Crop production losses associated with anthropogenic climate change for 1981–2010 compared with preindustrial levels

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The accumulated evidence indicates that agricultural production is being affected by climate change. However, most of the available evidence at a global scale is based on statistical regressions. Corroboration using independent methods, specifically process-based modelling, is important for improving our confidence in the evidence. Here, we estimate the impacts of climate change on the global average yields of maize, rice, wheat and soybeans for 1981–2010, relative to the preindustrial climate. We use the results of factual and non-warming counterfactual climate simulations performed with an atmospheric general circulation model that do and do not include anthropogenic forcings to climate systems, respectively, as inputs into a global gridded crop model. The results of a 100-member ensemble climate and crop simulation suggest that climate change has decreased the global mean yields of maize, wheat and soybeans by 4.1, 1.8 and 4.5%, respectively, relative to the counterfactual simulation (preindustrial climate), even when carbon dioxide (CO2) fertilization and agronomic adjustments are considered. For rice, no significant impacts (−1.8%) are detected. The uncertainties in estimated yield impacts represented by the 90% probability interval that are derived from the ensemble members are −8.5 to +0.5% for maize, −8.4 to −0.5% for soybeans, −9.6 to +12.4% for rice and −7.5 to +4.3% for wheat. Based on the yield impacts, the estimates of average annual production losses throughout the world for the most recent years of the study (2005–2009) account for 22.3 billion USD (B$) for maize, 6.5 B$ for soybeans, 0.8 B$ for rice and 13.6 B$ for wheat. Our assessment confirms that climate change has modulated recent yields and led to production losses, and our adaptations to date have not been sufficient to offset the negative impacts of climate change, particularly at lower latitudes.

KEYWORDS
climate change, crop yields, detection and attribution, ensemble simulations, losses and damages, production losses

1 | INTRODUCTION

Crop production is being affected by climate change (Cramer et al., 2014). When carbon dioxide (CO2) fertilization is considered, the global mean maize and wheat yields are estimated to have declined by 3.8 and 2.5% from 1980 to 2008, respectively, relative to a non-warming counterfactual condition (Lobell and Field, 2007; Lobell et al., 2011). The estimated impacts for rice and soybeans are positive but insignificant (+2.9 and +1.3%, respectively). European
wheat yields are estimated to have declined by 2.5% from 1989 to 2009 (Moore and Lobell, 2015). These findings are based on statistical regressions. Statistical approaches are useful; however, independent methods, such as process-based crop modelling and field experiments, are required to improve our confidence in these results (Sacks and Kucharik, 2011; Xiong et al., 2014). However, estimates of the impacts from historical climate change on global yields have not been presented because data on the agronomic technologies and management practices, which are essential model inputs when simulating historical yields, are not available. To overcome this limitation, researchers have proposed parameterizations to capture the changes in technology and management that occur in response to socio-economic and climate conditions (Challinor et al., 2010; Deryng et al., 2011; Waha et al., 2012; Iizumi et al., 2017b). A global gridded crop model (the Crop Yield Growth Model with Assumptions on climate and socioeconomics, CYGMA; Iizumi et al., 2017b) links agricultural research and development (R&D) expenditures to farmer access to high-yield technologies, which enables the model to simulate historical yield trends.

In addition, climate databases that can be applied for the detection and attribution of historical climate impacts on human and natural systems have recently become available. Demonstrating that a system affected by climate has changed statistically compared to its internal variability and evaluating the relative contributions of causal factors to individual changes are key components of detection and attribution (Hegerl et al., 2010; Cramer et al., 2014). The Database for Policy Decision Making for Future Climate Change (d4PDF; Shiogama et al., 2016; Imada et al., 2017; Mizuta et al., 2017) is one such database. It consists of atmospheric general circulation model (AGCM) outputs from 1951 to 2010 as forced by the observed sea surface temperatures (SSTs) and sea ice, as well as the concentrations of greenhouse gases (GHGs), ozone, anthropogenic aerosols, and volcanic sulphate aerosols (i.e., historical or factual climate simulations). Counterfactual or non-warming climate simulations forced by detrended SSTs and sea ice, the concentrations of GHGs and anthropogenic and volcanic aerosols in 1850, and the concentrations of ozone in 1961 (which represent the preindustrial climate) are also available in the database. The terms “factual” and “counterfactual” are based on earlier work in the field on detection and attribution (Lobell et al., 2011; Rosenzweig and Neofotis, 2013; Shiogama et al., 2014). One hundred ensemble members are available for both types of simulations. By using the database, we can quantify the likelihood of systematic responses in the atmosphere and in crop yields to anthropogenic forcings relative to their internal variability.

Here, we estimate the impacts of climate change on the average yields of major crops from 1981 to 2010 using bias-corrected factual and non-warming climate simulations and a global gridded crop model. The estimated yield impacts were further converted into economic production losses. Technological improvements and agronomic adjustments (changes in the sowing dates and crop thermal requirements) are considered in this study. Uncertainties in the estimated yield impacts associated with CO2 fertilization were also taken into account by simulating the yields under historical climate conditions with and without CO2 fertilization, as it is a known source of uncertainty when quantifying the yield impacts (e.g., Deryng et al., 2014). Our assessment offers estimates of the impacts that climate change has had on yields to date, based on the process-based modelling of the climate and cropping systems.

2 | DATA AND METHODS

2.1 | Factual and counterfactual ensemble climate simulation data

An unprecedentedly large, long-term ensemble of climate simulations extending from 1950 to 2010 with and without historical trends in external forcing as generated using the Meteorological Research Institute AGCM, version 3.2 (MRI-AGCM3.2; Mizuta et al., 2012) with a grid interval of 60 km has recently become publicly available. The factual simulation represents historical climate conditions that are influenced by both human activities and natural forcings, such as major volcanic eruptions. The counterfactual simulation represents a preindustrial climate that lacks appreciable human influences on the global climate. Each simulation type includes 100 ensemble members associated with small perturbations in SSTs that represent observational uncertainties. Additional details on the setup of the AGCM are available in Shiogama et al. (2016), Imada et al. (2017) and Mizuta et al. (2017).

The climatic variables used in this study include the daily mean, maximum and minimum 2-m air temperatures, precipitation, total cloud cover, relative humidity and 10-m wind speed. The wind speed data were corrected to be equal to those at the 2-m level, assuming logarithmic profiles. The total cloud cover was translated into a downward shortwave radiation flux using empirical relationships to fulfil the input requirements of the crop model. The relationships were specified as a regression line with total cloud cover as the explanatory variable and downward shortwave radiation as the explained variable for each location and each day of the year using the Japanese 55-year reanalysis data for the
1958–2014 period (Kobayashi et al., 2015; Harada et al., 2016).

2.2 Bias correction of AGCM data

The raw daily outputs from the AGCM were interpolated onto the 0.5°-resolution regular grid coordinate system using the inverse distance weighted average algorithm. The errors introduced by the interpolation are thought to be small because the resolution of the AGCM is close to 0.5°. The cumulative distribution function-based downscaling method (CDFDM; Iizumi et al., 2010, 2011, 2012, 2017a) was then applied to each of the climatic variables mentioned above. The empirically calculated shortwave radiation flux data were bias-corrected, instead of using the total cloud cover data.

The CDFDM algorithm is a nonparametric bias-correction method that adjusts the form and location of an empirical cumulative distribution obtained from daily data simulated by a climate model to be similar to that of the reference data. Daily data for the 1961–2000 period, which were derived from the latest global retrospective meteorological forcing data set S14FD (Iizumi et al., 2017a), were used as the reference data. Information on the errors associated with the AGCM was derived using a single member of the factual simulations (labelled “HPB_m001” in the d4PDF database), and the same error information was applied to the other ensemble members of the factual and counterfactual simulations. This assumption is reasonable because the same AGCM was used for all of the climate simulations; hence, the systematic component of the AGCM errors is thought to be identical across the ensemble members and simulation types.

For the bias correction, we used two 40-year windows (1951–1990 and 1971–2010) for consistency with the length of the reference period. During the period in which the two time windows overlapped (i.e., 1971–1990), the bias-corrected data derived from the latter time window were used for analysis. The bias correction was conducted for each grid cell, season (May–October and November–April) and climatic variable. Given the substantial computational costs of bias correction, we used the relatively simple algorithm, although more sophisticated algorithms (e.g., Cannon, 2016) are available.

2.3 Global gridded crop model

The CYGMA global gridded crop model (Iizumi et al., 2017b) was used. The model operates at 0.5° and has a daily time step. Yields under rainfed and irrigated conditions are simulated separately and then combined when calculating the average yield over a given spatial domain, such as a country.

In the model, crop development is modelled as a fraction of the accumulated growing degree days relative to the crop thermal requirements. Only spring wheat is considered, because the vernalization process is not currently incorporated into the model. Leaf growth and senescence are calculated according to the fraction of the growing season using the prescribed shape of the leaf area index curve. The yields are computed from the photosynthetically active radiation intercepted by the crop canopy, the radiation-use efficiency (RUE), the effects of CO2 fertilization on the RUE and the fraction of total biomass increments allocated to the harvestable component. The soil water balance sub-model, which is coupled with the snow cover sub-model, is used to calculate the actual evapotranspiration. Five different stress types, namely nitrogen (N) deficits, heat, cold, water deficits and water excesses are considered, and the most dominant stress type for a day decreases the daily potential increment of the leaf area and yield. The growth and yield of soybeans in the model are less sensitive to N deficit stress than are the other crops considered here because the soybean is a legume. All of the stress types except N deficits are functions of daily weather, and the tolerance of each crop to these stresses increases as the knowledge stock increases. The knowledge stock is an economic indicator that is calculated as the sum of the annual agricultural R&D expenditures for each country since the year 1961 with a certain obsolescence rate, and it represents the average level of agronomic technology and management among farmers in a given country.

The N application rates in the model increase and level off according to the changes in a country’s annual per capita gross domestic product (GDP) and per capita agricultural area. The sowing dates in the model are updated annually in response to changes in the temperature and moisture regimes. The crop thermal requirements are also updated every year based on long-term mean temperature conditions, which represent the use of longer-season varieties to prevent shortened crop durations and associated yield losses. More details on the modelling and its in-depth validation are available in Iizumi et al. (2017b).

2.4 Crop model simulations

Three types of crop simulations are conducted (Table 1). These simulation types consist of the following: (a) factual with CO2 fertilization run, (b) factual without CO2 fertilization run and (c) counterfactual run. All of the simulation types used the same inputs for N application rates, agricultural R&D expenditures and irrigation intensities, and they commonly covered the 1961–2010 period, although the data for 1981–2010 were analysed to estimate the recent yield impacts. The plant-extractable water-holding capacity of the soil (Dunne and Willmott, 1996) was a common input across the simulation types as well. The grid-cell amount of crop-specific N application rates was updated annually according to the reported per capita GDP (World Development Indicators) and per capita agricultural area (Food and Agriculture Organization of the United Nations (FAO) statistical database), in accordance with Iizumi et al. (2017b). The geographical distributions of the harvested area (irrigated plus
rainfed areas) for the crops were obtained from the global data set on monthly irrigated and rainfed crop areas around the year 2000 (Portmann et al., 2010). The irrigation intensity (the ratio of the irrigated area to the harvested area) changed annually according to the global historical irrigation data set (Siebert et al., 2015), under the assumption that annual growth rates in irrigation-equipped areas are the same across the four crops. This assumption may be unrealistic for particular crop-region combinations; however, crop-specific information is not available. Agronomic adjustments, such as shifts in sowing dates and switching to different cultivars with larger thermal requirements than before, were considered in the three simulation types, although no distinct adjustment occurred under the counterfactual non-warming condition.

In the factual crop simulations, annual yields with and without CO2 fertilization were computed separately to account for the uncertainties in the estimated yield impacts associated with CO2 fertilization. The global annual mean CO2 concentration increased from 317 ppm in 1961 to 389 ppm in 2010, which is consistent with the observations (Keeling et al., 2009), when CO2 fertilization was included. This concentration was fixed at the level from 1850 (287 ppm; IPCC, 2013) throughout the crop simulations when computing yields without CO2 fertilization. For both of the factual crop simulations, the bias-corrected historical climate simulation data were used as the weather inputs. In the counterfactual crop simulation, the CO2 concentration was fixed at 287 ppm, and the bias-corrected non-warming climate simulation data that represent preindustrial climate conditions were used. For all of the simulation types, a 30-year ((1951–1960)×3) soil moisture spinup was performed before individual simulations were conducted. The initial soil moisture condition thus varies by simulation type and ensemble member. The three simulation types were performed 100 times using individual members of the historical and non-warming climate simulations.

2.5 Spatial aggregation

The simulated grid-cell yields under irrigated and rainfed conditions were aggregated to country and global mean yields. The same procedure was used for all of the crop simulation types. We first averaged the grid-cell yields obtained for irrigated conditions and those obtained for rainfed condition using the annual extent of irrigated and rainfed areas as the weights. The calculated grid-cell mean yields over the irrigated and rainfed areas were then averaged using the grid-cell harvested area (the irrigated area plus the rainfed area) as the weights to obtain the mean country yields. Finally, the global mean yields were calculated from the mean country yields using the annual harvested area data in each country, as obtained from the FAO statistical database, as the weights. The modelled cropping seasons in the Southern Hemisphere extended over two consecutive years, as observed; therefore, the country mean yields were lacking for the first and last years of the crop simulations in that hemisphere. The global mean yields were computed only when the country yields were available for both hemispheres.

2.6 Yield impacts and statistical tests

Given the simulation design, we obtained three different simulated yields, $Y_{fw,i}$, $Y_{fo,i}$, and $Y_{co,i}$. Here, the suffix $i$ indicates the ensemble member; $Y_{fw}$ and $Y_{fo}$ represent the average yields in 1981–2010 under historical climate conditions with and without CO2 fertilization, respectively (ton/ha); and $Y_{co}$ represents the average yields within the same period under non-warming climate conditions (i.e., no CO2 fertilization occurs) (ton/ha). For all of the spatial scales (grid-cell, country or global levels), the yield impact with CO2 fertilization $\Delta Y_w$ (% relative to yield in a non-warming condition) was computed as follows:

$$\Delta Y_w = \frac{(Y_{fw,i} - Y_{co,i})}{Y_{co,j}} \times 100,$$

where $i$ and $j$ indicate a single member that was randomly sampled from the 100 ensemble members. The frequency distribution of the yield impact was constructed from 10,000 bootstrap replicates of $Y_{fw}$ and $Y_{co}$ obtained through resampling with replacement from the 100 ensemble members. Using these large ensembles allowed us to provide yield impact estimates in a probabilistic manner, and the use of the bootstrap resampling technique further improves the quantification of uncertainties in the estimated yield impacts that are due to internal variability. The distribution of the yield impacts without CO2 fertilization was obtained in the same manner using $Y_{fo}$ instead of $Y_{fw}$. Their mixture distribution for the yield impact ($\Delta Y$) was then generated with even weights. The weights for the individual distributions

| Experiment | Climate | CO2 fertilization | Technology and management | Period |
|------------|---------|------------------|---------------------------|--------|
| Factual run with CO2 fertilization ($Y_{fw}$) | Bias-corrected historical climate simulation data (100 ensemble members) | Considered. CO2 concentrations increased from 317 ppm in 1961 to 389 ppm in 2010. | Nitrogen application rates and the use of improved technology and management practices changed in response to per capita GDP, per capita agricultural area and with agricultural R&D expenditures, following Iizumi et al. (2017b). Sowing dates and crop thermal requirements changed according to long-term mean climate conditions. | 1961–2010 |
| Factual run without CO2 fertilization ($Y_{fo}$) | Bias-corrected non-warming climate simulation data (100 ensemble members) | Not considered. CO2 concentrations were fixed at 287 ppm, that is, the level for the year 1850. | | |
| Counterfactual run ($Y_{co}$) | Bias-corrected non-warming climate simulation data (100 ensemble members) | | | |

**TABLE 1** Summary of the crop model simulations
may differ; however, no information is available. The null hypothesis that the yield impact is zero \((\Delta Y = 0)\) was tested using these distributions. The significance level was set to 10%.

### 2.7 Production losses

The yield impacts estimated above were converted into economic production losses as follows:

\[
L = \frac{1}{5} \sum_{t=2005}^{2009} \sum_{c=1}^{C} \Delta Y_{c,t} / 100 \cdot Y_{c,t} \cdot A_{c,t} \cdot P_{c,t},
\]

where the suffixes \(c\) and \(t\) indicate the country and year, respectively; \(L\) is the average annual production loss at the global level (USD/year); \(\Delta Y\) is the estimated change in the country mean yield associated with climate change (%); \(Y\) is the country mean yield (ton/ha); \(A\) is the country’s harvested area (ha); and \(P\) is the country’s producer price (USD/ton). The data on the country’s yield, harvested area and producer price were obtained from the FAO statistical database. Consumer price data are also available. However, because the consumer prices were more variable than the producer prices, we used the producer price to avoid influencing the consumer prices due to compounding factors, such as oil prices, stock levels and others.

### 3 RESULTS

#### 3.1 Crop model performance in reproducing yield trends

The results of the crop model when the bias-corrected historical climate simulation data were used as inputs are shown in Figure 1. The model effectively captures the reported global mean yields over the last half century; the correlations between the simulated ensemble mean yields and FAO data ranged from 0.932 (soybean) to 0.981 (wheat) \((p < .001\) for the four crops) (Figure 1). The calculated root mean square
errors range from 0.20 ton/ha (or 11%) for soybeans to 0.82 ton/ha (or 26%) for rice, showing that the model has considerable skill in simulating yield trends. However, some differences were found. Most prominently, the simulated growth in global mean rice yields is more rapid than the actual growth. Possible reasons for the discrepancies are discussed below.

3.2 Estimated yield impacts: Geographical patterns

The impact on yields, as measured in terms of the differences in the average yield for 1981–2010 between the historical and non-warming conditions, showed a distinct geographical pattern. Yield increases were obtained at the mid and high latitudes, and yield losses were obtained at the low latitudes (Figures 2 and 3). This pattern was observed for all of the crops, and, as expected, it resembled the projected yield change under low-emissions scenarios (e.g., Müller et al., 2015).

The simulated negative and positive impacts on maize were both large in absolute terms, whereas those for rice were small. The impacts on wheat and soybeans fell between those of maize and rice. The impacts on maize and soybeans in many of the major producers (Brazil, Mexico and France) were significant (Figure 3); the United States, China and Argentina were important exceptions (Figure S2, Supporting information; two-tailed tests with a significance level of 10% were performed by bootstrap resampling over the ensemble members). The impacts on rice were insignificant in most of the producing areas. Significant impacts on wheat yields

**FIGURE 2** Estimated impacts of climate change on average yields for 1981–2010. Positive values indicate that climate change has increased the yields, and negative values indicate that climate change has decreased the yields relative to what would have occurred without climate change. The estimated yield impacts with and without CO$_2$ fertilization are evenly mixed to account for the uncertainty of CO$_2$ fertilization. The statistical significance of the yield impacts is shown in Figure 3.

**FIGURE 3** The statistical significances of the yield impacts estimated by the bootstrap resampling of the ensemble members. The estimated yield impacts with and without CO$_2$ fertilization are evenly mixed to account for the uncertainty of CO$_2$ fertilization. Two-tailed tests with a significance level of 10% are used.
appeared for some of the major producers (positive impacts were obtained for France and Pakistan, whereas negative impacts were obtained for India, Turkey and Argentina), but not for the remaining major producers (the United States, China, Russia, Canada and Australia).

In summary, the results show that the climate change that has occurred to date has caused recent yields to decrease significantly, by 31, 2, 14 and 25% in the global harvested areas for maize, rice, wheat and soybeans, respectively, when compared to non-warming conditions (i.e., the preindustrial climate). By contrast, the areas with significant yield increases accounted for 5–9% of the harvested area worldwide.

3.3 Estimated yield impacts: Global and country mean yields

On an ensemble mean basis, the use of a theoretical representation of CO₂ fertilization suggested that climate change has caused global mean maize yields to decrease by −2.4% (red distribution in Figure 4). If no CO₂ fertilization was assumed, the impacts were more severe (−5.6%; blue distribution in Figure 4). Because the amplitude of the observed CO₂ fertilization varies with the field conditions and crop cultivars (Ainsworth et al., 2008; Hasegawa et al., 2013), the estimated impacts of the theoretical CO₂ fertilization may be more optimistic than the actual outcome. Although the CO₂ fertilization of C₄ plants (maize) saturates at lower concentrations than that of C₃ plants (rice, wheat and soybeans), fertilization for C₄ plants occurs at concentrations that range from preindustrial (285 ppm in 1850) to current levels (389 ppm in 2010) (Wolfe and Erickson, 1993). Therefore, we used their mixture distribution to provide a more realistic measure of the impact (grey distribution in Figure 4).

The mixture distribution showed a −4.1% decrease in global mean maize yields ($p < 0.1$) relative to the non-warming condition, with the 90%-probability interval derived from the ensemble members of −8.5 to +0.5%. The country-specific impacts for maize ranged from −8.6% in India to +13.5% in France on an ensemble mean basis (Figure 5). For soybeans, the mixture distribution revealed a −4.5% decrease on a global mean basis ($p < 0.05$; the 90% probability interval of −8.4 to −0.5%); consistent negative impacts were obtained for the major producers. Importantly, the negative impacts for maize and soybeans were very likely, even when the uncertainty of CO₂ fertilization was considered. The impacts for wheat were sensitive to the assumptions made when representing CO₂ fertilization. The estimated ensemble mean impact for wheat was −4.7% ($p < .1$) when no CO₂ fertilization was assumed, whereas it was insignificant when CO₂ fertilization was considered. The wheat yield gains in some countries balanced the yield losses in other countries. The mixture distribution showed a −1.8% decrease in the global mean wheat yields ($p < 0.3$; the 90%-probability interval of −7.5 to +4.3%). For rice, no
significant impact appeared in the mixture distribution at the global (+0.9%; −9.6 to +12.4%) and country levels.

3.4 Economic production losses

Using the estimated yield impacts and the reported data on yield, harvested area and producer price, the average annual global production losses in 2005–2009 were estimated, and they accounted for −22.3 B$ for maize, −6.5 B$ for soybeans, −0.8 B$ for rice and −13.6 B$ for wheat on an ensemble mean basis (Table 2). The 90% probability intervals of the production impacts derived from the ensemble members were −49.3 B$ to −2.0 B$ for maize, −21.5 B$ to +3.5 B$ for soybeans, −21.8 B$ to +11.1 B$ for rice and −36.6 B$ to +5.1 B$ for wheat (note that a negative value indicated a loss whereas a positive value indicated a benefit). Although the estimated production losses had the uncertainty described above (Table 2 and Figure 6), it was likely that climate change has caused production losses for maize, soybeans and wheat relative to preindustrial levels. The production loss for rice was likely small, if not non-existent.

4 DISCUSSION

4.1 Discrepancies between modelled and reported yields

The differences between the simulated and reported yields are relatively small for the developed countries, as exemplified by maize and soybeans in the United States and with the exceptions of wheat in the United States and France (Figure 1). The model considers only spring wheat. This fact may explain the differences, as winter wheat accounts for a substantial portion of national wheat production in these countries (USDA, 1994). The larger differences occur in the developing countries rather than in the developed countries. Possible reasons include (a) the socioeconomic data in developing countries used as model inputs are less accurate and (b) although international agricultural research organizations have contributed to the dissemination of improved technology to developing countries, this process is not incorporated into our modelling. For rice that is largely grown in developing countries in Asia, triple cropping is not considered in the model due to the lack of reliable crop calendar data sets, although it sometimes operates in the low latitudes. These reasons may in part explain the relatively large discrepancies for rice.

4.2 Relative contributions of temperature and precipitation changes to yield impacts

The large climate and crop ensemble simulations reveal that significant yield impacts appear more clearly at the low and high latitudes than at the mid-latitudes, where several major
crop-producing areas, the American Midwest, Northeast China and the Argentine Pampas, are located (Figures 2 and 3). In the low latitudes where the current temperatures are already high, warming has led more crops to be exposed to physiologically critical temperatures (Gourdji et al., 2013) than under non-warming conditions, and it has led to yield losses (Figures 7 and S1). In the high latitudes, where low temperatures and snow cover are the primary limiting factors for crop production, the warming has benefited crop growth. The mid-latitudes are in the transition zone between the changes that have occurred in the low and high latitudes.

The tendency of regions with higher growing season temperatures to have lower yields (Figure 7) resembles the findings of Lobell and Gourdji (2012). The yields in semi-arid regions in the mid- to high latitudes, where water availability is a primary yield-limiting factor in the absence of irrigation, are negatively affected when precipitation decreases (Figures 8 and S1), although this tendency is unclear for wetter regions. The dominance of the role of temperature change over that of precipitation change in determining yield impacts is consistent with earlier analyses (Lobell et al., 2011). The importance of precipitation changes in drier regions (e.g., the Mediterranean) is also consistent with earlier statistical regressions (Moore and Lobell, 2015).

### 4.3 Comparisons of estimated yield impacts with other studies

A counterfactual analysis in statistical regressions (Lobell et al., 2011) indicates the yields under preindustrial climate conditions with the current technology (it assumes no trend in the growing season temperature and precipitation). On a global mean basis, the estimates from earlier statistical regressions and our process-based modelling show good consistency in most cases. The earlier estimates with CO₂ fertilization (Lobell et al., 2011) are −3.8, +2.9 and −2.5% for maize, rice and wheat, respectively, and the corresponding values from this study are −4.1, +0.9 and −1.8%. However, contrasting results appear for soybeans, for which the value from earlier work (Lobell et al., 2011) is +1.3%, whereas the value from this study is −4.5%.

The impacts at a country level produced by the two approaches resemble one another, with contrasting results for maize and wheat in France and soybeans in Argentina. The impacts for rice are smaller than they are for other crops, which is a common tendency across different approaches. Estimates from statistical regressions based on high-resolution data (Moore and Lobell, 2015) show negative impacts on maize in the Mediterranean region and positive impacts for other European regions, including France. These patterns are consistent with our estimates, suggesting that differences in resolution represent a possible reason for the differences across studies.

The contrasting impacts for wheat in France persist even when a regional statistical analysis (Moore and Lobell, 2015) and this study are compared. The lack of winter wheat in our modelling may explain the difference. The harvested soybean area doubled between 1981 and 2010 (FAO statistical database), whereas the corresponding increases were 1.3, 1.1 and 0.9 for maize, rice and wheat, respectively. The geographical distribution of the harvested area is fixed at the year 2000 level in our modelling, whereas a statistical
regression (Lobell et al., 2011) performed using FAO data accounts for the changes. This difference may explain the large differences in the results obtained by the two approaches for soybeans.

4.4 | Implications of climate change for yield trends

Although the present study assesses the impacts on the average yields for 1981–2010, our results have implications for the observed yield trends. Yield increases driven by technological improvements have been a predominant trend worldwide during the last half century. These increasing yield trends are common across the historical and non-warming crop simulations (Figure S3), as these trends have been driven to a greater degree by socio-economic factors than by climatic factors. Importantly, the estimated yield impacts in recent years are larger than those of previous years, because warming is the primary climatic driver of the estimated yield impacts (Figures 7 and 8). Therefore, when the estimated yield impacts are negative, the increasing yield trends have slowed down compared to those obtained under the non-warming conditions. When the impacts are positive, the increasing yield trends have accelerated relative to those obtained under the non-warming conditions.

4.5 | Limitations

This study has several limitations. Most importantly, our study is based on a single combination of a climate model and a crop model. The individual climate models have their
own biases in the climatic variables they simulate. Multi-climate model ensembles provide an approach to tackle this problem, but there are few climate databases equivalent to the d4PDF. Outputs from climate model inter-comparisons for detection and attribution (Gillett et al., 2016) are needed. Ensembles of multiple crop models or methods (Müller et al., 2015; Zhao et al., 2017) represent a promising means of improving the confidence of recent yield impacts, but there are few global gridded crop models that can simulate global yield trends. Furthermore, the downward shortwave radiation flux data used in this study were calculated empirically using the AGCM-simulated total cloud cover. The effects of aerosols on direct and diffuse insolation are not resolved in this study. The estimated yield impacts may be different when different data sets on the soil properties and harvested area are utilized for model inputs and aggregation (Anderson et al., 2015; Folberth et al., 2016; Porwollik et al., 2017).

5 | CONCLUSIONS

We present the estimates of the yield impacts and corresponding economic production losses for major crops at the global scale as associated with climate change for the 1981–2010 period relative to the preindustrial climate. The use of a large ensemble climate and crop simulation for historical and non-warming conditions (100 member each) enables us to detect the significant yield decreases at lower latitudes as well as the significant yield increases at higher
latitudes. These yield impacts are attributed to anthropogenic climate change. Our findings based on the process-based climate and crop modelling underpin the ideas that global crop production is being affected by climate change and that net production losses have likely occurred.

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