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Future climate change significantly alters interannual wheat yield variability over half of harvested areas

Authors: Weihang Liu[1,2,3], Tao Ye[1,2,3,4], Jonas Jägermeyr[5,6,7], Christoph Müller[7], Shuo Chen[1,2,3], Xiaoyan Liu[1,2,3] and Peijun Shi[1,2,3,8]

[1]Academy of Disaster Reduction and Emergency Management, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China

[2]Key Laboratory of Environmental Change and Natural Disaster, Ministry of Education, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China

[3]State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, China

[4]The Frederick S. Pardee Center for the Study of the Longer-Range Future and Department of Earth and Environment, Boston University, Boston, MA 02215, USA

[5]NASA Goddard Institute for Space Studies, New York, NY 10025, USA

[6]Center for Climate Systems Research, Columbia University, New York, NY 10025, USA

[7]Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, 14412, Potsdam, Germany

[8]Academy of Plateau Science and Sustainability, People's Government of Qinghai Province and Beijing Normal University, Xining 810016, China

Author for correspondence: Tao Ye (yetao@bnu.edu.cn)

Room B931, Jingshikeji Building, Beijing Normal University

No. 12 Xueyuannan Rd., Haidian District

Beijing 100082, China

Tel/fax: +86-10-58800268

Tel: +86-10-58800268, ORCID: 0000-0002-5037-8410

Future climate change significantly alters interannual wheat yield variability over half of harvested areas

Abstract

Climate change affects the spatial and temporal distribution of crop yields, which can critically impair food security across scales. A number of previous studies have assessed the impact of climate change on mean crop yield and future food availability, but much less is known about potential future changes in interannual yield variability. Here, we evaluate future changes in relative interannual global wheat yield variability (the coefficient of variation; CV) at 0.25° spatial resolution for two representative concentration pathways (RCP4.5 and RCP8.5). A multi-model ensemble of crop model emulators based on global process-based models is used to evaluate responses to changes in temperature, precipitation, and CO_2. The results indicate that over 60% of harvested areas could experience significant changes in interannual yield variability under a high-emission scenario by the end of the 21st century (2066–2095). 31% and 44% of harvested areas are projected to undergo significant reductions of relative yield variability under RCP4.5 and RCP8.5, respectively. In turn, wheat yield is projected to become more unstable across 23% (RCP4.5) and 18% (RCP8.5) of global harvested areas—mostly in hot or low fertilizer input regions, including some of the major breadbasket countries. The major driver of increasing yield CV change is the increase in yield standard deviation, whereas declining yield CV is mostly caused by stronger increases in mean yield than in the standard deviation. Changes in temperature are the dominant cause of change in wheat yield CVs, having a greater influence than changes in precipitation in 53% and 72% of global harvested areas by the end of the century under RCP4.5 and RCP8.5, respectively. This research highlights the potential challenges posed by increased yield variability and the need for tailored regional adaptation strategies.

Keywords: yield coefficient-of-variation; crop model emulator; contributions of climatic drivers; yield stability; global food security

1. Introduction

Interannual crop yield variability is one of the primary drivers of food system instability (IPCC 2019). Assessing the effects of climate change on yield variability is critical to understanding the impact of climate change on food security (FAO, 2019). Due to trends in global warming (Lobell *et al.,* 2011) and the changing frequency and intensity of climate extremes (Trnka *et al.,* 2014), potential decreases in the mean yields of crops and an increase in the interannual yield variability could adversely affect the livelihoods of producers, create spikes in food prices, lead to hunger (IPCC, 2014), and even cause political instabilities at a regional level (Sternberg, 2011). Previously, the impact of climate change on mean crop yield (Rosenzweig *et al* 2014, Lobell *et al* 2011) has been investigated with a focus on food availability (Wollenberg *et al.,* 2016). From a climate risk perspective, the concept of time of climate impact emergence has recently been introduced, linking mean yield changes with historical yield variability (Jägermeyr *et al* 2021). Yet, the impact of climate change on future interannual yield variability has not received sufficient attention (Wheeler *et al.,* 2013; Challinor *et al.,* 2014).

Interannual yield variability has always been one of the key risk indicators of crop production. Early studies have either assumed a stationary process without considering variability changes (Ray *et al.,* 2015; Tao *et al.,* 2016; Matiu *et al.,* 2017; Ceglar *et al.,* 2016) or linked changes in variability to non-climatic factors (Döring and Reckling 2018, Knapp and van der Heijden 2018, Kucharik and Ramankutty 2005, Müller *et al* 2018). Recent studies have provided evidence for changes in the interannual yield variability of major cereal crops and identified significant impacts of climate change at the global scale 0.5° grid level or at the country level (Osborne and Wheeler, 2013;

Iizumi and Ramankutty 2016). These studies have been followed up by regional, county-level analyses of the interannual yield variability of maize (Leng, 2017; Hawkins *et al.,* 2013; Lobell *et al.,* 2014). Efforts have also been devoted to projecting the impact of future climate change on interannual yield variability, focusing on wheat and maize at global and regional scales, using process-based crop models (Liu *et al.,* 2019; Moriondo *et al.,* 2011) and statistical models (Urban *et al.,* 2012; Ben-Ari *et al.,* 2018 Tigchelaar *et al.,* 2018). Results from these studies have indicated substantial changes in interannual yield variability as a result of climate change, and that the sign and magnitude of change varies by production region.

Climate-related risk assessment on crop yield requires reflecting the spatial heterogeneity of both agricultural systems and climate change effects relevant for interannual yield variability (Benami *et al.,* 2021). There are still major research gaps in our understanding of these linkages across regions. In terms of major staple crops, only changes in yield CV of wheat (Liu *et al.,* 2019) and maize have been analysed (Tigchelaar *et al.,* 2018) at the global scale. As these studies have used either site-based simulation or globally homogeneous warming perturbations, it is difficult to deduce robust conclusions on changes in interannual yield variability, reflecting the spatial heterogeneity of climate projections (Leng and Hall, 2020). In addition, although the mechanism of impact and the mean yield response to change in climate drivers (e.g., temperature, precipitation, and CO_2) have been intensively discussed (Zhu *et al.,* 2019; Schlenker and Roberts, 2009), the response of interannual yield variability to changes in the various climate drivers is not well understood.

The aim of this study is to evaluate potential changes in interannual wheat yield variability under two climate change scenarios globally, and to attribute individual contributions of temperature, precipitation, and CO_2. The main research questions are: 1) How could climate change affect interannual wheat yield variability on current wheat-growing areas by the end of the century? 2) How much of these changes can be

attributed to changes in temperature, precipitation, and their interaction, respectively? 3) To what extent can elevated CO_2 concentrations mitigate potential increases in yield variability? Answers to these questions will provide crucial information for climate risk assessment and effective adaptation measures.

We address these questions by conducting multi-model ensemble simulations with crop model emulators forced with global climate projections at high spatial resolution (0.25°). Statistical crop model emulators are developed based on simulations from global gridded crop models (GGCMs), facilitated by AgMIP's Global Gridded Crop Model Intercomparison Project (GGCMI). Crop model emulators have recently gained popularity as a powerful tool for assessing the impact of climate change on crop yield (Oyebamiji *et al* 2015, Lobell and Burke 2010, Holzkämper *et al* 2012, Raimondo *et al* 2020, Müller *et al* 2021). Emulators substantially improve computational efficiency and reduce data-processing requirements compared to running the original models, without sacrificing much prediction performance (Folberth *et al* 2019, Blanc and Sultan 2015, Blanc 2017, Franke *et al* 2020a, Ringeval *et al* 2020). The use of a large ensemble of GCM projections in combination with the ensemble of crop yield emulators allows for comprehensively evaluating changes in future yield variability and the associated distribution of extreme yield levels.

2. Materials and methods

2.1 Input data

2.1.1 Gridded crop model data for emulator construction

The input and output data for the simulation of global gridded wheat yield were obtained from the GGCMI phase 2 experiment dataset (Franke *et al.,* 2020b). The spatial resolution of this dataset is 0.5°. The input data included four different data types, i.e., climate, soil, atmospheric CO_2 concentration, and nitrogen fertilizer application

rates (Table S1, Franke *et al.,* 2020b). Baseline climate inputs were used from the AgMIP Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) forcing dataset (1980-2010), including daily maximum and minimum temperatures, precipitation, and solar radiation (Ruane *et al* 2015). Based on these baseline reference simulations, the GGCMI phase 2 experiment used systematic perturbations in each grid cell with seven temperature levels (from -1 K to +6 K in 1K interval, with +5K skipped), nine precipitation levels (from -50% to +30%, in 10% interval, with -40% skipped), four CO_2-concentration levels (360, 510, 660, and 810 ppm), and three nitrogen levels (10, 60, and 200 kg/ha) (Table S2; Franke et al. 2020b). Twelve GGCMs were then forced with each of these perturbations of the original reanalysis weather data. The GGCMs used a national and subnational crop calendar for wheat that is based on Sacks et al (2010), Portmann *et al* (2010), and environment-based extrapolations (Elliott *et al* 2015).

The output data contained irrigated and rainfed yield simulations from 1980 to 2010 for each of the different perturbation levels. In this study, we selected 8 out of the 12 crop models in the GGCMI phase 2 experiment for constructing the emulators. These were APSIM-UGOE, EPIC-IIASA, EPIC-TAMU, GEPIC, LPJ-GUESS, LPJmL, pDSSAT, and PEPIC. CARAIB was not included as it did not consider nitrogen stress. ORCHIDEE-crop was not included as it did not provide simulation results for spring wheat. PROMET and JULES were not included as they used different climate inputs. Although these eight crop models differed in their representation of crop phenology, leaf-area development, yield formation, root expansion, and nutrient assimilation, all accounted for the effects of water and heat stress and assumed no technological change (Blanc, 2017). All input and output data sets were provided by GGCMI at the standardized spatial resolution of 0.5°. More detailed descriptions of the individual crop models and the input and output data characteristics are available in the Supplementary Material (SM).

2.1.2 Data for emulator-based yield projections

To project a high spatial resolution global wheat yield, the Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset (Thrasher 2012), with a spatial resolution of 0.25°, was obtained from the National Aeronautics Space Administration (NASA). This database contains the global daily maximum/minimum near-surface air temperature and precipitation data from 21 GCMs from the Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor *et al* 2012) under two representative concentration pathways (RCP4.5 and RCP8.5), covering the years 1950–2100. Other RCPs are not available through NEX-GDDP.

The emulator-based projections used a national and subnational crop calendar for wheat from MIRCA2000 (Portmann *et al* 2010). Given that MIRCA2000 has only monthly resolution, it was assumed that the first day of the month was the date of planting, and the last day of the month was the date of harvesting (Elliott *et al* 2015). The calendar we used to project yield was only MIRCA2000 because if we used the calendar of the GGCMI phase 2, we would be troubled with the mismatch between the separated spring and winter wheat calendar and only wheat harvested areas in SPAM. Global wheat harvested area distribution around the year 2005 was obtained from the spatial production allocation model (SPAM) for rainfed and irrigated systems at five arc-minute resolution (You *et al* 2014).

2.2 Methods

The methodologies for evaluating changes in wheat yield variability under future climate scenarios includes the following steps (Figure 1): 1) Develop annual yield emulators for the process-based GGCMI crop models. 2) Conduct emulator-based yield projections based on the NEX-GDDP climate model ensemble. 3) Summarize the future changes in wheat yield variability relative to the baseline; decompose the changes in yield variability into changes in mean yield and yield standard deviation.

And 4) Separate the contributions from the changes in climatic drivers to the changes in the yield variability.

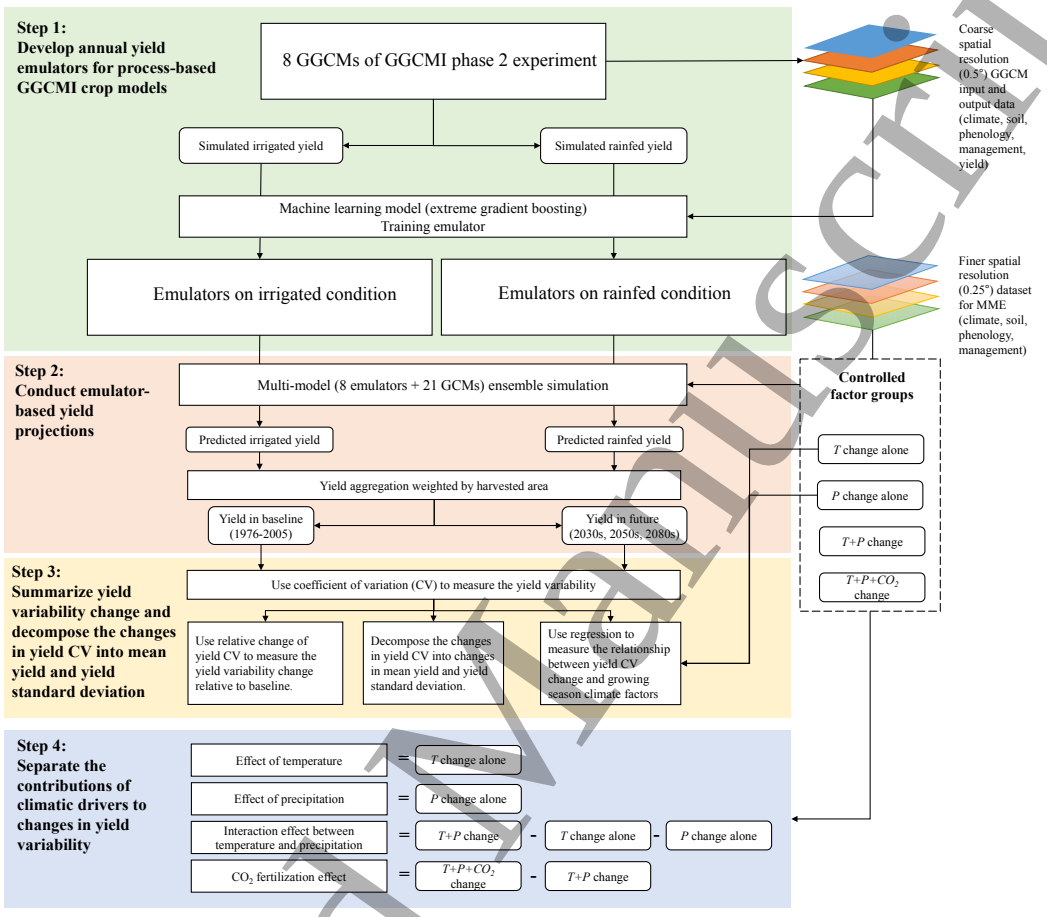


Figure 1 Framework for evaluating changes in global wheat yield interannual variability (*T:* temperature, *P:* precipitation).

2.2.1 Development of annual GGCM emulators by extreme gradient boosting

A previous study developed emulators of climatological-mean yield based on GGCMI phase 2 experiment data (Franke *et al.,* 2020a). We, however, develop an emulator capable of capturing year-to-year variability in yield. A machine-learning approach was used in this study for its flexibility for data-driven development of models with high accuracy (Folberth *et al.,* 2019) and its associated computational efficiency.

Development of the emulator consists of training—via a machine-learning (ML) algorithm—on specific GGCM input and output datasets, so that the emulator replicates

the complex process of yield simulation within the crop model. Variables that have been frequently reported to significantly influence wheat yield were prepared as the predicting variables, including climate, soil type, length of growing season, and management practices (Table S3). All the data for training were computed/adapted from the GGCMs' input and output datasets.

All prediction variables were computed/obtained from the GGCMI phase 2 data archive. The climate data are supplied as daily values and were, in a first step, aggregated to monthly sums or averages (MON). For each grid, the month of planting was defined as month 1 to harmonize, on a global basis, the order of months from planting. Subsequently, prediction variables were calculated for each month in the growing-season months and the entire growing season (GS, based on the planting and harvesting dates for the GGCMs). Soil properties were adopted primarily for the topsoil class. Additional characteristics like length of growing season were regarded as a cultivar characteristic. The total amount and fraction of the nitrogen fertilizer application and CO_2 concentration were uniform for each grid.

In total, 32 different emulators were trained for the eight GGCMs, each with two water management modalities (rainfed and irrigation) and two wheat types (spring wheat and winter wheat). An extreme gradient boosting (XGB) algorithm was used due to its better performance in terms of goodness-of-fit, cross-validation errors, and computation efficiency compared with a random forest algorithm (Folberth *et al.,* 2019). The predicting variables and the simulated yield in the GGCMs were randomly split into training and validation sets, which contained 75% and 25% of the samples (Yue *et al.,* 2019), respectively. Depending on the size of the dataset supplied by each GGCM, 1.7×10^6–2.3×10^7 (0.9×10^7–1.9×10^8) samples were used for model training and 0.6×10^6–0.8×10^7 (0.3×10^7–0.6×10^8) samples were used for validation of irrigation (rainfed) conditions, covering the period of 1981–2010. More details on emulator training, validation, and performance evaluation are available in SM and Figures S1 and S2.

2.2.2 Emulator-based wheat yield projections

The emulators were then used to project global wheat yield by using future GCM projections. It is important to ensure that emulator-based projections do not exceed the range of training samples to avoid unrealistic extrapolation effects (Franke *et al* 2020a, Folberth *et al* 2019). The GGCMI phase 2 perturbations were designed to accommodate high-end warming scenarios (RCP8.5-2080s). For growing season average maximum temperature, the range of training data (interannual and spatial variability in AgMERRA + GGCMI perturbation) covered the entire range of the GCM projections. CO_2 concentrations were averaged with a 30-year moving window and the highest CO_2 concentration under RCP8.5-2080s is 760 ppm.

Ensemble yield projections were conducted at the global level for grids with a spatial resolution of 0.25° for the years 1976–2005 (baseline), 2006–2035 (2030s), 2036–2065 (2050s), and 2066–2095 (2080s) under RCPs of 4.5 and 8.5. If the spring and winter wheat are grown in parallel at national or subnational level, we determined the wheat type with larger harvested areas according to MIRCA2000 (Portmann et al. 2010). The multi-model ensemble approach improves the robustness of future climate-change impact estimates and allows for analyses of spatial heterogeneity and inter-model uncertainty (Martre *et al.,* 2015). There were 336 future wheat yield estimates (21 GCMs × 8 emulators × 2 RCPs), each simulated for 4 × 30-year periods. Throughout all simulations, planting dates, cultivar selection, soil properties, and management practices were assumed to remain constant over time, which is consistent with the GGCMI Phase 2 experimental design A0 (Franke *et al* 2020b), which is used for training the emulators here. Final estimates of future yield responses are based on the median across the crop model emulators and GCMs.

2.2.3 Measuring the change in yield variability

Rainfed and irrigated yield were first aggregated to grid and national levels using an

area-weighted average (Müller *et al* 2017), as described in the following equation:

$$y_t = \frac{\sum_{i=1}^{n} y_{i,firr,t} \times area_{firr} + \sum_{i=1}^{n} y_{i,noirr,t} \times area_{noirr}}{\sum_{i=1}^{n} \left(area_{firr} + area_{noirr} \right)}. \quad (1)$$

where i is the index of any grid cell assigned to the spatial unit in year t, n is the number of grid cells in that spatial unit, $y_{i,firr,t}$ is the emulator-projected yield under fully irrigated conditions in grid cell i, and $y_{i,noirr,t}$ is the emulator-projected yield for rainfed conditions in grid cell i; $area$ is the harvested area in grid cell i, either due to fully irrigated or rainfed, obtained from SPAM.

We used the coefficient of variation (CV) a measure of interannual yield variability, where $CV = s/m$, in which s and m are the standard deviation and mean, respectively, over a reference period. We compare the baseline period (1976-2005) with six future scenario-periods: RCP4.5-2030s, RCP4.5-2050s, RCP4.5-2080s, RCP8.5-2030s, RCP8.5-2050s, and RCP8.5-2080s. The percentage change in yield CV in one of the six future scenario-periods relative to the baseline period is then measured by:

$$d_{scenario} = \frac{CV_{scenario} - CV_{baseline}}{CV_{baseline}} \times 100\% \quad (2)$$

2.2.4 The effects of changes in temperature, precipitation, and CO_2

The effects of changes in temperature, precipitation, and CO_2 were separated by using individual climate driver perturbed simulations, with one climate factor at a time taken from a climate scenario and the rest from the baseline. Four such climate driver sensitivity simulations (Table 1) were conducted to isolate the effects of changes in temperature, precipitation, their interaction effects, and the CO_2 fertilization effect.

Table 1 Climate driver sensitivity simulations

Climate drivers	Descriptions

"T"	Using future scenarios of temperature, other drivers taken from baseline
"P"	Using future scenarios of precipitation, other drivers taken from baseline
"T+P"	Using future scenarios of temperature and precipitation, holding CO_2 constant at 360 ppm
"T+P+CO_2"	Using future scenarios of temperature, precipitation, and CO_2

The climate driver sensitivity simulations listed in Table 1 allow for addressing the following:

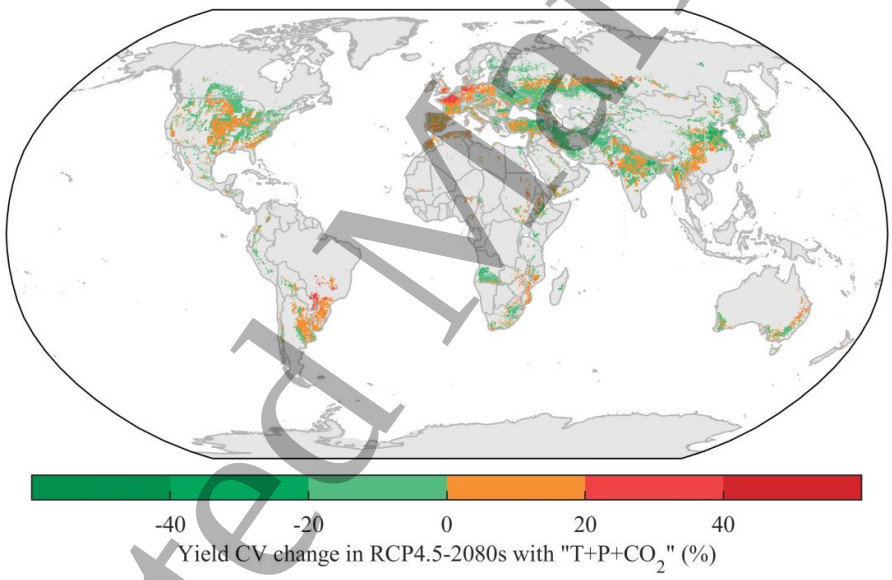
1) The effects of temperature and precipitation changes can be derived by comparing the results of groups "T" and "P" with the baseline simulations, respectively.
2) The interaction between temperature and precipitation changes can be evaluated using the difference between groups "T+P" and "T" + "P".
3) The effect of CO_2 fertilization can be evaluated using the difference between groups, "T+P+CO_2" and "T+P".

3. Results

3.1 Global patterns of future change in wheat yield interannual variability

By the end of the century, model simulations indicate an overall decrease in wheat yield CV, but in some regions, including major producing countries, there would be more unstable wheat yield (Figure 2). The spatial patterns of CV changes intensify towards the end of the century, indicating a more polarized pattern under the long-term scenarios RCP4.5-2080s and RCP8.5-2080s (Figure S3). Under RCP8.5-2080s, with the CO_2 fertilization effect ("T+P+CO_2"), the yield CV increases significantly in 18% of harvested areas ($p<0.05$; see Figure S4 for significance test), while 44% of harvested areas experience significant decrease of the yield CV ($p<0.05$). Under RCP4.5-2080s, with the CO_2 fertilization effect ("T+P+CO_2"), 23% of harvested areas undergoes significant increase of yield CV ($p<0.05$), while yield becomes more stable in 31% of harvested areas significantly ($p<0.05$). Western Europe, northern Australia, central US, South Asia, Southwest China, and Myanmar are found to experience a small increase

in yield CV (<40%). In eastern Europe, southern Australia, and central India yield CV is indicated to decrease by >20% under RCP8.5-2080s (Figure 2). The spatial patterns of changes are consistent across different scenarios and time periods, but the size of changes varies (Figure S5). The uncertainty across crop yield projections (standard deviation of CVs across all 8 emulators and 21 GCMs) ranged between 17%-119% with the CO_2 fertilization effect, with a global mean of 39% under RCP8.5-2080s. Uncertainty was most pronounced in central Europe to eastern Russia, and in the northern Indian production regions (Figure S6). We further break the total uncertainty to those associated with the emulators and those with the GCMs, by analysis of variance. Disagreement across the emulators explained less than 50% of the total variance in 47% of the harvested areas (Figure S7).



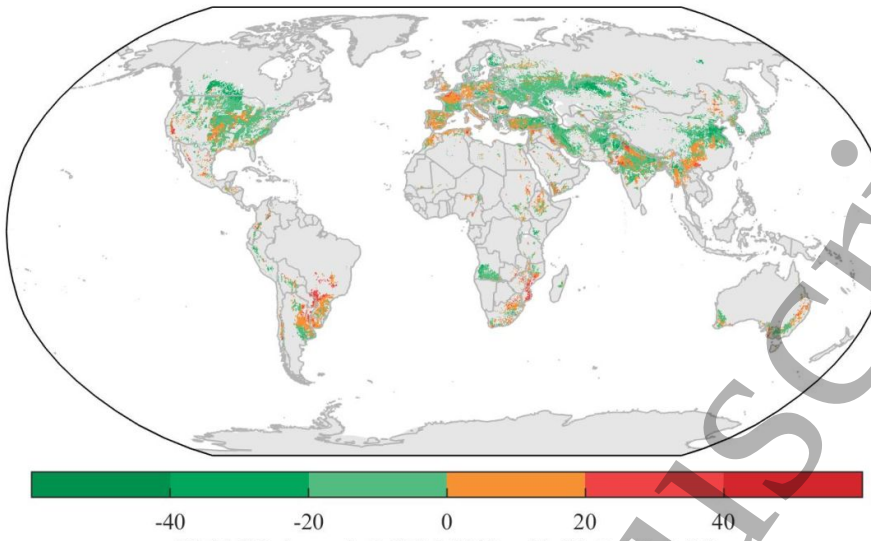


Figure 2 Changes in wheat yield CV (RCP4.5-2080s and RCP8.5-2080s) relative to the baseline (1976-2005) based on the median of 21 GCMs and 8 crop model emulators using perturbations of temperature, precipitation, and CO_2 concentration according to RCP4.5 and RCP8.5 ("T+P+CO_2").

Changes in yield CV are linked to changes in mean yield and yield standard deviation. Under RCP8.5-2080s, mean yield levels increase in 92.1% of harvested areas and the yield standard deviation increases in 95.3% of harvested areas (Figure S8). 30.8% of the areas in which CV is found to increase, CV changes are dominated by increases in yield standard deviation (|SD+| > |MY+|). In regions where CV is decreasing, 59.3% of the areas are dominated by mean yield increases (|SD+| < |MY+|) (Figure 3, Table 2). Under RCP4.5-2080s, mean yield levels and the yield standard deviation increase in 92.8% and 94.5% of the harvested areas, respectively (Figure S8). 42.7% of the areas in which CV is found to increase, CV changes are dominated by increases in yield standard deviation (|SD+| > |MY+|). In regions where CV is decreasing, 47.6% of the areas are dominated by mean yield increases (|SD+| < |MY+|) (Figure 3, Table 2).

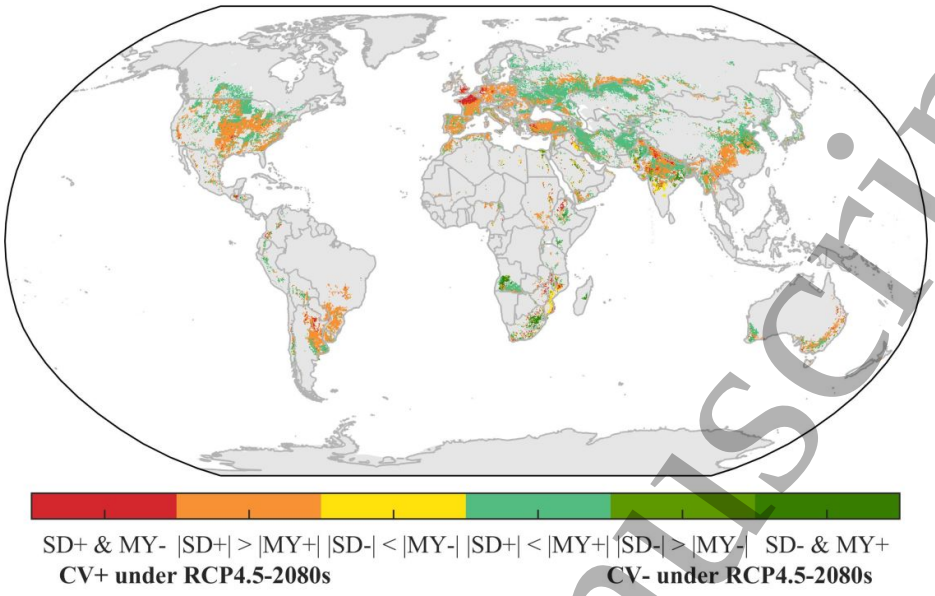


Figure 3 Factors of yield CV changes, including mean yield changes (MY) and yield standard deviation changes (SD). Positive changes are indicated with "+" and negative changes with "-". The |MY+| and |SD+| denote the absolute increase of mean yield and yield standard deviation, respectively.

Table 2 Attribution of wheat harvested area with yield CV changes to changes in mean yield (MY) and standard deviation (SD) under RCP4.5-2080s and RCP8.5-2080s.

Changes in yield CV	Category of SD and MY change	Fraction of harvested areas	
		RCP4.5	RCP8.5
CV+	SD+ & MY-	4.3%	5.2%
	|SD+| > |MY+|	42.7%	30.8%
	|SD-| < |MY-|	2%	0.6%

	|SD+| < |MY+|	47.6%	59.3%
CV-	|SD-| > |MY-|	0.9%	2.1%
	SD- & MY+	2.6%	2.0%

* "+" denotes positive changes, and the "-" denotes negative changes. "|SD+| > |MY+|" denotes the absolute value of increase in yield SD is greater than that in the mean yield.

3.2 Changes in the yield CV across different climatic regions

Changes in the wheat yield CV exhibited a clear relationship with the baseline regional temperature, precipitation, and nitrogen fertilizer application rate. In general, regions with hotter growing seasons (growing season average temperature >20 °C) or with lower nitrogen fertilizer application rates (nitrogen application rate < 200kg/ha), experienced the largest relative increase in wheat yield CV (Figure 4).

The increases in yield CV tend to be greater in regions with hotter growing seasons under both RCP4.5 and RCP8.5, including sub-Saharan Africa, India, Australia's wheat belt, South East US, and southern Brazil and Argentina. These are regions in which mean wheat yields are expected to decrease under high-emission climate change scenarios, whereas at higher latitudes with lower growing season temperatures mean wheat yields are generally projected to increase (Jägermeyr *et al* 2021). The change in yield CV undergoes smaller decline under RCP8.5 and even experiences subtle increase under RCP4.5 in regions with wetter growing seasons, which can be attributed to stronger variability of precipitation in wetter regions. Underperforming wheat production system regions, like Brazil, sub-Saharan Africa, and South East Asia, with lower levels of nitrogen application, are likely to experience a greater increase in yield CV under both RCP4.5 and RCP8.5.

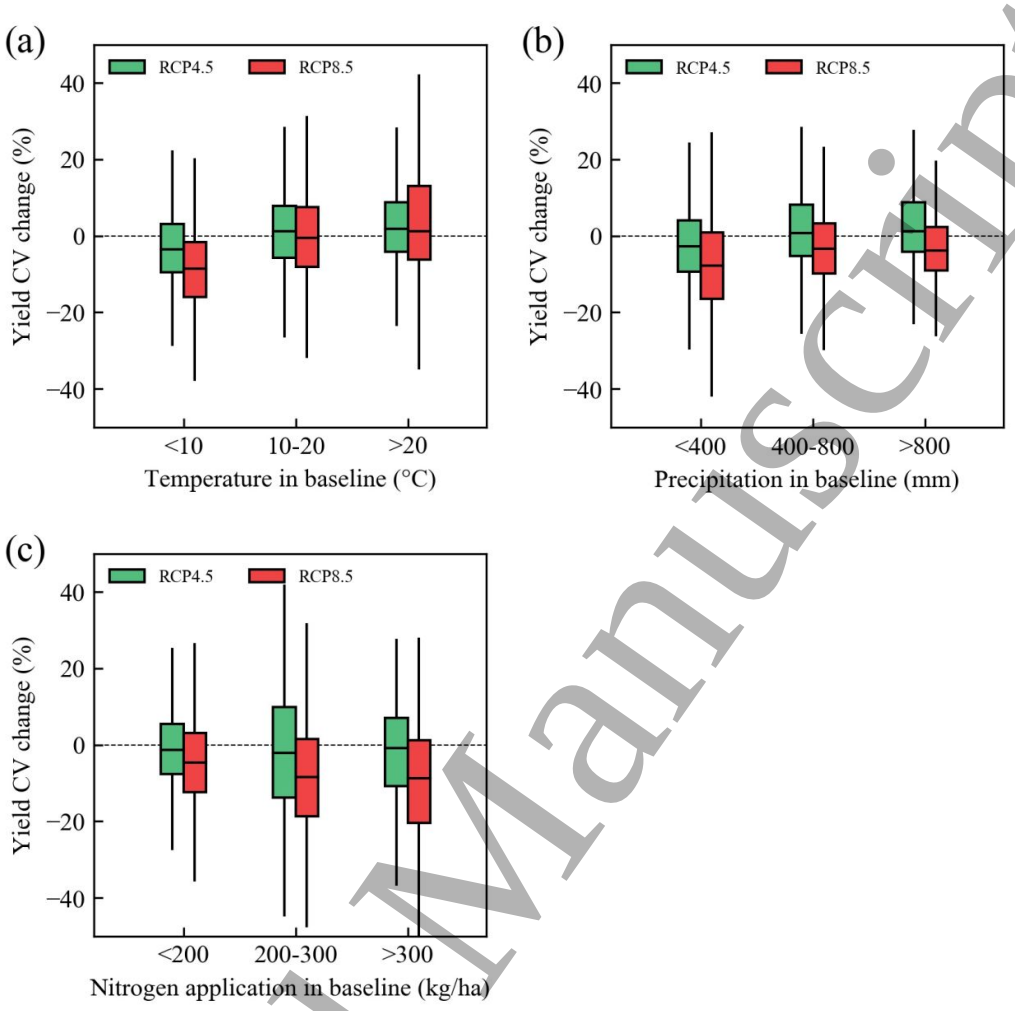


Figure 4 Wheat yield CV change under RCP4.5 and RCP8.5, separated by different climatic and management bins: growing season mean temperature (a), growing season total precipitation (b), and nitrogen fertilizer application (c). The bin classification refers to baseline reference conditions. CV change is based on the T+P+CO_2 simulations. Box-and-whisker plots show the distribution of yield CV changes across all cultivated grid cells in each class. The group divisions are based on approximately equal sample sizes.

3.3 Climatic drivers of and their relative contributions to the change in yield CV

In simulations based on individual climate drivers, temperature changes alone increase the yield CV for 55% and 56% of the harvested areas under RCP4.5-2080s and RCP8.5-2080s, respectively. Under RCP8.5-2080s the magnitude of increased yield CV with temperature change alone is larger than that with precipitation change alone, but the extent of the area affected by increasing yield CV is smaller (Figure 5). The yield CV increases in 64% and 60% of harvested areas when only precipitation change is

assumed under RCP4.5-2080s and RCP8.5-2080s, respectively (Figure 5).

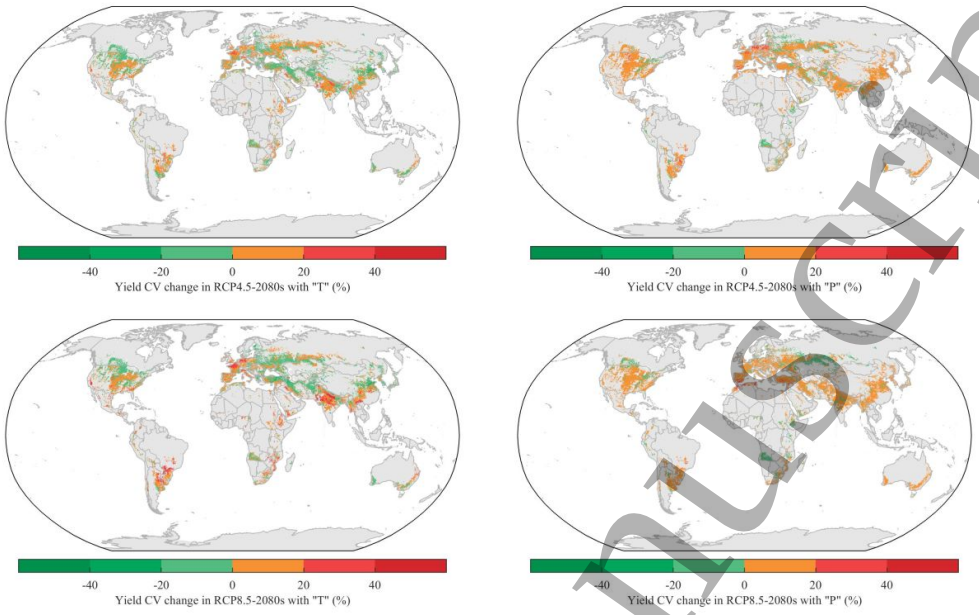
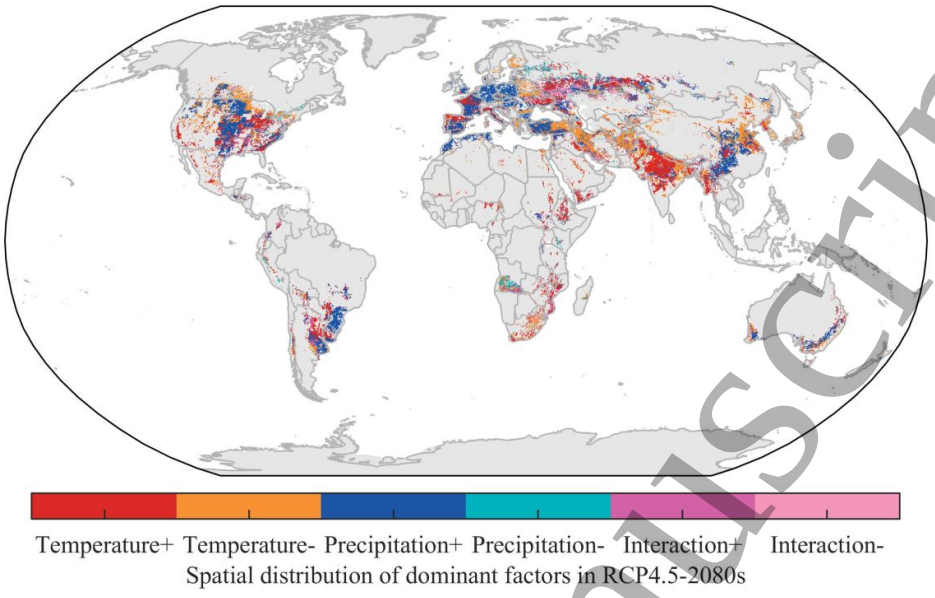


Figure 5 Changes in yield CV under isolated temperature and precipitation perturbations (RCP4.5-2080s and RCP8.5-2080s). Yield CV changes are shown as the median of 21 GCMs and 8 crop model emulators. "T" is the effect of temperature change, and "P" is the effect of precipitation change.

After separating the relative contributions of climate drivers under RCP4.5-2080s, precipitation was the dominant driver to increase the yield CV in 33% of harvested areas, even if the temperature change plays a more important role in yield CV change in over half of harvested areas (53%). The interaction between temperature and precipitation change played a dominant role in changes in yield CV in 10% of harvested areas. Under RCP8.5-2080s, temperature becomes a more important factor and was found to be the dominant driver in 72% of global wheat harvested areas, of which, yield CV increased in 41% of harvested areas. Precipitation was found to be the dominant driver in 21% of harvested areas, of which, yield CV increased in 17% of harvested areas. The interaction between temperature and precipitation played a dominant role in the change in yield CV in only 8% harvested areas (Figure 6).



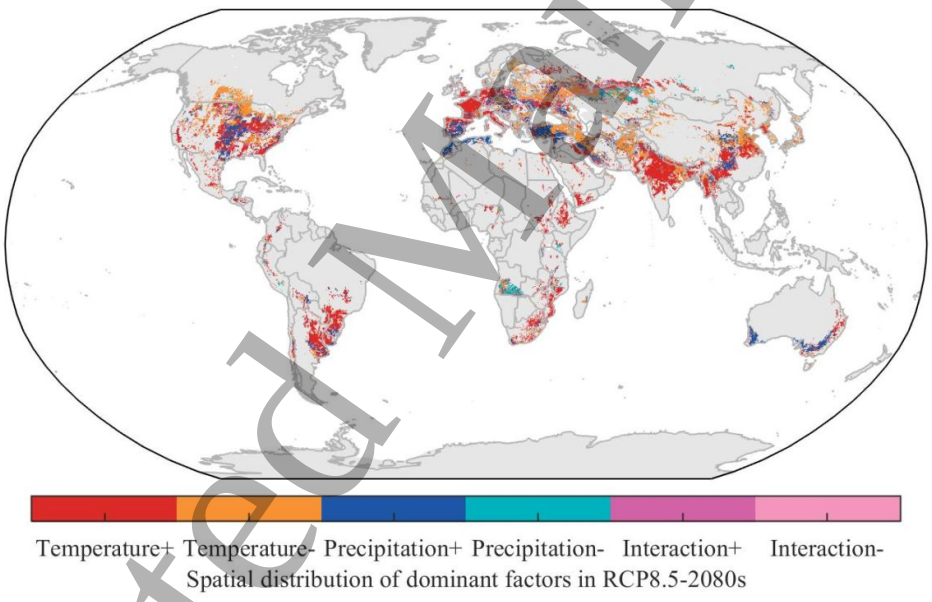


Figure 6 Major contributors to the change in wheat yield CV (RCP4.5-2080s and RCP8.5-2080s). The dominant factors driving the change in yield CV are defined as the driving factors that contribute the most to the increase (or decrease) in the yield CV in each grid cell. The suffix '+' attached to the driving factor name indicates increase in the CV, whereas a '-' indicates a reduction in the CV.

The elevated CO_2 concentration reduced the increase in yield CV, which was greatest in RCP8.5-2080s. The effect was strongest (>15%) in central Europe, south Asia, North and Southwest China, and North America. The mitigation effect was weaker under the other RCP4.5-2080s, but the spatial patterns were largely consistent with RCP8.5-

2080s (Figure 7).

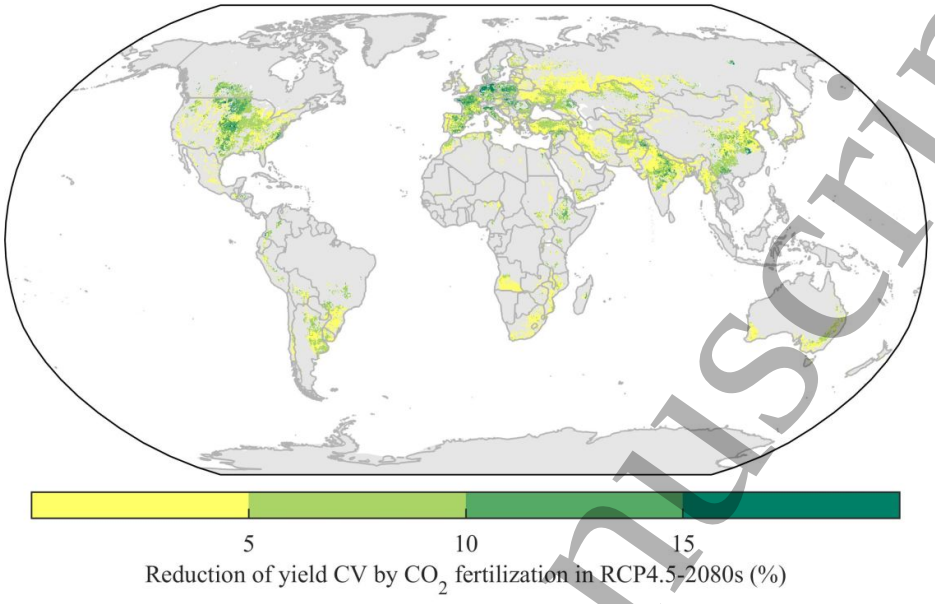


Figure 7 Reduction effect ("T+P+CO_2" - "T+P") on change in yield CV from CO_2 fertilization.

To elucidate the link between changes in yield CV and climate factors, we further examined the change in yield CV with climatic factors changes in mean, variability, and extremes of temperature and precipitation by using perturbation "T" and "P" results. A linear regression was conducted between median changes in yield CV and growing season climatic factors from food producing units (FPUs, Kummu *et al.,* 2010) (Figure

8). The change in yield CV was positively correlated with change in interannual variability ($T_{gs}interV$, Figure 8-c), intra-seasonal variability ($T_{gs}intraV$, Figure 8-d), and extreme degree day (EDD_{gs}, Figure 8-e) of temperature. The relationship between mean temperature and yield CV varied by region. For regions with hotter growing seasons ($T_{gs}mean$ > 10°C, Figure 8-a), a warming trend tended to increase the yield CV, and decrease the yield CV in regions with colder growing season ($T_{gs}mean$ < 10°C, Figure 8-b). For the effect of precipitation change, results from grid cells with rainfed systems showed that change in yield CV was negatively correlated with change in total precipitation ($P_{gs}mean$, Figure 8-f), but positively correlated with interannual variability of precipitation ($P_{gs}interCV$, Figure 8-g), and drought intensity (consecutive drought days, CDD_{gs}, Figure 8-h), all statistically significant.

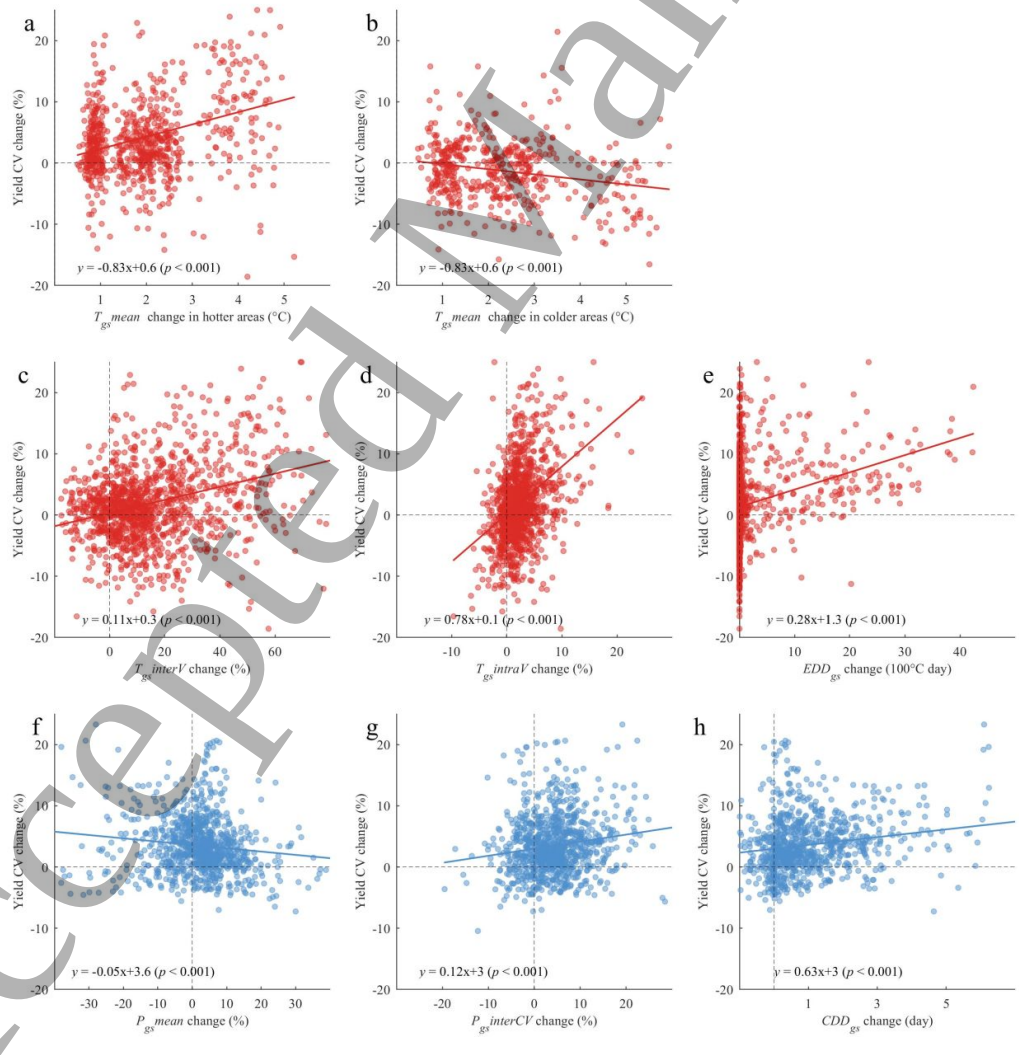


Figure 8 Correlations of changes in yield CV with the changes in mean, variability, and extremes of temperature and precipitation at the FPU level relative to the baseline. In each panel, the changes in growing season climate factor are: (a) mean temperature (baseline value > 10°C), (b) mean temperature (baseline value < 10°C), (c) interannual variability (standard deviation) of mean temperature, (d) intra-season variation of daily temperature, (e extreme degree days, (f) total precipitation, (g) interannual variability (coefficient of variation) of precipitation, and (h) consecutive drought days.

4. Discussion

4.1 Changes in future wheat yield variability

Our results indicate that wheat yield CV might increase significantly in 18% of the global harvested area under a high-emission climate change scenario. In turn, yield variability is found to decrease in 44% of currently cultivated areas, regions in which mean yields are projected to increase under climate change. Globally, our findings are consistent with those of earlier studies indicating that declining yield variability is wide-spread but increasing yield variability is found across important breadbasket regions (Iizumi and Ramankutty 2016, Leng 2017). Site-based simulation results for a 2°C warming scenario (Liu *et al.,* 2019) have provided a more pessimistic estimation, with wheat yield CV increases in 36 out of the 60 sites, including the CO_2 fertilization effect. Our results confirm higher yield variability in hot regions as reported by (Liu *et al.,* 2019) and in regions with low nitrogen fertilizer application rates as reported by (Han *et al.,* 2020). Similarly, the low yield CV in high nitrogen fertilizer application rates regions is consistent with the findings of nutrients-driven intensification that additional nutrient inputs raise mean crop yields and thus decrease yield CV (Müller *et al* 2018).

A detailed comparison of yield CV changes between site-based projections (Liu *et al* 2019b) and our gridded projections demonstrates the importance of revealing spatial heterogeneity of yield variability changes. Changes in yield CV were identified as significantly increasing at all 14 sites for the 2°C warming scenario (Liu *et al.,* 2019). Among the 14 sites, our estimates were consistent with 10 of the 14 stations. For the

other 46 sites, our results are largely consistent with the 25 sites across the central U.S., South America, the Middle East, the western European coastline, and Southern Russia; but are different in the direction of change for other sites. Spatial heterogenous yield variability changes are the main cause of inconsistence between our projections and Liu et al. (2019). This is the case in Glen and Bloemfontein in South Africa, and Dharwar in India for the four inconsistent sites, as well as 11 out of the other 21 inconsistent sites, including those in northwest US, around the western or northern coast of the Black Sea, in central southern Russia, North China, and south-eastern Australia. Besides, another cause may be the choice of the crop model ensemble and underlying uncertainties. We examined our results for each crop model emulator. The direction of each site-based change in yield CV reported by Liu *et al.* (2019) can be found in the result of at least one of our emulators, indicating GCMs-crop models ensemble combination is critical to yield projection.

Spatial heterogeneity of crop yield variability creates a huge challenge for agricultural risk management (Benami *et al* 2021). The spatially heterogeneous yield CV changes are also found in earlier reports that yield variability changes in rice and wheat are sensitive to spatial resolution (Iizumi *et al* 2018). Previous yield variability projections conducted with site-based, process-based models have found that regional yield variability changes are not consistent across different sites (Liu *et al* 2020). Thus, the gridded process-based crop models can provide an overview of global or regional changes in yield variability (Parkes *et al* 2018, Ostberg *et al* 2018). The ability to represent this spatial heterogeneity in yield variability in light-weight emulators allows for more comprehensive assessments of the risk of changes in yield variability.

4.2 Climatic drivers of changes in future wheat yield variability

The present results indicate strong links between changes in the wheat yield CV and changes in temperature and precipitation. Previous reports have suggested that changes in yield interannual variability are closely related to changes in the variability

(both interannual and intra-seasonal) (Iizumi *et al.,* 2013; Peng *et al.,* 2018) and extremes of climate factors (Chen *et al.,* 2018; Iizumi and Ramankutty, 2016). In addition, due to the non-linear relationship between yield and temperature, changes in the mean temperature, away from the optimal range, will increase the interannual yield CV (Urban *et al.,* 2012; Tigchelaar *et al.,* 2018). The response of the interannual yield variability to changes in precipitation is more complex than for temperature. In general, changes in precipitation have smaller effects on irrigated yield than on rainfed yield (Kothari *et al.,* 2019; Tubiello *et al.,* 2002). In rainfed systems, yield interannual variability has been known to be closely related to interannual variability of rainfall, as well as frequency and intensity of drought (Webber *et al.,* 2018). The effect of total precipitation change largely depends on the baseline humidity of the production region. For drylands, increasing total precipitation increases mean yield (Fronzek *et al.,* 2018) and consequently reduces CV. Also, the interaction between temperature and precipitation changes can mitigate the increase in yield CV, although the magnitude of the interaction effect on change in yield CV is modest, within 10%. This is similar to the mitigation effect of irrigation on heat stress (Zaveri and B. Lobell, 2019). However, the interaction effect cannot be explicitly explained, depending on the timing, intensity, and volume of rainfall (Tack *et al.,* 2017).

Higher atmospheric CO_2 concentrations mitigate variability changes in crop yield (Urban *et al.,* 2015), a consistent finding across different scenarios and time periods (Figure 7). The mitigation effect is mainly attributed to increases in mean crop yield under elevated CO_2. Wheat as a C3 crop is known to have a high capacity to benefit from elevated CO_2 levels, which has been confirmed by various previous experiment-based evidences (Kimball 2016, Toreti *et al* 2020) . Negative effects of global warming on future wheat yield could potentially be fully compensated by yield-amplifying effects of elevated atmospheric CO_2 concentrations (Ye *et al.,* 2020).

4.3 Uncertainties

The spatial pattern of uncertainty in our results is consistent with different uncertainty distribution between high and low latitudes provided by crop model simulation (Xiong *et al* 2020). Including the CO_2 fertilization effect would further increase the total size of uncertainty in the projected yield. This is in agreement with a recent analysis on sources of uncertainty regarding GCMs and GGCM statistical emulators (Müller *et al.,* 2021).

The use of emulator ensemble simulation enabled the estimation of wheat yield variability change driven by climate change. Nevertheless, our approach has two limitations. First, crop damage from climate extremes is a major driving force of interannual yield variability (Trnka *et al.,* 2014), but the capability of most crop models in reproducing extreme climate damage to crops is still limited (Rötter *et al.,* 2018). For instance, process-based crop models of the GGCMI phase 1 experiment fail to reproduce yield impact from too wet conditions (Li *et al* 2019). Also, process-based crop models underestimate the extremeness of the 2003 heat-drought (Schewe *et al* 2019). We employ newly developed crop model emulators to project future wheat yield and these emulators are capable of capturing the direction of yield anomalies due to climate extremes, indicating the type of extreme event-induced yield variability that is captured by the models (heat, drought) will increase yield variability in a fair share of current cropland. Second, interannual yield variability driven by non-climatic factors is not considered in our analysis. These non-climatic factors can strongly affect yield variability (Albers *et al* 2017) and changes in management can also strongly affect yield levels under climate change (Minoli *et al* 2019, Zabel *et al* 2021).

4.4 Implications

The spatial scale of our estimates reached the sub-province scale in China and the sub-state scale in the US and thus provided more insight than previous global estimates.

First, gridded estimated yield variability change could provide more detail on spatial heterogeneity in local areas. Such local spatial differences were pronounced in South Africa, eastern Africa, and Central Russia. Second, when there is a need to estimate regional or country-level aggregated yield variability change, our gridded estimates could enable straightforward aggregation rather than upscaling from site-based estimates—these estimates rely heavily on the representativeness of sites.

High-spatial resolution gridded estimates of future yield variability change enabled global estimates of future change in yield CV. Globally, changes in yield CV tend to decrease in 44% of global harvested areas; but still yields would become more unstable in 18% of global harvested areas under RCP8.5-2080s, including several major production regions and countries. This indicates potential challenges to the stability of grain supply, market pricing, and consequently, the whole food system in the context of future climate change. It is important for local and regional economies to proactively implement adaptation measures and policy support (Iizumi and Ramankutty, 2016). In light of this, our results can provide details of spatial heterogeneity in local areas and identify regions with urgent needs, including those hot and low-fertilizer application regions. The predominant climate driver is also identified, so that adaptation strategies can be tailored for regional or local challenges.

To face the challenge of increased yield interannual variability, adaptations including mean-increasing and variance-reducing strategies (Mehrabi and Ramankutty, 2019), are needed because the changes in relative yield variability (CV) are sourced from both changes in mean yield and yield standard deviation (Figure S9). The focus on the relative yield variability (CV) rather than absolute (e.g. SD) reflects the producer perspective, where the variability around the mean is relevant (storage, financial buffers) even if the mean is increasing in the long-term. Shifting cultivars (Olmstead and Rhode, 2011; Liu *et al.,* 2010) and adjusting planting dates (Lobell, 2014; Huang *et al.,* 2020) have been recognized as effective adaptation options to address heat stress. Likewise,

reinforcing irrigation equipment and adjusting irrigation strategies could relieve water shortages (Zhao *et al.,* 2020). Additionally, increasing nitrogen application rates in underperforming wheat production system regions could mitigate the increase in yield CV (Han *et al.,* 2020). From a risk management perspective, the risk in increased yield CV requires better domestic inter-temporal reserves of wheat grain to smooth fluctuations in interannual production, market supply, and commodity price and better financial buffers at the producer level, to mitigate financial losses from local less-than-average yields.

5. Conclusions

This study presents one of the first projections of future wheat yield interannual variability change at high spatial resolution and disentangles the impacts from changes in temperature, precipitation, and CO_2 on those changes. Our results reveal that future climate change alters wheat yield interannual variability in over 60% of harvested areas. Wheat yield variability may decrease in over 40% of global wheat harvested areas under a high-emission climate change scenario (RCP8.5-2080s), while under RCP4.5-2080s only 31% of harvested areas undergo the declined yield CV. However, 23% and 18% of harvested areas experience increased yield CV under RCP4.5-2080s and RCP8.5-2080s, respectively. Greater increase in yield standard deviation than that in the mean yield was the main reason for the increase yield variability under both RCP4.5 and RCP8.5. Yields in hotter or lower fertilizer regions are projected to become more unstable. Worldwide, changes in temperature have a stronger influence on changes in yield variability compared with precipitation in 72% of global harvested areas under RCP8.5-2080s, whereas under RCP4.5-2080s the areas controlled by temperature changes are smaller (predominant in 53% of harvested areas). The global mean of yield CV reduction due to rising CO_2 concentration across current harvested areas are 5% and 8% under RCP4.5-2080s and RCP8.5-2080s, respectively. High spatial resolution patterns of changes in wheat yield variability, as well as site-specific major driver

identification results, have great implications for policy-making with regard to where food supply and farmer income need to be stabilized by additional measures in wheat production throughout the world.

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