_2 effects remains a crucial area of research. Relative yield changes with and without CO_2 effects are much closer in C_4 maize than in the C_3 crops.

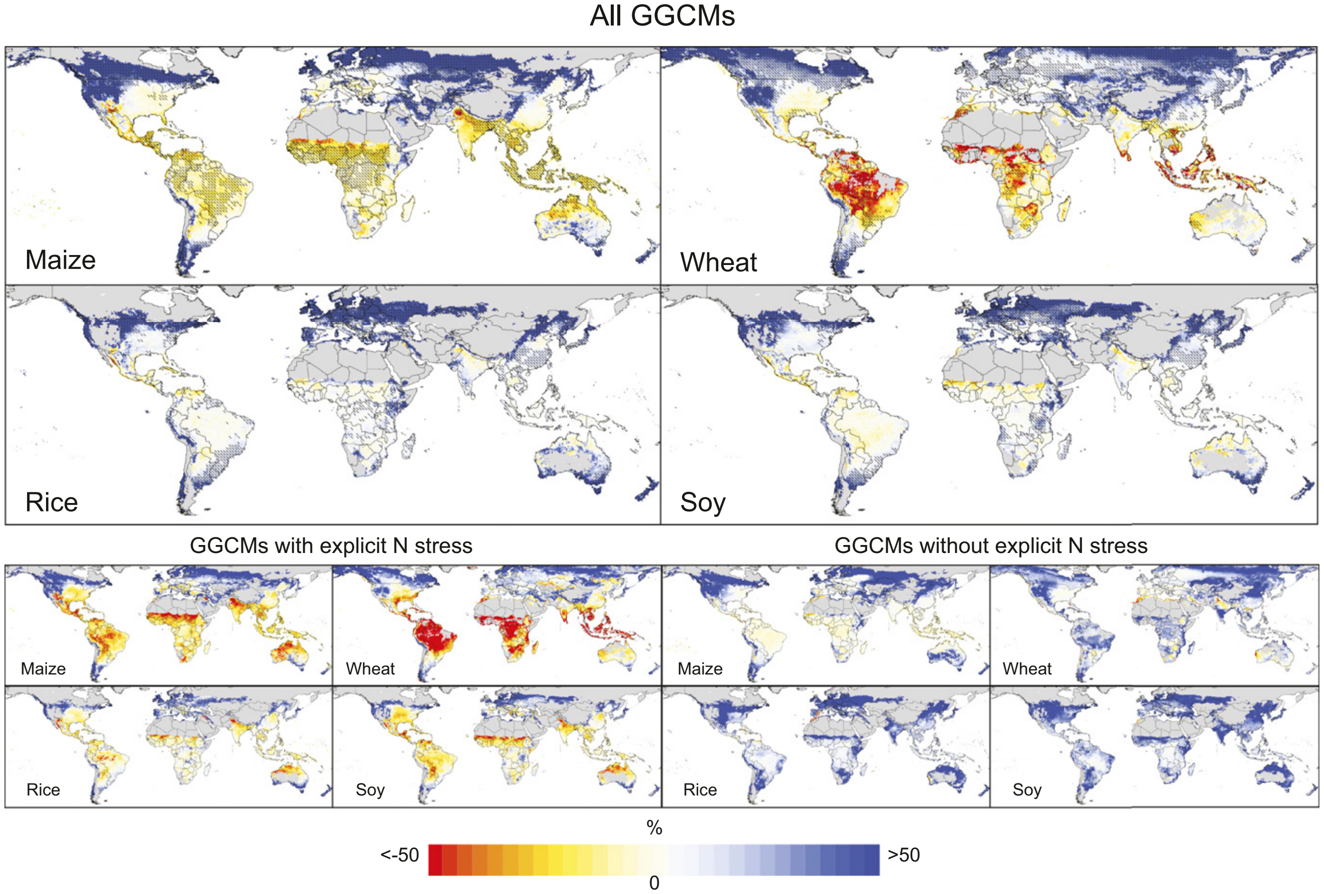

Fig. 3. Median yield changes (%) for RCP8.5 (2070–2099 in comparison to 1980–2010 baseline) with CO_2 effects over all five GCMs x seven GGCMs (6 GGCMs for rice) for rainfed maize (35 ensemble members), wheat (35 ensemble members), rice (30 ensemble members), and soy (35 ensemble members). Hatching indicates areas where more than 70% of the ensemble members agree on the directionality of the impact factor. Gray areas indicate historical areas with little to no yield capacity. The bottom 8 panels show the corresponding yield change patterns over all five GCMs x four GGCMs with nitrogen stress (20 ensemble members from EPIC, GEPIC, pDSSAT, and PEGASUS; except for rice which has 15) (*Left*); and 3 GGCMs without nitrogen stress (15 ensemble members from GAEZ-IMAGE, LPJ-GUESS, and LPJmL).

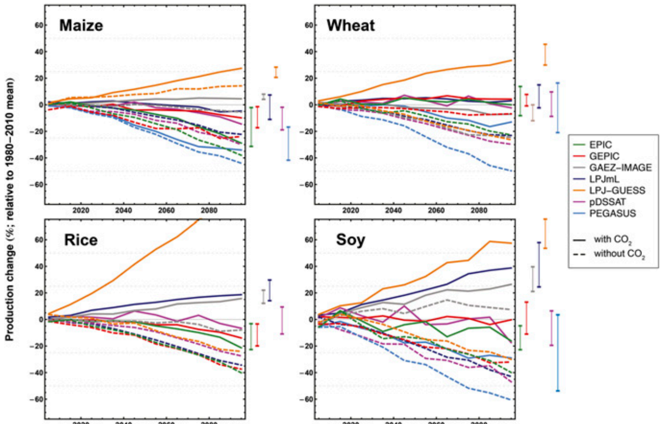

Fig. 4. Relative change (%) in RCP8.5 decadal mean production for each GGCM (based on current agricultural lands and irrigation distribution) from ensemble median for all GCM combinations with (solid) and without (dashed) CO_2 effects for maize, wheat, rice, and soy; bars show range of all GCM combinations with CO_2 effects. GEPIC, GAEZ-IMAGE, and LPJ-GUESS only contributed one GCM without CO_2 effects.

In near decades, relative yield changes display a lower range, both with and without CO_2 effects, but after the 2050s that range widens considerably. LPJ-GUESS, a potential yield model that allows for nutrient-unlimited yield increases, consistently displays the highest relative changes with CO_2 effects for all crops.

The projected yield changes both with and without CO_2 effects for PEGASUS (an ecosystem model) are more negative than the LPJ ecosystem models (note that PEGASUS does not simulate rice), which is likely due to its utilization of radiation use efficiency (RUE) instead of leaf-level photosynthesis (40) for CO_2 effects and the inclusion of explicit heat stress. RUE-based models simulate a universal saturating response to CO_2 and affect water efficiency via adjustment of canopy conductance. In the leaf-level models, stomatal opening controls both photosynthesis (CO_2 availability) and transpiration. Recently, Free-Air CO_2 Enrichment (FACE) experiment results (40) are being used more intensively to calibrate and test crop models in AgMIP.

4.4 Quantifying Uncertainty from GCMs and RCPs. GCMs and RCPs contribute substantially to the uncertainties of the results (Fig. 5). Uncertainty is higher for soybean and rice than for maize and wheat, because they have more concentrated production areas and are therefore more sensitive to regional differences in GCM projections. Uncertainties are greater in the later decades of the century, where GCM inputs and GGCM results can lead to uncertainties several times larger in the highest RCP8.5 than in the lowest RCP2.6. Uncertainty is higher for all crops when CO_2 effects are included, especially in soybean (which is not directly limited by nitrogen) and in the end of the century when [CO_2] is highest. Note that the RCP nomenclature is misleading for earlier decades, because RCP4.5 actually has slightly higher [CO_2] than RCP6.0 until ~2060 (42).

5. Discussion and Conclusions

The models used in this GGCM intercomparison are tools to analyze the response of crops to climate change, and to better understand risks and opportunities in regard to food production and food security. For this information to be useful for decision makers, it needs to include analysis of sources of uncertainty due to multiple greenhouse gas emissions pathways, climate models, and crop impact models (44). The work presented here begins to characterize the uncertainty cascade for GGCM simulations, including greenhouse gas emission scenarios, global climate simulations, variations in structure and implementation in crop models, and assumptions about agricultural management, in a framework that can be compared across sectors.

Because of such variations in model structure, processes, inputs, assumptions, parameterizations, and outputs, the ensemble results from the GGCM intercomparison need to be used with care and may not be appropriate for certain studies (see recommendations on data use in *SI Appendix*). Although the experimental design and climate change scenarios were meant to harmonize simulations to facilitate full comparability, several differences remain that affect the GGCMs' response to climate change and their utility for different types of assessments, including economic analyses. Particularly important are the parameterization of CO_2 effects, handling of fertilizer applications, simulation of actual vs. potential yields, and the extent of calibration. AgMIP is addressing these in continuing work.

Given these important caveats, we can conclude that the results from the GGCMs used in this study show general agreement with previous results, especially for those models that include nitrogen stress (e.g., 6, 32, 45). They indicate negative impacts on major crops in many agricultural regions at higher levels of warming. The inclusion of ecosystem-based models in this analysis has increased the range of uncertainty (previous analyses primarily used site-based models). Relative global average model response to climate is more similar once CO_2 effects are removed, indicating that model parameterization of CO_2 effects (on both photosynthesis and transpiration) remains a vital area of research.

There is ample reason to be concerned in regard to climate change and crop production. Many regions throughout the world are projected to experience climate change-induced reductions

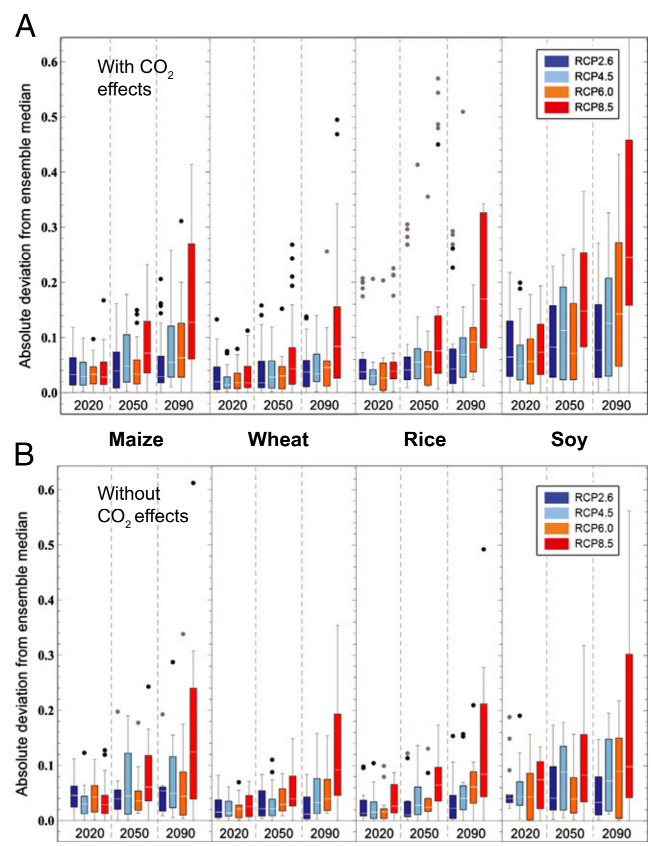

Fig. 5. Absolute deviation of decadal average production changes from ensemble median yield changes (as fraction of 1980–2010 reference period mean production) for all GCM × GGCM combinations in RCP2.6 (dark blue), RCP4.5 (light blue), RCP6.0 (orange), and RCP8.5 (red) for maize, wheat, rice, and soy with (*Upper*) and without (*Lower*) CO_2 effects. Simulations in *A* with CO_2 effects included five GCMs and seven GGCMs (35 members), whereas GAEZ-IMAGE, GEPIC, and LPJ-GUESS ran only a single GCM without CO_2 effects, resulting in 23 members in *B*.

in crop yields in the climate scenario–crop model ensemble tested here, and additional challenges are mounting (e.g., pests, water supply, and soil degradation). The 2012 drought in the United States led to a reduction of maize yields of up to 25% (which is moderate compared with the impacts projected here for some regions at higher levels of temperature increase), but US maize exports declined by an even greater percentage (46). Although some high-latitude regions may become more climatically viable for crops, further study is needed to determine whether soil quality is sufficient for sustained agricultural production in these locations.

AgMIP is dedicated to exploring the underlying mechanisms behind GGCM differences and to quantifying uncertainties in climate change impact assessments. AgMIP further endeavors to improve agricultural models and expand the community of trans-disciplinary modelers, thus supporting effective adaptation and mitigation decisions in agriculture at both global and regional scales.

Materials and Methods

Critical sources of uncertainty for climate change impacts on agricultural productivity are identified and characterized, including contrasts in results arising from a range of global crop models, global climate models, and RCPs (42). *SI Appendix* provides a full description of materials and methods.

Simulations are driven using 20 climate scenarios from the Coupled Model Intercomparison Project Phase 5 archive with five GCMs and four RCPs, each bias-corrected at daily resolution based on the historical Water and Global Change forcing dataset derived from the European Centre for Medium-Range Weather Forecasts 40 Year Re-analysis (13). The reference period used throughout this analysis is 1980–2010. All models submitted simulations with CO_2 effects for five GCMs for maize, wheat, and soybean (35 members). All models except PEGASUS simulated five GCMs for rice (30 members). All models simulated the Hadley Centre Global Environment Model (HadGEM) climate model without CO_2 effects, but only LPJmL, pDSSAT, PEGASUS, and EPIC simulated the other four GCMs (23 members for maize and wheat without CO_2 effects, and 18 members for rice).

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