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# Impacts of climate change and increasing carbon dioxide levels on yield changes of major crops in suitable planting areas in China by the 2050s

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ABSTRACT

Maize, rice, and wheat are the major staple food crops in China and are crucial components of national food security and economic development. The cultivation and production of these crops are expected to be affected by climate change and elevated atmospheric carbon dioxide ($CO_2$) concentration, and have drawn considerable public attention. The objective of this experiment was to understand the impact of future climate change (including increased temperature and changed precipitation patterns) and elevated $CO_2$ concentration on variations of crop yields in their suitable planting areas. We conducted a spatial grid-based analysis of maize, rice, and wheat yields using projections of future climate generated by a multi-model ensemble of global climate models for three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5) in suitable planting areas in China for the 2030s (2021–2040) and the 2050s (2041–2060). Suitable areas for the planting of maize, rice, and wheat under the high-emission scenarios migrated slightly northward over time. Yield of all three crops would be expected to remain stable or to slightly increase across China in the future. A possible reason for this result may be because the positive effects of increased precipitation and $CO_2$ offset the negative effect of increased temperature on crop yields, resulting in a much more appropriate growth environment and increased biomass accumulation and crop yield. In addition, this study also indicated that changes in crop yields were mainly driven by temperature and $CO_2$ factors. The potential effects of climate change and elevated $CO_2$ concentration on migration of planting areas and yield fluctuations for crops should be given greater attention in the future.

## 1. Introduction

Agriculture is the foundation of economic development and social stability in China, providing staple food supplies and representing a major contributor to the global production of cereal crops (FAO, 2012). Maize (*Zea mays* L.), rice (*Oryza sativa* L.), and wheat (*Triticum aestivum* L.) are cultivated and produced in most of the croplands in China (http://data.stats.gov.cn). Historically, the cultivation of maize, rice, and wheat has been identified as migrating northward in China mainly due to climate change factors (including changing temperatures and precipitation and attendant extreme weather events) and elevated atmospheric carbon dioxide ($CO_2$) concentration (e.g., Ning et al., 2019; Sloat et al., 2020). For all three cereal crops mentioned above, reductions in yield due to higher temperatures and lower precipitation have occurred mainly in northern China (e.g., Zhang and Huang, 2012; Ray et al., 2015). Future projections of climate variations have also been widely reported using general circulation model (GCM) outputs. According to these model outputs, some studies have suggested that the planting areas of crops may extend northward and eastward to varying degrees in China under future climate scenarios, as a result of greater warming in northern China (Hu and Liu, 2013; Zhang et al., 2017; Wang and Hijmans, 2019; Zhang and Niu, 2020). The suitable planting areas of major cereal crops are correlated with their yield changes in China (Ning et al., 2019). The influence of future climate anomalies on crop yield variability is worthy of considerable attention, especially as it affects changes to planting areas (Schauberger et al., 2017).

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Two approaches are usually taken to estimate the impacts of climate change and elevated $CO_2$ concentration on crop yields: (i) process-based crop models, which mechanistically or functionally represent the effect of weather, soil conditions, management practices, and abiotic stresses on crop growth and yields; or (ii) statistical techniques, usually in the form of regression analysis, that empirically estimate the effect of weather conditions on crop yields while controlling for other factors by applying historical observations (Blanc and Sultan, 2015). Statistical models are more easily applicable and may include indirect effects of climatic variability, such as those related to frost, weeds, pests, and diseases, or extreme temperature and rainfall events, all of which are not well captured by process-based crop models (Kristensen et al., 2011). Statistical models may also inherently include the effects of gradual increase in atmospheric $CO_2$ concentration within the yield effects. Thus, statistical models have been widely applied to predict crop yield responses to climate change and elevated $CO_2$ concentration on global and regional scales, particularly in China (Lobell and Field, 2007; Shi et al., 2013).

Recently, some studies have adopted statistical regression models from *meta*-analysis to determine the central trends of crop yields in response to changes in climatic variables from studies differing in crops, regions, scenarios, time periods, and analytical approaches. Based on global *meta*-analysis, Challinor et al. (2014) analyzed the different response patterns of crop yields to climate change in tropical and temperate regions. In China, Xie et al. (2019) established 288 samples according to the results of relevant papers and applied a *meta*-analysis method to assess the projected impact of climate change and elevated $CO_2$ concentration on the future yields of major crops under a unified scenario. Liu et al. (2020) followed Xie et al. (2019) and assessed the impacts of climate change and elevated $CO_2$ concentration on the future yield of major crops using *meta*-analysis at national and subregional levels based on a dataset of 667 published simulations. These studies reported negative effects of increased temperature and positive effects of increased precipitation and atmospheric $CO_2$ concentration on yields of major crops (i.e., maize, rice, and wheat) in China in the future (Xie et al., 2019; Liu et al., 2020). However, most of the present studies using *meta*-analysis, or empirical or mechanistic models have appeared to exclude the consideration of crop yield changes caused by the large uncertainty in crop planting area. It is therefore important to combine the ongoing migration of agricultural lands with statistical models derived from *meta*-analysis to estimate crop yield changes in China under future climate.

Therefore, we assessed the changes in areas suitable for the planting of maize, rice, and wheat based on grid data from 2006 to 2060 simulated by six bias-correction and spatial disaggregation (BCSD) climate projections in the fifth phase of the Coupled Model Intercomparison Project (CMIP5) archive under three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5) in combination with the agricultural climatic resources in China. Based on the distribution of crops, crop yield changes under the future climate scenarios were simulated by statistical models proposed by Xie et al. (2019), which were driven solely by weather data for each grid cell based on its crop type. The objective of this analysis was to understand the impact of future climate change (including increased temperature and changed precipitation patterns) and elevated $CO_2$ concentration on variations of crop yields in their suitable planting areas. The results may further help policymakers to develop adaptation strategies and will provide reference values for the sustainable development of agriculture.

## 2. Data and methods

Brief details of all datasets used for our calculations are presented in Table 1. These datasets have previously been used to validate the applicability of models to simulate crop irrigation water requirements in China under future climate conditions (Zhang et al., 2019). In this section we describe how these datasets were used to evaluate the suitable planting areas for crops and to simulate the crop yield changes under climate change and elevated $CO_2$ concentration at grid cell level. We also describe how we conducted a comparison of this method with other datasets and articles. Only the simulation using projected global climate forcing consistent with the given RCPs (2006.1–2060.12) was used. The future years were divided into three periods: the 2010s (January 2006 to December 2016; as a historical scenario in this study), the 2030s (January 2021 to December 2040), and the 2050s (January 2041 to December 2060). The RCP2.6, RCP4.5, and RCP8.5 emission scenarios reflected the range of year 2100 radiative forcing values from 2.6 to 8.5 W $m^{-2}$ and were used for impacts and adaptation assessment for future crop production in this study (Moss et al., 2010; Van Vuuren et al., 2011). Of these RCPs, RCP2.6 is a peak-and-decline scenario with a turning point in mid-century; RCP4.5 is a scenario that starts to stabilize radiative forcing from 2070; and RCP8.5 is characterized by a continuously increasing radiative forcing pathway over time, and corresponds

**Table 1**
Details of the datasets used in this study.

| Variable | Download link and access date | Format and resolution (lon by lat) | Description | Reference |
|---|---|---|---|---|
| Elevation | http://research.jisao.washington.edu/data_sets/elevation/; 2014.12 | NetCDF; 0.5 × 0.5 | This dataset was compiled from the National Center for Atmospheric Research TerrainBase global digital elevation model | – |
| Monthly mean air temperature<br>Monthly maximum air temperature<br>Monthly minimum air temperature<br>Monthly mean precipitation | https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Projections:%20Complete%20Archives; 2012.8 | | These data were derived from multi-model ensemble mean of six general circulation models (i.e., CanESM2, CCSM4, CSIRO-Mk3-6–0, GISS-E2-R, IPSL-CM5A-LR, and MPI-ESM-LR) with equal weight under the future climate scenarios of RCP2.6, RCP4.5, and RCP8.5 obtained from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DCHP). Data from the DCHP were downscaled to a finer resolution using the bias-correction and spatial disaggregation statistical technique. | Maurer et al. (2007)<br>Reclamation (2013) |
| Crop calendar | http://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php; 2010.12 | | This dataset was the result of digitizing and georeferencing existing observations of planting and harvesting dates, mainly compiled from the U.S. Department of Agriculture and Food and Agriculture Organization. The calendars of maize, rice (main season), rice 2 (second season), wheat, and winter wheat were all considered in this study and assumed to be stable to the middle of the 21st century. | Sacks et al. (2010) |
| Annual mean atmospheric carbon dioxide concentration | http://www.pik-potsdam.de/‘mmalte/rcps/; 2010.5 | Text | These data were globally homogeneous fixed annual mean atmospheric carbon dioxide mixing ratios under RCPs that forced the CMIP5 models | Meinshausen et al. (2011) |

to the pathway with the highest greenhouse gas emissions among the total set of RCPs (Moss et al., 2010; Van Vuuren et al., 2011).

### 2.1. Calculation of indicators for estimating the distribution of the suitable planting areas and yield changes for crops

The pretreatment of the data obtained from the datasets mentioned above included the following (Zhang et al., 2017; Zhang and Niu, 2020): (1) Because there were no available daily data published by the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections, the monthly mean air temperatures were used to calculate the daily mean air temperatures using linear interpolation. This method was applied to obtain the days consistently above 10 °C and 18 °C and the ≥ 0 °C and ≥ 10 °C active accumulated temperature using the five-day running-mean method and the accumulation method over the year, respectively; (2) The monthly mean air temperatures were also used to calculate the annual mean air temperatures; (3) On the basis of the specified annual mean atmospheric $CO_2$ concentrations, altitude above sea level, and latitude, the monthly mean maximum and minimum air temperatures were also used to empirically estimate reference evapotranspiration by the Penman–Monteith method, mainly using temperature data [see Allen et al. (1998) and Zhang et al. (2018)]; and (4) Reference evapotranspiration was considered to be an estimate of potential evapotranspiration, and was used with monthly mean precipitation to calculate the 6-month and 12-month standardized precipitation evapotranspiration index (SPEI) for different crops (Vicente-Serrano et al., 2010a, 2010b). The 6-month and 12-month SPEI are relevant to agriculture and can be used to evaluate the link between climate and crop yields by evaluating how crop yields are affected when threshold SPEI values are exceeded (Prabnakorn et al., 2018). Based on the crop calendar data, 6-month SPEI values ending at the harvest month were used for maize (almost always planted in single-cropping systems). The 12-month SPEI values ending in December were used for rice (contains single-cropping rice, double-cropping rice, and triple-cropping rice) and wheat (contains spring wheat and winter wheat) to capture soil moisture condition trends during the growing season.

### 2.2. Distribution of suitable planting areas for crops

All of the data were used to obtain the appropriate temperature, precipitation, and elevation ranges (as the main agricultural resource factors). These data classified the climatic zones in terms of their suitability for crop planting distribution in China. This approach was referred to as the maximum entropy model and the multi-criteria evaluation method (Duan and Zhou, 2011; He and Zhou, 2012). These factors were derived not only from their importance on crop growth, but also from their contributions to the geographic distribution of crop planting (see Table 2). An SPEI threshold of −1.29 was used to distinguish the economic viability on a yield basis for agricultural production (Hao et al., 2014). A grid cell with parameter values falling within all of the ranges for a crop listed in Table 2 was regarded as a suitable planting area for that crop. During every period (i.e., 2010s, 2030s, and 2050s), areas that met the requirements of climate indicators for crop growth in more than 80% of years, calculated by the empirical frequency method, were regarded as suitable planting areas with an 80% assurance rate (Zhang et al., 2017).

### 2.3. Yield changes for crops

Xie et al. (2019) referenced Challinor et al. (2014) and proposed statistical regression models derived from a *meta*-analysis of maize, rice, and wheat in China. The *meta*-analysis was based on 34 articles, and resulted in a database of 287 samples. These articles were collected and filtered from five databases (Web of Science, ScienceDirect, Google Scholar, China National Knowledge Infrastructure, and Wanfang Data) using specific inclusion criteria. Only articles using crop models to quantitatively evaluate variations in crop yields caused by projected climate changes under the Special Report on Emissions Scenarios and RCP scenarios to 2100 in the whole of or parts of China were included in this study. Then a general linear model was fit to the extracted annual data for different crop types to assess the central trend in crop yield change ($\Delta Y/Y$) for two continuous climatic variables [temperature increase ($\Delta T$) and precipitation change ($\Delta P/P$)] and a categorical climatic variable (whether or not $CO_2$ effects were considered) using 49% of the samples at the national level:

$$(\Delta Y/Y)_i = -2.568 \times \Delta T_i + 0.371 \times (\Delta P/P)_i + 16.48 \times CO_{2,i} + \alpha - 0.589 + \varepsilon$$

where $(\Delta Y/Y)_i$ is the crop yield change (%) under climate change and elevated $CO_2$ concentration for the $i$th sample (i.e., the projected yield in the given future scenario as a percentage change from the current yield). $\Delta T_i$ and $(\Delta P/P)_i$ are the temperature increase (°C) and precipitation change (%) of the $i$th sample, respectively. $CO_{2,i}$ is a binary variable (=1 or 0) that denotes whether the $i$th sample considered $CO_2$ effects. $\alpha$ is a constant term: –10.160 for maize, –4.375 for rice, and 0 for wheat. $\varepsilon$ denotes the regression error term. This linear model was estimated by weighted least squares regression to deal with the samples with heteroscedasticity in different articles, and had a coefficient of determination ($R^2$) of 0.573. The ranges of climate variables (temperature increase and precipitation change) in this study were within those found by Xie et al. (2019) to ensure the applicability of the regression model. According to this statistical climate-driven yield change model, crop yield changes in suitable planting areas during the 2030s and 2050s compared with the 2010s could be estimated based on climate variables (i.e., temperature, precipitation, and $CO_2$ effects) under future conditions in China.

**Table 2**
Main agricultural resource factors determining suitable planting areas for rice, maize, and wheat in China at national and annual scales.

| Crop | ≥0°C active accumulated temperature (°C days) | ≥10 °C active accumulated temperature (°C days) | Time consistently above 10 °C (days) | Time consistently above 18 °C (days) | Annual mean air temperature (°C) | Annual precipitation (mm) | Standardized precipitation evapotranspiration index (SPEI) threshold | Elevation (m) | References |
|---|---|---|---|---|---|---|---|---|---|
| Maize | 2047.0–7179.9 | 1320.3–7164.3 | 125–309 | – | 2.9–22.1 | 125.3–1708.3 | 6-month SPEI > −1.29 | ≤1500 | Jia (2011); He and Zhou (2012); Hao et al. (2014) |
| Rice | – | 2548.0–9224.0 | – | 59–335 | – | 542.0–1890.0 | 12-month SPEI > −1.29 | ≤2710 | Chen (2010); Duan and Zhou (2011); Hao et al. (2014) |
| Wheat | 2300.0–4500.0 | – | – | – | – | 200.0–750.0 | 12-month SPEI > −1.29 | 100–2400 | Zhou (2010); Hao et al. (2014) |

### 2.4. Scenario simulations and migration analysis of the center of gravity

To analyze the climatic factors that drive the migration of crop yield changes in suitable planting areas, multiple model runs were conducted to obtain the distributions of suitable crop planting areas and yield changes from 2021 to 2060 based on: (1) only changing temperature (considering only the temperature factors and leaving the precipitation factors unchanged since the 2010s and without considering $CO_2$ effects); (2) only precipitation (considering only the precipitation factors and leaving the temperature the 2010s and without considering $CO_2$ effects); and (3) only $CO_2$ (considering only the $CO_2$ effects and leaving the factors of temperature and precipitation unchanged since the 2010s). The SPEI was also recalculated considering temperature, precipitation, and $CO_2$ effects. By comparing the differences in the changes between the temperature-only, precipitation-only, and $CO_2$-only scenarios, model sensitivity to climatic factors could be investigated to assess the effects of climate change and elevated $CO_2$ concentration on crop yield changes in suitable planting areas.

The spatial migration (both distance and direction) of the centers of gravity for suitable planting areas was assessed in this study based on coordinate changes in order to describe the overall changes in patterns of crop yield under different RCP scenarios and time periods. The related calculation formula was as given in Zhang et al. (2017):

$$D = \sqrt{(y_{i+1} - y_i)^2 + (x_{i+1} - x_i)^2}$$

where $D$ represents the movement distance of the center of gravity from year $i$ to $i + 1$, $x$ and $y$ were the longitude (°) and latitude (°) of the center of gravity. The shifts of the yield changes from crop suitable cultivation areas between the 2010s and 2030s are not shown in this study.

### 2.5. Comparison with other studies

A spatially explicit global dataset of historical yields for maize, rice, and wheat for the period 1981–2016 was developed and published by Iizumi et al. (2014) and Iizumi and Sakai (2020). The dataset was selected to verify if potential planting areas simulated by models in this study were positioned within or close to the actual production areas. This Global Dataset of Historical Yield (GDHYv1.2 + v1.3; https://doi.pangaea.de/10.1594/PANGAEA.909132) offers historical and spatial patterns of annual yield estimations at a spatial resolution of 0.5° for major crops, including, maize, rice, and wheat. The grid-cell yield data were estimated using global agricultural datasets related to the crop calendar around 2000 from Sacks et al. (2010). The harvested area around 2000 was obtained from the M3-Crops data, satellite-derived crop-specific vegetation index, FAO-reported country yield statistics, and production share by cropping season in the 1990s from the USDA (Iizumi and Sakai, 2020). For China, GDHY used the historical data from several census-based inventories such as the FAO and USDA reports. Therefore, the CMIP5 multi-model data for the period of the 2010s (2006–2016) under the RCP2.6 scenario were regarded as historical data in this study. These data were used to calculate the areas suitable for the planting (with an 80% assurance rate) of maize, rice, and wheat, to be compared with the suitable planting areas (again, with an 80% assurance rate of reported crop distributions during 2006–2016) derived from GDHY data to test the efficacy of the method used in this study. Crop yield changes derived from this study were compared with previous estimates of future crop yield changes in China that were global or regional estimates covering China, and were excluded in the *meta*-analysis of Xie et al. (2019) (see Deryng et al., 2011).

R (version 3.3.1; Statistics Department of the University of Auckland, https://www.r-project.org/) was used to pre-treat data (described in Section 2.1, above), and to calculate the suitable planting areas and yield changes of maize, rice, and wheat separately under future climate in China. All calculation and analysis were conducted at 0.5° × 0.5° grid cell level without marginal cropland share. The main R packages used in these calculation procedures were "raster", "ncdf4", "TTR", "SPEI", "geosphere", "rgeos", and "SDMTools". To explicitly interpret results, China was divided into the following six regions based on geographic distribution (following the recommendation made in the China Rural Statistical Yearbook): North China (NC), Northeast China (NEC), East China (EC), Central-South China (CSC), Southwest China (SWC), and Northwest China (NWC).

## 3. Results

### 3.1. Comparison of this study with GDHY and other studies

This study overestimated the historical areas for maize planting in northwestern NWC, northern NC, and parts of central and eastern China; and for wheat planting in northwestern NWC and northern NC. The study underestimated the historical areas for maize planting in southern SWC and CSC, and northern NEC; for rice in parts of NEC and NC, northwestern NWC, and southern CSC; and for wheat in northern CSC and EC (Fig. 1). In general, this study achieved relatively good consistency between estimated planted areas of crops and GDHY. Some misestimations of the planted area (compared with GDHY) might be caused by the soil and topography in the Junggar Basin and Meadow Steppe of Inner Mongolia. Agricultural management measures and economic and policy factors can also affect the planting distribution of crops (e.g., irrigation in the North China Plain and the policy of "one billion and eight hundred million acres of arable land red line"), resulting in some discrepancies between our results and the historical distribution data of crops planted in China (Zhang et al., 2017). There were also some limitations of the GDHY dataset resulting in it not producing a true cropland mask, such as the use of crop-specific harvested area around 2000 from the M3-Crops data [see Monfreda et al. (2008)], the limited spatial coverage sourced from the crop calendar data used [see Sacks et al. (2010)] that covered only 76–92% of the global harvested area, and the use of time-constant production shares on harvested area by season in the 1990s (Iizumi and Sakai, 2020).

The results of this study were close to previous estimates of crop yield changes in China in the future (Table 3). Increased yields of rice and wheat were indicated in both previous studies and in this study. Only the results of yield changes for maize were not consistent with previously published studies. Some studies indicated that maize yield stagnation and reduction were seen in most of China, especially under the high emission scenarios (e.g., Rosenzweig et al., 2014; Müller et al., 2015; Yin et al., 2015). However, increased maize yields were simulated across China in this study. This discrepancy was mainly caused by the different methods used to simulate crop yield changes, the different climatic data from different GCMs used to force crop models, and the different consideration of crop cultivation distributions. For example, Yin et al. (2015) used the model outputs of potential yield from four global gridded crop models (GGCMs) based on the fixed crop distributions derived from a global irrigated and rain-fed crop area data, and indicated that adaptation measures such as changing planting area could partially or even completely offset the negative effects of climate change on crop yields. Moreover, the uncertainty in yields resulting from crop models was always larger than the uncertainty derived from GCMs in the greater part of China (Müller et al., 2015; Yin et al., 2015). In general, the results shown in Table 3 demonstrated the effectiveness of the methods used in this study to simulate the yield changes of crops under future climate scenarios in China.

### 3.2. Spatio-temporal distribution of yield changes in suitable planting areas for maize

In the 2030s, under the RCP2.6, RCP4.5, and RCP8.5 scenarios, the suitable maize planting areas (the spatial extent of maize yield changes) were widely distributed in southern NEC and NC, northern CSC and EC, eastern SWC, and northwestern NWC and mainly concentrated in

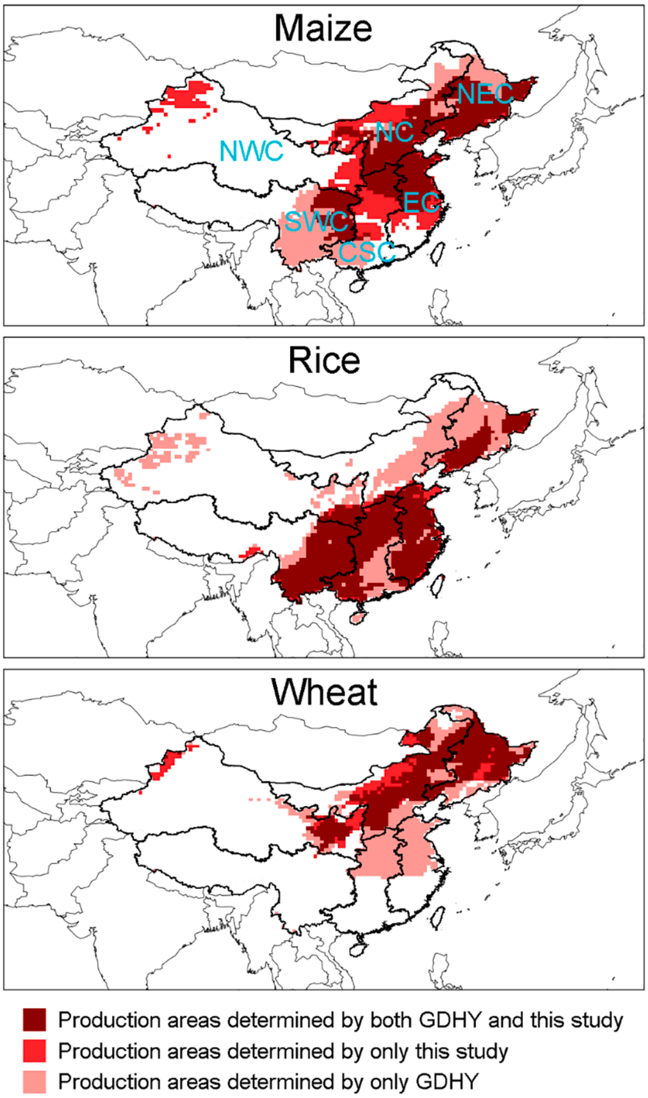


**Fig. 1.** Production areas for maize, rice, and wheat in China simulated by this study under a representative concentration pathway scenario (RCP2.6) compared with production areas derived from the Global Dataset of Historical Yield [GDHY; a global gridded dataset of historical yields for maize, rice, and wheat for the period 1981–2016 published by Iizumi and Sakai (2020)] from 2006 to 2016. These production areas were calculated at an 80% assurance rate. NC, NEC, EC, CSC, SWC, and NWC represent the regions of North China, Northeast China, East China, Central-South China, Southwest China, and Northwest China, respectively. The South China Sea is not shown in this figure.

China's northeast–southwest corn belt, covering 32.52%, 28.45%, and 34.24%, respectively, of the total area of China. The areas with the largest percentage yield increase were mainly concentrated in northwestern NWC under the RCP2.6 scenario and in northern NC and NEC under the RCP8.5 scenario (Fig. 2). There was little difference in suitable planting areas under these three scenarios except in NEC under the RCP4.5 scenario.

In the 2050s, under the RCP2.6 scenario, there was no clear change in the suitable planting areas compared with the 2030s; the areas with substantial yield increase were located in southern CSC and eastern SWC. Under the RCP4.5 scenario, the suitable planting areas expanded northward to cover NEC. And under the RCP8.5 scenario, the suitable maize planting areas mostly disappeared from CSC. Compared with the 2030s, the areas with substantial yield increase in the 2050s under RCP 8.5 were not obvious in northern NC and NEC. The suitable planting areas occupied 34.26%, 33.69%, and 33.30% of the total area of China under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively in the 2050s. Moreover, only the proportion of suitable planting areas under the RCP4.5 scenario considerably increased with a slight northward spatial migration in the 2050s relative to the 2030s.

### *3.3. Spatio-temporal distribution of yield changes in suitable planting areas for rice*

In the 2030s, under the RCP2.6, RCP4.5, and RCP8.5 scenarios, the suitable rice planting areas were widely distributed throughout China except for some regions in NC, northern NEC and NWC, and the Qinghai–Tibet Plateau, reaching 27.85%, 26.81%, and 23.65%, respectively, of the total area of China. The areas with the largest percentage yield increase were mainly concentrated in NEC under the RCP8.5 scenario (Fig. 3). There was little difference in suitable planting areas under these three scenarios.

In the 2050s, under the RCP2.6 scenario, there was no clear change in the suitable planting areas; the areas with the largest percentage yield increase were found in southern SWC and CSC. Under the RCP4.5 scenario, the suitable planting areas clearly increased with a northward spatial expansion in the NEC. And under the RCP8.5 scenario, the areas of suitable planting substantially increased in NEC and southern SWC. The suitable planting areas occupied 30.25%, 31.11%, and 30.66% of the total area of China under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. The proportion of suitable rice planting areas under these three scenarios clearly increased over time, with northward spatial expansion occurring at different levels in the 2050s than in the 2030s.

### *3.4. Spatio-temporal distribution of yield changes in suitable planting areas for wheat*

In the 2030s, under the RCP2.6, RCP4.5, and RCP8.5 scenarios, the suitable wheat planting areas were mainly located in NEC, NC, and eastern and northwestern NWC, representing 19.61%, 12.99%, and 16.14%, respectively, of the total area of China. The areas with largest percentage yield increase were found in northern NC and NEC (Fig. 4). There was little difference in suitable wheat planting areas under these three scenarios except in NEC under the RCP4.5 scenario.

Compared with the 2030s, the areas with the largest percentage yield increase were not so obvious in the 2050s under these future scenarios. Under the RCP2.6 scenario, the suitable planting areas in the 2050s were similar to those in the 2030s. In contrast, under the RCP4.5 scenario, the suitable wheat planting areas expanded to cover northern NEC and NC. And under the RCP8.5 scenario, the suitable planting areas moved slightly northward to northern NEC and NC, and also remained in parts of northwestern and eastern NWC. The suitable planting areas occupied 20.42%, 20.52%, and 19.66% of the total area of China under RCP2.6, RCP4.5, and RCP8.5, respectively. The proportion of suitable wheat planting areas under the RCP4.5 and RCP8.5 scenarios showed clear increases with time, with northeastward spatial expansion in the 2050s compared with the 2030s.

### *3.5. Migration of the center of gravity for crop yield changes*

Under the RCP2.6 scenario, the centers of gravity for yield changes of the three crops migrated slightly from the 2030s to the 2050s (Fig. 5). For maize, the center of gravity shifted northeastward about 27 km from (37.70°N, 113.73°E) in the 2030s to (37.86°N, 113.96°E) in the 2050s. For rice, the center of gravity migrated eastward about 38 km from (31.30°N, 113.00°E) in the 2030s to (31.37°N, 113.39°E) in the 2050s. And for wheat, the center of gravity moved northeastward about 62 km from (43.43°N, 116.45°E) in the 2030s to (43.84°N, 116.78°E) in the 2050s.

Under the RCP4.5 scenario, the centers of gravity for the yield change of the three crops showed a much longer migration distance from the 2030s to 2050s (Fig. 5). For maize, the center of gravity shifted

**Table 3**
Estimated spatial variation trends of yield for three crops in six regions of China.

| Source | Method | Climate scenario | Carbon dioxide effects | Baseline period | Future period | Crop type | Spatial variation trend of yield in regions of China ("↑" is increase; "↓" is decrease; "→" is steady; and "×" is no data) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Northeast China (NEC) | North China (NC) | East China (EC) | Central-South China (CSC) | Northwest China (NWC) | Southwest China (SWC) |
| Balkovič et al. (2014) | EPIC model × 1 GCM | Four RCPs | ✓ | 1990–2000 | 2041–2060 | Wheat | → | ↑ | ↓ | ↓ | ↑ | ↑ |
| | | | | | 2080–2099 | Wheat | → | ↑ | → | ↓ | ↑ | ↑ |
| Rosenzweig et al. (2014) | 7 GGCMs (EPIC, GEPIC, GAEZ-IMAGE, LPJmL, LPJ-GUESS, pDSSAT, and PEGASUS) × 5 GCMs | RCP8.5 | ✓ | 1980–2010 | 2070–2099 | Maize | → | → | → | → | ↑ | ↑ |
| | | | | | | Rice | ↑ | ↑ | → | → | ↑ | ↑ |
| | | | | | | Wheat | ↑ | ↑ | → | → | ↑ | ↑ |
| Deryng et al. (2014) | PEGASUS model × 18 GCMs | RCP8.5 | ✓ | 1971–2000 | 2071–2100 | Maize | ↑ | ↑ | ↓ | ↓ | ↑ | ↓ |
| | | | | | | Spring wheat | ↑ | ↑ | × | × | ↑ | × |
| Yin et al. (2015) | 4 GGCMs (EPIC, GEPIC, pDSSAT, and PEGASUS) × 5 GCMs | RCP8.5 | ✓ | 1981–2010 | 2070–2099 | Maize | ↓ | ↓ | ↓ | ↓ | ↓ | ↑ |
| | | | | | | Rice | ↑ | ↑ | → | → | ↑ | ↑ |
| | | | | | | Wheat | → | ↓ | ↓ | ↓ | ↑ | ↓ |
| Müller et al. (2015) | 6 GGCMs (EPIC, GEPIC, LPJmL, LPJ-GUESS, pDSSAT, and PEGASUS) × 5 GCMs | RCP2.6 | ✓ | 1980–2009 | 2070–2099 | Maize | ↑ | ↑ | ↑ | ↑ | ↓ | ↑ |
| | | RCP8.5 | ✓ | 1980–2009 | 2070–2099 | Rice | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | | | | | Wheat | ↑ | ↑ | ↑ | ↑ | × | × |
| | | | | | | Maize | ↓ | ↓ | ↓ | ↓ | ↓ | ↓ |
| | | | | | | Rice | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | | | | | Wheat | ↑ | ↑ | ↑ | ↑ | ↓ | × |
| This study | Statistical regression models × 6 GCMs | RCP2.6 | ✓ | 2006–2016 | 2041–2060 | Maize | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | RCP8.5 | ✓ | 2006–2016 | 2041–2060 | Rice | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | | | | | Wheat | ↑ | ↑ | × | × | ↑ | × |
| | | | | | | Maize | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | | | | | Rice | ↑ | ↑ | ↑ | ↑ | ↑ | ↑ |
| | | | | | | Wheat | ↑ | ↑ | × | × | ↑ | × |

*Note:* GCM, general circulation model; GGCM, global gridded crop model; RCP, representative concentration pathway scenarios; EPIC, Environmental Policy Integrated Climate model; GEPIC, GIS-based EPIC model; GAEZ-IMAGE, Global Agro-Ecological Zones - Integrated Model to Assess the Global Environment; LPJmL, Lund-Potsdam-Jena managed Land model; LPJ-GUESS, Lund-Potsdam-Jena General Ecosystem Simulator model; pDSSAT, parallel Decision Support System for Agro-technology Transfer models; and PEGASUS, Predicting Ecosystem Goods And Services Using Scenarios model.

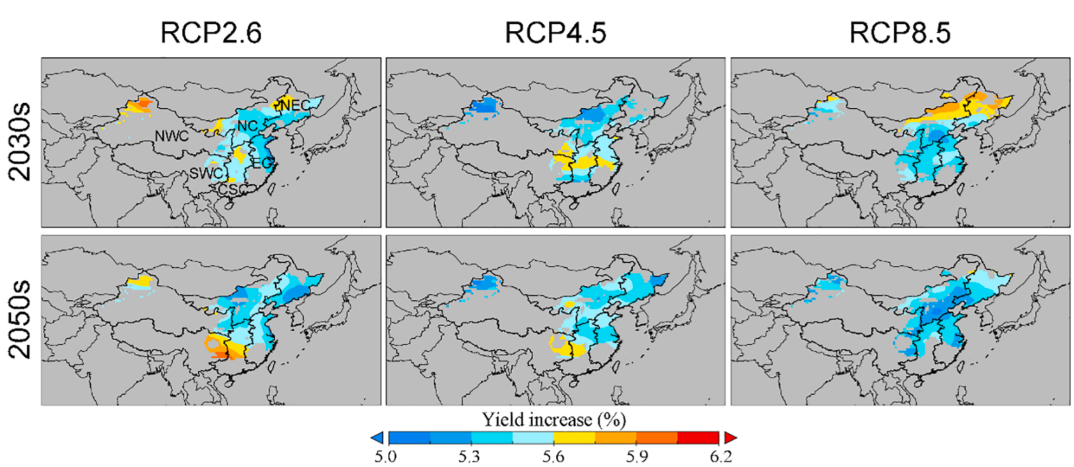


**Fig. 2.** Maize yield changes in the 2030s (2021–2040) and 2050s (2041–2060) compared with the 2010s (2006–2016) in suitable planting areas in China under three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5). NC, NEC, EC, CSC, SWC, and NWC represent the regions of North China, Northeast China, East China, Central-South China, Southwest China, and Northwest China, respectively. The South China Sea is not shown in this figure.

northeastward about 271 km from (36.98°N, 112.09°E) in the 2030s to (38.54°N, 114.45°E) in the 2050s. For rice, the center of gravity migrated northeastward about 283 km from (30.15°N, 112.15°E) in the 2030s to (32.11°N, 114.04°E) in the 2050s. The migration distance was greatest for wheat, with the center of gravity clearly moving northeastward about 404 km from (42.49°N, 112.40°E) in the 2030s to (43.97°N, 116.95°E) in the 2050s.

Under the RCP8.5 scenario, all of the centers of gravity for the yield

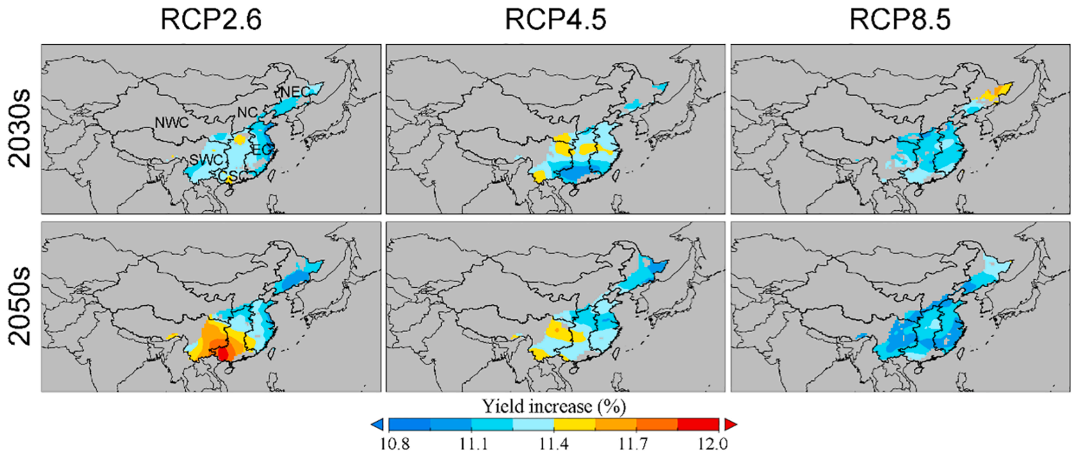


**Fig. 3.** Rice yield changes in the 2030s (2021–2040) and 2050s (2041–2060) compared with the 2010s (2006–2016) in suitable planting areas in China under three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5). NC, NEC, EC, CSC, SWC, and NWC represent the regions of North China, Northeast China, East China, Central-South China, Southwest China, and Northwest China, respectively. The South China Sea is not shown in this figure.

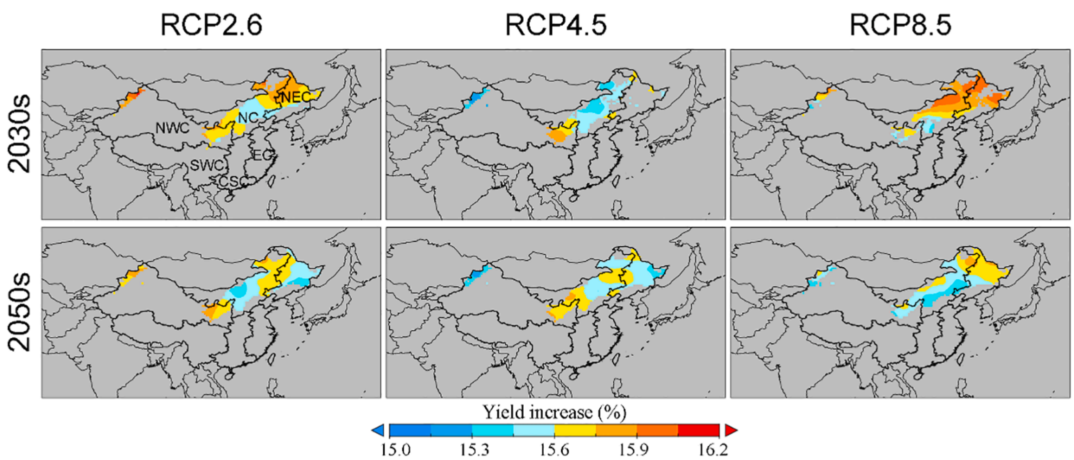


**Fig. 4.** Wheat yield changes in the 2030s (2021–2040) and 2050s (2041–2060) compared with the 2010s (2006–2016) in suitable planting areas in China under three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5). NC, NEC, EC, CSC, SWC, and NWC represent the regions of North China, Northeast China, East China, Central-South China, Southwest China, and Northwest China, respectively. The South China Sea is not shown in this figure.

changes of the three crops were observed to clearly migrate from the 2030s to 2050s (Fig. 5). For maize, the center of gravity shifted northeastward about 115 km from (38.52°N, 114.23°E) in the 2030s to (39.49°N, 114.73°E) in the 2050s. The centers of gravity for the yield changes of rice and wheat migrated northwestward about 87 km from (31.65°N, 114.75°E) in the 2030s to (32.29°N, 114.22°E) in the 2050s for rice, and about 46 km from (43.98°N, 117.04°E) in the 2030s to (44.39°N, 116.93°E) in the 2050s for wheat. Of the three crops, the migration distance under RCP8.5 was greatest for maize.

The overall migration direction from the 2030s to the 2050s for these three crops (red arrows in Fig. 5) was generally similar to the migration direction under the temperature-only scenario (orange arrows). The migration distances for the three crops were longer under the temperature-only and $CO_2$-only scenarios, indicating the greater impacts of these two parameters on the overall migration distance compared with the impact of precipitation. Under the precipitation-only scenario (green symbols and arrows), most of the centers of gravity for the yield change of the three crops varied only slightly over time. Additionally, under the RCP4.5 scenario, the overall migration direction and distance for all three crops were similar to the migration under the $CO_2$-only scenario.

## 4. Discussion

### *4.1. Relationship between climatic variables and variations in the distribution of crops*

Previous research has shown that temperature and precipitation have major and consistent influences on the distribution of crops in China. Zhang et al. (2019) applied an ensemble of six GCMs (also, CanESM2, CCSM4, CSIRO-Mk3-6–0, GISS-E2-R, IPSL-CM5A-LR, and MPI-ESM-LR) from the CMIP5 archive driven by multiple RCP scenarios which were obtained from the DCHP to investigate the effects of climate change and elevated $CO_2$ concentration on crop irrigation water requirements in China. The results of that study indicated that: (1) slight cooling was predicted in NC and NEC and in northern NWC under the RCP2.6 scenario. NEC had the least warming under the RCP scenarios; (2) more precipitation was predicted in NEC, southern SWC and CSC, and northwestern NWC, especially under the high-emission RCP scenarios. These patterns of climate variability can explain the locations of areas with substantial crop yield increases. Li et al. (2015) showed that the rice production zone in China move northeastward over 370 km from 1949 to 2010, in part in response to temperature increases. Increasing precipitation observed in most of the southern regions and parts of the northern regions of China may have caused the

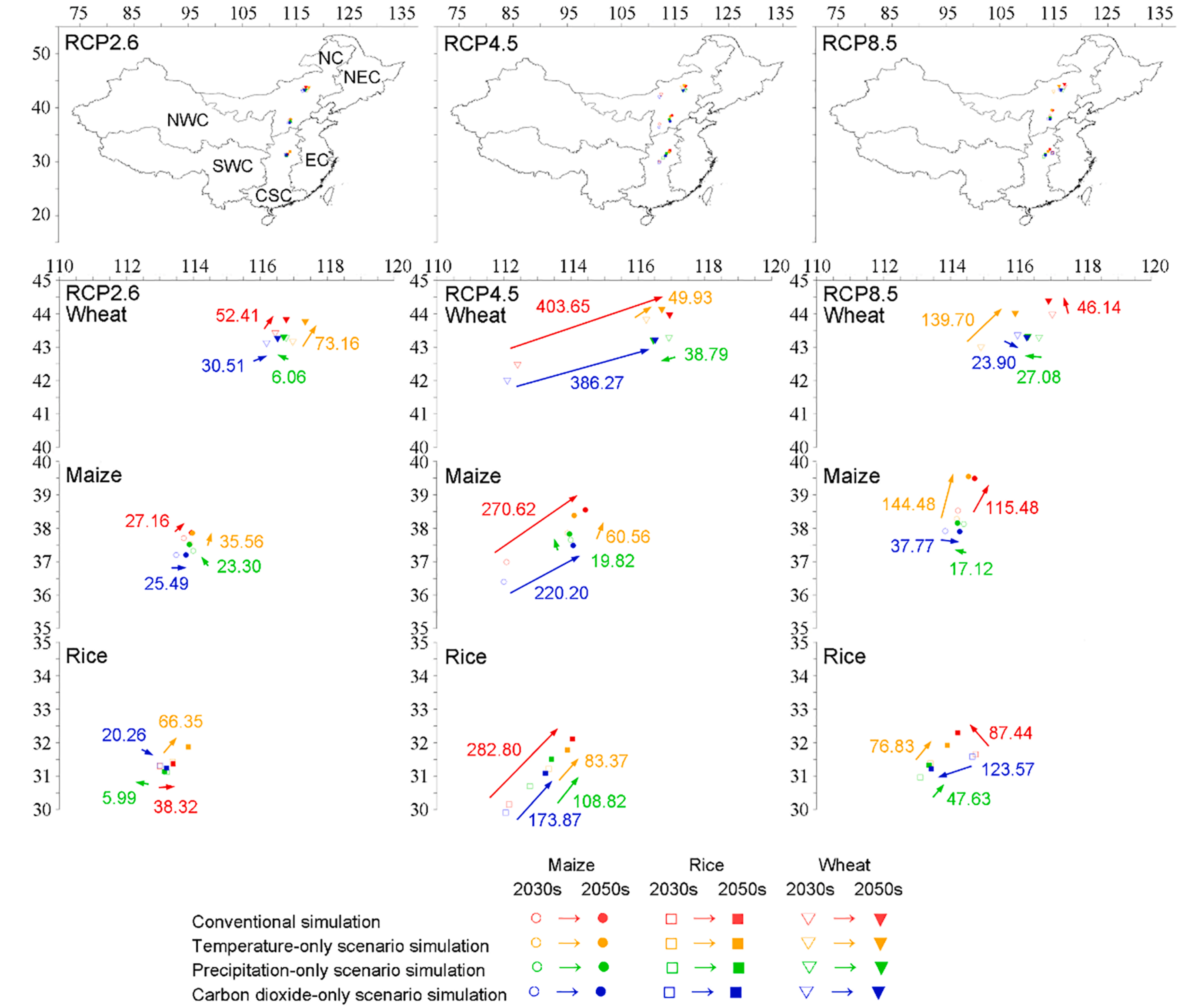


**Fig. 5.** Migration of the centers of gravity of yield changes from suitable planting areas of maize, rice, and wheat that are driven by either temperature, precipitation, or carbon dioxide effects alone in China in the 2030s (2021–2040) and 2050s (2041–2060) under three representative concentration pathway scenarios (RCP2.6, RCP4.5, and RCP8.5). The unit of migration distance is km. NC, NEC, EC, CSC, SWC, and NWC represent the regions of North China, Northeast China, East China, Central-South China, Southwest China, and Northwest China, respectively. The South China Sea is not shown in this figure.

concentration of suitable planting areas in these regions (Xu and Xu, 2012; Zhao et al., 2014). The migration distance was greater under the high-emission RCPs as a result of the faster warming trend and increasing precipitation (Xu and Xu, 2012; Zhao et al., 2014). Furthermore, more severe and more frequent droughts will likely happen in some parts of northern China, causing a remarkable reduction in suitable planting areas (especially in the NEC region) and long-distance migration for cultivation of maize and wheat under the medium-emission scenario in the early part of the 21st century (Liu et al., 2012; Wang and Chen, 2014). In addition to the likely changes in temperature and precipitation, increasing atmospheric $CO_2$ concentration also has important effects on crop plants, including reductions in stomatal conductance and transpiration that may contribute to increased crop water use efficiency and decreased water requirements (Deryng et al., 2016). The $CO_2$ concentration will not level off under the RCP scenarios to the mid-2100s. Greater increases in $CO_2$ concentration over time were estimated under the high-emission RCPs (Zhang et al., 2019). When $CO_2$ effects are included, the suitable planting area for crops is expected to enlarge in water-limited areas (Ficklin et al., 2010; Deryng et al., 2016).

### 4.2. Relationship between climatic variables and yield changes of crops

Temperature and precipitation also affect the yields of crops in China. The simultaneous occurrence of high temperatures and low precipitation is always unfavorable for crop productivity, causing yield losses due to heat and water stress for crops in large portions of China (Tao et al., 2016). In addition, increasing atmospheric $CO_2$ levels may lead to a short growing season and an increase in photosynthetic rate, leaf area, biomass, and crop yield (Deryng et al., 2016). The regression models for yield used in this study always showed negative correlations between crop yield and temperature increases, and positive correlations between crop yield and increases in precipitation and $CO_2$ in China. Overall, higher temperatures may not generally decrease crop yields, largely because the negative effect of higher temperature on crop yields is offset by higher precipitation while the benefits of $CO_2$ fertilization are retained (Pongratz et al., 2012; Zhang and Huang, 2012; Chen et al., 2018). Knox et al. (2016) applied a *meta*-analysis of climate change effects on seven crops in Europe and also found that projected average crop yield increased by 8% by the 2050s. Thus, the increased temperature, precipitation, and $CO_2$ level under the RCP8.5 scenario, especially in northern China, caused the areas suitable for crop planting to migrate slightly northward, and the centers of gravity for crop yield change may also shift northward (Wang and Hijmans, 2019). Readers should be aware that the optimum water and heat requirements for crop planting and yield enhancement are region and crop specific, and may cause different migration distances for different crops (Tao et al., 2016; Lombardozzi et al., 2018).

### *4.3. Limitations of this study*

We note the following potential limitations of our study:

(1) Climate variability is an important driving force of the distribution and yield variability of crops in most regions of China (Ray et al., 2015). However, the lack of consideration of other environmental factors and socio-economic factors affecting crop distribution and production (mainly including land cover and land use, edaphic conditions, extreme weather events, pests, diseases, and crop varieties) may result in some discrepancies between our results and the actual conditions of crops in China (Pongratz et al., 2012; Tigchelaar et al., 2018). For example, land cover and soil physiochemical properties (texture, pH, organic matter, drainage, etc.) are always considered as evaluation criteria to generate land suitability for crop cultivation using geostatistical methods (e.g., multi-criteria evaluation) (Elsheikh et al., 2013). However, in China, these are not primary factors for crop planting distribution at grid cell level. Substantial farmland cultivation is conducted on unsuitable soils because of pressures resulting from shortages of soil and water resources (e.g., terraced fields in the Loess Plateau and salt-alkali tolerant rice planted at the edge of the Taklimakan Desert) (Zhang et al., 2014). Schauberger et al. (2017) also indicated that these environmental and socio-economic data are difficult to obtain, or do not increase model performance in some cases. Furthermore, high-efficiency agricultural management technologies may further affect the results by increasing crop yield and expanding planting area to include some low soil fertility or water-deficient areas. Heterogeneity in cropping intensity is also a likely source of scale dependency for crop yields (Challinor et al., 2015).

(2) Some temperature indicators were calculated from daily mean temperatures that were derived from monthly mean air temperature using linear interpolation (and even combined with a running mean method). These methods can lead to some flattening of the daily temperature variations and to some overestimation of cropland suitability. Additionally, SPEI was normally distributed around a grid-specific mean precipitation – potential evapotranspiration that used positive values to indicate moisture conditions wetter than average (Vicente-Serrano et al., 2010a, 2010b). In this analysis, SPEI was used to indicate a suitable economic condition for agricultural production (Hao et al., 2014). SPEI should probably be combined with some other drought indices such as aridity index to further reflect climate conditions for the whole of China.

(3) Yield variation was due to the multiple averaging methods applied in this study (across a multi-model ensemble of six GCMs, regression model alone, etc.). There is still significant opportunity to improve our method in order to reduce estimation variability and uncertainty. The statistical regression method used in this study may integrate heterogeneity from different studies that were included in the *meta*-analysis (Liu et al., 2020). $CO_2$ effects were considered as a simple binary variable (rather than a continuous variable) in our method of simulating yield, and therefore the method could not fully reflect the effect of $CO_2$ on crop yield changes. Moreover, there was no differentiation in $CO_2$ sensitivity for individual crops in this method, and that may contribute large uncertainty to estimating crop yield changes. $CO_2$ fertilization may improve crop water use efficiency, thereby affecting both C3 and C4 plants and increasing the photosynthesis rate of C3 plants (e.g., wheat, rice) (Degener, 2015). However, C4 plants such as maize are comparatively independent of the effects associated with changes in $CO_2$ concentration (Degener, 2015).

(4) The Sacks et al. (2010) dataset was used to specify the crop calendars used in this study of future crop planting. However, future crop production will be influenced by climate change and elevated $CO_2$ concentration. Plant developmental rates will increase due to the predicted higher temperatures, permitting the use of cultivars adapted to a shorter growing season (Foyer et al., 2016).

## 5. Conclusions

In China, crop production is the foundation of economic development and social stability, providing a large amount of the staple food supplies. Crop cultivation and production in China face enormous challenges and opportunities under predicted climate changes scenarios. The results of this study indicated that the suitable areas for the planting of maize, rice, and wheat may migrate northward over time. Therefore, future research will be required to develop crop production systems that will improve grain production under different climatic conditions in different areas. The results of this study also indicated that yields for maize, rice, and wheat under the predicted future climate conditions would be expected to remain stable or to slightly increase, thereby helping to ensure food security. Moreover, areas of China with substantial yield increases in the future should be given special attention to determine crop production methods that will mitigate adverse effects of climate variability. Further studies should be carried out to develop and improve statistical regression models used to estimate the spatio-temporal variations of distribution and yield change for crops in order to promote the sustainability of agricultural development. Migration of crop cultivation areas should be sufficiently considered in future related research regarding crop yield estimations. Accurately estimating suitable crop production areas and yields could become an important tool for policy makers to use to plan for crop production methods and strategies to deal with climate change.

## CRediT authorship contribution statement

**Yajie Zhang:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft. **Haishan Niu:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing - review & editing. **Qiang Yu:** Funding acquisition, Project administration, Supervision, Writing - review & editing.

## Declaration of Competing Interest

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

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