GGCMI Phase II: globally gridded crop simulation model response to uniform changes in CO_2, temperature, water, and nitrogen levels

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Abstract. Concerns about food security under climate change motivate efforts to better understand future changes in crop yields. Process-based crop models, which represent plant physiological processes, are necessary tools for this purpose since they allow representing future conditions not sampled in the historical record and new locations where cultivation may shift. However, models remain uncertain and differ in many critical details. The Global Gridded Crop Model Intercomparison (GGCMI) Phase II experiment, an activity of the Agricultural Model Intercomparison and Improvement Project (AgMIP), is designed to allow systematic evaluation and "emulation" of model responses to multiple interacting factors, including carbon dioxide, temperature, water availability, and nitrogen application (CTWN). In this paper we describe the GGCMI Phase II experimental protocol (simulations run with systematic uniform perturbations of historical climate) and its simulations (from twelve crop models and five crops); identify responses that are robust across models and those that remain uncertain; and present an emulator or statistical representation of model responses. Modeled yields show robust decreases to warmer mean climatologies in almost all regions, with a nonlinear dependence that means yield changes in warmer baseline locations are more sensitive to temperature increases. Inter-model uncertainty is qualitatively similar across all the four input dimensions, but is highest in high-latitude regions where crops may be grown in the future.

1 Introduction

Understanding crop yield response to a changing climate is critically important, especially as the global food production system will face pressure from increased demand over the next century. Climate-related reductions in supply could therefore have severe socioeconomic consequences. Multiple studies using different crop or climate models concur in predicting sharp yield reductions on currently cultivated cropland under business-as-usual climate scenarios, although their yield projections show considerable spread (e.g. Rosenzweig et al., 2014; Schauberger et al., 2017; Porter et al. (IPCC), 2014, and references therein). Modeling crop responses continues to be challenging, as crop growth is a function of complex interactions between climate inputs and management practices. Intercomparison projects targeting model responses to important drivers are critical to improve future projections.

Computational models have been used to project crop yields since the 1950's, beginning with statistical models that attempt to capture the relationship between input factors and resultant yields (e.g. Heady, 1957; Heady and Dillon, 1961). These statistical models were typically developed on a small scale for locations with extensive histories of yield data. The emergence of electronic computers allowed development of numerical models that simulate the process of photosynthesis and the biology and phenology of individual crops (first proposed by de Wit (1957) and Duncan et al. (1967) and attempted by Duncan (1972); for a history of crop model development see Rosenzweig et al. (2014)). A half-century of improvement in both models and computing resources means that researchers can now run crop simulations for many years at higher spatial resolution on the global scale.

Both types of models continue to be used, and comparative studies have concluded that when done carefully, both approaches can provide similar yield estimates (e.g. Lobell and Burke, 2010; Moore et al., 2017; Roberts et al., 2017; Zhao et al., 2017). Models tend to agree broadly in major response patterns, including a reasonable representation of the spatial pattern in historical yields of major crops (e.g. Elliott et al., 2015; Müller et al., 2017) and projections of shifts in yield under future climate scenarios.

Process-based models do continue to struggle with some important details, including reproducing historical year-to-year variability (e.g. Müller et al., 2017), reproducing historical yields when driven by reanalysis weather (e.g. Glotter et al., 2014), and low sensitivity to extreme events (e.g. Glotter et al., 2015; Jägermeyr and Frieler, 2018; Schewe et al., 2019). These issues are driven in part by the diversity of new cultivars and genetic variants, which outstrips the ability of academic modeling groups to capture them (e.g. Jones et al., 2017). Models also do not simulate many additional factors affecting production, including but not limited to: pests, diseases, and weeds. For these reasons, individual studies must generally re-calibrate models to ensure that short-term predictions reflect current cultivars and management levels, and long-term projections retain considerable uncertainty (Wolf and Oijen, 2002; Jagtap and Jones, 2002; Iizumi et al., 2010; Angulo et al., 2013; Asseng et al., 2013, 2015). Inter-model discrepancies can also be high in areas not yet cultivated (e.g. Challinor et al., 2014; White et al., 2011). Finally, process-based models present additional difficulties for high-resolution global studies because of their complexity and computational requirements. For global economic impacts assessments, it is often impossible to integrate a set of process-based crop models directly into an integrated assessment model to estimate the potential cost of climate change to the agricultural sector.

Nevertheless, process-based models are necessary for understanding the future yield impacts of climate change. Cultivation may shift to new areas, where no yield data are currently available and therefore statistical models cannot be applied. Yield data are also often limited in the developing world, where future climate impacts may be the most critical. Finally, only process-based models can capture the growth response to novel conditions and practices that are not represented in historical data (e.g. Pugh et al., 2016; Roberts et al., 2017). These novel changes can include the direct fertilization effect of elevated CO_2, and changes in management practices that may mitigate climate-induced damages.

The Global Gridded Crop Model Intercomparison (GGCMI) Phase II experiment involves running a suite of process-based crop models across historical conditions perturbed by a set of discrete steps in different input parameters, including an applied nitrogen dimension. The experimental protocol involves 756 different parameter combinations for each model and crop, with simulations providing near-global coverage at a half degree spatial resolution. The experiment was conducted as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013, 2014), an international effort conducted under a framework similar to the Climate Model Intercomparison Project (CMIP) (Taylor et al., 2012; Eyring et al., 2016). The GGCMI protocol builds on the AgMIP Coordinated Climate-Crop Modeling Project (C3MP) (Ruane et al., 2014; McDermid et al., 2015) and contributes to the AgMIP Coordinated Global and Regional Assessments (CGRA) (Ruane et al., 2018; Rosenzweig et al., 2018). GGCMI Phase II is designed to allow addressing goals such as understanding where highest-yield regions may shift under climate change; exploring future adaptive management strategies; understanding how interacting input drivers affect crop yield; quantifying uncertainties across models and major drivers; and testing strategies for producing lightweight emulators of process-based models. In this paper, we describe the GGCMI Phase II model experiments and present initial summary results.

2 Methods

GGCMI Phase II is the continuation of a multi-model comparison exercise begun in 2014. The initial Phase I compared harmonized yields of 21 models for 19 crops over a 30-year historical (1981-2010) scenario with a primary goal of model evaluation (Elliott et al., 2015; Müller et al., 2017). Phase II compares simulations of 12 models for 5 crops (maize, rice, soybean, spring wheat, and winter wheat) over the same historical time series (1981-2010) used in Phase I, but with individual climate or management inputs adjusted from their historical values. The reduced set of crops includes the three major global

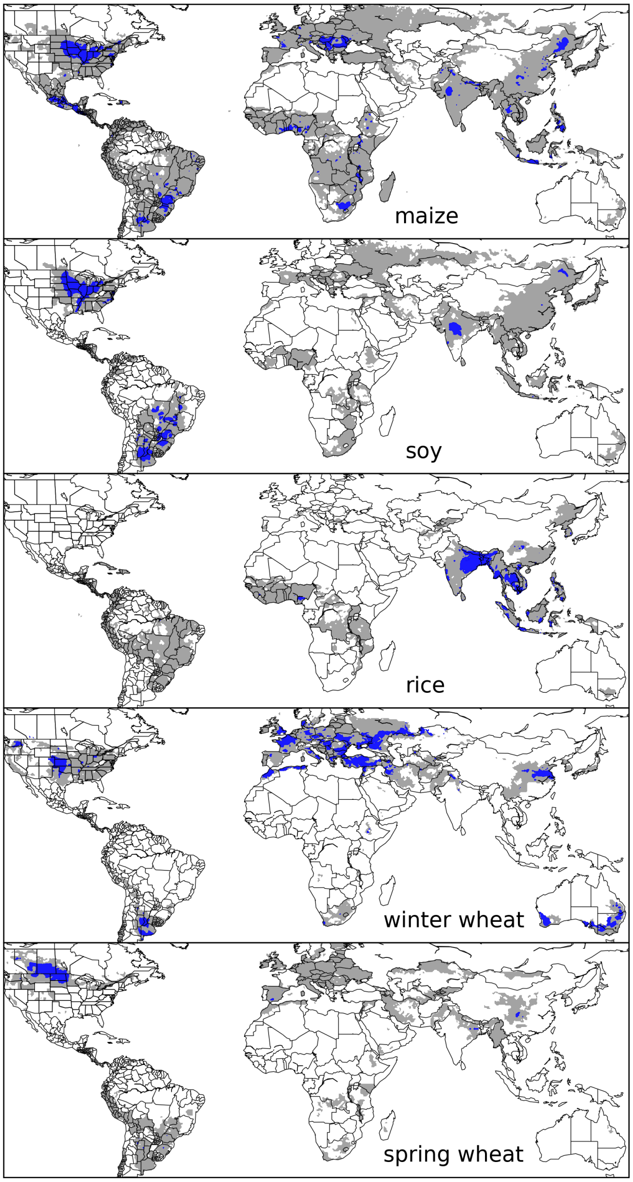

Figure 1. Presently cultivated area for rainfed crops. Blue indicates grid cells with more that 20,000 hectares (∼10% of the equatorial grid cell). Gray contour shows area with more that 10 hectares cultivated. Cultivated areas for maize, rice, and soy are taken from the MIRCA2000 ("monthly irrigated and rainfed crop areas around the year 2000") dataset (Portmann et al., 2010). Areas for winter and spring wheat areas are adapted from MIRCA2000 data and sorted by growing period. For analogous figure of irrigated crops, see Figure S1.

cereals and the major legume and accounts for over 50% of human calories (in 2016, nearly 3.5 billion tons or 32% of total global crop production by weight (Food and Agriculture Organization of the United Nations, 2018).

Table 1. GGCMI Phase II input levels. Temperature and precipitation values indicate the perturbations from the historical climatology. W-percentage does not apply to the irrigated (W_{inf}) simulations, which are all simulated at the maximum beneficial levels of water. Bold font indicates the 'baseline' historical level. One model provided simulations at the T + 5 level. See Figure S3 in the supplement for number of simulations associated with each combination of input levels.

Input variable	Tested range	Unit
CO_2 (C)	**360**, 510, 660, 810	ppm
Temperature (T)	-1, **0**, 1, 2, 3, 4, 6	°C
Precipitation (W)	-50, -30, -20, -10, **0**, 10, 20, 30, (and W_{inf})	%
Applied nitrogen (N)	10, 60, **200**	kg ha^{-1}

The guiding scientific rationale of GGCMI Phase II is to provide a comprehensive, systematic evaluation of the response of process-based crop models to CO_2, temperature, water, and applied nitrogen (collectively referred to as "CTWN"). The dataset is designed to allow researchers to:

- Enhance understanding of how models work by characterizing their sensitivity to input climate and nitrogen drivers.
- Study the interactions between climate variables and nitrogen inputs in driving modeled yield impacts.
- Explore differences in crop response to warming across the Earth's climate regions.
- Provide a dataset that allows statistical emulation of crop model responses for downstream modelers.

The experimental protocol consists of 9 levels for precipitation perturbations, 7 for temperature, 4 for CO_2, and 3 for applied nitrogen, for a total of 672 simulations for rainfed agriculture and an additional 84 for irrigated (Table 1). For irrigated simulations, limitations from actual water supply are not considered. Temperature perturbations are applied as absolute offsets from the daily mean, minimum, and maximum temperature time series for each grid cell. Precipitation perturbations are applied as fractional changes at the grid cell level, and CO_2 and nitrogen levels are specified as discrete values applied uniformly over all grid cells. Limits for the climate variable perturbations are selected to represent reasonable ranges for potential climate changes in the medium term. In most cases, historical daily climate inputs are taken from the 0.5 degree NASA AgMERRA daily gridded re-analysis product specifically designed for agricultural modeling, with satellite-corrected precipitation (Ruane et al., 2015), but two models (JULES and PROMET) require sub-daily input data and use alternative sources. Note that CO_2 changes are applied independently of changes in climate variables, so that higher CO_2 is not associated with higher temperatures. The resulting GGCMI Phase II dataset captures a distribution of crop responses over the potential space of future climate conditions.

The 12 models included in GGCMI Phase II are all process-based crop models that are widely used in impacts assessments (Table 2). Although some models share a common base (e.g. the LPJ family or the EPIC family of models), they have sub-

Table 2. Models included in GGCMI Phase II and the number of C, T, W, and N simulations that each performs, with 756 as the maximum. "N-Dim." indicates whether the simulations include varying nitrogen levels. Two models provide only one nitrogen level. All models provide the same set of simulations across all modeled crops, but some omit individual crops. (For example, APSIM does not simulate winter wheat.)

Model (Key Citations)	**Maize**	**Soy**	**Rice**	**Winter wheat**	**Spring wheat**	**N dim.**	**Simulations per crop**
APSIM-UGOE, Keating et al. (2003); Holzworth et al. (2014)	X	X	X	X	X	X	44
CARAIB, Dury et al. (2011); Pirttioja et al. (2015)	X	X	X	X	X	–	252
EPIC-IIASA, Balkovič et al. (2014)	X	X	X	X	X	X	39
EPIC-TAMU, Izaurralde et al. (2006)	X	X	X	X	X	X	765
JULES, Osborne et al. (2015); Williams and Falloon (2015); Williams et al. (2017)	X	X	X	–	X	–	252
GEPIC, Liu et al. (2007); Folberth et al. (2012)	X	X	X	X	X	X	430
LPJ-GUESS, Lindeskog et al. (2013); Olin et al. (2015)	X	–	–	X	X	X	756
LPJmL, von Bloh et al. (2018)	X	X	X	X	X	X	756
ORCHIDEE-crop, Wu et al. (2016)	X	–	X	x	–	X	33
pDSSAT, Elliott et al. (2014); Jones et al. (2003)	X	X	X	X	X	X	756
PEPIC, Liu et al. (2016a, b)	X	X	X	X	X	X	149
PROMET, Hank et al. (2015); Mauser et al. (2015)	X	X	X	X	X	X†	261
Totals	12	10	11	11	11	10	5240

sequently developed independently. Differences in model structure mean that several key factors are not standardized across the experiment, including "non-nitrogen" nutrients, carry-over effects across growing years including residue management and soil moisture, and the extent of simulated area for different crops. Growing seasons are standardized across models (with assumptions based on Sacks et al. (2010) and Portmann et al. (2008, 2010)), but vary by crop and by location on the globe. For example, maize is sown in March in Spain, in July in Indonesia, and in December in Namibia. All stresses are disabled other than factors related to nutrients, temperature, and water (e.g. alkalinity and salinity). No additional nitrogen inputs, such as atmospheric deposition, are considered, but some model treatments of soil organic matter allows additional nitrogen release through mineralization. See Elliott et al. (2015) for further details on model setup for intercomparison in the GGCMI protocol. Not all modeling teams provide the full simulation protocol, for instance, CARIAB and JULES do not simulate the nitrogen dimension and some crops are not parameterized in each model (see Table 2 for details). Note that the three models that provide less than 50 simulations are excluded from the emulator analysis (APSIM-UGOE, EPIC-IIASA, and ORCHIDEE-crop).

Each model is run at 0.5 degree spatial resolution and covers all currently cultivated areas and much of the uncultivated land area. (See Figure 1 for the present-day cultivated area of rainfed crops, and Figure S1 in the Supplemental Material for irrigated crops.) Coverage extends considerably outside currently cultivated areas because cultivation will likely shift under climate change. However, areas are not simulated in some cases if they are assumed to remain non-arable even under an extreme climate change; these regions include Greenland, far-northern Canada, Siberia, Antarctica, the Gobi and Sahara Deserts, and central Australia. All models produce as output crop yields (tons ha^{-1} year^{-1}) for each 0.5 degree grid cell. Because both yields and yield changes vary substantially across models and across grid cells, we primarily analyze relative change from a baseline. We take as the baseline the scenario with historical climatology (i.e. T and P changes of 0), C of 360 ppm, and applied N at 200 kg ha^{-}1. The GGCMI Phase II simulations are designed for evaluating changes in yield but not absolute yields, since they omit detailed calibrations. To provide some evaluation of the skill of the process-based models used, we repeat the evaluation exercises of Müller et al. (2017) for GGCMI Phase I.

3 Results

Crop models in the GGCMI Phase II ensemble show broadly consistent responses to climate and management perturbations in most regions, with a strong negative impact of increased temperature in all but the coldest regions. We illustrate this result for rainfed maize in Figure 7, which shows yields across all grid cells for the primary Köppen-Geiger climate regions (Rubel and Kottek, 2010). In warming scenarios with precipitation held constant, all models show decreases in maize yield in the 'warm temperate', 'equatorial', and 'arid' regions that account for nearly three-quarters of global maize production. These impacts are robust for even moderate climate perturbations. In the 'warm temperate' zone, even a 1 degree temperature rise with other variables held fixed leads to a median yield reduction that exceeds the variance across models. A 6 degree temperature rise results in median loss of $\sim$25% of yields with a signal to noise ratio of nearly three to one. A notable exception is the 'cold continental' region, where models disagree strongly, extending even to the sign of impacts. Other crops show similar responses to warming, with robust yield losses in warmer locations and high inter-model variance in the 'cold continental' regions (Figure S5).

The effects of rainfall changes on maize yields shown in Figure 7 are also as expected and are consistent across models. Increased rainfall mitigates the negative effect of higher temperatures by counteracting the increased evapo-transpiration to some degree, most strongly in arid regions. Decreased rainfall amplifies yield losses and also increases inter-model variance; i.e. models agree that the response to decreased water availability is negative in sign but disagree on its magnitude. We show only rainfed maize here; see Figure S6 for comparison between rainfed and irrigated case. As expected, irrigated crops are more

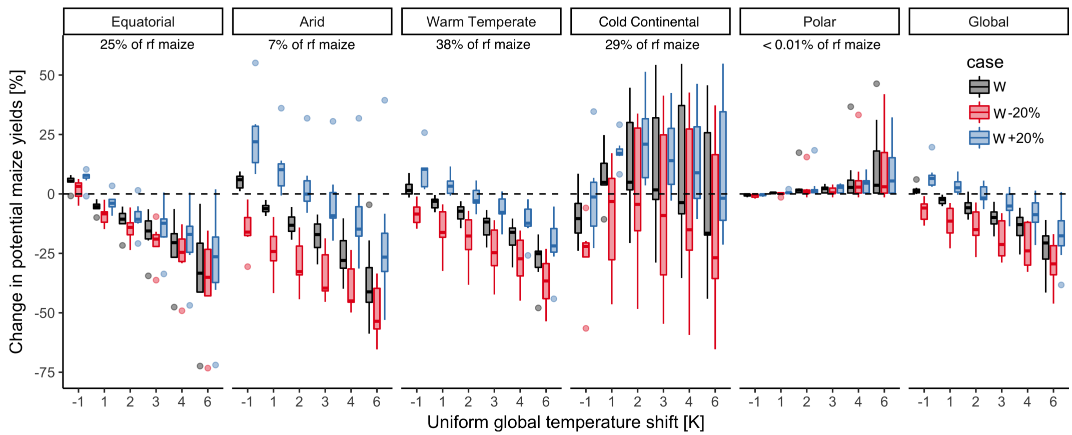

Figure 2. Illustration of the distribution of regional yield changes across the multi-model ensemble, split by Köppen-Geiger climate regions (Rubel and Kottek, 2010). We show responses of a single crop (rainfed maize) to applied uniform temperature perturbations, for three discrete precipitation perturbation levels (-20%, 0%, and +20%), with CO_2 and nitrogen held constant at baseline values (360 pmm and 200 kg ha^{-1} yr^{-1}). Y-axis is fractional change in the regional average climatological potential yield relative to the baseline. Box-and-whiskers plots show distribution across models, with median marked; edges are first and third quartiles, i.e. box height is the interquartile range (IQR). If all models like within 1.5·IQR then whiskers extend to maximum and minimum of simulations, else the outlier is shown separately. Outliers in the tropics (strong negative impact of temperature increases) are the pDSSAT model; outliers in the high-rainfall case (strong positive impact of precipitation increases) are the JULES model. Figure shows all modeled land area; see Figure S4 in the supplemental material for currently-cultivated land and Figure S5 for other crops. Panel text gives the percentage of rainfed maize presently cultivated in each climate zone (data from Portmann et al., 2010). Note that Rubel and Kottek (2010) use the name ‘Snow’ rather than ‘Cold continental’. Outside high-latitude regions (’Cold continental’ and ‘Polar’), models generally agree, with projected declines under increasing temperatures larger than inter-model variance. The right panel (Global) shows yield responses to a globally uniform temperature shift; note that these results are not directly comparable to simulations of more realistic climate scenarios.

resilient to temperature increases in all regions, especially so where water is limiting. See Figures S7-15 in the supplement for other crops.

Mapping the distribution of baseline yields and yield changes shows the geographic dependencies that underlie these results. Crop cultivation areas and yield changes with respect to the T+4 scenario show distinct geographic pattern (Figure 3). Absolute yield potentials show strong spatial variation, with much of the Earth’s surface area unsuitable for any of these crops. In general, models agree most on yield response in regions where yield potentials are currently high and therefore where crops are currently grown. Models show robust decreases in yields at low latitudes, and highly uncertain median increases at most high latitudes, possibly due to how crop failures are considered across different models. For wheat crops see Figure S16 wheat projections are more uncertain, possibly because simulation calibration is especially important (e.g. Asseng et al., 2013).

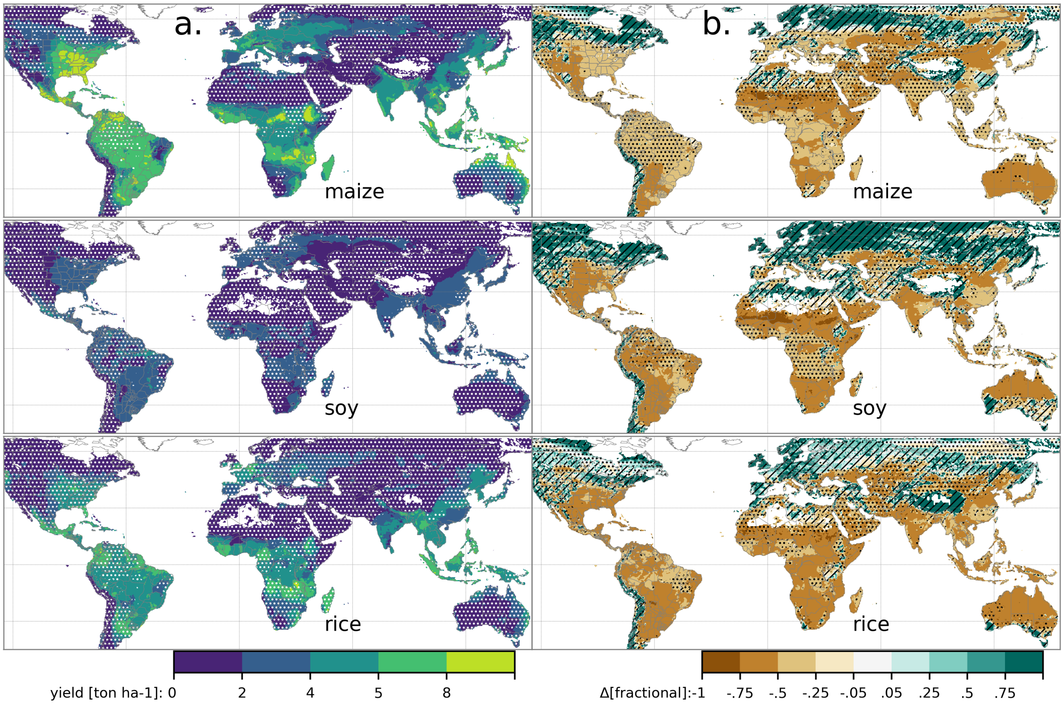

Figure 3. Illustration of the spatial pattern of potential yields and potential yield changes in the GGCMI Phase II ensemble, for three major crops. Left column (a) shows multi-model mean climatological yields for the baseline scenario for (top–bottom) rainfed maize, soy, and rice. Wheat shows a qualitatively similar response, see Figure S16 in the supplemental material. White stippling indicates areas where these crops are not currently cultivated. Absence of cultivation aligns well with the lowest yield contour (0-2 ton ha^{-1}). Right column (b) shows the multi-model mean fractional yield change in the extreme T + 4 °C scenario (with other inputs at baseline values). Areas without hatching or stippling are those where confidence in projections is high: the multi-model mean fractional change exceeds two standard deviations of the ensemble. ($\Delta > 2\sigma$). Hatching indicates areas of low confidence ($\Delta < 1\sigma$), and stippling areas of medium confidence ($1\sigma < \Delta < 2\sigma$). Crop model results in cold areas, where yield impacts are on average positive, also have the highest uncertainty.

3.1 Simulation Assessment

The Müller et al. (2017) procedure evaluates response to year-to-year temperature and precipitation variations in a control run driven by historical climate and compares it to detrended historical yields from the FAO (Food and Agriculture Organization of the United Nations, 2018) by calculating the Pearson product moment correlation coefficient. The procedure is sensitive to the detrending method and the area mask used to aggregate yields. Here we use a 5-year running mean removal and the MICRA area mask for aggregation. In some cases the time series are shifted by one year to account for errors in FAO or model year reporting. The procedure offers no means of assessing CO_2 fertilization, since CO_2 has been relatively constant over the historical data collection period. Nitrogen introduces another source of uncertainty into the analysis, since the GGCMI Phase figures/global_sim_CG_pr.png

Figure 4. Illustration of the distribution of regional yield changes across the multi-model ensemble, split by Köppen-Geiger climate regions for precipitation.

II runs impose fixed, uniform nitrogen application levels that are not realistic for individual countries. We evaluate up to three control runs for each model, since some modeling groups provide historical runs for three different nitrogen levels.

Results are similar to those of GGCMI Phase I, with reasonable fidelity at capturing year-over-year variation, with differences by region and crop stronger than difference between models. (That is, Figure 8 shows more similarity in horizontal than vertical bars.) No single model is dominant, with each model providing near best-in-class performance in at least one location-crop combination. For example, maize in the United States is consistently well-simulated while maize in Indonesia is problematic figures/global_sim_CG_C.png

Figure 5. Illustration of the distribution of regional yield changes across the multi-model ensemble, split by Köppen-Geiger climate regions for Carbon.

(mean Pearson correlation coefficients of 0.68 and 0.18, respectively). In some cases, especially in the developing world, low correlation coefficients may indicate not only model failure but also problems in FAO yield data.

In general, correlation coefficients in GGCMI Phase II are slightly below those of Phase I, likely because of unrealistic nitrogen levels, lack of country level calibration in some models, and restriction to only the MICRA aggregation mask in this study. (Compare Figure 8 to Müller et al. (2017) Figures 1–4 and 6.) Additionally, the time period used in this case is slightly different from the time period used in Müller et al. (2017). Note that in this methodology, simulations of crops with low year-to-year variability such as irrigated rice and wheat will tend to score more poorly than those with higher variability.

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Figure 6. Illustration of the distribution of regional yield changes across the multi-model ensemble, split by Köppen-Geiger climate regions for Nitrogen.

Some models do show particular strength for particular crops. For example, the EPIC family of models, and especially the EPIC-TAMU model, perform particularly well for soy across all regions. In other cases a model has particular strength in only certain crop and region combinations. For example, the strongest correlation coefficient in Figure 8 is that for the pDSSAT model for maize in the U.S. (the example crop-model-location used in many example figures in this paper), but pDSSAT slightly under performs for maize in other regions. These model assessment results are similar to those for GGCMI Phase I in Müller et al. (2017).

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Figure 7. Illustration of the distribution of regional irragation water demand across the multi-model ensemble, split by Köppen-Geiger climate regions for....

4 Discussion and Conclusions

The GGCMI Phase II experiment provides a database designed to allow detailed study of crop yields from process-based models under climate change. The use of systematic input parameter variations facilitates not only comparing the sensitivities of process-based crop yield models to changing climate and management inputs but also evaluating the complex interactions between driving factors (CO_2,, temperature, precipitation, and applied nitrogen). Its global extent also allows identifying geographic shifts in high yield potential locations. We expect that the simulations will yield multiple insights in future studies, and show a selection of preliminary results. We discuss below implications from XXX

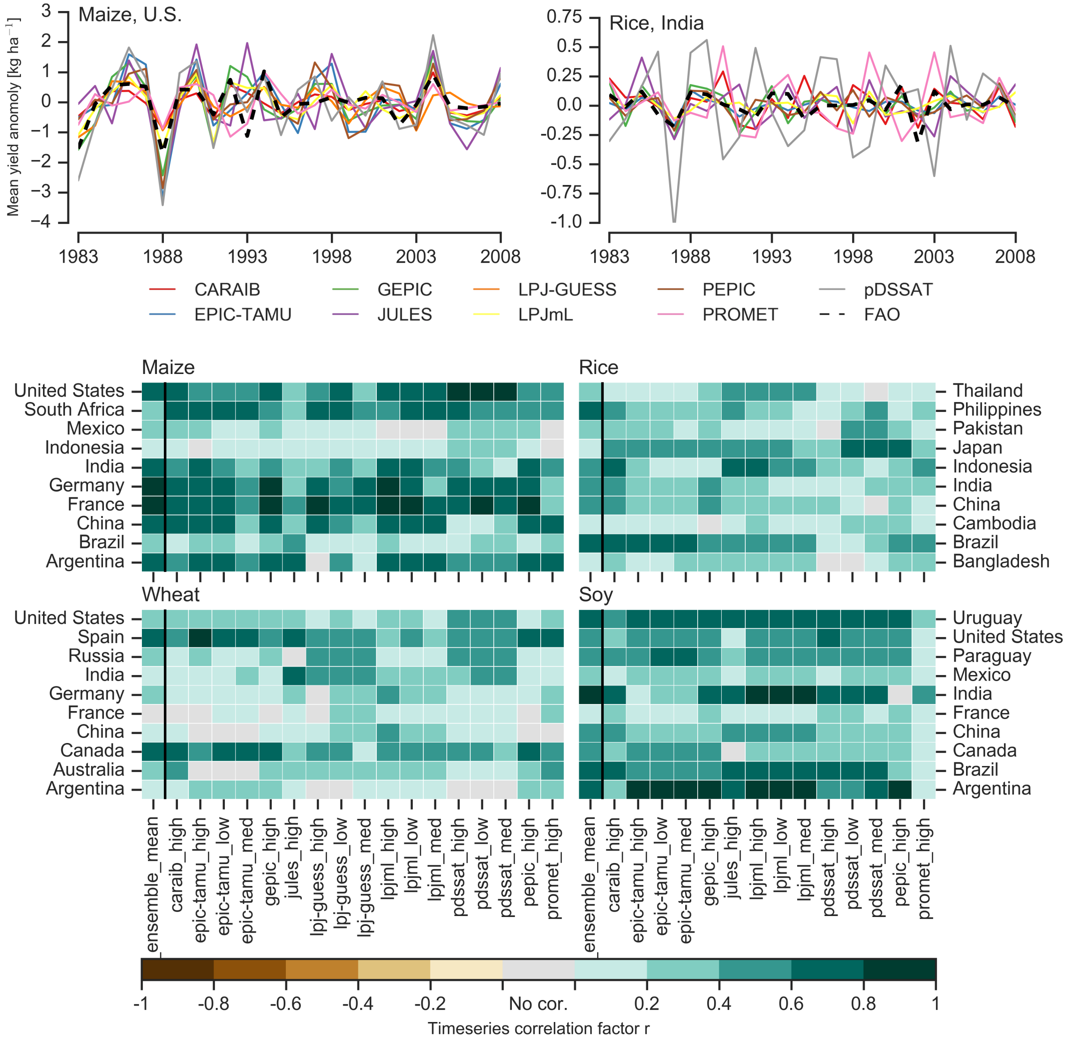

Figure 8. Time series of correlation coefficients between simulated crop yield and FAO data (Food and Agriculture Organization of the United Nations, 2018) at the country level. The top panels indicate two example cases: US maize (a good case), and rice in India (mixed case), both for the high nitrogen application case. The heatmaps illustrate the Pearson r correlation coefficient between the detrended simulation mean yield at the country level compared to the detrended FAO yield data for the top producing countries for each crop with continuous FAO data over the 1981-2010 period. Models that provided different nitrogen application levels are shown with low, med, and high label (models that did not simulate different nitrogen levels are analogous to a high nitrogen application level). The ensemble mean yield is also correlated with the FAO data (not the mean of the correlations). Wheat contains both spring wheat and winter wheat simulations where supplied, else one or the other (see Table 2). The Pearson r correlation coefficients are similar to those of GGCMI Phase I, with reasonable fidelity at capturing year-over-year variation, with differences by region and crop stronger than difference between models as indicated by more horizontal bars than vertical bars of the same color.

First, the GGCMI Phase II simulations allow identifying major areas of uncertainty. Inter-model uncertainty is qualitatively similar across all four inputs tested at the globally aggregate level with some notable exceptions. For example, soy, a nitrogen-fixing legume, is insensitive to nitrogen addition, while wheat is particularly uncertain in its response to CO_2, levels and water availability (Figure S22). Across geographic regions, projections are most robust in the low latitudes where yield impacts are largest, and most uncertain in the high latitudes where yields may increase. Model differences in projected high-latitude yield changes appear driven more by differences in baseline than in future yields. PROMET, for example, involves a stronger response to cold than does LpJML, with frost below -8 °C irreversibly killing non-winter crops and prolonged periods of below-optimum temperatures also leading to complete crop failure. Over the high-latitudes regions simulated by both models, 52% of grid cells in PROMET report 0 yield in the present climate vs. 11% of cells in the T+4 scenario, leading to a strong yield gain in warmer future climates. In LpJML, the same high-latitude area is suitable for cultivation even in baseline climate, with crop failure rates of 4% and 5% in present and T+4 cases, so that projected yield changes are modest (Figure S23.)

Second, the GGCMI Phase II simulations demonstrate the sensitivity of climate-driven yield impacts to the locations of cultivated land. One counterintuitive result apparent in the simulations is that warmer temperatures drive steeper yield reductions in irrigated than rainfed maize when considered only over currently cultivated land, even though water availability increases crop resiliency to temperature increases at any given location (compare Figure **??** to Figure 7 and Figures S6 to S7). The effect results from geographic differences in cultivation: irrigated maize is grown in warmer locations where the impacts of warming are more severe. (See Figures S8-S15 for other crops.) Geographic effects also mean that nitrogen fertilization produces stronger responses in irrigated than non-irrigated wheat and maize, presumably because those rainfed crops are limited by water availability (Figure S21).

In general, the development of multi-model ensembles involving systematic parameters sweeps has large promise for increasing understanding of potential future crop responses and for improving process-based crop models.

Code and data availability. The simulation yield outputs are available on zenodo.org. See Appendix A1 for data DOIs. All other simulation output variables are availble upon request to the corresponding author.

Appendix A

A1 Data Access

Simulation yield output dataset can be found at the DOIs located in table A1.

Author contributions. J.E., C.M, A.R., J.F., and E.M. designed the research. C.M., J.J., J.B., P.C., M.D., P.F., C.F., L.F., M.H., C.I., I.J., C.J., N.K., M.K., W.L., S.O., M.P., T.P., A.R., X.W., K.W., and F.Z. performed the simulations. J.F., J.J., A.S., M.L., and E.M. performed the analysis and J.F. and E.M. prepared the manuscript.

Table A1. DOI's for model yield data outputs. All yield output data can be found at https://doi.org/10.5281/zenodo/XX. Where XX is the value found in the table.

Model	**Maize**	**Soy**	**Rice**	**Winter wheat**	**Spring wheat**
APSIM-UGOE	2582531	258235	2582533	2582537	2582539
CARAIB	2582522	2582508	2582504	2582516	2582499
EPIC-IIASA	2582453	2582461	2582457	2582463	2582465
EPIC-TAMU	2582349	2582367	2582352	2582392	2582418
JULES	2582543	2582547	2582545	–	2582551
GEPIC	2582247	258225	2582251	2582260	2582263
LPJ-GUESS	2581625	–	–	2581638	2581640
LPJmL	2581356	2581498	2581436	2581565	2581606
ORCHIDEE-crop	2582441	–	2582445	2582449	–
pDSSAT	2582111	2582147	2582127	2582163	2582178
PEPIC	2582341	2582433	2582343	2582439	2582455
PROMET	2582467	2582488	2582479	2582490	2582492

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