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Research Article

# Incorporating temperature-adapted growing periods enhances simulation of crop yield sensitivity to temperature in global gridded crop models

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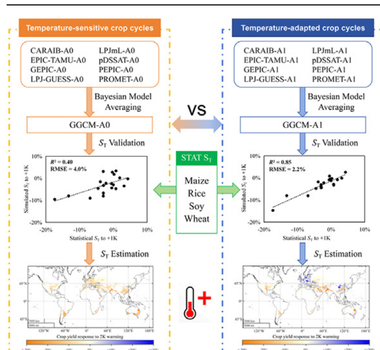
## HIGHLIGHTS

- GGCM ensembles were optimized against statistically-inferred $S_T$ by Bayesian Model Averaging.
- GGCM ensembles assuming cultivar adaptation show better fit to statistically-inferred $S_T$.
- GGCMs may overestimate maize $S_T$ while underestimate rice/wheat $S_T$.
- It is essential to adopt dynamic phenological parameters in real-world $S_T$ estimation.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Global Gridded Crop Models (GGCMs) have been widely used to simulate the impacts of global warming on crop production, but their accuracy in capturing the real-world temperature sensitivity of crop yields remains unclear. Here, we evaluated the performance of eight GGCM emulators (incorporating versus not incorporating cultivar adaptation of crop growing periods at 0.5° × 0.5° resolution) in modelling yield sensitivities to 1 K temperature increase ($S_T$) and optimized their ensembles against statistically-inferred $S_T$ for maize, rice, and wheat using a Bayesian Model Averaging approach. Our results suggest that multi-GGCM ensembles assuming a fixed crop growing period (i.e., a gradually temperature-adapted crop cultivar) show higher goodness-of-fit to statistically-inferred $S_T$ than those assuming a temperature-sensitive growing period for the crops in major food-producing countries. When setting a temperature-adapted growing period instead of a temperature-sensitive growing period in the GGCM ensembles, the $R^2$ between GGCM-simulated and statistically-inferred $S_T$ increased from 0.63 to 0.81 for maize, 0.28 to 0.52 for rice, and 0.40 to 0.85 for wheat, meanwhile the RMSE was reduced for all three crops across their respective top 20 producing countries. The crop models may exaggerate historical responses of crop growing periods to climate warming, resulting in an overestimation of yield $S_T$ for maize and an underestimation of yield $S_T$ for rice and wheat in major food-producing countries. The study highlights the importance of adopting dynamic phenological parameters in GGCM simulations to reflect crop cycle adaptation under global warming.

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## 1. Introduction

Global warming has significantly impacted crop productivity since the 1980s (IPCC, 2023; Lobell et al., 2011). Quantifying crop yield sensitivity to 1 K temperature increase ($S_T$) is critical for assessing crop responses and adaptation strategies under global warming, as it provides a unified metric to compare, reconcile, and integrate results from different studies of climate change impacts on crop yields. Based on multiple reports utilizing field experiments, statistical models, and process-based models, global $S_T$ values were estimated to be −6.0 % for wheat, −3.2 % for rice, and −7.4 % for maize (Zhao et al., 2017). These estimates are highly uncertain because climate adaptation measures, including shifts in growing periods, cultivar selection, irrigation enhancement, and crop switching, could potentially offset or even reverse warming-induced yield declines (Challinor et al., 2014; Minoli et al., 2022, 2024; Sloat et al., 2020; Wang et al., 2022).

Among the major adaptation measures, avoiding growing period shortening under warming has proven to be an effective strategy to offset crop yield losses induced by air temperature rise in most regions, especially in the temperate and continental climate zones (Franke et al., 2022; Minoli et al., 2019). This adaptation can be achieved through selecting cultivars with higher thermal-unit requirements, altering vernalization requirements, or using photoperiod-sensitive varieties at increasing air temperatures (Carr et al., 2022; Minoli et al., 2019; Parent et al., 2018; Rezaei et al., 2018). Accordingly, studies across China (He et al., 2020; Hu et al., 2017; Zhang et al., 2022), South Asia (Abbas et al., 2017; Naz et al., 2022), Europe (Parent et al., 2018), and the United States (Butler et al., 2018) show that impacts of warming on crop growing periods have been significantly mitigated through cultivar shifts over recent decades, implying the importance of incorporating growing period adaptation in crop productivity projections.

Given that neglecting growing period adaptation could result in an overestimation of crop $S_T$, there have been several model simulation studies incorporating dynamic crop phenological parameters under climate change (Franke et al., 2022; Hoffman et al., 2020; Minoli et al., 2019; Minoli et al., 2022; Peng et al., 2020; Zabel et al., 2021). For instance, the Global Gridded Crop Model Intercomparison (GGCMI) Phase 2 experiment employed a dynamic thermal time (required for a crop to mature) to ensure a constant growing period under climate change in some simulation scenarios (Franke et al., 2020a). However, there is a great disagreement between various GGCMs in the GGCMI phase 2 for simulating the temperature sensitivity of global crop production (Franke et al., 2020a; Minoli et al., 2019). The limited scope of previous assessments regarding the accuracy of GGCMs in simulating $S_T$ makes it challenging to select suitable models or model ensembles for projecting crop yield responses to global warming. Furthermore, the GGCM performance in simulating crop yields is associated not only with the model structure but also with the field management and phenology settings (Folberth et al., 2019; Heinicke et al., 2022; Schewe et al., 2019). Therefore, exploring the effects of growing period settings on the model's explanatory power is conducive to understanding uncertainties in crop $S_T$ simulations and facilitates a better evaluation of potential yield gains through growing period adaptation to temperature rise.

In the study, we compared the $S_T$ estimates from eight GGCM emulators against those inferred from historical statistics in major producing countries for maize, rice, and wheat. Employing a multi-model weighted ensemble approach with and without consideration of growing period adaptation, this study aims to address the following scientific questions: (a) Does setting a fixed growing period (i.e., a gradually temperature-adapted crop cultivar) instead of a temperature-sensitive one in the GGCMs better simulate global $S_T$ of food crops? (b) How will crop yield change with air temperature rise neglecting versus considering growing period adaptation?

## 2. Materials and methods

### 2.1. Data on crop yield response to temperature rise

#### 2.1.1. Crop model simulations and emulators

We used the GGCMI Phase 2 emulators for eight process-based crop models to simulate yield sensitivities to temperature rise of maize, rice, winter wheat, and spring wheat. The evaluation of yield simulation performance for the eight crop models can be found in Müller et al. (2017) and Franke et al. (2020a). The GGCMI Phase 2 emulators are global gridded statistical models developed by Franke et al. (2020b) based on crop model simulated yield as a function of systematic changes in $CO_2$, temperature, water supply, and nitrogen application (CTWN). The GGCMI Phase 2 emulators well reproduce yield response to the imposed perturbations of CTWN simulated by the respective GGCMs for both in-sample and out-of-sample tests (Franke et al., 2020b). The model simulation experiments of GGCMs involving different levels of CTWN are repeated for two adaptation scenarios in the GGCMI Phase 2: A0 simulations assume no adaptation in cultivar choice, so that crop growing periods shorten in warmer climates; A1 simulations assume that adaptation in cultivar choice maintains fixed crop growing periods. So the GGCMI Phase 2 emulators include A0 and A1 versions for various GGCMs. According to the GGCMI Phase 2 experimental protocol, the baseline air temperature, precipitation, and $CO_2$ concentration for the emulators are the climatological means across the 1981–2010 period obtained from the AgMERRA (Agricultural-modified Modern-Era Restrospective Analysis for Research and Applications) dataset (https://data.giss.nasa.gov/impacts/agmipcf/agmerra/).

Here, we used the emulators to estimate crop yield response to seven warming levels (0 K to +6 K) under irrigated and rainfed conditions separately, and weighted averages based on the irrigated and rainfed areas for each crop at national- and global-scale. The irrigated and rainfed area data for maize and rice were obtained from Portmann et al. (2010), while wheat area data were obtained from Franke et al. (2020a), who partitioned the wheat areas into spring and winter varieties. All crop area data used in this study were based on the MIRCA2000 (Monthly Irrigated and Rainfed Crop Areas around the year 2000) dataset. The spatial resolution of each grid cell for model input and output data is 0.5° × 0.5°. To enable comparison between GGCM-simulated and statistically-inferred $S_T$, a bottom-up spatial aggregation approach is employed to convert 0.5° × 0.5° grid data to national scale. First, simulated irrigated and rainfed yields in each grid cell for maize, rice, and wheat are multiplied by corresponding areas to calculate grid-level production. Second, National total production is obtained by summing all grid cells within each country, then divided by total crop area to derive national crop yields comparable with administrative data. Finally, the national-scale simulated $S_T$ is calculated as the percentage change in national-scale simulated crop yields between the baseline temperature scenario and the +1 K warming scenario. In this study, we simulated crop $S_T$ under three nitrogen fertilization scenarios to examine the robustness of our main conclusions (Fig. S1 in the Supplementary mateirals): (1) country-specific nitrogen fertilizer consumption in 2005 (https://www.ifastat.org/databases/plant-nutrition), (2) uniform nitrogen fertilizer application of 200 kg/ha, and (3) nitrogen fertilizer application of 300 kg/ha in areas where 200 kg N/ha falls short of crop requirements. To ensure comparability with previous studies (Minoli et al., 2019), the simulation results presented and analyzed in the main text are obtained from the 200 kg/ha nitrogen fertilizer application scenario.

To compare the performance of model simulations neglecting cultivar adaptation (A0) and those considering new cultivars to maintain original growing period (A1), we selected emulators for the crop models that have both A0 and A1 simulation scenarios in the GGCMI Phase 2 database. The GGCMI Phase 2 emulators employed in the study for the eight crop models are shown in Table 1. The eight crop models are CARAIB, EPIC-TAMU, GEPIC, LPJ-GUESS, LPJmL, pDSSAT, PEPIC, and

**Table 1**
Crop models included in Global Gridded Crop Model Intercomparison (GGCMI) Phase 2 emulators for maize, rice, winter wheat and spring wheat.

| Emulator | Maize | Rice | Winter wheat | Spring wheat |
|---|---|---|---|---|
| CARAIB-A0 | √ | √ | √ | √ |
| CARAIB-A1 | √ | √ | √ | √ |
| EPIC-TAMU-A0 | √ | √ | √ | √ |
| EPIC-TAMU-A1 | √ | √ | √ | √ |
| GEPIC-A0 | √ | √ | √ | √ |
| GEPIC-A1 | √ | √ | √ | √ |
| LPJ-GUESS-A0 | √ | — | — | — |
| LPJ-GUESS-A1 | √ | — | — | — |
| LPJmL-A0 | √ | √ | √ | √ |
| LPJmL-A1 | √ | √ | √ | √ |
| pDSSAT-A0 | √ | √ | √ | √ |
| pDSSAT-A1 | √ | √ | √ | √ |
| PEPIC-A0 | √ | √ | √ | √ |
| PEPIC-A1 | √ | √ | √ | √ |
| PROMET-A0 | √ | √ | √ | √ |
| PROMET-A1 | √ | √ | √ | √ |

PROMET (detailed in Supplementary Text, Table S1, and Table S2 in the Supplementary materials). In the GGCMI Phase 2 simulation experiments, the A0 simulations used a fixed planting date and a constant potential heat unit (PHU) required for a crop from planting to mature at grid scale across different warming scenarios, in which the harvest dates and growing season length alter with climate change. Meanwhile, the A1 simulations ran a model with seven different choices of cultivar parameters, one per warming level to maintain baseline crop growing periods (Franke et al., 2020a). While all other GGCMs used harmonized baseline growing period information, CARAIB-A1 forced harvest on the same day as in its inherent baseline calendar; EPIC-TAMU-A1, GEPIC-A1, PEPIC-A1, LPJ-GUESS-A1, and LPJmL-A1 calculated the long-term average PHU for each warming level based on the fixed planting and maturity dates at grid scale; pDSSAT-A1 proportionally adjusted the phenological GDD parameters to reproduce the target baseline growing period length under different warming levels; PROMET-A1 determined a phenological acceleration/retardation factor for each crop and grid cell by iteratively working out which factor value would produce the same harvest date in the baseline calendar. The GGCM descriptions regarding model parametrization and phenology simulation can be found in the material provided by Minoli et al. (2019).

#### 2.1.2. Statistically-inferred $S_T$ for model evaluation

To establish validation benchmarks for GGCM performance assessment, we utilized empirical crop $S_T$ datasets at country scale from Agnolucci et al. (2020). These datasets were derived from statistical crop yield models for 18 crop types, among which the models for rice, wheat, and maize have demonstrated high accuracy and reliability (Agnolucci et al., 2020). Agnolucci's datasets were generated based on annual yield and input data from FAOSTAT Database (www.fao.org/faostat/en/#data) and weather data from the Climate Research Unit of the University of East Anglia (Harris et al., 2014). We selected Agnolucci's datasets for several reasons: firstly, Agnolucci et al. (2020) employed a robust statistical approach to estimate the change in crop productivity when the air temperature increases by 1 °C compared to the past thirty years in each country, which allows for a model evaluation for the GGCMI Phase 2 experiment in terms of $S_T$ simulation worldwide. When analyzing the statistical relationships between crop yield and its determinants, Agnolucci et al. (2020) evaluated the impacts of air temperature rise on crop yields by decomposing effects of weather, irrigation, pesticides, and fertilizers on historical yield variations, and took into account within-country and across-countries variation but also similarities, as well as unobserved diversity through fixed or random effects. They also incorporated country-specific time trends to proxy for factors that could positively (e.g., technological advance) or negatively (e.g., soil erosion) affect crop yields. The estimated yield sensitivity models for rice, wheat, and maize can reproduce credible yield data while partially capturing the variation across countries and years (Agnolucci et al., 2020). Secondly, the dataset used to obtain $S_T$ covers at most the years between 1986 and 2012 according to the data availability. Although the specific start and end years vary across countries and crops, the time period is comparable to the GGCMI Phase 2 experiment. It should be noted that the historical statistical data of wheat $S_T$ do not distinguish between spring and winter wheat. Therefore, we weighted the simulated $S_T$ of spring wheat and winter wheat by their respective areas in each grid cell to obtain the simulated wheat $S_T$ in the top 20 wheat-producing countries.

Due to the spatial concentration of global food production, we carried out model evaluation in the global top 20 producing countries for each food crop. The top 20 producers of maize, rice, and wheat contributes approximately 90 %, 97 %, and 89 % of total global production, respectively. Thus, the model performance in the top 20 producers for each crop essentially reflects the model explanatory power for global $S_T$.

### 2.2. The bayesian model averaging approach

To cope with the large discrepancy in yield projections by crop models, a multi-model ensemble strategy that weights models based on their fit to historical data, the Bayesian Model Averaging (BMA) approach, has been recommended to reduce projection bias due to the influence of under-performing models (Gao et al., 2021; Li et al., 2023; Zheng et al., 2023). In the GGCMI Phase 2 experiment, there are many reasons other than growing period setting that could result in the underperformance of the GGCMs. Therefore, we adopted the BMA approach to assign ensemble weights to each GGCM to minimize the interference of underperforming models and generate the A0 ensemble models and the A1 ensemble models for maize, rice, and wheat.

BMA differs from the other multi-model ensemble methods in that it uses posterior probabilities as model weights based on Bayesian theory (Zheng et al., 2023). The posterior probability is a crucial criterion in evaluating an individual model's performance, delivering a dependable depiction of uncertainty. Assuming that $Q$ is the predictor variable, in this study it represents $S_T$. The set of models comprising all individual predictor models can be denoted as $H = \{H_1, H_2, H_3, ..., H_m\}$. The set of actual data is represented by $D = [Q_1, Q_2, Q_3, ..., Q_n]$, where $Q_n$ is the statistical temperature sensitivity of crop yield at country $n$. The posterior distribution of $Q$ for a given sample $D$ is as follows:

$$p(Q|D) = \sum_{i=1}^{m} p(H_i|D) p(Q|H_i, D) \tag{1}$$

where $p(Q|H_i, D)$ is the posterior distribution of $Q$. $p(H_i|D)$ is the probability of $H_i$ being the best model considering the given sample $D$, which represents the posterior probability of model $H_i$.

The mean and variance of the posterior distribution of $Q$ can be defined as follows:

$$E(Q|D) = \sum_{i=1}^{m} p\left(H_i|D\right) E\left[p\left(Q|H_i, D\right)\right] = \sum_{i=1}^{m} w_i H_i \tag{2}$$

$$\mathrm{Var}(Q|D) = \sum_{i=1}^{m} \left(H_i - \sum_{i=1}^{m} w_i H_i\right)^2 + \sum_{i=1}^{m} w_i \sigma_i^2 \tag{3}$$

where $w_i = p(H_i|D)$ denotes the weights of the model. $\sigma_i^2$ is the variance.

The Akaike information criterion (AIC) (Akaike, 1992; Portet, 2020) was used to evaluate the BMA weights of the individual model following Gao et al. (2021) and Zheng et al. (2023) in this study as its simulation performance was found to be superior to that of the Bayesian information criterion (Kass and Wasserman, 1995). Lower AIC values indicate better model performance. The AIC equations are shown as follows:

$$\mathrm{AIC}_k = 2p - 2\ln\left(L_k\right) \tag{4}$$

$$w_k \approx \frac{\exp\left(-\mathrm{AIC}_k/2\right)}{\sum_{l=1}^{k} \exp\left(-\mathrm{AIC}_l/2\right)} \tag{5}$$

where $\mathrm{AIC}_k$ is the value of the AIC for model $k$, $p$ denotes the number of calibration parameters of model $k$.$\hat{L}_k$ is the maximum likelihood value of model $k$, and $w_k$ is the weight of an individual model $k$. $l$ is an index that iterates through all candidate models in the ensemble during the summation. The study utilized GGCM emulators rather than original GGCMs to standardize parameter structures and dimensions across different crop models, thereby simplifying the evaluation of model BMA weights based on the AIC method.

### 2.3. Benchmark metrics

Two criteria of goodness-of-fit were used to evaluate the model performance in the top 20 producers for each crop, namely Root Mean Squared Error (RMSE, Eq. (6)) and $R^2$ (Eq. (7)):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\mathrm{stat}_i - \mathrm{sim}_i\right)^2} \tag{6}$$

$$R^2 = \left(\frac{\sum_{i=1}^{N}\left(\mathrm{sim}_i - \overline{\mathrm{sim}}\right)\left(\mathrm{stat}_i - \overline{\mathrm{stat}}\right)}{\sqrt{\sum_{i=1}^{N}\left(\mathrm{sim}_i - \overline{\mathrm{sim}}\right)^2}\sqrt{\sum_{i=1}^{N}\left(\mathrm{stat}_i - \overline{\mathrm{stat}}\right)^2}}\right)^2 \tag{7}$$

where $\mathrm{stat}_i$ is the $i$th statistical value from Agnolucci et al. (2020), $\mathrm{sim}_i$ is the corresponding simulated value from GGCMs, $\overline{\mathrm{sim}}$ and $\overline{\mathrm{stat}}$ denote the mean value of simulations and statistics, respectively, and $N$ is the number of countries.

## 3. Results

### 3.1. Performance of the GGCMI Phase 2 models in $S_T$ simulation

The performance of the GGCMI Phase 2 models varies considerably in $S_T$ simulation for different crops and growing period scenarios (Tables 2): (1) For maize, LPJmL-A0 and CARAIB-A1 have a great advantage in terms of AIC value in their respective scenarios. Thus, the BMA approach assigns almost all the weight to LPJmL-A0 and CARAIB-A1 for multi-model ensemble to simulate maize $S_T$. (2) For rice, in Scenario A0, the absolute value or spatial heterogeneity of $S_T$ is not well captured in the top 20 rice producers regardless of the model (AIC>59). As no model has a significant advantage in the A0 scenario, the BMA approach distributes weights to EPIC-TAMU-A0 (41 %), GEPIC-A0 (9 %), LPJmL-A0 (1 %), pDSSAT-A0 (8 %), and PEPIC-A0 (41 %) jointly to simulate rice $S_T$. Meanwhile, in Scenario A1, PROMET-A1 shows the lowest AIC value in $S_T$ simulation (AIC=47.88) for rice, so PROMET-A1 is given major weights to simulate rice $S_T$. (3) For wheat, GEPIC has the lowest AIC values among all the models in both A0 (AIC=16.10) and A1 (AIC=−19.20) scenarios. Consequently, the BMA approach gives major weights to GEPIC to simulate wheat $S_T$ in both A0 and A1 scenarios.

### 3.2. Evaluation of the A0 and A1 ensemble models

The A1 ensemble model demonstrates higher goodness of fit than the A0 ensemble model for $S_T$ simulation in top 20 producers for maize, rice, and wheat (Fig. 1). When setting a temperature-adapted growing period instead of a temperature-sensitive growing period in model simulation, $R^2$ between statistical and simulated $S_T$ increased from 0.63 to 0.81 for maize, 0.28 to 0.52 for rice, and 0.40 to 0.85 for wheat, meanwhile the RMSE is reduced from 1.6 % to 1.4 % for maize, 6.7 % to 5.5 % for rice, and 3.3 % to 1.8 % for wheat. Additionally, we compared A0 and A1 ensemble models for the top 10 rice producers (accounting for 91 % of global rice production) and found that the A1 ensemble model achieved an $R^2$ of 0.80 in simulating rice $S_T$, substantially higher than the A0 ensemble model (Fig. S2 in the Supplementary materials).

According to the country-specific $S_T$ simulated by the A0 and A1 models, it can be found that the gap of goodness-of-fit between the A0 and A1 models results from overestimation of $S_T$ for maize and underestimation of $S_T$ for rice and wheat by the A0 models (Fig. 2). The A0 ensemble model overestimates temperature sensitivity of maize yield in China, Argentina, Russia, and Germany, meanwhile, the A1 ensemble model performs closer to the statistics in these countries. Moreover, the A0 model underestimates temperature sensitivity of rice yield in India, Indonesia, Bangladesh, Thailand, Vietnam, Myanmar, and Japan; meanwhile, the A1 model accurately simulates rice $S_T$ in the countries listed above, which leads to a significantly better fit of the A1 model to statistical rice $S_T$ than the A0 model. Similarly, the A1 model better simulates wheat $S_T$ in the top 20 wheat producers than the A0 model, especially in Pakistan.

### 3.3. Crop yield response to temperature rise with and without cultivar adaptation

By the BMA model ensembles that best reproduce the real-world $S_T$ of the crops, we predicted warming-induced changes in crop productivity at different levels of temperature rise. According to the BMA ensemble results, cultivar adaptation of growth duration is able to mitigate the negative impacts of temperature rises on crop productivity for maize and wheat at global scale (Fig. 3). Under the 2 K warming scenario, irrigated productivity of maize, winter wheat, and spring wheat is projected to decline by 10.4 %, 7.3 %, and 12.6 % globally in the absence of cultivar adaptation, yet by 1.2 %, 0.7 %, 3.9 %, and 1.9 % when incorporating cultivar adaptation, respectively. In contrast to maize and wheat, the yield loss of irrigated rice resulting from 2 K warming is approximately 21 % in both A0 and A1 scenarios at the global scale. With adequate irrigation, cultivar adaptation is likely to offset 91 %, 88 %, 85 %, and 82 % of maize yield loss induced by 1 K, 2 K, 3 K, and 4 K warming, respectively. It could also compensate for 60 %, 46 %, 32 %, and 19 % of winter-wheat yield loss and 94 %, 85 %, 77 %, and 69 % of spring-wheat yield loss induced by temperature increases from 1 K to 4 K, respectively. Moreover, the yield gains of cultivar adaptation to temperature rise for maize are similar under irrigated and rainfed conditions. Nevertheless, for wheat, the yield compensation effects diminish under conditions of non-adequate water supply. Additionally, we found that the BMA values are consistent with the arithmetic mean of multi-model results in Scenario A0, but there is a large discrepancy in Scenario A1. Specifically, the BMA approach predicts a more negative response to global warming in rice and wheat than the arithmetic mean method.

**Table 2**
The model performance and weights in simulating $S_T$ in the top 20 producers for maize, rice, and wheat (A0: assuming temperature-sensitive growing periods; A1: assuming temperature-adapted growing periods; lower Akaike information criterion (AIC) values indicate better model performance).

| | | | CARAIB | EPIC-TAMU | GEPIC | LPJ-GUESS | LPJmL | pDSSAT | PEPIC | PROMET |
|---|---|---|---|---|---|---|---|---|---|---|
| Maize | A0 | AIC | 7.27 | 16.67 | 17.3 | 8.03 | −26.77 | 49.12 | 33.04 | 98.07 |
| | | Weight | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| | A1 | AIC | −32.93 | −3.02 | −17.86 | 17.30 | 8.90 | 55.86 | 28.15 | 87.91 |
| | | Weight | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Rice | A0 | AIC | 72.04 | 59.86 | 62.82 | —— | 67.21 | 63.19 | 59.85 | 70.73 |
| | | Weight | 0.00 | 0.41 | 0.09 | —— | 0.01 | 0.08 | 0.41 | 0.00 |
| | A1 | AIC | 72.87 | 65.64 | 63.23 | —— | 118.16 | 58.17 | 76.56 | 47.88 |
| | | Weight | 0.00 | 0.00 | 0.00 | —— | 0.00 | 0.01 | 0.00 | 0.99 |
| Wheat | A0 | AIC | 26.60 | 30.88 | 16.10 | —— | 39.50 | 32.75 | 44.13 | 23.80 |
| | | Weight | 0.01 | 0.00 | 0.97 | —— | 0.00 | 0.00 | 0.00 | 0.02 |
| | A1 | AIC | 67.94 | 21.39 | −19.20 | —— | 33.83 | 72.65 | 25.69 | 117.30 |
| | | Weight | 0.00 | 0.00 | 1.00 | —— | 0.00 | 0.00 | 0.00 | 0.00 |

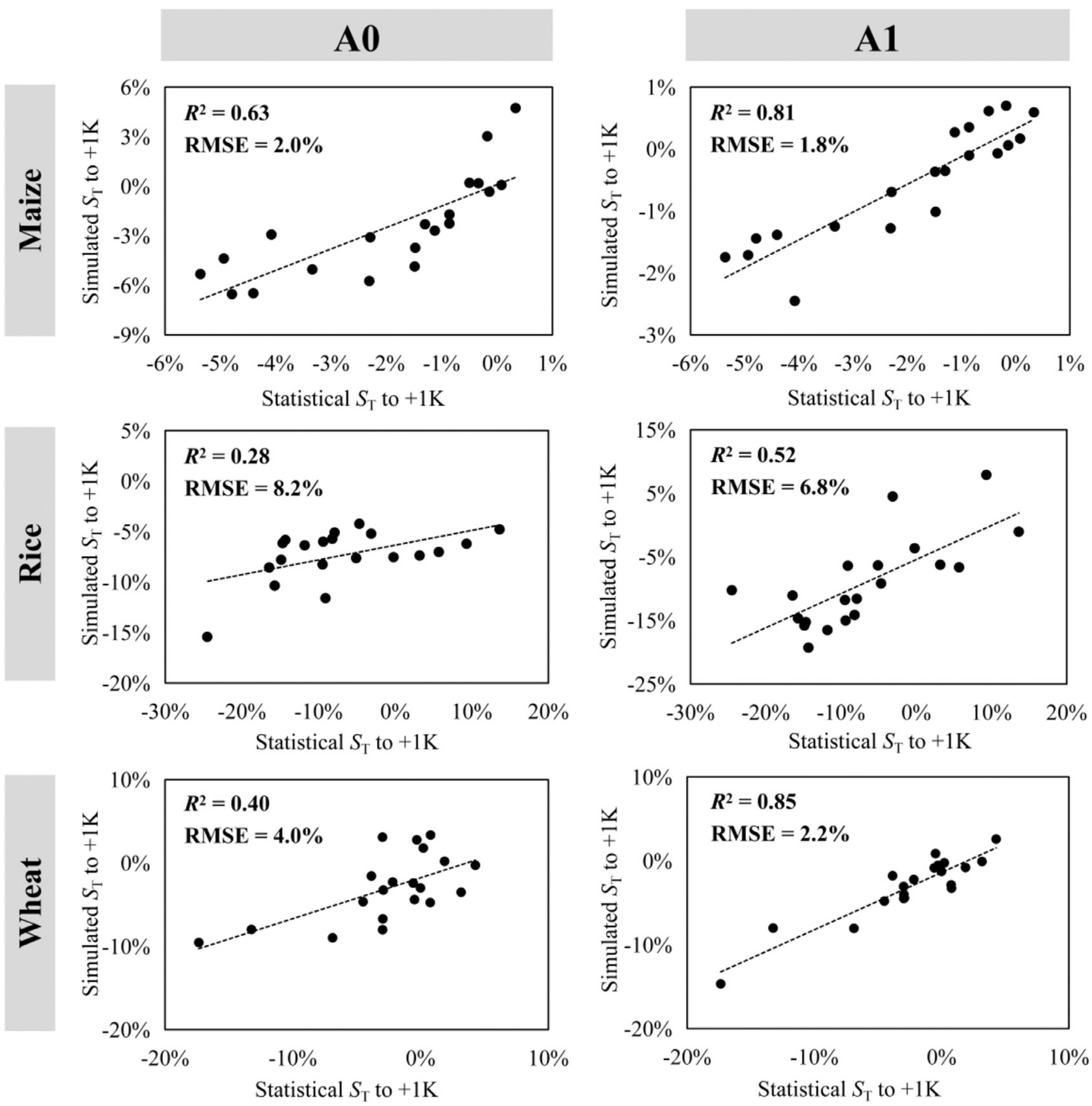


**Fig. 1.** Comparison between statistical and simulated $S_T$ in top 20 producers for maize, rice, and wheat by the A0 and A1 ensemble models. A0: $S_T$ simulation assuming temperature-sensitive growing periods; A1: $S_T$ simulation assuming new cultivars to maintain original growing periods.

Cultivar adaptation of growth duration is expected to alter the global spatial pattern of maize and wheat yield responses to air temperature rise (Figs. 4 and 5). Cultivar adaptation reduces temperature sensitivity of maize yields in most regions, and is projected to offset negative effects of 2 K warming on maize productivity except in hot desert climate regions of Central and South Asia. For winter wheat, cultivar adaptation reverses negative effects of increasing temperatures on irrigated productivity in Europe, highlands in China, and the Southern Wheatbelt in Australia, while it may lead to a decline in rainfed productivity in Central Asia and Mediterranean. For spring wheat, cultivar adaptation compensates for yield losses induced by temperature rise in major producing countries except India. Furthermore, there is minimal variance in the spatial distribution of rice yield response to 2 K warming between A0 and A1 (Figs. 4 and 5), which implies that cultivar adaptation to

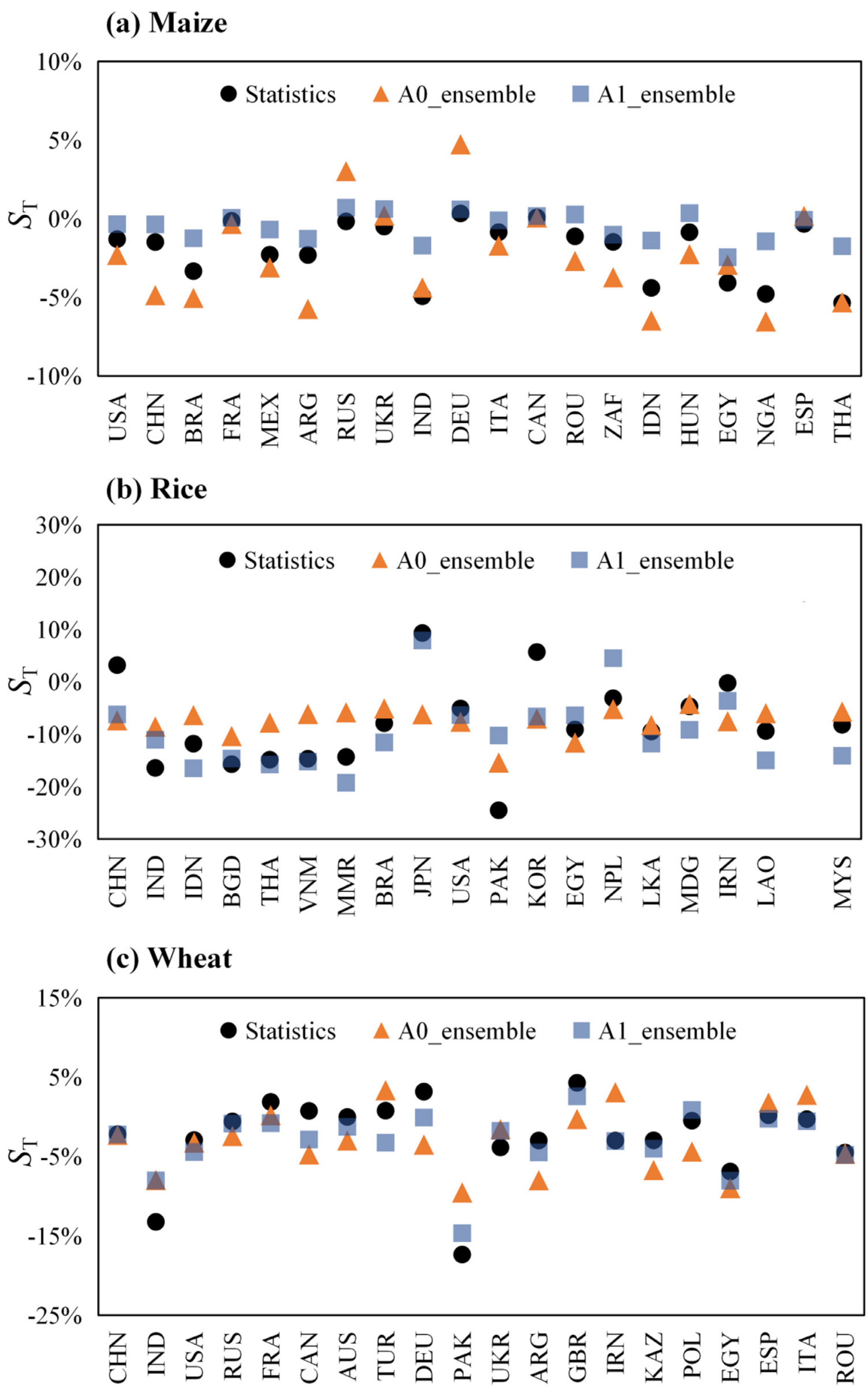


**Fig. 2.** The statistical and simulated $S_T$ in the top 20 producers for (a) maize, (b) rice, and (c) wheat at country (or region) scale.

maintain growing period lengths will play a limited role in improving rice productivity under warming climate.

## 4. Discussion

While several studies have assessed cultivar adaptation effects on crop yield under global warming based on GGCMI Phase 2 simulations, the performance of GGCMs in modelling crop $S_T$ lacks careful evaluation even though it is critical for climate warming impact assessment (Franke et al., 2020a; Jägermeyr et al., 2021; Minoli et al., 2019; Zabel et al., 2021). Here we compared simulated crop $S_T$ with statistical data to assess the performance of GGCMs in crop $S_T$ simulation with different model settings and ensembles. Based on the Bayesian Model Averaging of crop $S_T$ simulations, we found that incorporating cultivar adaptation of growing periods into GGCMs can better simulate yield responses to temperature rise for maize, rice, and wheat in ma-

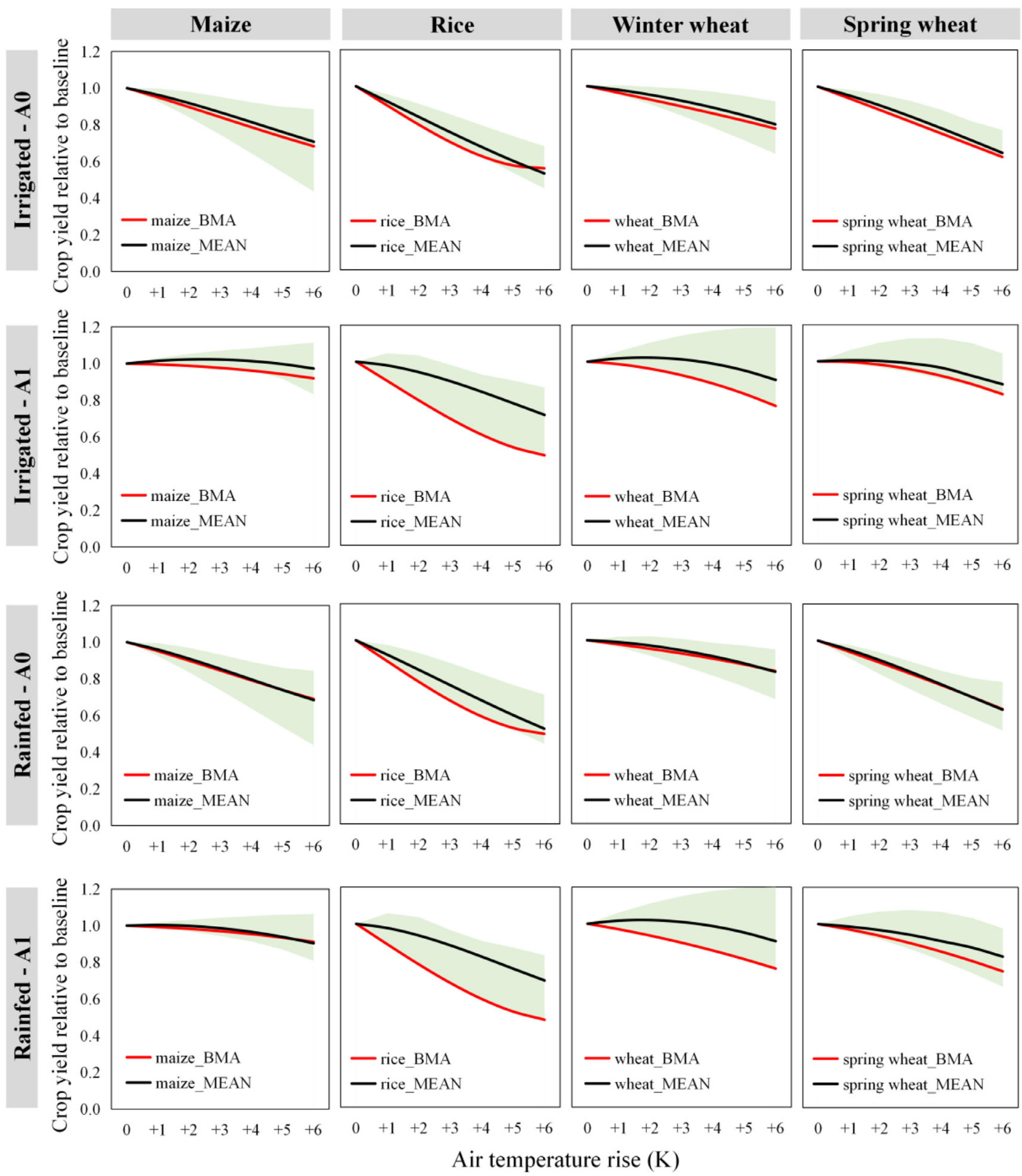


**Fig. 3.** Crop yield changes relative to the baseline climate scenario with air temperature rises from 0 K to 6 K at the global scale based on area weighting. The red curves represent the multi-model ensemble projections by the Bayesian Model Averaging (BMA) approach. The black curves represent the arithmetic mean values of the multi-model projections. The green shades represent the ranges of maximum and minimum values for the multi-model projections. Irrigated-A0 and irrigated-A1 refer to the A0 and A1 model simulation with adequate irrigation. Rainfed-A0 and rainfed-A1 refer to the A0 and A1 model simulation with rainfed conditions.

jor food-producing countries. This confirms recent findings that growing period adaptation of food crops in response to global warming has been a widespread phenomenon around the world (Abbas et al., 2017; Butler et al., 2018; He et al., 2020; Hu et al., 2017; Karapinar et al., 2020; Parent et al., 2018; Sacks and Kucharik, 2011; Tao et al., 2012; Zhu et al., 2018; Zhang et al., 2022). Taking the statistical $S_T$ as a reference, previous systematic studies on crop $S_T$ may overestimate the negative impact of 1 K warming on maize productivity but underestimate the decline of rice productivity under climate warming, without consideration of cultivar adaptation (Wang et al., 2020a; Zhao et al., 2017). The comparison results reveal the importance of adopting dynamic phenological parameters (e.g., dynamic GDD) in GGCMs. Next, how to implement this will require tailored strategies in various agricultural zones to ensure that cultivars are actually available and adaptation is not overestimated (Zabel et al., 2021).

Compared to previous GGCM model ensemble studies (Minoli et al., 2019), we found that the GGCM ensembles optimized by goodness-of-fit to statistics predicted more negative responses of rice and wheat yields to global warming in the A1 scenario. Minoli et al. (2019) calculated the median ensemble of GGCMs and showed that cultivar adaptation can offset crop yield losses up to +6 K warming in many regions, while our study based on the BMA approach suggests that yield losses may only be avoided at low and moderate levels of warming through cultivar adaptation. This is because the better performing models project that the impact of heat stress on crop productivity will gradually outweigh growing period shortening, especially for wheat with a lower optimum temper-

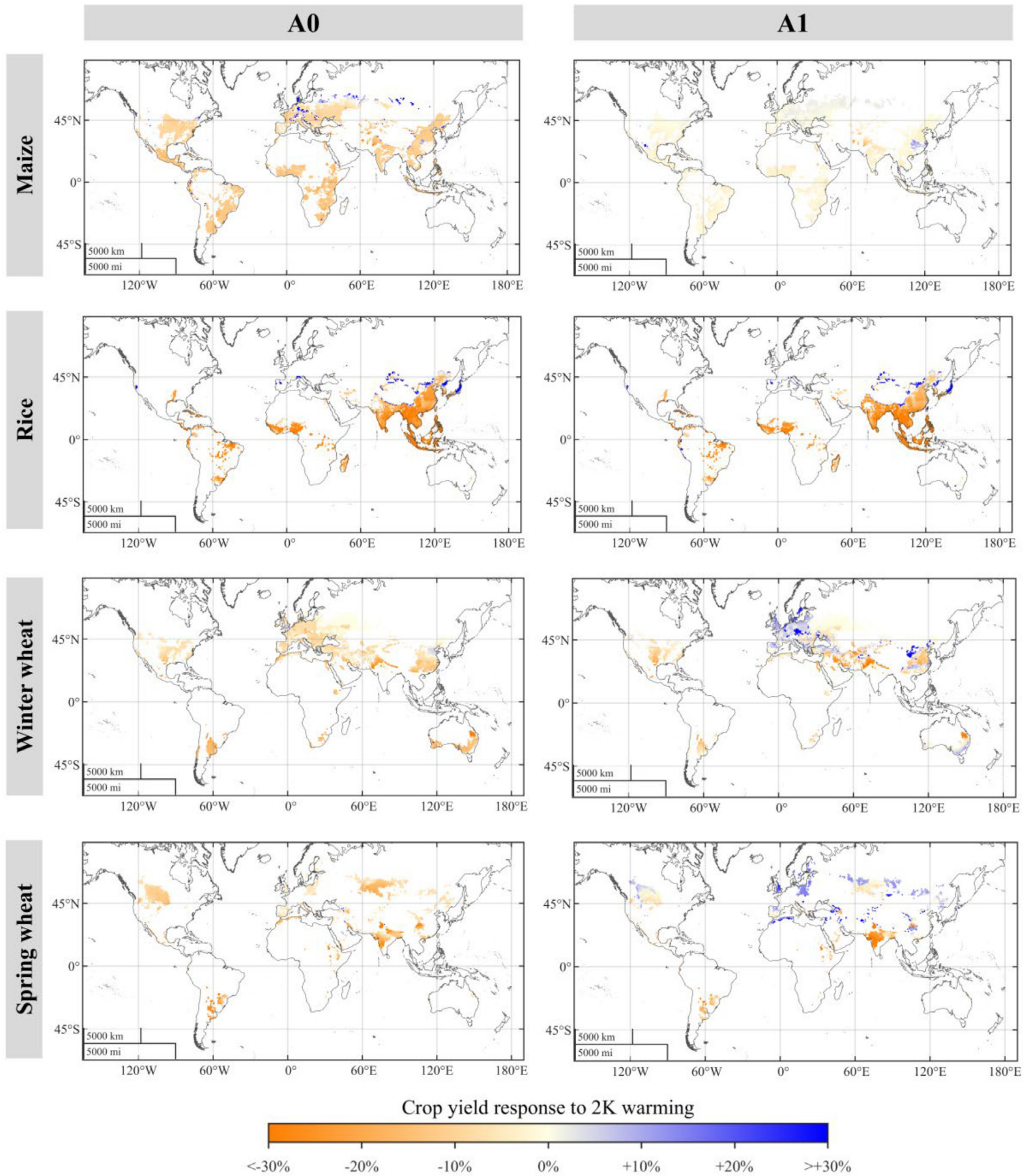


**Fig. 4.** Spatial distribution of crop yield responses to 2 K warming relative to the baseline climate under adequate irrigation projected by the BMA ensemble model. The maps are masked by crop extents of harvested areas greater than 2,500 hectares per 0.5° grid. Map scale units: 'km' is kilometer; 'mi' is mile.

ature for growth. Given a considerable uncertainty in yield projections induced by model ensemble approaches, more real-world observations and statistics are needed in the future to constrain and modify multi-model projections from a model mechanism perspective (Wang et al., 2020b; Yin et al., 2022).

In order to enable inter-comparison between multiple models with different structures, the GGCMI Phase 2 study adopted 'the greatest common factor' of different crop models—maintaining growing period lengths under warming as a representative measure for cultivar adaptation simulation. This assumption may lead to "maladaptation" of crop productivity in some areas, but provides insight into how crop modifications could alter projected impacts on yields. For instance, rice is the only crop herein for which maintaining growth duration does not mitigate the adverse effects of climate warming. Despite being a heat-tolerant crop, most of the rice is planted in hot regions or summer seasons. In some areas, the average temperature during the rice growing season has already exceeded the optimum temperature for rice photosynthetic assimilation (Wang et al., 2020a). Maintaining the original growth duration may further increase probability of heat and drought stress at rice reproductive stages under climate warming (Dubey et al., 2020; Wang et al., 2022). To build climate resilience in rice, it is recommended to shift planting dates to avoid heat stress (Ding et al., 2020), breed new heat-tolerant cultivars (Xu et al., 2021), and move rice-planting zones in the context of global warming (Li et al., 2015). While GGCMs accurately simulate rice $S_T$ in most rice-producing regions, poor performance in Pakistan and South Korea reduces the overall accuracy across the top 20 rice producers. This reflects the GGCMs' limitations in capturing climate-resilient management practices for rice planting in some areas. Next step, incorporating genetics × environment × management ($G \times E \times M$) functions into phenology module to simulate and op-

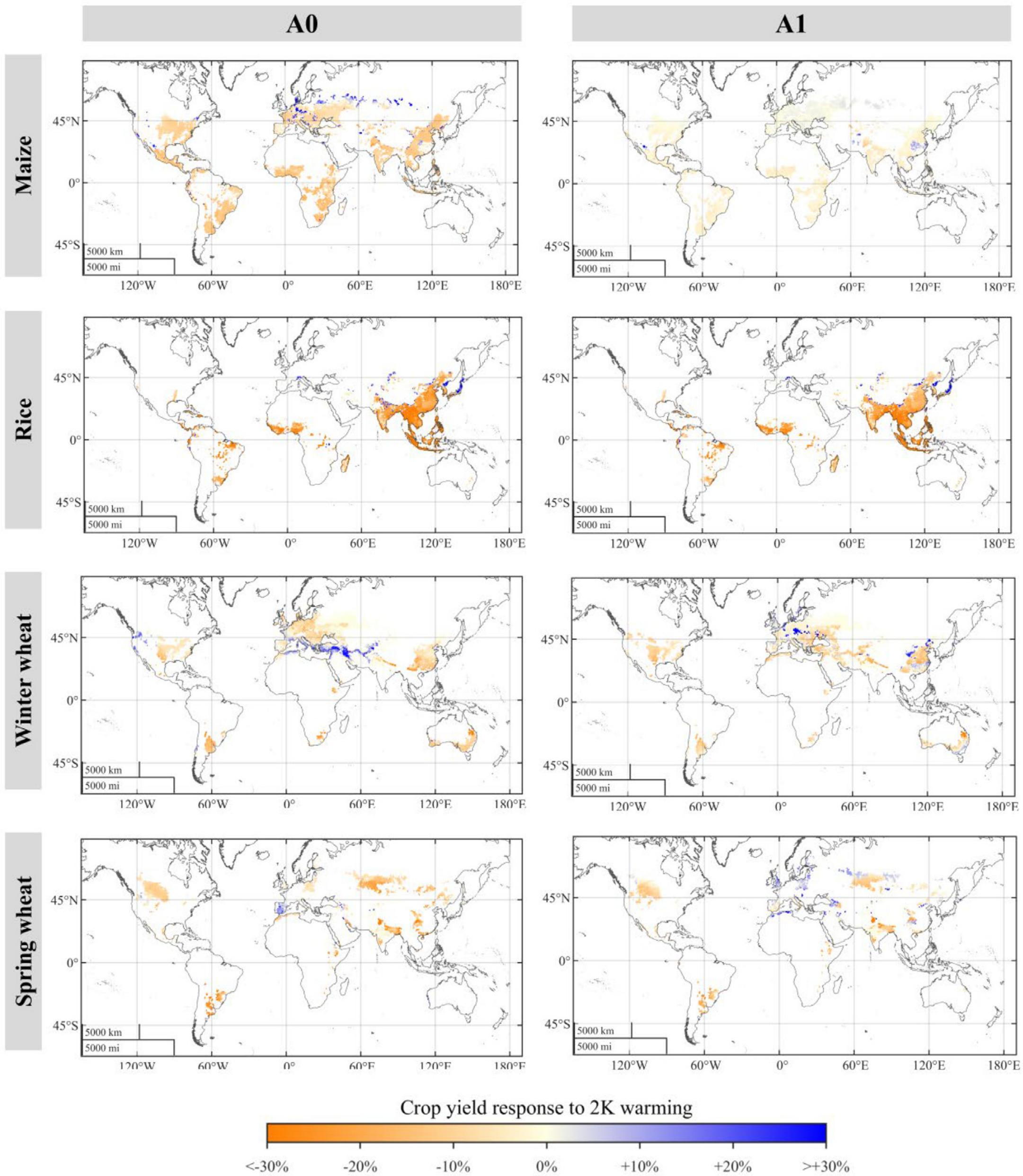


**Fig. 5.** Spatial distribution of crop yield responses to 2 K warming relative to the baseline climate under rainfed conditions projected by the BMA ensemble model. The maps are masked by crop extents of harvested areas greater than 2,500 hectares per 0.5° grid. Map scale units: 'km' is kilometer; 'mi' is mile.

timize sowing, flowering, and harvesting periods will contribute to an integrated assessment of climate resilience for different crop cultivars (Peng et al., 2020).

Although statistical models technically show superior performance in reproducing historical data and greater computational efficiency, they are less reliable when extrapolating to unobserved climate conditions in future scenarios (Hu et al., 2024). In contrast, GGCMs maintain predictive capability under novel climate conditions by simulating biophysical processes and threshold effects. Moreover, GGCMs serve as indispensable tools for optimizing field practices, such as planting date adjustments and cultivar selection, by providing mechanistic insights for agricultural decision-making and climate change adaptation under unprecedented climate conditions (Peng et al., 2020). Therefore, we utilized historical statistical results of crop yield responses to one-degree warming for GGCM validation, and employed adjusted GGCM ensembles to predict yield changes for higher warming scenarios in this study, aiming to provide implications for GGCM structure improvement and climate change impact analysis.

## 5. Conclusions

In this study, we optimized the GGCM ensembles by the Bayesian Model Averaging approach based on the GGCMs' goodness-of-fit to the statistically-inferred $S_T$. Two types of GGCM ensemble models were generated: (1) GGCM-A0, which assumes a temperature-sensitive growing period with fixed phenological parameters under global warming, and (2) GGCM-A1, which assumes a fixed growing period with dynamic phenological parameters under global warming. We found that the GGCM-A1 ensembles show stronger positive correlations and higher goodness-of-fit to statistically-inferred $S_T$ of maize, rice, and wheat in major food-producing countries than the GGCM-A0 ensembles. When setting a temperature-adapted crop cycle instead of a temperature-sensitive cycle in the GGCM ensembles, the $R^2$ between GGCM-simulated and statistically-inferred $S_T$ increased from 0.63 to 0.81 for maize, 0.28 to 0.52 for rice, and 0.40 to 0.85 for wheat, meanwhile the RMSE was reduced for all four crops across their respective top 20 producing countries at a nitrogen application rate of 200 kg/ha. Moreover, the model evaluation results suggest that the GGCM-A0 may exaggerate crop phenological responses to climate warming, leading to an overestimation of $S_T$ for maize and an underestimation of $S_T$ for rice and wheat in major food-producing countries. Globally, the $S_T$ of irrigated maize, rice, winter wheat, and spring wheat are projected to be −0.5 %, −10.5 %, −1.4 %, and −0.4 % by the optimized GGCM-A1 ensembles. We projected that cultivar adaptation of growth duration can mitigate the adverse effects of temperature rises on crop productivity for maize, winter wheat, and spring wheat. However, for rice, maintaining growing periods may increase the risk of heat stress and yield loss under global warming. Additionally, our study reveals considerable uncertainty in rice and wheat yield projections induced by different multi-model ensemble methods. Hence, more real-world observations and statistics are needed in the future to constrain and modify multi-model predictions from a model mechanism perspective.

## Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## CRediT authorship contribution statement

**Xiaobo Wang:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Shaoqiang Wang:** Supervision, Resources, Funding acquisition. **Christian Folberth:** Writing – review & editing, Supervision, Resources. **Rastislav Skalsky:** Supervision, Resources. **Juraj Balkovic:** Supervision, Resources. **Florian Kraxner:** Project administration. **Xia Li:** Funding acquisition, Conceptualization. **Jinyuan Liu:** Validation, Formal analysis, Data curation. **Bangyou Zheng:** Writing – review & editing, Supervision, Project administration.

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## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.geosus.2026.100430.

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