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Global wheat production with 1.5 and 2.0°C above pre-industrial warming

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Abstract

Efforts to limit global warming to below 2°C in relation to the pre-industrial level are under way, in accordance with the 2015 Paris Agreement. However, most impact research on agriculture to date has focused on impacts of warming >2°C on mean crop yields, and many previous studies did not focus sufficiently on extreme events and yield interannual variability. Here, with the latest climate scenarios from the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project, we evaluated the impacts of the 2015 Paris Agreement range of global warming (1.5 and 2.0°C warming above the pre-industrial period) on global wheat production and local yield variability. A multi-crop and multi-climate model ensemble over a global network of sites developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP) for Wheat was used to represent major rainfed and irrigated wheat cropping systems. Results show that projected global wheat production will change by −2.3% to 7.0% under the 1.5°C scenario and −2.4% to 10.5% under the 2.0°C scenario, compared to a baseline of 1980–2010, when considering changes in local temperature, rainfall, and global atmospheric CO_2

concentration, but no changes in management or wheat cultivars. The projected impact on wheat production varies spatially; a larger increase is projected for temperate high rainfall regions than for moderate hot low rainfall and irrigated regions. Grain yields in warmer regions are more likely to be reduced than in cooler regions. Despite mostly positive impacts on global average grain yields, the frequency of extremely low yields (bottom 5 percentile of baseline distribution) and yield interannual variability will increase under both warming scenarios for some of the hot growing locations, including locations from the second largest global wheat producer—India, which supplies more than 14% of global wheat. The projected global impact of warming <2°C on wheat production is therefore not evenly distributed and will affect regional food security across the globe as well as food prices and trade.

KEYWORDS
1.5°C warming, climate change, extreme low yields, food security, model ensemble, wheat production

1 | INTRODUCTION

The global community agreed with the Paris agreement to limiting global warming to 2.0°C, with the stated ambition to attempt to cap warming at 1.5°C (UNFCCC, 2015). While limiting the extent of climate change is critical, the more ambitious 1.5°C mitigation strategy will likely require considerable mitigation effort in the agricultural land use sector (Fujimori et al., 2018), with some studies suggesting this would actually have more negative consequence for food security than climate change impacts of 2.0°C (Frank et al., 2017; Ruane, Antle, et al., 2018; van Meijl et al., 2018). However, these economic land use studies generally only consider the average effects of climate change and not the changes in yield variability and risk of yield failure, key factors constraining intensification efforts in many developing regions (Kalkuhl, Braun, & Torero, 2016). Further such studies have generally not considered real cultivars nor typical production conditions.

Agricultural production and food security is one of many sectors already affected by climate change (Davidson, 2016; Porter, Xie, & Challinor, 2014). Wheat is one of the most important food crops, providing a substantial portion of calories for about four billion people (Shiferaw et al., 2013). Wheat production systems' response to warming can be substantial (Asseng et al., 2015; Liu et al., 2016; Rosenzweig et al., 2014), but restricted warming levels of <2.0°C global warming above pre-industrial are under-represented in previous assessments (Porter et al., 2014). Thus, assessing the impact of 1.5 and 2.0°C global warming above pre-industrial conditions on crop productivity levels, including the potential benefits of associated carbon dioxide (CO_2) fertilization, and the likelihood of extremely low-yielding wheat harvests, is critical for understanding the challenges of global warming for global food security.

Several simulation studies have assessed the changes in global wheat production due to the changes in climate and CO_2 concentration (Assenget al., 2015, 2018; Rosenzweig et al., 2014). However, previous studies have almost all considered more extreme warming and most of current studies investigated the impact of global warming >2.0°C, which means that previous impact assessments lacked details for <2°C of warming. Also, many previous studies did not focus sufficiently on extreme events and yield interannual variability (Challinor, Martre, Asseng, Thornton, & Ewert, 2014; Challinor, Watson, et al., 2014; Porter et al., 2014). Therefore, in terms of food security, it is important to analyze the effect of the new 1.5 and 2.0°C warming scenarios on the interannual variability of crop production. In particular, studies on impact of 1.5 and 2.0°C global warming on wheat production at a global and regional scale are missing.

Process-based crop simulation models, as tools to quantify the complexity of crop growth as driven by climate, soil, and management practice, have been widely used in climate change impact assessments at different spatial scales (Challinor, Martre, et al., 2014; Challinor, Watson, et al., 2014; Chenu et al., 2017; Ewert, Rötter, et al., 2015; Porter et al., 2014), including multi-model ensemble approaches (Assenget al., 2015, 2013; Wang, Martre, et al., 2017; Wang, Lin, et al., 2017). The multi-model ensemble approach has been proven to be a reliable method in reproducing the main effects anticipated for climate chance when simulations are compared with field experimental observations (including changes in temperature, heat events, rainfall, atmospheric CO_2 concentration [CO_2], and their interactions) (Assenget al., 2015, 2013, 2018; Wallach et al., 2018; Wang, Martre, et al., 2017; Wang, Lin, et al., 2017).

Here, we applied a global network of 60 representative wheat production sites and an ensemble of 31 crop models (Asseng et al., 2015, 2018) developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP) Wheat Team (Rosenzweig et al., 2013) with climate scenarios from five Global Climate Models

(GCMs) from the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project (Mitchell et al., 2017; Ruane, Phillips, & Rosenzweig, 2018) to evaluate the impacts of the 2015 Paris Agreement range of global warming (1.5 and 2.0°C warming above the pre-industrial period, referred hereafter as "1.5 scenario" and "2.0 scenario") on global wheat production and yield interannual variability. We hypothesize that the mean impacts of warming may not differ greatly between the two scenarios as losses due to accelerated development are compensated by gains from elevated CO_2. However, we expect that the higher frequency of extreme events under 2.0°C (Ruane, Phillips, et al., 2018) would result in greater damages of heat and drought stress, greater inter-annual variability, and higher risk of yield failures. Such information could supply important nuance in understanding the implications of the two levels of warming and associated mitigation efforts of the two warming scenarios.

2 | MATERIALS AND METHODS

2.1 | Model inputs for global simulations

An ensemble of 31 wheat crop models was used to assess climate change impacts for 60 representative wheat-growing locations developed by the AgMIP-Wheat team (Assenget al., 2015, 2018; Wallach et al., 2018). All models in the ensemble were calibrated for the phenology of local cultivars and used site-specific soils and crop management. The multi-model ensemble used here has been tested against observed field data and showed reliable response to changing climate in several previous studies, including responses of model ensemble to elevated CO_2, post-anthesis chronic warming and different heat shock treatments during grain filling (Asseng et al., 2018; Wallach et al., 2018). Hoffman et al. (2015) and Ruane et al. (2016) showed that a multi-model ensemble can also reproduce some of observed seasonal yield variability. The 60 locations are from key wheat-growing regions in the world (Supporting Information Table S1 in Appendix S1). Locations 1–30 are high rainfall or irrigated wheat-growing locations representing 68% of current global wheat production. These locations were simulated without water or nitrogen limitation. Details about these locations can be found in Asseng et al. (2015). Locations 31–60 are low rainfall locations with average wheat yield <4 t/ha and represent 32% of current global wheat production (Asseng et al., 2018).

Thirty-one wheat crop models (Supporting Information Table S2 in Appendix S1) within AgMIP were used for assessing impacts of 1.5 and 2.0°C global warming above pre-industrial time on global wheat production (Asseng et al., 2018). The 31 wheat crop models considered here have been described in publications. All model simulations were executed by the individual modeling groups with expertise in using the model they executed. All modeling groups were provided with daily weather data, basic physical characteristics of soil, initial soil water, and N content by layer and crop management information. One representative cultivar, either winter or spring type, was selected for each location after consulting with local experts or literature. Different wheat types may be used at different locations in one country (e.g., China, Russia, and United States), to cover some of the possible heterogeneity in cultivar use (Supporting Information Table S1 in Appendix S1). Observed local mean sowing, anthesis, and maturity dates were supplied to modelers with qualitative information on vernalization requirements and photoperiod sensitivity for each cultivar. Observed sowing dates were used and cultivar parameters calibrated with the observed anthesis and maturity dates by considering the qualitative information on vernalization requirements and photoperiod sensitivity. More details about model inputs are provided in the supplementary methods and in Asseng et al. (2018).

2.2 | Future climate projections

Baseline (1980–2010) climate data for each wheat modeling site come from the AgMERRA climate dataset, which combines observations, reanalysis data, and satellite data products to provide daily climate forcing data for agricultural modeling (Ruane, Goldberg, & Chryssanthacopoulos, 2015). Climate scenarios here are consistent with the AgMIP Coordinated Global and Regional Assessments (CGRA) 1.5 and 2.0°C World study (Rosenzweig et al., 2018; Ruane, Antle, et al., 2018; Ruane, Phillips, et al., 2018), utilizing the methods summarized below and in the Supporting Information Appendix S1 and fully described by Ruane, Phillips, et al. (2018). Climate changes from large (83–500 member for each model) climate model ensemble projections of the +1.5 and +2.0°C scenarios from the Half a Degree Additional Warming, Prognosis and Projected Impacts project (HAPPI; Mitchell et al., 2017) are combined with the local AgMERRA baseline to generate driving climate scenarios from five GCMs (MIROC5, NorESM1-M, CanAM4 [HAPPI], CAM4-2degree [HAPPI], and HadAM3P) for each location (Ruane, Phillips, et al., 2018). Only five GCMs here were used due to data availability at the time the study was conducted. Specifically, HAPPI ensemble changes in monthly mean climate, the number of precipitation days, and the standard deviation of daily maximum and minimum temperatures are imposed upon the historical AgMERRA daily series using quantile mapping that forces the observed conditions to mimic the future distribution of daily events (Ruane, Phillips, et al., 2018; Ruane, Winter, McDermid, & Hudson, 2015). This results in climate scenarios that maintain the characteristics of local climate while also capturing major climate changes. As in previous AgMIP assessments, solar radiation changes from GCMs introduce uncertainties that can at times overwhelm the impact of temperature and rainfall changes and thus were not considered here other than small radiation effects associated with changes in the number of precipitation days (Ruane, Winter, et al., 2015).

HAPPI anticipates atmospheric [CO_2] for 1.5 scenario (1.5°C above the 1861–1880 pre-industrial period = ~0.6°C above current global mean temperature; Morice, Kennedy, Rayner, & Jones, 2012) and 2.0 scenario (2.0°C above pre-industrial = ~1.1°C above current global mean temperature) at 423 ppm and 487 ppm ([CO_2] in the center of the 1980–2010 current period is 360 ppm). Uncertainty around these CO_2 levels from climate models' transient and equilibrium climate sensitivity is not explored here, although [CO_2] for 2.0°C warming may be slightly overestimated (Ruane, Phillips, et al., 2018).

This large climate × crop model setup enabled a robust multi-model ensemble estimate (Martre et al., 2015; Wallach et al., 2018) as well as analysis of spatial heterogeneity (Liu et al., 2016) and inter-model uncertainty. There were 11 treatments (baseline, five GCMs for 1.5 and five GCMs for 2.0 scenarios) simulated for 60 locations and 30 years (see additional detail on climate scenarios in Supporting Information Appendix S1 and in Ruane, Phillips, et al., 2018).

2.3 | Aggregation of local climate change impacts to global wheat production impacts

Simulation results were up-scaled using a stratified sampling method, a guided sampling method to improve the scaling quality (van Bussel et al., 2016), with several points per wheat mega region when necessary (Gbegbelegbe et al., 2017). During the up-scaling process, the simulation result of a location was weighted by the production the location represents as described below (Asseng et al., 2015). Liu et al. (2016) recently showed that stratified sampling with 30 locations across wheat mega regions resulted in similar temperature impact and uncertainty as aggregation of simulated grid cells at country and global scale. And Zhao et al. (2016) indicated that the uncertainty due to sampling decreases with increasing number of sampling points. We therefore doubled the 30 locations from Asseng et al. (2015) to 60 locations (Supporting Information Table S1 in Appendix S1) to cover contrasting conditions across all wheat mega regions.

Before aggregating local impacts at 60 locations to global impacts, we determined the actual production represented by each location following the procedure described by Asseng et al. (2015). The total wheat production for each country came from FAO country wheat production statistics for 2014 (www.fao.org). For each country, wheat production was classified into three categories (i.e., high rainfall, irrigated, and low rainfall). The ratio for each category was quantified based on the Spatial Production Allocation Model (SPAM) dataset (https://harvestchoice.org/products/data). For some countries where no data were available through the SPAM dataset, we estimated the ratio for each category based on the country-level yield from FAO country wheat production statistics. The high rainfall production and irrigated production in each country were represented by the nearest high rainfall and irrigated locations (locations 1–30). Low rainfall production in each country was represented by the nearest low rainfall locations (locations 31–60).

For each climate change scenario, we calculated the absolute regional production loss by multiplying the relative yield loss from the multi-model ensemble median (median across 31 models and five GCMs) with the production represented at each location. Global wheat production loss was determined by adding all regional production losses, and the relative impacts on global wheat production were calculated by dividing simulated global production loss by historical global production. Similar steps with global impacts were used for calculating the impacts on country scale impacts, except that only the local impacts from corresponding locations in each country were aggregated to the country impacts.

We also tested the significance of the differences in the estimated impacts and the changes in simulated yield inter-annual variability between the two warming scenarios. More detailed steps about impact aggregation and significance tests can be found in the supplementary methods.

2.4 | Environmental clustering of the 60 global locations

The 60 global wheat-growing locations were clustered in order to analyze the results by groups of environments with similar climates (Supporting Information Figure S5 in Appendix S1). A hierarchical clustering on principal components of the 60 locations was performed based on four climate variables for 1981–2010: the growing season (sowing to maturity) mean temperature, the growing season cumulative evapotranspiration, the growing season cumulative solar radiation, and the number of heat stress days (maximum daily temperature >32°C) during the grain filling period. All data were scaled (centered and reduced to make the mean and standard deviation of data to be zero and one, respectively) prior to the principal component analysis.

After determining the wheat yield impacts for each of the 1.5 and 2.0°C scenarios, yield variability for both scenarios was assessed, including the extreme low yield probability and yield interannual variability. For each location, we determined the yield threshold of the bottom 5% from the yield series for the baseline period and calculated the cumulative probability series of simulated yields under 1.5 and 2.0°C scenarios. Next, the probability of occurrence for extreme low yield for each scenario was assessed as the corresponding cumulative probability of the yield threshold of the bottom 5% from baseline period from the cumulative probability series. Interannual yield variability was quantified as the coefficient of variation of simulated yields over the 30-year simulation period. In all cases, the multi-model median from the 31 models was employed.

3 | RESULTS

3.1 | Impacts of 2015 Paris Agreement compliant warming

Compared with the present baseline period (1980–2010; 0.67°C above pre-industrial), the HAPPI scenarios gave projected temperature increases of 1.1–1.4°C (25%–75% range of 60 locations) for the 60 wheat-growing locations spread over the globe under the 1.5 scenario and 1.6–2.0°C under the 2.0 scenario (Supporting Information Figure S1 in Appendix S1). Temperature increase during the wheat-growing season (sowing to maturity) typically warms about 0.5°C less than the annual mean under both warming scenarios: 0.7–1.0°C (25%–75% range of 60 locations) under the 1.5 scenario and

1.0°C to 1.5°C under 2.0 scenario (Supporting Information Figure S2 in Appendix S1). In the HAPPI scenarios, annual rainfall is projected to increase in most of the 60 locations under both warming scenarios (Supporting Information Figure S3 in Appendix S1; Ruane, Phillips, et al., 2018).

Based on baseline climate conditions (1980–2010), we categorized the 60 wheat production sites into three environment types (temperate high rainfall, moderately hot low rainfall, and hot irrigated; Supporting Information Figure S5 in Appendix S1). Across these environments, increasing temperatures reduce wheat crop duration due to accelerated phenology (Supporting Information Figure S22a in Appendix S1). As a consequence, the crop duration declines with future climate change scenarios compared with the baseline. For most of the locations from temperate high rainfall and moderately hot low rainfall regions, simulated cumulative growing season evapotranspiration (ET) and growing season rainfall decreased slightly under the 1.5 and 2.0 scenarios (Supporting Information Figure S20b and S21b in Appendix S1). In hot irrigated regions, simulated cumulative evapotranspiration decreased (in average by −16 and −25 mm) under both warming scenarios during the crop duration (Supporting Information Figure S20b in Appendix S1), while simulated cumulative rainfall increased slightly (usually <10 mm) in more than half of the locations (Supporting Information Figure S21b in Appendix S1) due to projected increase in annual rainfall (Supporting Information Figure S3 in Appendix S1). The decrease in cumulative ET was mostly due to shorter crop duration (in average by −4.9 and −7.2 days) due to warming, as shown with significant negative relationship between growing season cumulative ET and crop duration in all hot irrigated locations (Supporting Information Figure S23 in Appendix S1). For example, cumulative ET decreased by about 2.2 mm with a shortening of the growing season by 1 day in Aswan, Egypt. Heat stress days (daily maximum air temperature >32°C; Porter & Gawith, 1999) during grain filling already occur in almost all regions, but their frequency increases under both warming scenarios, particularly in moderately hot low rainfall (in average by 1.0 and 1.6 days) and hot irrigated locations (in average by 1.8 and 2.5 days; Supporting Information Figure S22b in Appendix S1).

Simulated impacts on wheat yields for the 1.5 and 2.0 scenarios (Figure 1) are negatively correlated with baseline crop season mean temperature (Figure 2a), suggesting that cooler regions will benefit more from moderate warming. For example, most locations with crop growing season mean temperature (sowing to maturity) <15°C will have mostly positive yield changes, while for growing season mean temperature >15°C, any increase in temperature will reduce grain yields (Figure 2a) despite the growth stimulation from elevated [CO_2]. Generally, regions which produce the largest proportion of wheat globally are projected to have small positive yield changes under both scenarios, but there are exceptions such as India, which is currently the world's second largest wheat producer (Figure 2).

The projected changes in growing season climate variables have a significant impact on simulated grain yield under the two warming scenarios at most global locations. As shown in Supporting Information Table S4 in Appendix S1, a significant negative relationship between simulated grain yield and growing season mean temperature and the number of heat stress days during grain filling were found at most locations, especially for hot irrigated locations, while a significant positive relationship between simulated grain yields and growing season cumulative ET, solar radiation, and rainfall (only for rainfed locations) were found in almost all locations. For example, wheat grain yield at Griffith, Australia, was projected to decrease by 0.44 t/ha per °C increase in growing season mean temperature, and decrease by 0.067 t/ha per day increase in heat stress days, but increase by 0.008 t/ha per mm increase in growing season cumulative ET. In addition, shortening the growing season duration was also found to negatively impact simulated wheat yield significantly. For example, wheat yield was projected to decrease by 0.1 t/ha per day reduction in growing season duration, in Indore, India. Growing season rainfall also showed significant positive effects on projected grain yield in most rainfed locations (Supporting Information Table S4 in Appendix S1), however, projected growing season rainfall declined in most locations, except for small rainfall increases in a few hot irrigated locations (Supporting Information Figure S21b in Appendix S1).

When scaling up from the 60 locations, we found that wheat yields in about 80% of wheat production areas will increase under 1.5 scenario, but usually by <5% (Figure 3). Largest positive impacts under 1.5 scenario are projected for United States (6.4%), the third largest wheat producer in the world. Loss in wheat yields under the 1.5 scenario is projected mostly for Central Asia, Africa, and South America (Figure 3), regions with generally high growing season temperatures, shorter crop duration, and more heat stress days during grain filling (Supporting Information Figure S14 in Appendix S1). Further yield declines in these countries are expected with the 2.0 scenario, including in large wheat-producing countries such as India (−2.9%; Figure 3).

Analysis for the three environment types projects a larger yield increase for temperate high rainfall regions (3.2% and 5.5% under 1.5 and 2.0 scenarios, respectively) than for moderately hot low rainfall (2.1% and 2.4%) but a decline in hot irrigated regions (−0.7% and 0.02%; Supporting Information Figures S9 and S10 in Appendix S1). These positive values contrast with the negative trend found across a meta-analysis, with a large uncertainty range, with local temperature change of 1.5–2.0°C, despite positive effects from elevated [CO_2] (Challinor, Martre, et al., 2014; Challinor, Watson, et al., 2014).

Up-scaled to the globe, wheat production on current wheat-producing areas is projected to increase by 1.9% (−2.3% to 7.0%, 25th percentile to 75th percentile) under the 1.5 and by 3.3% (−2.4% to 10.5%) under the 2.0 scenario (Figure 4a and Supporting Information Figure S8a in Appendix S1). The differences in estimated ensemble median impacts between the two warming levels may be small, but significant, as indicated by a statistical test for the model ensemble median of the global impacts ($p < 0.001$). Under the Representative Concentration Pathway 8.5 (RCP8.5) for the 2050s, with a global mean temperature increase of 2.6°C above pre-industrial, global wheat production are suggested to increase by 2.7% (Asseng et al., 2018), highlighting the non-linear nature of climate change impact.

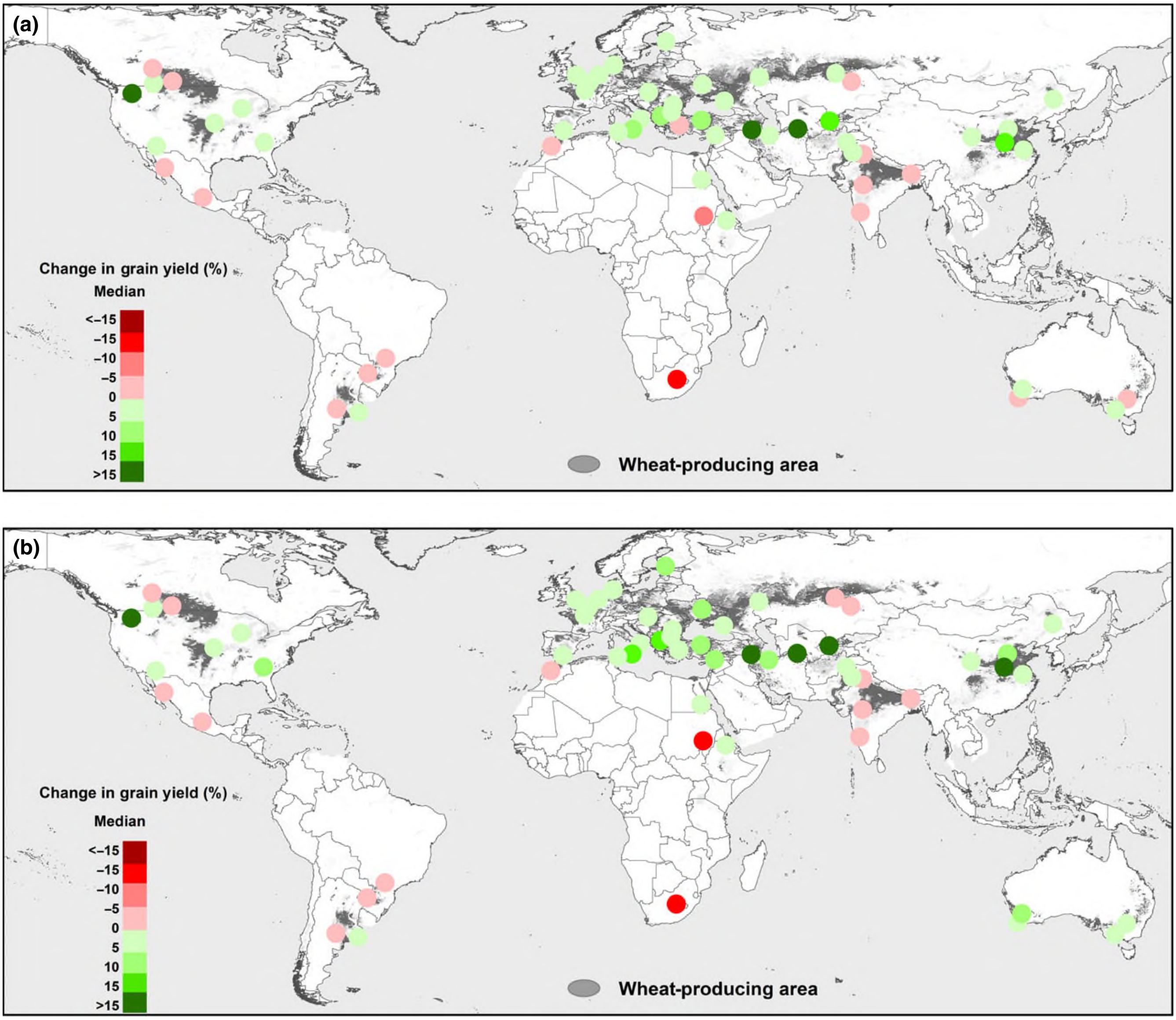


FIGURE 1 Impact of (a) 1.5 and (b) 2.0 scenarios on wheat grain yield for 60 representative global wheat-growing locations. Relative changes in grain yield were the median across 31 crop models and five GCMs, calculated with simulated 30-year mean grain yields for baseline, 1.5 and 2.0 scenarios (HAPPI), including changes in temperature, rainfall, and atmospheric [CO_2], using region-specific soils, cultivars, and crop management

When up-scaling the impact for different wheat types (Supporting Information Figure S26 in Appendix S1), the impact on global wheat production of the multi-model medians was 0.76% and 1.26% for spring wheat types (planted at 39 global locations) under 1.5 and 2.0 scenarios but 3.2% and 5.7% for winter wheat types (planted at 21 global locations), respectively.

3.2 | More variable yields in hot and dry areas

While the 30-year average yield is projected to increase under the 1.5 and 2.0 scenarios across many regions, the risk of extremely low yields may increase, especially in some of the hot–dry locations. The probability of extreme low yields (yields lower than the bottom 5 percentile of the 1981–2010 distribution) will increase significantly in more than half of the moderately hot low rainfall locations under both scenarios (Figure 5 and Supporting Information Figure S19a in Appendix S1). For the hot irrigated locations, the probability of extreme low yields will increase significantly in about half of the locations (Supporting Information Figures S13 and S19a in Appendix S1). In some hot irrigated locations, the likelihood of extreme low yields will increase by up to five times, that is from 5% under baseline to 11% and 22% under 1.5 warming and 2.0 warming scenarios, respectively, for example, in Wad Medani from Sudan. But in other hot irrigated locations (e.g., Maricopa in United States, Aswan in Egypt, and Balcarce in Argentina) and most of temperate high rainfall locations, the extreme low yield probability will decrease or remain unchanged for the two warming scenarios (Supporting Information Figures S11 and S19a in Appendix S1). The likelihood of

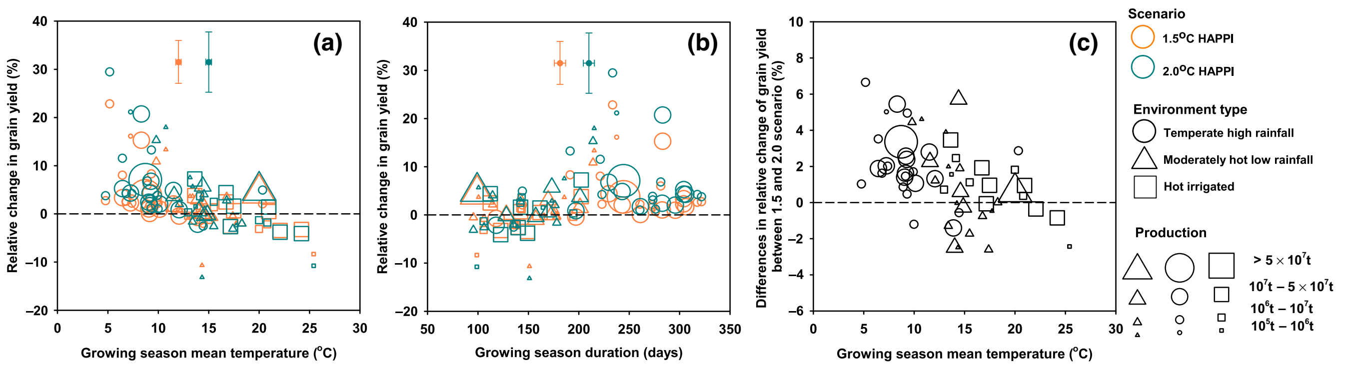


FIGURE 2 Projected Impact of the 1.5 and 2.0 scenarios on wheat grain yield and crop duration. Simulated change in grain yield vs. (a) growing season mean temperature and (b) mean growing season duration (sowing to maturity) for the 1.5 (orange) and 2.0 (dark cyan) scenarios (HAPPI). (c) Differences in relative change in grain yield between the 1.5 and 2.0 scenarios vs. growing season mean temperature for 60 representative wheat-producing global locations. Relative changes in grain yield were the median across 31 crop models and five GCMs, calculated with simulated 30-year (1981–2010) mean grain yields for baseline, the 1.5 and 2.0 scenarios (including changes in temperature, rainfall, and [CO_2]) using region-specific soils, cultivars, and crop management. The size of symbols indicates the production represented by each location (using 2014 FAO country wheat production statistics). The vertical and horizontal range crosses indicate the median 25%–75% uncertainty range of relative change in grain yields, growing season mean temperature, and crop duration across the 31 crop models and five GCMs, respectively. In (a), r^2 of linear regressions were 0.32 and 0.33 under 1.5 and 2.0 scenarios, respectively ($p < 0.001$)

extreme low yields will increase significantly from 1.5 warming to 2.0 warming scenarios only at three locations (from 11% to 22% at Wad Medani in Sudan, from 14% to 15% at Swift Current in Canada, and from 7% to 11% at Bloemfontein in South Africa) and remain to be same at all other locations.

To determine the reasons for the changes in extreme low yield probability, relationships between changes in growing season variables and changes in extreme low yield probability were quantified with linear regressions. As shown in Supporting Information Figure S24 in Appendix S1, only growing season mean temperature, maximum temperature, minimum temperature, heat stress days, and cumulative rainfall (only in rainfed locations) were found to be significantly related to changes in extreme low yield probability (all $p < 0.05$), but with relatively poor correlation (r between 0.26 and 0.61). Among these variables, growing season maximum temperature explained most of the changes in extreme low yield probability, with $r = 0.54$ and 0.61 for the 1.5 and 2.0 scenarios, respectively (Supporting Information Figure S24 in Appendix S1). The probability of extreme low yields was projected to increase by 10% and 9% per °C increase in growing season maximum temperature under 1.5 and 2.0 scenarios, respectively.

Under 1.5 warming scenario, the inter-annual variability of simulated grain yields was projected to increase significantly in only few locations (mostly in hot irrigated locations, Supporting Information Figure S19b in Appendix S1), while moderate warmings of 2.0°C above pre-industrial are projected to increase the inter-annual variability of simulated grain yields in about 50% of hot irrigated locations and parts of moderately hot low rainfall locations significantly, including Sudan, Bangladesh, Egypt, and India (Figure 6). For example, inter-annual variability of simulated grain yields is projected to increase by 23%–35% in Wad Medani from Sudan under 1.5 and 2.0 scenarios, respectively. The inter-annual variability of simulated grain yields will increase significantly from 1.5 warming to 2.0 warming scenarios at five moderately hot low rainfall locations and four hot irrigated locations and remain to be same at all other locations. For example, the inter-annual variability of simulated grain yields will increase by 20% and 27% at Bloemfontein in South Africa under 1.5 and 2.0 scenarios, respectively. No significant changes in the interannual variability of simulated grain yields were found in most of the temperate high rainfall locations under two warming scenarios (Figure 6 and Supporting Information Figure S19b in Appendix S1).

The relationship between changes in growing season variables (including growing season duration, cumulative ET, cumulative solar radiation, cumulative rainfall, mean temperature, maximum temperature, minimum temperature, and heat stress days) and changes in yield interannual variability (CV) was also quantified with linear regressions. As shown in Supporting Information Figure S25 in Appendix S1, only growing season duration, cumulative ET, and heat stress days were statistically significantly related to changes in yield interannual variability ($p < 0.05$), but with relatively poor correlation coefficients ($0.24 < r < 0.38$). Among these variables, growing season heat stress days explains most of the changes in yield interannual variability, with $r = 0.38$ and 0.34 for the 1.5 and 2.0 scenarios, respectively (Supporting Information Figure S25 in Appendix S1). Yield interannual variability was projected to increase by 2.6% and 2.0% per day increase in growing season heat stress days under the 1.5 and 2.0 scenarios, respectively.

4 | DISCUSSION

With the latest climate scenarios from the HAPPI project, we used a multi-crop and multi-climate model ensemble over a global network of sites to represent major rainfed and irrigated systems to assess global wheat production and local yield interannual variability under 1.5 and 2.0°C warming above pre-industrial, which considered changes in local temperature, rainfall, and global [CO_2]. Under the

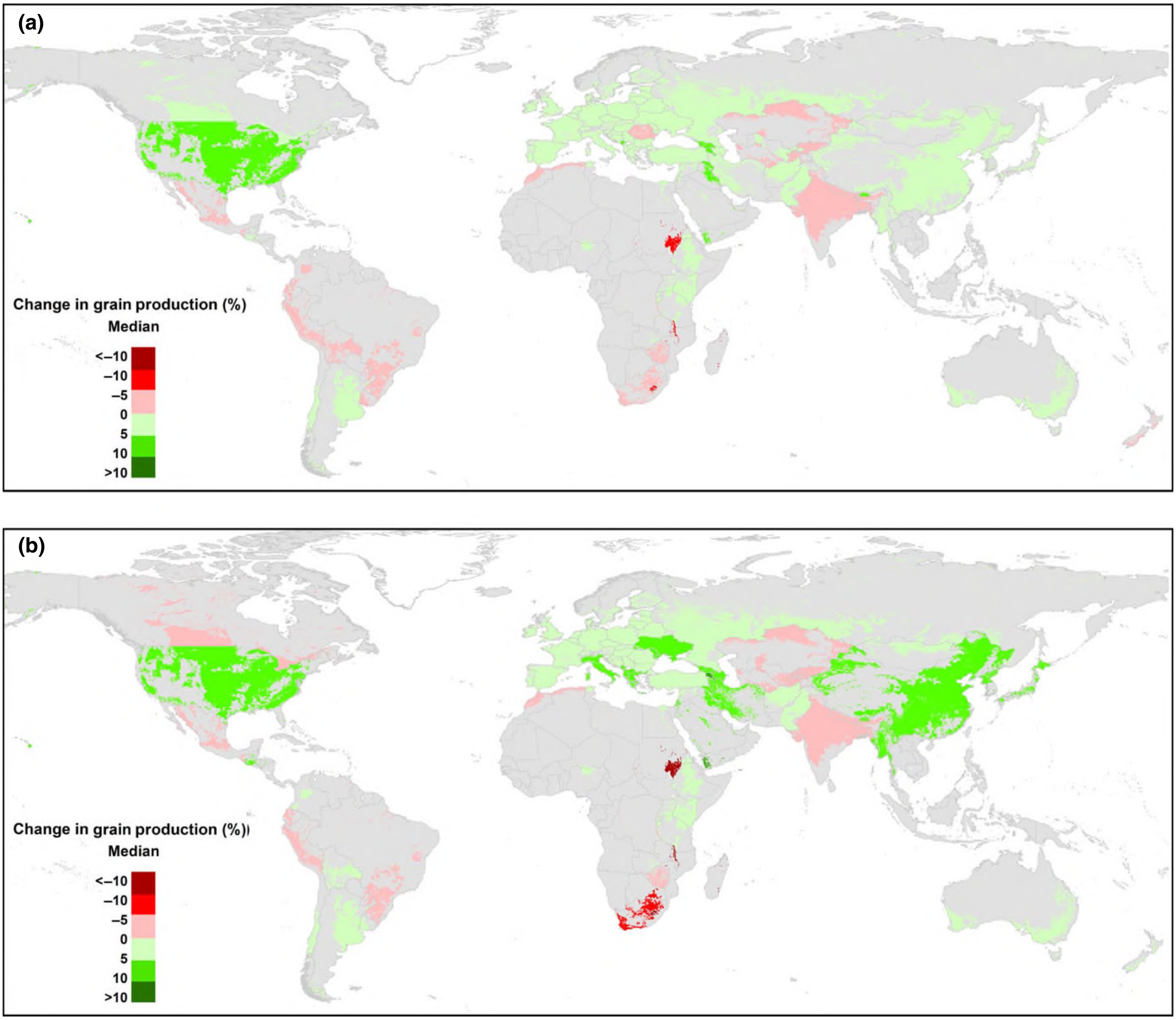


FIGURE 3 Simulated multi-model ensemble projection of global wheat grain production for wheat-growing area per country under the 1.5 and 2.0 scenarios (HAPPI). Relative climate change impacts on grain production under (a) the 1.5 and (b) 2.0 scenarios (including changes in temperature, rainfall, and [CO_2]) compared with the 1981–2010 baseline. Impacts were calculated using the average over 30 years of yields and the medians across 31 models and five GCMs, using region-specific soils, current cultivars, and crop management. Impacts from 60 global locations were aggregated to impacts on country production by weighting the irrigated, high rainfall, and low rainfall production, based on FAO wheat production statistics

two warming scenarios, climate impact on wheat yield can be largely attributed to elevated [CO_2], shorter wheat growth duration due to increasing growing season temperature and a decrease in cumulative evapotranspiration in most of the 60 locations (Supporting Information Table S4 and Figure S20–22 in Appendix S1). In addition, even with restricted warming levels, increasing weather variability also negatively impacts projected wheat production (Supporting Information Table S4 and Figure S22 in Appendix S1). However, considering the uncertainty related to [CO_2] in the 1.5 and 2.0°C scenarios (see below), the small differences in yield impact for the two scenarios do not allow concluding on the putative benefits of a limitation of global warming to 1.5°C compared with 2.0°C for global wheat yield production.

4.1 | Changes in atmospheric CO_2 concentration drive the impacts of 1.5 and 2.0°C scenarios on wheat yield

Using four independent methods (Liu et al., 2016; Zhao et al., 2017), global wheat yields had been previously projected to decline by an average of −5.0% for each increase in 1.0°C global warming, but in the absence of concomitant atmospheric [CO_2] increase. Similar findings have been reported for various typical wheat cultivation regions in Europe when applying a systematic climate sensitivity analysis (Pirttioja et al., 2015). In a sensitivity analysis with the same crop model ensemble for the same 60 representative locations, global wheat production could increase by about 15.8% when CO_2

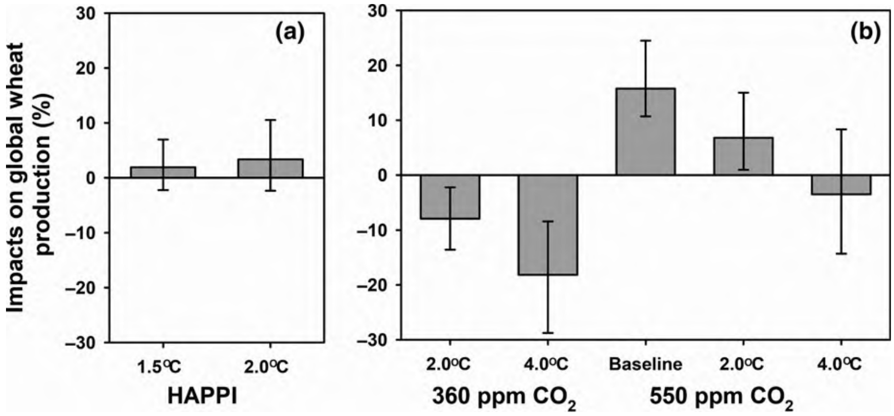
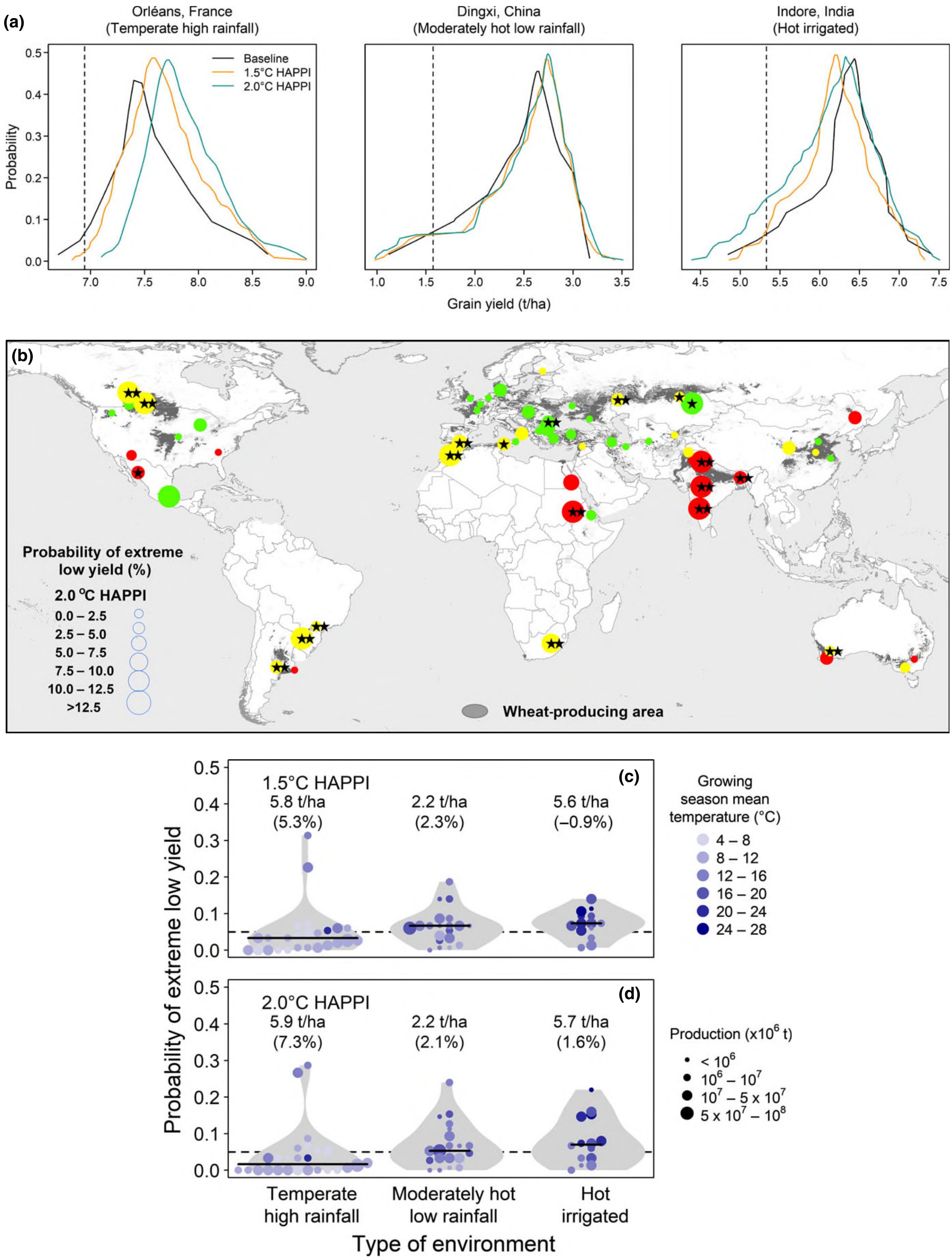


FIGURE 4 Simulated global impacts of climate change scenarios on wheat production. Relative impact on global wheat grain production for (a) 1.5 and 2.0 warming scenarios (HAPPI) with changes in temperature, rainfall, and atmospheric [CO_2]. Atmospheric [CO_2] for the 1.5 and 2.0 scenarios was 423 and 487 ppm, respectively. (b) Local temperature increase by +2°C (360 ppm CO_2 +2°C) and +4°C (360 ppm CO_2 +4°C) for the baseline period with historical [CO_2] (360 ppm) and elevated [CO_2] (550 ppm) for no temperature change (baseline), +2°C (550 ppm [CO_2] +2°C) and +4°C (550 ppm [CO_2] +4°C). Impacts were weighted by production area (based on FAO statistics). Relative change in grain yields was calculated from the mean of 30 years projected yields and the ensemble medians of 31 crop models (plus five GCMs for HAPPI scenarios) using region-specific soils, cultivars, and crop management. Error bars are the 25th and 75th percentiles across 31 crop models (plus five GCMs for HAPPI scenarios)

increased from 360 to 550 ppm. The two HAPPI scenarios include 423 and 487 ppm [CO_2], and the impacts from CO_2 fertilization under the two scenarios are a proportion of the impacts with those for 550 ppm [CO_2]. When assuming a linear response of wheat yield to elevated CO_2 (Amthor, 2001), the impacts of elevated CO_2 under 1.5 and 2.0 scenarios would be 5.2% and 10.5%, respectively, if nitrogen was not limiting. As the overall impacts of climate change under 1.5 and 2.0 scenarios were 1.9% and 3.3%, thus, we can conclude that most of the projected increases in global wheat production under the 1.5 and 2.0 scenarios can be attributed to a CO_2 fertilization effect (Figure 4b and Supporting Information Figure S8b in Appendix S1). This conclusion is consistent with field observations in a range of growing environments (Kimball, 2016; O'Leary et al., 2015) and with a rate of 0.06% yield increase per ppm [CO_2] derived from a meta-analysis of simulation results (Challinor, Martre, et al., 2014; Challinor, Watson, et al., 2014). The CO_2 fertilization effect is often found to dominate model-based projections of future global wheat productivity (Rosenzweig et al., 2014; Ruiz-Ramos et al., 2018; Wheeler & von Braun, 2013), but with substantial uncertainties and regional differences (Deryng et al., 2016; Kersebaum & Nendel, 2014; Müller et al., 2015).

The relatively low warming levels of the HAPPI scenarios (0.6 and 1.1°C above 1980–2010 global mean temperature) but high increases in [CO_2] suggest that CO_2 fertilization effects also dominate here (Kimball, 2016; O'Leary et al., 2015), but could be less, if nitrogen is limiting growth. However, the impacts here could be slightly overoptimistic with estimates of heat stress, as most of crop models do not account for well-established canopy warming under elevated CO_2 (Kimball et al., 1999; Webber et al., 2018). Also, Schleussner et al. (2018) have shown that CO_2 uncertainties at 1.5 and 2.0°C, which is not considered here, are comparable to the effect of 0.5°C warming increments. This indicated possible differences in

FIGURE 5 Projected impacts of the 1.5 and 2.0 scenarios on the probability of extreme low wheat yields. (a) Grain yield distribution at three locations representative of the three main types of environments (see below) for the 1981–2010 baseline and for the 1.5 and 2.0 scenarios (HAPPI; including changes in temperature, rainfall, and [CO_2]). The yield distribution at the 60 global sites is given in Supporting Information Figures S11–S13 in Appendix S1. The vertical dashed lines indicate the value of extreme low yields (defined as the lower 5% of the distribution) for the baseline. (b) Probability of extreme low yield (≤5% of the baseline distribution) for the 2.0 scenario at 60 representative global wheat-growing locations for clusters of temperate high rainfall or irrigated locations (green; 26 locations), moderately hot low rainfall locations (yellow; 20 locations), and hot irrigated locations (red; 14 locations). In (b), ★ and ★★ indicate the changes in extreme low yield between warming scenarios and baseline was significant at $p < 0.05$ and $p < 0.01$, respectively. (c) and (d) Probability of extreme low yields for each type of environment for the 1.5 and 2.0 scenarios, respectively. Horizontal dashed lines are the probability of extreme low yield for the baseline (defined as the bottom 5% of the baseline distribution). Horizontal thick solid lines are the median probability of extreme low yield. The circles are the 60 global locations shown in (c and d), their size indicates the production represented at each location (using FAO country wheat production statistics) and their color indicated the growing season mean temperature at each location for the 1.5 and 2.0 scenarios. Within each environment type, the circles have been jiggled along the horizontal axis to make it easier to see locations with similar probability values, which means that the horizontal positions of circles in each environment type were used to avoid the overlapping of circles and have no meaning. The shaded areas show the distribution of the data. Numbers above each box are the mean yields for the baseline period and in parenthesis the average yield impacts of the 1.5 and 2.0 scenarios compared with the 1981–2010 baseline yield. See Supporting Information Material and Methods in Appendix S1 for more details on clustering of wheat-growing environments



(a)
Orléans, France
(Temperate high rainfall)
Dingxi, China
(Moderately hot low rainfall)
Indore, India
(Hot irrigated)
Baseline
1.5°C HAPPI
2.0°C HAPPI
Probability
Grain yield (t/ha)
(b)
Probability of extreme low yield (%)
2.0 °C HAPPI
0.0 – 2.5
2.5 – 5.0
5.0 – 7.5
7.5 – 10.0
10.0 – 12.5
>12.5
Wheat-producing area
(c)
1.5°C HAPPI
5.8 t/ha
(5.3%)
2.2 t/ha
(2.3%)
5.6 t/ha
(–0.9%)
(d)
2.0°C HAPPI
5.9 t/ha
(7.3%)
2.2 t/ha
(2.1%)
5.7 t/ha
(1.6%)
Probability of extreme low yield
Growing season mean temperature (°C)
4 – 8
8 – 12
12 – 16
16 – 20
20 – 24
24 – 28
Production (x10^6 t)
< 10^6
10^6 – 10^7
10^7 – 5 x 10^7
5 x 10^7 – 10^8
Temperate high rainfall
Moderately hot low rainfall
Hot irrigated
Type of environment

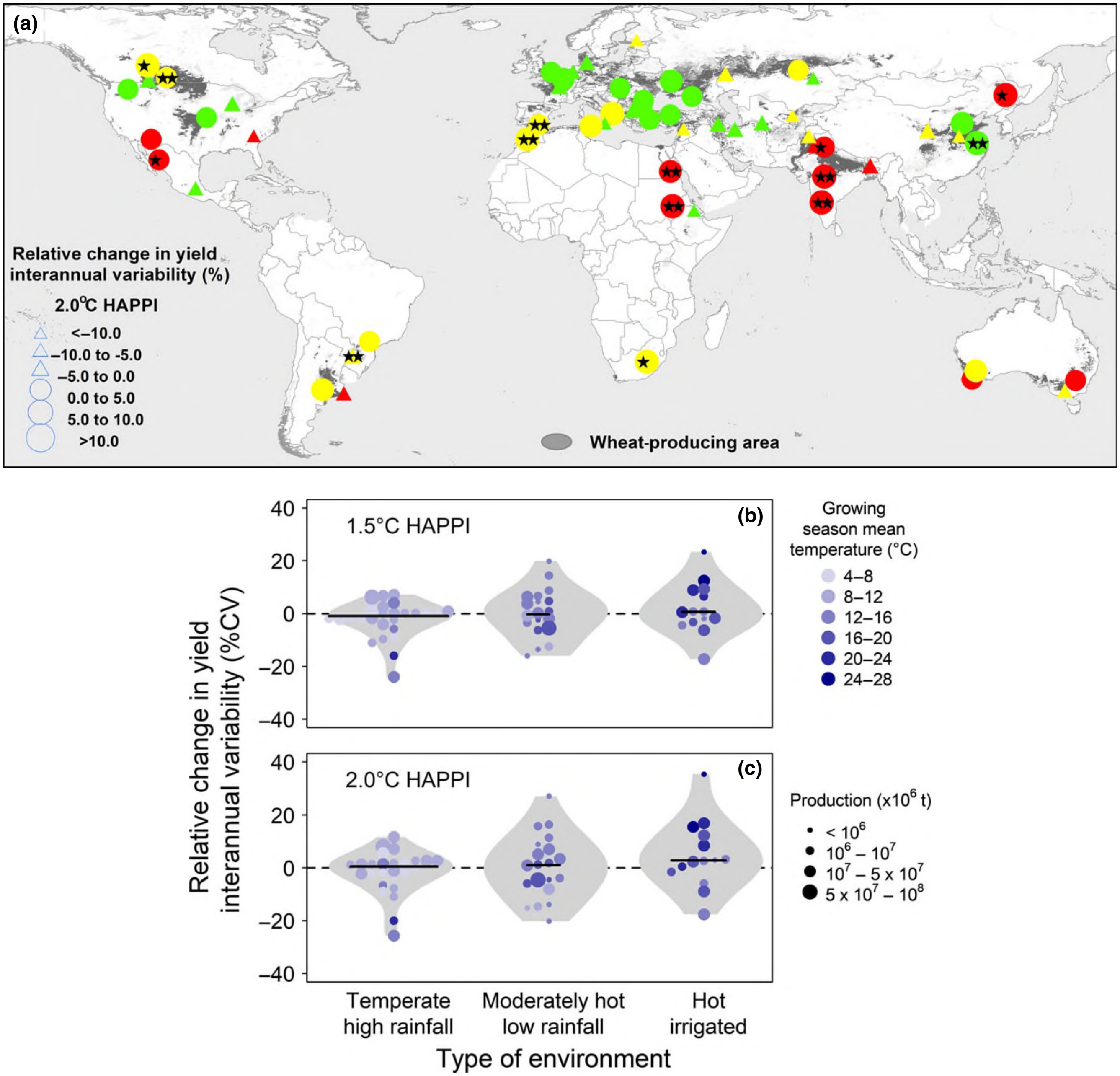


FIGURE 6 Projected impacts of 1.5 and 2.0 scenarios on wheat yield interannual variability. (a) Relative climate change impacts for the 2.0°C warming scenarios (HAPPI) compared with the 1981–2010 baseline on interannual yield variability (coefficient of variation) at 60 representative global wheat-growing locations for clusters of temperate high rainfall or irrigated locations (green; 26 locations), moderately hot low rainfall locations (yellow; 20 locations), and hot irrigated locations (red; 14 locations). In (a), ★ and ★★ indicate the changes in interannual yield variability between warming scenarios and baseline was significant at $p < 0.05$ and $p < 0.01$, respectively. The circles and triangles showed increased and decreased interannual variability, respectively. (b) and (c) Relative climate change impacts for the 1.5 and 2.0 scenarios compared with the 1981–2010 baseline on interannual yield variability (coefficient of variation) in temperate high rainfall or irrigated (26 locations), moderately hot low rainfall (20 locations), and hot irrigated (14 locations) locations. Horizontal thick solid lines are the median change in interannual yield variability for each environment type. The circles are the 60 global locations shown in (a), their size indicates the production represented at each location (using FAO country wheat production statistics) and their color indicated the growing season mean temperature at each location under the 1.5 and 2.0 scenarios. Within each environment type, the circles have been jiggled along the horizontal axis to make it easier to see locations with similar probability values, which means that the horizontal positions of circles in each environment type were used to avoid the overlapping of circles, and have no meaning. The shaded areas show the distribution of the data

impacts on wheat production in the simulated 1.5 or 2.0°C worlds (Seneviratne et al., 2018), as a transient 1.5 or 2.0°C world may see higher CO_2 concentrations because of the lagged response of the climate system (peak warming around 10 years after zero CO_2 emissions are reached) and differences in aerosol loadings (Wang, Lin, et al., 2017). Ruane, Phillips, et al. (2018) also noted uncertainties related to CO_2 impacts in the 1.5 and 2.0°C worlds, as well as peculiarities in the definition of CO_2 concentrations in HAPPI. CO_2 is also identified as the primary cause of increases between 1.5 and 2.0°C worlds in Rosenzweig et al. (2018). Our study focused on stabilized 1.5 and 2.0°C worlds rather than the transient pathways that get us there, which will include gradually increasing CO_2 concentrations even as some scenarios include an overshoot in global mean temperatures. Elevated CO_2 concentrations are expected to have a particularly strong initial effect, although the benefits will saturate as CO_2 concentrations increase in RCP8.5 or other higher emission pathways.

4.2 | The interannual yield variability and the risk of extreme low yields will increase in a 1.5 and 2.0°C world

Unlike the simulated grain yield impacts, aggregating the simulated yield variability from representative locations to regions or globally with a multi-model ensemble approach has not been tested with observed data. Different aggregation method may result in different characteristics of climate-forced crop yield variance at different spatial scales. Therefore, the simulated yield variability at local scale was not aggregated to region or global scale.

The fraction of yield interannual variability accounted for by weather-forced yield variability may vary substantially depending on the region (Ray, Gerber, & Macdonald, 2015; Ruane et al., 2016); therefore, comparing simulated and observed yield interannual yield variability is critical to analyze changes in yield variability. However, there are no time series data which would allow a scientific model-observation comparison for all the 60 global locations and even for regions where historical yield records are available, they usually do not allow an evaluation of model performance due to missing information on sowing date, cultivar use, crop management of fertilizer N and irrigation, soil characteristics, initial soil conditions, and bias in the reported yields (Guarin, Bliznyuk, Martre, & Asseng, 2018). While for these reasons, it is not possible for us to project meaningfully how interannual yield variability will change at regional or global scale, our study supplies important information on how the additional half degree of warming will impact on yield variability, considering the parallel changes in mean yield levels associated with the combined warming and elevated CO_2 levels. This information is urgently required by national governments and international policy makers in assessing the relative risks and costs of mitigating to 1.5°C warming vs. 2.0°C warming.

Here, we compared our simulated interannual yield variability for the 60 global locations with the estimated global interannual yield variability from statistic yield data in Ray et al. (2015) (Supporting Information Figure S27 in Appendix S1) and we found that the spatial patterns of interannual yield variability were similar for the two studies. For example, both studies showed interannual yield variability and estimated climate-induced yield variability were high at locations in southern Russia, Spain, and Kazakhstan, and were small at locations in western Europe, India, and some locations in China. Climate-driven yield variability is generally higher in more intensive cropping systems, and many regions around the world now actively pursue intensification of currently low-yielding smallholder cropping systems. Therefore, our current projections of estimates of climate-driven yield variability under the two warming scenarios may be conservative, if some regions will experience intensification and climate change simultaneously.

Extreme low-yielding seasons can impact the livelihood of many farmers (Morton, 2007), but also disturb global markets (e.g., Russian heat wave in 2010; Welton, 2011), or even destabilize entire regions of the world (e.g., Arab Spring in 2011; Gardner et al., 2015). Climate scenarios used for this study included monthly mean changes and shifts in the distribution of daily events within a season but did not include changes in interannual variability; these changes are therefore largely the result of warmer average conditions pushing wheat closer to damaging biophysical thresholds. A recent study based on the HAPPI 1.5 and 2.0 scenarios also identified an increased frequency of interannual drought conditions in regions with declining or constant total precipitations (Ruane, Phillips, et al., 2018), although skewness toward drought in the interannual distribution was small and highly geographically variable.

Despite mostly positive impacts on average yields, projections suggest that the frequency of extreme low yields will increase under both scenarios for some of the hot growing locations (for both low rainfall and irrigated sites), including India, that currently supply more than 14% of global wheat (FAO, 2014). Similarly, an increase in the frequency of crop failures has been shown with 1.5°C global warming above the pre-industrial period for maize, millet, and sorghum in West Africa (Parkes, Defrance, Sultan, Ciais, & Wang, 2018). On the other hand, Faye et al. (2018) did not detect a change in yield variability for the same three crops in West African between the 1.5 and 2.0°C warming scenarios using HAPPI climate data. In our study, the change in climate extremes occurs due to projected shifts in mean temperatures (which bring wheat cropping systems closer to heat stress thresholds) as well as shifts in the distribution of daily temperatures, which can increase or decrease the frequency of future heat waves. Coupled changes in projected precipitation may also exacerbate drought and heat stress yield damage.

4.3 | Impact of 1.5 and 2.0°C scenarios on wheat production and food security

Wheat yields have been stagnating in many agricultural regions (Brisson et al., 2010; Lin & Huybers, 2012; Ray, Ramankutty, Mueller, West, & Foley, 2012). Shifting agriculture polewards has been considered elsewhere, but might not be always possible or feasible for adapting to increasing temperature due to land use and land suitability constraints. Measures such as change in sowing date and irrigation management, improved heat- and drought-resistant cultivars, reduced trade barriers, and increased storage capacity (Schewe, Otto, & Frieler, 2017) will be necessary to adapt to changes in temperature and precipitation for improving food security. However, since the largest estimated yield losses and increased probability of extreme low yields occur in tropical areas (that is, in hot environment with low-temperature seasonality) and under irrigated systems, the above-mentioned measures would probably not be sufficient. Therefore, it will be challenging to find effective incremental solutions and might need to consider transformation of the agricultural systems in some regions (Asseng et al., 2013; Challinor, Martre, et al., 2014; Challinor, Watson, et al., 2014). In this study, the extreme low yield probability and inter-annual yield variability of simulated yield were projected to increase significantly in parts of hot irrigated locations and moderately hot low rainfall locations, and further increase could be expected from 1.5 scenario to 2.0 scenario, especially for inter-annual yield variability. This indicated that more efforts will be needed for adaptation for food security in these locations.

4.4 | Uncertainties

Here, we up-scaled the climate warming impacts from 60 representative global locations to country and global scales, following the approach by Asseng et al. (2015). The 60 locations were selected with local experts to be representative of each region, and high-quality model inputs for each location were obtained (Supporting Information Table S1 in Appendix S1). Liu et al. (2016) and Zhao et al. (2017) recently showed that up-scaled simulations for representative locations, as suggested by van Bussel et al. (2015), have similar temperature impacts to 0.5^{o} x 0.5^{o} global grid simulations or statistical approaches. The projected impact for spring wheat reported here is similar to that reported by Iizumi et al. (2017), who reported global spring wheat production to increase by 1.43%–1.60% and 1.43%–1.61% under 1.5 and 2.0 scenarios using a global gridded simulation approach under different Shared Socioeconomic Pathways.

To analyze risks of the extreme low yields, we used a well-tested multi-model ensemble (Asseng et al., 2015, 2013, 2018; Ruane et al., 2016; Wallach et al., 2018) instead of individual wheat models, as the model ensemble has shown to reproduce observed yields and observed yield interannual variability. In Asseng et al. (2015), the multi-model ensemble median reproduced observed wheat yield under different warming treatments, with wheat-growing season temperature ranging from 15 to 32°C, including extreme heat conditions. Asseng et al. (2018) recently demonstrated that a multi-model ensemble could also simulate the impact of heat shocks and extreme drought on wheat yield.

Global warming will also affect weeds, pests, and diseases, which are not considered in our analysis, but could significantly impact crop production (Jones et al., 2017; Juroszek & von Tiedemann, 2013; Stratonovitch, Storkey, & Semenov, 2012). Possible agricultural land use changes were not considered here, which could increase production (Nelson et al., 2014), but also accelerate further greenhouse gas emissions (Porter, Howden, & Smith, 2017), adding to the uncertainty of future impact projections.

Projections in this study were designed to be consistent with the AgMIP Coordinated Global and Regional Assessments (CGRA) of 1.5 and 2.0°C warming and therefore add additional detail and context to linked analysis of climate, crop, and economic implications for agriculture across scales (Ruane, Antle, et al., 2018). Here, the mean impact of 1.5 and 2.0°C warming above preindustrial on global wheat production is projected to be small but positive. In addition, the significant differences between estimated ensemble median impacts from the two warming scenarios indicate a potential yield benefit from higher global warming level. However, in our study, the uneven distribution of impacts across regions, including projected average yield reductions in locations with rapid population growth (e.g., India), the increased probability of extreme low yields and a higher inter-annual yield variability, will be more challenging for food security and markets in a 2.0°C world than in 1.5°C world, particularly in hot growing locations.

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CONFLICT OF INTERESTS

The authors declare no competing interests.

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