Title: Impacts of 1.5°C and 2.0°C global warming above pre-industrial on potential winter wheat production of China

Authors: Zi Ye[1, #], Xiaolei Qiu[1, #], Jian Chen[1], Davide Cammarano[2], Zhonglei Ge[1], Alex C. Ruane[3], Leilei Liu[1], Liang Tang[1], Weixing Cao[1], Bing Liu[1,*], Yan Zhu[1,*]

Affiliations

[1] National Engineering and Technology Center for Information Agriculture, Key Laboratory for Crop System Analysis and Decision Making, Ministry of Agriculture, Jiangsu Key Laboratory for Information Agriculture, Nanjing Agriculture University, Nanjing, China

[2] Department of Agronomy, Purdue University, West Lafayette, IN, 47907, U.S.A

[3] NASA Goddard Institute for Space Studies, New York, NY 10025, U.S.A

[#] Zi Ye and Xiaolei Qiu contributed equally to this study.

***Corresponding author:**

Yan Zhu, Tel: 86-25-84396598, Fax: 86-25-84396672, Email: yanzhu@njau.edu.cn

Bing Liu, Tel: 86-25-84399791, Fax: 86-25-84396672, Email: bingliu@njau.edu.cn

Highlights:

- **i)** Climate warming shortened vegetative period, but not for reproductive period
- **ii)** Global warming tended to increase yield in the north, but decrease in the south
- **iii)** Elevated CO_2 could offset the negative impacts of increasing temperature mostly
- **iv)** Total production will increase by 2.8% and 8.3% under 1.5°C and 2.0°C scenarios
- **v)** Most of potential wheat production increase was observed in the north subregions

Abstract

Keeping global temperatures below 2.0°C above pre-industrial condition and pursuing efforts toward the more ambitious 1.5°C goal in the late 21st century was the main target from the Paris Agreement in 2015. Here we assessed the likely challenges for the China's winter wheat production under 1.5°C and 2.0 °C increase of global temperature, with four wheat crop models (CERES-Wheat, Nwheat, WheatGrow, and APSIM-Wheat) and the latest climate projections from the Half a degree Additional warming, Projections, Prognosis and Impacts project (HAPPI). Instead of using average "winter type" wheat cultivar, and same management and soil inputs for whole region, location-specific winter wheat cultivars with local agronomic information were calibrated for each of the representative wheat growing area of China, allowing a better spatial agronomic representation of the whole wheat planting area. The mean growing season temperature (GST) during the winter wheat vegetative stages was projected to increase by 0.6 to 1.4°C for the 1.5°C scenario, and 0.9 to 1.8 °C for the 2.0°C scenario, while during the reproductive stage was decreased between 0 and 0.9°C for the 1.5°C scenario and -0.3 and 1.1°C for the 2.0°C scenario. Growing season duration (GSD) for the whole period was shortened by 6 to 15 days for the 1.5°C scenario and 8 to 18 days for the 2.0°C scenario, as a result of higher GST under global warming. Increase in GST and decrease in GSD was more obvious in the Southwest Subregion (SWS) than subregions in the north. The shortening GSD for the whole wheat growth period was mostly from the shortening vegetative period, as no appreciable difference in number of days from anthesis to maturity was found for the whole regions. Although there is variability among models, the indication is that wheat yields were projected to increase in the North Subregion (NS), the Huang-Huai

Subregion (HHS), and the Middle-lower Researches of Yangzi River Subregion (MYS), but to decrease in the SWS under two warming scenarios. The effects of elevated CO_2 concentration were mostly beneficial and tended to offset the negative impacts of increasing temperature at both global warming scenarios, with a rate of 7-14% yield increase per 100-ppm, except for locations with GST of baseline higher than 11°C. Aggregating to regional wheat production, the total winter wheat production of China was projected to increase by 2.8% (1.6% to 3.0%, 25th percentile to 75th percentile) and 8.3% (7.0% to 9.6%, 25th percentile to 75th percentile) under 1.5°C and 2.0°C scenarios, and most of increase was observed in the north subregions due to the largest wheat planting area. Our results will lay the foundation for developing adaptation strategies to future climate change to ensure China and global wheat supply and food security.

Key words

Winter wheat; Crop model ensemble; Potential yield changes; Growing season duration; Total production, Climate change impacts

1. Introduction

With the increase in greenhouse gas emissions during past decades, continuous global warming resulted in record-breaking global temperature increase (Anderson and Kostinski, 2011; Coumou et al., 2011; Coumou et al., 2013; Parry et al., 2007; Zhao et al., 2017). In order to keep global temperatures from rising further, the Paris Agreement signed in 2015 aims at achieving an overall increase of 2.0°C with an ambition threshold of 1.5°C (UNFCCC, 2016). Crop production is one of the sectors that is mostly impacted by climate variability, and the projected climate changes could cause further vulnerability for achieving global food security (Field et al., 2014). Assessing the potential 1.5°C and 2.0°C warming impacts on global or regional crop production can help to addressing food security and agricultural adaptation more effectively.

A large number of studies have attempted to explore the effects of climate change on wheat phenology, growth and yield through various methods including field experiments, statistical analysis methods, and crop simulation models (Asseng et al., 2015; Challinor et al., 2014; Liu et al., 2016a; Schauberger et al., 2017; Wall et al., 2011; Wang et al., 2015; Zhao et al., 2017). As observed in warming experiments, increasing air temperature usually shortened wheat growth period, especially for vegetative stage, but the impacts on crop yield depends on the latitude of the experiments (Asseng et al., 2015; Asseng et al., 2019; Fang et al., 2015; Hou et al., 2012; O'Leary et al., 2015; Tian et al., 2012). When warming temperature exceed the crop threshold temperature, the impacts of temperature increase on physiological processes and yield formation of wheat could be detrimental (Asseng et al., 2011; Porter and Gawith, 1999), such as on leaf area development (White et al., 2012), growth rate (Ottman et al., 2012), photosynthetic rate (Ciais et al., 2005), canopy senescence (Farooq et al., 2011; Kadam et al., 2014), and root elongation (Tahir et al., 2010). Higher temperature will accelerate the grain filling rate, and lead to a decrease in grain weight (Dias and Lidon, 2009). Otherwise, warming temperature could be beneficial for biomass accumulation and yield formation of wheat in cooler environments (Grant et al., 2011; Ottman et al., 2012). In addition, higher temperatures can cause water stress due to the increase of soil evapotranspiration and crop water demand, which causes reduced stomatal conductance, resulting in decreased CO_2 absorption (Barnabás et al., 2008; Bell et al., 2010; Hatfield et al., 2011). The fertilizer effect of elevated CO_2 concentration mainly through enhanced crop photosynthesis, as observed in free-air CO_2 enrichment (FACE) systems (Cai et al., 2016; Erbs et al., 2015; O'Leary et al., 2015; Verrillo et al., 2017), would also alter the climate change impacts on wheat growth and yield.

Process-based crop models providing an implementation of crop physiological growth process and its interactions with genotype, soil, management, and weather conditions (Cao, 2008; Lobell et al., 2009; Sumberg, 2012; van Ittersum et al., 2013), have been widely used to simulate crop growth and development from the local up to global scales to assist in climate change impact assessments (Chenu et al., 2017). For example, Wang et al. (2015) found that the flowering date of spring wheat and winter wheat will be advanced 10 days for RCP 4.5 and 18 days for RCP 8.5 and delayed 2 days for RCP 4.5 and 14 days for RCP 8.5 respectively due to reduced cumulative vernalization days in eastern Australia. Using WheatGrow model and downscaled outputs from three GCMs, Lv et al. (2013) assessed the effects of climate change on wheat yields in the main wheat production regions of China under scenarios of A2 (a high greenhouse-gas-emission scenario), A1 (a low-emissions scenario) and B1 (a medium-emission scenario), and found that the flowering date was advanced and the potential yield was increased in most of wheat planting area under three warming scenarios. Climate projections of 1.5°C and 2.0°C increase, like the "Half a degree Additional warming, Prognosis and Projected Impacts" (HAPPI), have been made since the Paris Agreement (Mitchell et al., 2017). These projections allow us to compare against current conditions and evaluate climate impacts on crop production.

Several studies found that an ensemble of crop models was a better way to reproduce crop growth and grain yield formation under various climate sensitivity studies (e.g. increasing temerature, elevated CO_2, post-anthesis chronic warming and heat shock) (Asseng et al., 2013; Asseng et al., 2019; Martre et al., 2015). With an ensemble of 30 different wheat models and 30 global representative locations, Asseng et al. (2015) found that a 1ºC increase of temperature would cause a 6% reduction in wheat production at global scale. However, it has been found that there is no need to have such a large ensemble to be confident in the usefulness of it. Rosenzweig and Hillel (2015) showed how a mini-ensemble of two crop models could be used to quantify the impact of climate change on smallholders systems of Sub-Saharan Africa.

China is the world's largest wheat producer, which accounts for 18% of global wheat production (FAO, 2018). Quantifying the projected impacts of 1.5ºC and 2.0ºC warming on wheat production is essential for ensuring stable wheat supply and food security in China and even the world. Liu et al. (2019) assessed impacts of 1.5ºC and 2.0ºC warming on global wheat production with a global network of 60 eco-sites, which included 5 representative locations from China. As a widespread cultivated crop in China, wheat is subjected to different regional climates, cultivar types, and management practices in the whole country. Therefore, detailed local-specific model inputs including cultivar, soil and management (e.g. sowing date, planting density, fertilizer application, irrigation strategy), which usually lacked in previous studies are important for reliable country-scale climate change assessments. The spatial variation in climate condition during wheat growth period across whole wheat planting area of China could result in highly divergent warming impacts on wheat growth and yield (Ruane et al., 2018; Tao et al., 2017b; Tao et al., 2014). In addition, quantifying the impacts of global warming on total wheat production of China, which has been rarely studied, is another key aspect for national agriculture policy.

In this study, an ensemble of four wheat models was used to study the impacts of 1.5ºC and 2.0ºC increase in air temperature on winter wheat phenology and grain yield across the main growing areas of China. The objectives of this study were: (1) to quantify the changes of growing season temperature and growth duration under 1.5ºC and 2.0ºC increases in global average temperature; (2) to determine the spatial variation of projected impacts of 1.5ºC and 2.0ºC global warming on wheat yield and total regional wheat production in different wheat planting subregions of China.

2. Materials and methods

2.1 Study region

The study region included 13 provinces ranging from south to north in the main winter wheat production region of China. Wheat planting area and production in the study region account for more than 83% of the whole wheat planting area, and more than 88% of total wheat production in China (National Bureau of Statistics of China, 2015) (Fig. 1a). The whole study region was divided into four subregions according to the eco-climate condition and geographical location (Jin, 1996), including the North Subregion (NS), the Huang-Huai Subregion (HHS), the Middle-Lower Reaches of Yangzi River Subregion (MYS), the Southwest Subregion (SWS) (Fig. 1a). Due to large spatial scale of each subregion, there are still obvious differences in topography and climate within each subregion. Therefore, each subregion was divided into two or three eco-zones in wheat production system (Fig. 1b). There are 10 different eco-zones in the whole study region. In order to better reproduce the spatial variation of the actual winter wheat production, 129 meteorological stations located across the study region were used (Fig. 1b).

2.2 Data sources

Observed daily climate data at 129 meteorological stations during baseline period (31 years from 1980 to 2010) came from the China Meteorological Data Sharing Service System (http://data.cma.cn/), including daily maximum and minimum air temperatures, sunshine hours and precipitation. Climate scenarios of global warming 1.5°C and 2.0°C above pre-industrial level came from the Half a degree Additional warming, Projections, Prognosis and Impacts project (HAPPI) (Mitchell et al., 2017). The daily climate data for each station were generated from the two warming scenarios (named as 1.5ºC and 2.0ºC scenarios), combined with the local baseline climate data, according to the method from previous studies (Ruane et al., 2015; Ruane et al., 2018). Four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1, were used for each global warming scenario due to data availability at the time when the study was conducted. Observed sunshine hours were converted to daily solar radiation (Pohlert, 2004), since some crop models need solar radiation as model input. Following the HAPPI guidelines, CO_2 concentration used in this study was 390ppm, 423ppm and 487ppm for baseline, 1.5ºC and 2.0ºC scenarios, respectively.

The crop data came from agro-meteorological experimental network operated by the China Meteorological Administration. Crop data were available at the 129 stations, including wheat phenology (including sowing, emergence, flowering, and maturity), cultivar information, grain yield, and management practice. There were obvious spatial differences of sowing date at 129 stations, as shown in Fig. S1. Different cultivar types were used for different eco-zones within a subregion, and the planted wheat cultivars in each station have changed over the 1980-2010, due to better cultivars available. Therefore, 1 to 3 commonly used cultivars were selected for each eco-zone as representative cultivars, based on the planting times (e.g. they were planted at least for six growing seasons to obtain sufficient observed data for model calibration and evaluation) (Table S1). In total, 19 representative wheat cultivars from 41 stations were selected in the whole study region (Fig. 2). Generally, the stations where the representative cultivars located scattered across the whole winter wheat planting region, which means that the representative cultivars here have good spatial representation of the cultivar types in each of the main wheat production area of China. All these cultivars were from field experiments in 1990s and 2000s to represent the current typical cultivar types.

Soil data used for model calibration and evaluation at the 129 agro-meteorological stations were matched with the observed soil data at the nearest sites from the second national soil census data set in China, including soil type, soil depth, number of layers, structure of particle size, organic carbon, pH, cation exchange capacity, total nitrogen concentration, bulk density (Fig. S2), which was obtained from the Soil Science Data Center (http://soil.geodata.cn/) (Soil Data Center). The data of winter wheat planting area in China came from MAPSPAM (http://mapspam.info), and it was raster data with 5 arc-minute grid cells (Fig. 1a).

2.3 Crop models

Four wheat growth models were used for this study, including DSSAT-CERES-Wheat, DSSAT-Nwheat, WheatGrow and APSIM-Wheat. CERES-Wheat and Nwheat were integrated in DSSAT framework (v4.7), and a typical crop model in DSSAT consists of a Soil module, a Crop Template module which can simulate different crops by defining species-specific input files, a Weather module, and a module for dealing with competition for light and water among the soil, plants, and atmosphere (Jones et al., 2003). WheatGrow model (v3.0) mainly consists of five submodules, including apical development and phenological development (Yan et al., 2000), photosynthesis and biomass production (Liu et al., 2003), dry matter partitioning and organ establishment (Liu et al., 2001), yield and quality formation (Pan et al., 2007; Pan et al., 2006), and soil water and nutrient balance (Hu et al., 2004; Yang, 2004). In WheatGrow, physiological development time was used for quantifying the development stage, and the dynamic of wheat development and growth was simulated by daily time steps. The APSIM modelling framework (v7.9) includes modules for a diverse range of crops, pastures and trees, soil processes and a full range of management controls. APSIM-Wheat is one of the crop modules, which give process-based simulations of wheat growth and development, dry matter accumulation, and yield formation by daily steps (www.apsim.info) (Keating et al., 2003). CERES-Wheat, WheatGrow, Nwheat, and APSIM-Wheat have been widely used in the estimation of wheat yield potential around the world (Asseng et al., 2015; Asseng et al., 2011; Deihimfard et al., 2018; Lv et al., 2013; Paymard et al., 2018; Rivington and Koo, 2011).

2.4 Model calibration and evaluation

133 and 122 records from the 19 representative cultivars at 41 stations were used for calibration and evaluation, respectively. The details of observed data used in model calibration and evaluation can be found in Table S1. Management practices, including sowing date, sowing density, water and nitrogen application recorded at each station were used as model inputs. Observed anthesis and maturity dates, and grain yield were used for calibration and evaluation of the crop models. Crop phenology (time to anthesis and maturity) was calibrated first, by adjusting the crop parameters that dealt with crop development. Next, grain yield was calibrated by adjusting parameters that models' use for simulating grain yield (Table S2). During the calibration, a trial-and-error method was used to adjust parameters of each cultivar for four models to minimize the error between the simulated and observed anthesis date, maturity date, and grain yield (Figure S3).

The fitness between observed and simulated anthesis date, maturity date and grain yield were assessed with root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Oi - Si)^2}{N}}$$

where Oi and Si were the observed and simulated values, respectively; N was the total number of samples.

2.5 Impact assessment

To evaluate the impact of climate change on wheat production, the crop models were run without water or nutritional stresses (because the impact of temperature and CO_2 were the main factors to be analyzed) across the 129 stations. The models were run using the baseline weather (1980-2010) and the 1.5ºC and 2.0ºC scenarios. For stations which used the representative cultivars during the baseline period, the corresponding representative cultivars were used for two warming scenarios, and for stations without any of the 19 representative cultivars, the nearest representative cultivar in each eco-zone was used. The sowing date for 1.5ºC and 2.0ºC scenarios was same as baseline sowing date, as no adaptation through shifting sowing date was considered here. In addition, the planting density was 500 plants·m^{-2} for each scenario, and the CO_2 concentration used in the simulations for baseline, 1.5ºC and 2.0ºC scenarios was 390ppm, 423ppm and 487ppm, respectively.

The projected impacts of climate warming on growing season temperature (GST), growing season duration (GSD) and potential grain yield were analyzed. The GST and GSD during the whole growth period (from sowing to maturity, GST-w and GSD-w), vegetative period (from sowing to anthesis, GST-v and GSD-v), and reproductive period (from anthesis to maturity, GST-r and GSD-r) were calculated from the simulated phenology (including anthesis and maturity date) for each crop model under baseline and different GCMs. Then the mean GSTs and GSDs for 1.5ºC and 2.0ºC scenario were determined as average GSTs and GSDs from the four wheat models and four GCMs. The spatial characteristics of impacts on GST, GSD and potential yield from 129 stations in the whole study region were displayed with ArcGIS 10.4 software. And the integration process was the inverse distance weighted method (IDW).

In order to quantify the impacts of elevated CO_2 concentration on wheat grain yield, the four wheat models were run both with and without CO_2 fertilization effects for the whole study region. The impacts of elevated CO_2 on potential yield were determined as the differences between simulated potential yield with and without CO_2 fertilization effects.

We assessed the impacts on total regional wheat production (for different subregions and whole study region) as well as on wheat yield, because the impacts on total regional production was conductive to further analysis of self-sufficiency for China's wheat production under global warming and could provide critical information for national scale adaptation strategies for food security in the future. The climate impacts on potential grain yield were first simulated at each station. Then, the local impacts were interpolated into a 0.5°×0.5° grid, which is the same resolution of wheat planting area in MAPSPAM (http://mapspam.info) across the whole region with inverse distance weighted (IDW) method. The yield impacts for each grid were aggregated into regional production impacts for different subregions and whole region using the planting area in MAPSPAM as a weight factor. The upscaling of impacts from local to regional scales was done in ArcGIS. The impact upscaling was done for each model and GCMs first, and then they were averaged for all wheat models and GCMs.

3. Results

3.1 Model evaluation

Comparison of simulated and observed anthesis date, maturity date, and grain yield in model evaluation for four models were shown in Figure 3. 19 representative wheat cultivars were validated using 122 records, with an average of more than 6 records for each cultivar. Phenology was well simulated by all the models, with a RMSE between 7 to 9 days. But some models showed a larger divergence on grain yield with a RMSE between 1.1 to 1.7 $t \cdot ha^{-1}$.

3.2 Changes in wheat growing season temperature under 1.5ºC and 2.0ºC scenarios

Distinct spatial differences across the whole study region in mean growing season temperature (GST) and its changes under 1.5ºC and 2.0ºC scenarios were shown in Figure 4. The mean GST during vegetative (GST-v) and whole stage (GST-w) were warmer in the south (MYS and SWS) and cooler in the north (NS and HHS) under all scenarios, while GST at reproduction stage (GST-r) was warmer in the north and cooler in the south, mostly due to the obvious spatial differences in wheat phenology (Table S1 and Fig. S4). For the baseline period, average GST-w, GST-v and GST-r for the whole wheat growing region were 9.6ºC (between 5.8ºC and 13.0ºC), 7.6ºC (between 3.5ºC and 11.4ºC), and 20.8ºC (between 18.8ºC and 22.3ºC), respectively. The NS had the coolest GST-v, with an average of 5.9ºC (between 3.5ºC and 7.1ºC), and the warmest GST-v was found in SWS, with an average of 9.2ºC (between 7.0ºC and 11.4ºC). At reproductive period, the northern subregions experienced warmer growing temperature than the southern subregions, with the highest GST-r of 22.3ºC in eastern NS. The differences in GST-w between the northern and the southern subregions were less than the differences in GST-v (Fig. 4 a, d, g).

The spatial distribution of GST changes under 2.0ºC scenario were similar with that under 1.5ºC scenario, but the more obvious changes under 2.0ºC scenario were found in the southern subregions (Fig. 4). GST-w and GST-v under 1.5ºC scenario were projected to increase by 0.5 to 1.2ºC and 0.6 to 1.4ºC, while GST-r was projected to decrease by 0 to 0.9°C in most of wheat growing area. GST-w, GST-v, and GST-r changes were 0.8 to 1.4ºC, 0.9 to 1.8ºC, and -1.1 to 0.3ºC under 2.0ºC scenario, respectively. Higher increase in GST-w and GST-v and larger decrease in GST-r were found in parts of SWS than other regions under both warming scenarios.

3.3 Changes in growing season duration under 1.5ºC and 2.0ºC scenarios

The spatial distribution characteristics of the ensemble mean value of simulated growing season duration (GSD) was shown in Figure 5. Under baseline period, the average growth duration for vegetative period (GSD-v), reproductive period (GSD-r), and whole growth period (GSD-w) were 197 days, 36 days, and 233 days across the whole region. Generally, GSD-v and GSD-w were shorter in the south subregions than in the north subregions, while longer GSD-r was found in the south subregions than the north subregions. For example, GSD-v and GSD-w were about 52 days and 48 days longer in NS than in SWS, while GSD-r was about 4 days longer in SWS than in NS (Fig. 5 a, d, g).

Global warming reduced GSD-v and GSD-w in the whole wheat growing region under two warming scenarios, and the spatial distribution of GSD changes were similar for GSD-v and GSD-w (Fig. 5). Under 1.5ºC and 2.0ºC scenarios, GSD-v was shortened by about 12 and 15 days in SWS, and 8 and 10 days in other three subregions, respectively. As shown in Figure 5, 1.5ºC and 2.0ºC scenarios almost had no effect on growth duration at reproductive period in the whole wheat growing region. For example, GSD-r in NS, HHS, and MYS were shortened about 0.2 days, while it was prolonged about 0.7 days in SWS under 2.0ºC scenario. Therefore, the shortening of growth duration for whole growth period was mostly attributed to the shortening in vegetative period among four subregions.

3.4 Impacts of 1.5°C and 2.0ºC scenarios on winter wheat yield and regional production of China

The simulated wheat potential yield and impacts of increasing temperature and elevated CO_2 concentration were shown in Figure 6. The wheat potential yield for whole study region from individual models showed large inter-model variations, owing to large uncertainties between different crop models. But the spatial patterns of simulated wheat potential yields were consistent for four models (Fig. 6). Wheat potential yields for all four models were higher in the north and lower in the south (Fig. 6 a-e). Highest potential yields were observed in NS and HHS, especially in their east, with an average of 9.0 $t \cdot ha^{-1}$ and 9.3 $t \cdot ha^{-1}$, respectively. The potential yields were the lowest in SWS with 6.5 $t \cdot ha^{-1}$. The projected effects of increasing temperature and elevated CO_2 concentration showed increase on wheat potential yields significantly in NS, HHS and MYS, especially in HHS, while it showed decrease in SWS. The projected effects of increasing temperature and elevated CO_2 concentration differed among the models, and the effects from high to low were CERES-Wheat, WheatGrow, APSIM-Wheat, and Nwheat. The average changes of wheat potential yield in the four subregions which is NS, HHS, MYS and SWS were 4.5% (2.8% to 6.7%), 3.8% (1.6% to 5.9%), 0.3% (-1.4% to 1.6%), and -7.2% (-18.1% to 3.9%) under 1.5ºC scenario, and 10.7% (8.7% to 13.7%), 9.6% (6.6% to 12.4%), 4.8% (2.8% to 6.6%), and -3.6% (-15.9% to 8.0%) under 2.0ºC scenario, respectively.

Without CO_2 fertilization effect, global warming of 1.5ºC and 2.0ºC scenarios projected to increase grain yield at most of stations from NS and HHS with cooler growing season temperature, but to decrease grain yield at all stations from MYS and SWS with warmer growing season temperature. For example, grain yield at most stations of NS was projected to increase about 0 to 0.2 $t \cdot ha^{-1}$ (0 to 2.7%) and 0 to 0.3 $t \cdot ha^{-1}$ (0 to 3.3%) under 1.5ºC and 2.0ºC scenarios, with vary small spatial variability, but grain yield in SWS was projected to decrease about 0 to1.3 $t \cdot ha^{-1}$ (0 to 23.7%) and 0.2 to 1.5 $t \cdot ha^{-1}$ (2.0% to 28.4%), with large spatial variability. As shown in Fig. 7, the effects of elevated CO_2 concentration were mostly beneficial and tended to increase grain yield by 0.2 to 0.4 $t \cdot ha^{-1}$ and 0.6 to 1.0 $t \cdot ha^{-1}$ under 1.5°C and 2.0°C scenarios, respectively. The relative impacts of elevated CO_2 from 390ppm to 423ppm under 1.5°C scenario were 3.3%, 3.3%, 3.3%, 4.0% in NS, HHS, MYS and SWS, respectively. Under 2.0°C scenario, about 6.0% higher CO_2 effects can be expected in the whole planting area averagely than that under 1.5°C scenario. After taking CO_2 effects into account in the assessment, the CO_2 fertilization effect tended to offset the negative effect with increasing temperature in MYS, especially under 2.0°C scenario. The relationship between the growing season temperature (GST-w) under baseline and impacts on potential yield under two warming scenarios was shown in Fig. 8. Generally, the negative impacts of 1.5ºC and 2.0ºC global warming would be fully cancelled out by the positive effects of elevated CO_2 at locations with a GST-w larger than 11°C.

The impacts of climate change under 1.5°C and 2.0°C scenarios on regional winter wheat production were similar with the impacts on grain yield. Without CO_2 effect, the winter wheat production was projected to increase slightly in NS and HHS, but to decrease in MYS and SWS (Fig. 9). With CO_2 effect, the potential winter wheat production in NS, HHS, and MYS showed an enormous improvement under two global warming scenarios, but still showed a slight decrease in SWS. However, due to the differences of planting area between four subregions (Fig. 1a), impacts on regional potential wheat production showed distinct spatial differences across the whole region (Fig. 9). For example, although similar relative impacts on grain yield and regional production were found in NS and HHS, the HHS experienced the largest absolute increase of 4.6×10^6 t and 11.7×10^6 t in potential production among four subregions under 1.5°C and 2.0°C scenarios with CO_2 effect, as HHS has the largest wheat planting area (Fig. 1a). When aggregated to the whole wheat growing region of China, the simulated potential winter wheat production was 172×10^6 t for the existing winter wheat planting area of China under baseline, and the total regional potential wheat production was projected to increase by 2.8% (1.6% to 3.0%, 25th percentile to 75th percentile) and 8.3% (7.0% to 9.6%, 25th percentile to 75th percentile) under 1.5°C and 2.0°C scenarios with CO_2 effect, but to decrease by 0.5% (-1.2% to 2.6%, 25th percentile to 75th percentile) and 0.7% (0.3% to 3.7%, 25th percentile to 75th percentile) under 1.5°C and 2.0°C scenarios without CO_2 effect, respectively.

4. Discussion

Model inputs, model parameters and model structure could be the source of uncertainty in crop model-based climate change impact assessments (Tao et al., 2017a). As an important source for uncertainties in model parameters, selection of cultivars used for a specific region in crop models is important for the regional impact assessment. Most previous studies usually used a "winter type" wheat cultivar for a large geographical region (e.g. one cultivar for each province in Chen et al. (2018) and Lv et al. (2013)). Here in this study, local cultivar-specific information for model calibration and evaluation were collected, and the cultivars used here were mostly the actual cultivars recommended by the local agricultural extension department and have been widely planted during last decades in each eco-subregion. In addition, detailed management and soil information for each station were available, allowing a better spatial agronomic representation of the wheat planting area. As wheat is widespread (mainly from 26°13'N to 40°68'N) in China and covers different regional climates and production conditions, there were large spatial variation in cultivar types, soil, and management practices. For example, observed differences in wheat phenology date (e.g. jointing, heading, and maturity) across the study region can be more than two month (Liu et al., 2014; Xiao et al., 2018), and result in significant differences among locations in responses to climate change, because different cultivar types could have substantial variations in their responses to changes in climate variables under different production systems (Tao et al., 2014). Therefore, it is worthwhile to use multiple cultivars across the whole study region in order to better determine the diverse responses of actual wheat production system to climate change, even there is a slightly large discrepancy between observed and simulated yield. Though more observed records from different stations than previous impact assessment studies (Chen et al., 2018; Lv et al., 2013), were used to calibrate the parameters of representative cultivars. We still recognized the potential uncertainties in model parameters for multiple cultivars when calibrating them with observed yield records, and this could lead to large uncertainties in projected impacts (Liu et al., 2018). In addition, as key model inputs, climate projections for the target scenarios (1.5ºC and 2.0ºC scenarios) could also affect projected impacts. Thus, climate projections of an ensemble of four GCMs were used here to reduce the uncertainty due to different GCMs (Fig. S7 and Fig. S8).

Uncertainties due to crop models, which were usually ignored in most pervious regional impact assessments for China, have been shown here with the simulated yields and projected impacts from the four wheat models. As powerful tools to project climate impacts on crop yields, the differences of crop models in simulated yields and projected impacts can be contributed to model structure or model algorithms, and parameters among the four wheat models (Rosenzweig et al., 2014; Wallach et al., 2018).The multi-model ensemble has been suggested as a reliable approach to decrease impact uncertainty of crop model structure in several crops (Asseng et al., 2013; Asseng et al., 2019; Bassu et al., 2014; Li et al., 2015; Palosuo et al., 2011; Wallach et al., 2018). Here, an ensemble of four wheat models was applied to assess the impacts of 1.5ºC and 2.0ºC warming scenarios under the latest IPCC special report on wheat production in China. Although differences were found between four wheat models, similar general spatial pattern of climate warming impacts across the whole study region can be observed (Lv et al., 2017). Higher variations of climate impacts among crop models than GCMs (Fig. S8) indicated that the uncertainty due to crop models could be the main source of uncertainty in assessment results here, in line with previous studies (Asseng et al., 2013 & 2019).

In addition, the projected impacts on total wheat production for the whole study region might carry uncertainties from upscaling method. There have two main upscaling methods in the regional application of crop models, including aggregation from sampling and grid-scale simulations (Ewert et al., 2014; Nendel et al., 2013; Xu et al., 2020; Zhao et al., 2015). The main challenge for grid-scale simulations is the limited quality of input data (e.g. weather, soil profile, crop management, and yield observations) for each grid. In this study, sampling method which assumed the simulated impacts from selected points to represent an area was used for upscaling impacts, and uncertainties due to upscaling were not inevitable because the resultant impact data uses one value to represent many other (Zhao et al., 2015). However, the characteristic of this method is that when accurate data collected based on the sampling point to represent an area, the uncertainty from sampling decreases with increasing number of sampling points (van Bussel et al., 2015; Zhao et al., 2016). Here, we used 129 stations (e.g. sampling points) and 19 representative cultivars across the whole study region, and this could help to reduce the uncertainty in the impact upscaling.

The larger uncertainty of simulated yield and yield impacts in SWS than other subregions could be mainly due to crop models. As shown in Fig. S7, simulated wheat yields and yield impacts under different GCMs by the same model were similar, but the wheat yields simulated under same GCM by different models had a large variation, especially for CERES-Wheat model (Fig. S8 and Fig. S9). Temperature affects many processes of wheat growth such as phenology and yield formation and the algorithms of temperature affecting crop growth in different model could be different (Asseng et al., 2011; Jones et al., 2003; Keating et al., 2003; Liu et al., 2016b; Pan et al., 2007; Pan et al., 2006; Yan et al., 2000). In fact, a previous study by Asseng et al (2015) has indicated that larger variations among models could be expected under higher growing season temperatures. In addition, Wang et al. (2017) has shown that more than 50% of uncertainty in simulating grain yields was due to variations in modelling crop responses of physiological processes to temperature in 29 wheat models for growing season temperature from 14ºC to 33ºC. The baseline growing season temperature in SWS was the highest and temperature changes under two warming scenarios were also the largest among four subregions. Therefore, the larger variation of simulated yield and yield impacts in SWS could be due to its higher growing season temperature. These results agree with the findings of Asseng et al. (2013) who found that the largest models' divergence to temperature changes happened in the hotter environment of Australia.

The impact of global warming on the productivity of cereal crops in the future has received widespread attention. However, existing studies mostly predicted the impact of cereal crops based on the previous Coupled Model Intercomparison Project phase 5 (CMIP5) climate scenario (Mueller et al., 2015; Shin et al., 2017; Urban et al., 2015; Wang et al., 2017a), and most of them have almost investigated the impact of global warming >2.0ºC, which means previous impact assessments lacked details for <2.0 ºC of warming, especially for China. Those results cannot be reliably translated into impacts for the 1.5ºC and 2.0ºC warming scenarios, because a scenario includes changes not only in temperature, but also in CO_2 concentration, rainfall and other climate variables, all of which can affect crop production. In keeping with the global nature of the Paris Agreement, it is important to evaluate impacts of the new scenarios for the largest wheat producer-China. In this study, 1.5ºC and 2.0ºC global warming scenarios which include 4 GCMs provided by

HAPPI and four wheat growth models were used to assess the climate warming impacts on wheat growing season temperature (GST), growing season duration (GSD), and potential grain yield at 129 stations across the main winter wheat planting area of China. In addition, many previous studies did not focus sufficiently on national scale's responses under climate change. Therefore, in term of food security, it is important to analyze the effect of the new scenarios on the China's regional wheat production and this could provide critical information for adaptation strategies for food security in the future. Combining wheat yield impacts with existing winter wheat planting area, winter wheat production of China was projected to increase by 2.8% (1.6% to 3.0%, 25th percentile to 75th percentile) and 8.3% (7.0% to 9.6%, 25th percentile to 75th percentile) under 1.5^{o}C and 2.0^{o}C scenarios, which was quite similar with previous projections by different approaches (Liu et al., 2019, Rosenzweig et al., 2018). For example, based on a 31-wheat model ensemble and 60 global representative locations, global warming was projected to increase wheat grain production of China by 3.4% and 6.5% under 1.5^{o}C and 2.0^{o}C scenarios, respectively (Liu et al., 2019).

Increasing temperature advances the flowering date as a result of phenological development accelerated (Wang et al., 2015), and this has been observed worldwide under warming scenarios in field warming experiments (Cai et al., 2016; Fang et al., 2013; Tan et al., 2018; Tian et al., 2014), long-term observations (Liu et al., 2014; Wang et al., 2013) and the model-based simulations (Asseng et al., 2004; Lv et al., 2013; Wang et al., 2015; Wang et al., 2013). In this study, flowering date was projected to advance obviously (e.g. about 10 days in southern subregions under 2.0^{o}C scenarios), and more advancement was observed projected for southern subregions than northern subregions. It was similar to the study of Cai et al. (2016), in which increasing growing season mean temperature 1.3-2.0°C notably shortened wheat pre-heading duration around 10 days from the FACE experiment in a location from MYS. In another field warming study in a location from NS, wheat flowering date was advanced by 15-17 days under 2.5-2.8°C warming in growing season temperature (Tan et al., 2018). Phenology of some crops like winter wheat was not only affected by temperature also day length. With detailed response functions for temperature and day length, the four process-based wheat crop models used here can simulate the effects of both temperature and day length on wheat phenology. For example, the multi-model ensemble can reproduce wheat anthesis and maturity under various growing season temperature in T-FACE experiments in Arizona, U.S (Asseng et al., 2015). However, we were unable to separately quantify the changes in photoperiod and temperature to explain the reason for advanced flowering date here, because climate warming have changed growing season temperature and photoperiod conditions simultaneously.

The projected reduction in whole wheat growing season duration was mostly due to the shortening vegetative period. Shortening vegetative period due to climate warming could shift the wheat reproductive stage into a cool period, resulting in no obvious changes in GST for reproductive period under 1.5°C and 2.0°C scenarios. Therefore, wheat reproductive period, even with climate warming, tended to be stable in most of locations or even prolonged slightly at parts of locations in SWS. Similar findings could be observed in field warming experiments (Cai et al., 2016; Fang et al., 2013; Tian et al., 2014) and the model-based simulations (Asseng et al., 2004; Lv et al., 2013).

As changes of solar radiation under 1.5°C and 2.0°C scenarios were small for crop production (-0.9% to 0.3%), the quantified impacts on wheat production here could be mainly attributed to increasing temperature and elevated CO_2 concentration. Different climate conditions across the main wheat planting area resulted in divergent responses of wheat growth and grain yield to climate warming. Without CO_2 fertilization, wheat potential yield tended to increase in the cooler northern regions, while it tended to decrease in the warmer southern regions under both climate scenarios. In Australia, Wang et al (2017) also indicated that climate warming could benefit for the cooler wheat growing regions, but damage the wheat production in hot growing area. Similar responses could be found at global-scale simulations for wheat (Balkovič et al., 2014) and soybean (Ramirez-Cabral et al., 2016). The divergent yield responses between different subregions could be a result of tradeoff between shortening growth period and increasing biomass growth rate during vegetative period. While increasing temperature shortened wheat vegetative period, wheat biomass growth rate could increase under climate warming, as the average temperature during vegetative period under baseline period were much lower than the optimal temperatures for biomass growth, especially in northern subregions, and increasing temperature could be beneficial for biomass accumulation in these regions (Fig. 4). For example, in northern subregions, increasing potential wheat biomass accumulation at anthesis under two warming scenarios indicated that the improved biomass growth rate could offset the negative effects of shortening growth period (Fig. S5 and Fig. S6). However, for the southern subregions, wheat vegetative period was shortened more than the northern subregions, and the increase in biomass growth rate could not mitigate the negative effects of shortening wheat growth period, result in a decreased potential wheat biomass accumulation at anthesis under two warming scenarios (Fig. S5 and Fig. S6).

Testing the crop models before applying them for projecting crop production under future scenarios is essential for the confidence in our projections. The algorithms related to high temperature with high CO_2 in several wheat models were developed and improved by using observations from free-air CO_2 enrichment experiments (Asseng et al., 2013; Long et al., 2006). Asseng et al. (2019) and O'Leary et al. (2015) have shown that the predictions from the tested multi-model ensemble reproduced observed impacts on biomass and yield (especially for relative changes of grain yields and biomass) well under changing climate conditions, including heat shock, high temperatures and elevated CO_2 concentration (up to 550ppm). As the four models used have been tested for CO_2 effects in these previous studies, we didn't conduct further model validation under elevated CO_2 conditions. Similar with several previous studies which used crop models to evaluate crop productivity under higher CO_2 concentration scenarios (Asseng et al., 2004; Liu et al., 2019; Rosenzweig et al., 2018; Schauberger et al., 2017; Schleussner et al., 2018; Tao et al., 2009; Wang et al., 2019; Wang et al., 2017b), we combined GCMs and crop models to assess the future wheat productivity in China under 1.5 and 2.0°C scenarios with the corresponding atmospheric CO_2 concentration range. Generally, similar CO_2 fertilization effects can be observed across the whole wheat planting area in China. Among most of locations, the impacts of elevated CO_2 under 1.5°C and 2.0°C scenarios would be 0.2 to 0.4 $t \cdot ha^{-1}$ and 0.6 to 1.0 $t \cdot ha^{-1}$ yield increases, respectively, indicating a rate of 7-14% and 7-12% yield increase per 100-ppm. This is consistent with field observations and simulation results from a wide range of growing environments (Challinor et al., 2014; Kimball, 2016; O'Leary et al., 2015). Comparing wheat yield impacts with and without CO_2 effects, most of positive yield impacts can be attributed to the elevated CO_2, and similar conclusion was indicated by Liu et al. (2019). However, the fertilization effects of elevated CO_2 can't totally offset the negative impacts of 1.5ºC and 2.0ºC global warming at locations with higher growing season temperature (>11°C), and similar conclusion can be found from the simulations at 60 global representative wheat locations under the same warming scenarios, but with a higher growing season temperature threshold of 15ºC (Liu et al., 2019).

Studies have shown that wheat yield in 56% of China's wheat planting areas is stagnant recently (Ray et al., 2012). This study shows that under 1.5ºC and 2.0ºC scenarios without any adaptation measures, potential yield will be improved in northern China slightly, but significant negative impact will be experienced in southern China. A limitation of simulated potential yield is that the changes in spatial and temporal pattern of precipitation were not considered, because this study focused on impacts of increasing temperature and elevated CO_2 on yield potential, and winter wheat production in the study area is usually irrigated in northern China or experiencing high rainfall during growing season in southern China. However, projected decrease in precipitation in northern China under climate warming (Fang et al., 2013), will be challenging for the wheat irrigation, which is essential for maintaining high yield level in about 90% of wheat production in northern China currently.

Adaptation strategies, including shifting sowing date, breeding new cultivars with better heat resistance, and adjusting wheat planting area (Challinor et al., 2007; Gouache et al., 2012; Jingsong et al., 2012; Tao et al., 2012) have been proposed in order to better deal with climate changes. In addition, region-specific adaptation strategies should be provided according to the climate and production scenarios in different subregions. For instance, wheat growth duration was projected to be affected more in southern regions than northern regions, which suggested that adaptation strategies to maintain wheat phenology (e.g. shifting sowing date and breeding new cultivars with different thermal requirements) will be more needed in southern subregions. The climate warming impacts on wheat production were quantified without considering the changes of land use. Climate warming may increase thermal resources for crop production, especially in northern China, which could lead to expansion of crop planting area. For example, the expansion of northern boundary of crop planting have resulted in a 2.2% increase in national production of three major crops (maize, wheat, and rice) from 1981 to 2010 in China (Yang et al., 2015). This indicates that the increasing available wheat planting area in the north region where irrigation facilities have high availability could be a high priority for ensuring higher national wheat production under climate change in China, due to the projected positive climate warming impacts on wheat potential yield here.

5. Conclusion

Global warming was projected to reduce GSD, especially in vegetative period, due to higher GST under global warming 1.5°C and 2.0°C scenarios in China. Without CO_2 fertilization, wheat potential yield tended to increase in both cooler northern subregions, while it tended to decrease in both warmer southern subregions under both climate scenarios. The effects of elevated CO_2 concentration were mostly beneficial and tended to offset the negative impacts of increasing temperature especially in MYS at both global warming scenarios. The total regional winter wheat production of China was projected to increase by 2.8% (1.6% to 3.0%, 25th percentile to 75th percentile) and 8.3% (7.0% to 9.6%, 25th percentile to 75th percentile) under 1.5°C and 2.0°C scenarios, and most of increase was observed in the north subregions due to the largest wheat planting area. Adaptation strategies, including shifting sowing date, breeding new cultivars with better heat resistance, and increasing available wheat planting area in the north region where irrigation facilities have high availability could be a high priority for ensuring higher national wheat production under climate change in China.

Acknowledgements

This work was supported by the National Key Research and Development Program of China (2019YFA0607404), the Fundamental Research Funds for the Central Universities (KJQN201902), the National Science Foundation for Distinguished Young Scholars (31725020), the National Natural Science Foundation of China (31801260, 51711520319), the Natural Science Foundation of Jiangsu province (BK20180523), the NSFC-RS International Cooperation and Exchanges Project (31611130182). We thanked the Soil Data Center of National Earth System Science Data Sharing Service Infrastructure, National Science & Technology Infrastructure of China (http://soil.geodata.cn) for providing data support.

References

Anderson, A., Kostinski, A., 2011. Evolution and Distribution of Record-Breaking High and Low Monthly Mean Temperatures. Journal of Applied Meteorology and Climatology, 50(9): 1859-1871. https://doi.org/10.1175/JAMC-D-10-05025.1

Asseng, S. et al., 2015. Rising temperatures reduce global wheat production. Nature Climate Change, 5(2): 143-147. https://doi.org/10.1038/nclimate2470

Asseng, S. et al., 2013. Uncertainty in simulating wheat yields under climate change. Nature Climate Change, 3(9): 827-832. https://doi.org/10.1038/nclimate1916

Asseng, S., Foster, I., Turner, N.C., 2011. The impact of temperature variability on wheat yields. Global Change Biology, 17(2): 997-1012. https://doi.org/10.1111/j.1365-2486.2010.02262.x

Asseng, S. et al., 2004. Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO_2. Field Crops Research, 85(2): 85-102. https://doi.org/10.1016/S0378-4290(03)00154-0

Asseng, S. et al., 2019. Climate change impact and adaptation for wheat protein. Global Change Biology, 25(1): 155-173. https://doi.org/10.1111/gcb.14481

Balkovič, J. et al., 2014. Global wheat production potentials and management flexibility under the representative concentration pathways. Global and Planetary Change, 122: 107-121. https://doi.org/10.1016/j.gloplacha.2014.08.010

Barnabás, B., Jäger, K., Fehér, A., 2008. The effect of drought and heat stress on reproductive processes in cereals. Plant Cell & Environment, 31(1): 11-38. https://doi.org/10.1111/j.1365-3040.2007.01727.x

Bassu, S. et al., 2014. How do various maize crop models vary in their responses to climate change factors? Global Change Biology, 20(7): 2301-2320. https://doi.org/10.1111/gcb.12520

Bell, J.E., Sherry, R., Luo, Y., 2010. Changes in soil water dynamics due to variation in precipitation and temperature: an ecohydrological analysis in a tallgrass prairie. Water Resources Research, 46(3): 374-381. https://doi.org/10.1029/2009WR007908

Cai, C. et al., 2016. Responses of wheat and rice to factorial combinations of ambient and elevated CO_2 and temperature in FACE experiments. Global Change Biology, 22(2): 856-874. https://doi.org/10.1111/gcb.13065

Cao, W., 2008. Digital farming technology. Science press, Beijing. (in Chinese)

Challinor, A.J. et al., 2014. A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change, 4(4): 287-291. https://doi.org/10.1038/nclimate2153

Challinor, A.J., Wheeler, T.R., Craufur, P.Q., Ferroa, C.A.T., Stephensonc, D.B., 2007. Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures. Agriculture Ecosystems & Environment, 119(1): 190-204. https://doi.org/10.1016/j.agee.2006.07.009

Chen, Y., Zhang, Z., Tao, F., 2018. Impacts of climate change and climate extremes on major crops productivity in China at a global warming of 1.5 °C & 2.0 °C. Earth System Dynamics,9(2): 543-562. https://doi.org/10.5194/esd-9-543-2018

Chenu, K. et al., 2017. Contribution of crop models to adaptation in Wheat. Trends in Plant Science, 22(6): 472-490. https://doi.org/10.1016/j.tplants.2017.02.003

Ciais, P. et al., 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature, 437(7058): 529-533. https://doi.org/10.1038/nature03972

Coumou, D., Lehmann, J., Robinson, A., Rahmstorf, S., 2011. Increase of record-breaking temperature and precipitation extremes in a warming world, in: AGU Fall Meeting. AGU, San Francisco, CA, USA

Coumou, D., Robinson, A., Rahmstorf, S., 2013. Global increase in record-breaking monthly-mean temperatures. Climatic Change, 118(3): 771-782. https://doi.org/10.1007/s10584-012-0668-1

Deihimfard, R., Eyni-Nargeseh, H., Mokhtassi-Bidgoli, A., 2018. Effect of future climate change on wheat yield and water use efficiency under semi-arid conditions as predicted by APSIM-Wheat model. International Journal of Plant Production, 12(2): 115-125. https://doi.org/10.1007/s42106-018-0012-4

Dias, A.S., Lidon, F.C., 2009. Evaluation of grain filling rate and duration in bread and durum wheat, under heat stress after anthesis. Journal of Agronomy and Crop Science, 195(2): 137-147. https://doi.org/10.1111/j.1439-037X.2008.00347.x

Erbs, M., Manderscheid, R., Luig, A., Kage, H., Weigel, H.J., 2015. A field experiment to test interactive effects of elevated CO_2 concentration (FACE) and elevated canopy temperature (FATE) on Wheat. Procedia Environmental Sciences, 29(18): 60-61. https://doi.org/10.1016/j.proenv.2015.07.157

Estrella, N., Sparks, T.H., Menzel, A., 2007. Trends and temperature response in the phenology of crops in Germany. Global Change Biology, 13(8): 1737–1747. https://doi.org/10.1111/j.1365-2486.2007.01374.x

Ewert, F. et al., 2014. Uncertainties in scaling-up crop models for large-area climate-change impact assessments, in: Rosenzweig, C., Hillel, D. (Eds.), handbook of climate change and agroecosystems: The Agricultural Model Intercomparison Project (AgMIP). World Scientific Publishing Company: 262-277.

Fang, S., Cammarano, D., Zhou, G., Tan, K., Ren, S., 2015. Effects of increased day and night temperature with supplemental infrared heating on winter wheat growth in North China. European Journal of Agronomy, 64: 67-77. https://doi.org/10.1016/j.eja.2014.12.012

Fang, S., Su, H., Liu, W., Tan, K., Ren, S., 2013. Infrared warming reduced winter wheat yields and some physiological parameters, which were mitigated by irrigation and worsened by delayed sowing. PLos One, 8(7): e67518. https://doi.org/10.1371/journal.pone.0067518

FAO, 2018. FAO Statistical Yearbook 2018. http://www.fao.org/faostat/en/#data/QC

Farooq, M., Bramley, H., Palta, J.A., Siddique, K.H.M., 2011. Heat stress in wheat during reproductive and grain-filling phases. Critical Reviews in Plant Sciences, 30(6): 491-507. https://doi.org/10.1080/07352689.2011.615687

Field, B. et al., 2014. Climate change 2014: impacts, adaptation, and vulnerability – IPCC WGII AR5 summary for policymakers, 1-32 pp.

Gouache, D. et al., 2012. Evaluating agronomic adaptation options to increasing heat stress under climate change during wheat grain filling in France. European Journal of Agronomy, 39(3): 62-70. https://doi.org/10.1016/j.eja.2012.01.009

Grant, R.F. et al., 2011. Controlled warming effects on wheat growth and yield: field measurements and modeling. Agronomy Journal, 103(6): 1742. https://doi.org/10.2134/agronj2011.0158

Hatfield, J.L. et al., 2011. Climate impacts on agriculture: implications for crop production. Agronomy Journal, 103(2): 351-370. https://doi.org/10.2134/agronj2010.0303

Hou, R., Zhu, O., Li, Y., Wilson, G.V., Li, H., 2012. Is the change of winter wheat yield under warming caused by shortened reproductive period? Ecology and Evolution, 2(12): 2999-3008. https://doi.org/10.1002/ece3.403

Hu, J., Cao, W., Jiang, D., Luo, W., 2004. Quantification of water stress factor for crop growth simulation I. Effects of drought and waterlogging stress on photosynthesis, transpiration and dry matter partitioning in winter wheat. Acta Agronomica Sinica, 30(4): 315-320. (in Chinese with English abstract)

Jin, S., 1996. Wheat ecology of China. Agriculture Science Press of China. (In Chinese)

Jingsong, S., Guangsheng, Z., Xinghua, S., 2012. Climatic suitability of the distribution of the winter wheat cultivation zone in China. European Journal of Agronomy, 43(3): 77-86. https://doi.org/10.1016/j.eja.2012.05.009

Jones, J.W. et al., 2003. The DSSAT cropping system model. European Journal of Agronomy, 18(3): 235-265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kadam, N.N. et al., 2014. Chapter three - agronomic and physiological responses to high temperature, drought, and elevated CO_2 interactions in cereals. Advances in Agronomy, 127: 111-156. https://doi.org/10.1016/B978-0-12-800131-8.00003-0

Keating, B.A. et al., 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy, 18(3): 267-288.

https://doi.org/10.1016/S1161-0301(02)00108-9
Kimball, B.A., 2016. Crop responses to elevated CO_2 and interactions with H_2O, N, and temperature. Current Opinion in Plant Biology, 31: 36-43. https://doi.org/10.1016/j.pbi.2016.03.006
Li, T. et al., 2015. Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. Global Change Biology, 21(3): 1328-1341. https://doi.org/10.1111/gcb.12758
Liu, B. et al., 2016a. Similar estimates of temperature impacts on global wheat yield by three independent methods. Nature Climate Change, 6(12): 1130-1136. https://doi.org/10.1038/nclimate3115
Liu, B. et al., 2016b. Modelling the effects of heat stress on post-heading durations in wheat: A comparison of temperature response routines. Agricultural and Forest Meteorology, 222: 45-58. https://doi.org/10.1016/j.agrformet.2016.03.006
Liu, B. et al., 2014. Post-heading heat stress and yield impact in winter wheat of China. Global Change Biology, 20(2): 372-381. https://doi.org/10.1111/gcb.12442
Liu, B. et al., 2019. Global wheat production with 1.5 and 2.0°C above pre-industrial warming. Global Change Biology, 25: 1428-1444. https://doi.org/10.1111/gcb.14542
Liu, L. et al., 2018. Uncertainty in wheat phenology simulation induced by cultivar parameterization under climate warming. European Journal of Agronomy, 94: 46-53. https://doi.org/10.1016/j.eja.2017.12.001
Liu, T. et al., 2001. Quantitative simulation on dry matter partitioning dynamic in wheat organs. Journal of Triticeae Crops, 21: 25-31. (in Chinese with English abstract)
Liu, T., Cao, W., Luo, W., Wang, S., Yin, J., 2003. A simulation model of photosynthetic production and dry matter accumulation in wheat. Journal of Triticeae Crops, 21: 26-30. (in Chinese with English abstract)
Lobell, D.B., Cassman, K.G., Field, C.B., 2009. Crop yield gaps: their importance, magnitudes, and causes. Annual Review of Environment and Resources, 34(1): 179-204. https://doi.org/10.1146/annurev.environ.041008.093740
Long, S.P., Ainsworth, E.A., Leakey, A.D.B., Nösberger, J., Ort, D.R., 2006. Food for thought: lower-than-expected crop yield stimulation with rising CO_2 concentrations. Science, 312(5782): 1918-1921. https://doi.org/10.1126/science.1114722
Lv, Z., Liu, X., Cao, W., Zhu, Y., 2013. Climate change impacts on regional winter wheat production in main wheat production regions of China. Agricultural and Forest Meteorology, 171-172(3): 234-248. https://doi.org/10.1016/j.agrformet.2012.12.008
Lv, Z., Liu, X., Cao, W., Zhu, Y., 2017. A model-based estimate of regional wheat yield gaps and water use efficiency in main winter wheat production regions of China. Scientific Reports, 7(1): 6081. https://doi.org/10.1038/s41598-017-06312-x
Martre, P. et al., 2015. Multimodel ensembles of wheat growth: many models are better than one. Global Change Biology, 21(2): 911-925. https://doi.org/10.1111/gcb.12768
Mitchell, D. et al., 2017. Half a degree additional warming, prognosis and projected impacts (HAPPI): background and experimental design. Geoscientific Model Development, 10(2): 571-583. https://doi.org/10.5194/gmd-10-571-2017
Mueller, B. et al., 2015. Lengthening of the growing season in wheat and maize producing regions. Weather and Climate Extremes, 9: 47-56. https://doi.org/10.1016/j.wace.2015.04.001
National Bureau of Statistics of China, 2015. China Statistical Yearbook 2015. China Statistics Press,

Beijing. (in Chinese)
Nendel, C. et al., 2013. Simulating regional winter wheat yields using input data of different spatial resolution. Field Crops Research, 145: 67-77. https://doi.org/10.1016/j.fcr.2013.02.014
O'Leary, G.J. et al., 2015. Response of wheat growth, grain yield and water use to elevated CO_2 under a Free Air CO_2 Enrichment (FACE) experiment and modelling in a semi-arid environment. Global Change Biology, 21(7): 2670-2686. https://doi.org/10.1111/gcb.12830
Ottman, M.J., Kimball, B.A., White, J.W., Wall, G.W., 2012. Wheat growth response to increased temperature from varied planting dates and supplemental infrared heating. Agronomy Journal, 104(1): 7-16. https://doi.org/10.2134/agronj2011.0212
Palosuo, T. et al., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: A comparison of eight crop growth models. European Journal of Agronomy, 35(3): 103-114. https://doi.org/10.1016/j.eja.2011.05.001
Pan, J., Zhu, Y., Cao, W., 2007. Modeling plant carbon flow and grain starch accumulation in wheat. Field Crops Research, 101(3): 276-284. https://doi.org/10.1016/j.fcr.2006.12.005
Pan, J. et al., 2006. Modeling plant nitrogen uptake and grain nitrogen accumulation in wheat. Field Crops Research, 97(2): 322-336. https://doi.org/10.1016/j.fcr.2005.11.006
Parry, M.L. et al., 2007. Climate change 2007: Impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change. Summary for policymakers. Cambridge University Press, 37(6): 2407. https://doi.org/10.2134/jeq2008.0015br
Paymard, P., Bannayan, M., Haghighi, R.S., 2018. Analysis of the climate change effect on wheat production systems and investigate the potential of management strategies. Natural Hazards, 91(3): 1237-1255. https://doi.org/10.1007/s11069-018-3180-8
Pohlert, T., 2004. Use of empirical global radiation models for maize growth simulation. Agricultural and Forest Meteorology, 126(1): 47-58. . https://doi.org/10.1016/j.agrformet.2004.05.003
Porter, J.R., Gawith, M., 1999. Temperatures and the growth and development of wheat: a review. European Journal of Agronomy, 10(1): 23-36. https://doi.org/10.1016/S1161-0301(98)00047-1
Ramirez-Cabral, N.Y.Z., Kumar, L., Taylor, S., 2016. Crop niche modeling projects major shifts in common bean growing areas. Agricultural and Forest Meteorology, 218-219: 102-113. https://doi.org/10.1016/j.agrformet.2015.12.002
Ray, D.K., Ramankutty, N., Mueller, N.D., West, P.C., Foley, J.A., 2012. Recent patterns of crop yield growth and stagnation. Nature Communications, 3: 1293-1299. https://doi.org/10.1038/ncomms2296
Rivington, M., Koo, J., 2011. Report on the meta-analysis of crop modelling for climate change and food security survey. Climate Change, Agriculture and Food Security Challenge Program, Frederiksberg, 73. https://doi.org/10.13140/RG.2.1.4599.1522
Rosenzweig, C. et al., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences of the United States of America, 111(9): 3268-3273. https://doi.org/10.1073/pnas.1222463110
Rosenzweig, C., Hillel, D., 2015. Handbook of climate change and agroecosystems: the agricultural model intercomparison and improvement project integrated crop and economic assessments, Part 2. Imperial College Press London, pp. 125-158.

Rosenzweig, C. et al., 2018. Coordinating AgMIP data and models across global and regional scales for 1.5°C and 2.0°C assessments. Philosophical Transactions of the Royal Society A: Mathematical, 376(2119): 20160455. https://doi.org/10.1098/rsta.2016.0455

Ruane, A.C., Goldberg, R., Chryssanthacopoulos, J., 2015. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. Agricultural and Forest Meteorology, 200: 233-248. https://doi.org/10.1016/j.agrformet.2014.09.016

Ruane, A.C., Phillips, M.M., Rosenzweig, C., 2018. Climate shifts within major agricultural seasons for +1.5 and +2.0 °C worlds: HAPPI projections and AgMIP modeling scenarios. Agricultural and Forest Meteorology, 259: 329-344. https://doi.org/10.1016/j.agrformet.2018.05.013

Schauberger, B. et al., 2017. Consistent negative response of US crops to high temperatures in observations and crop models. Nature Communications, 8: 13931. https://doi.org/10.1038/ncomms13931

Schleussner, C.F. et al., 2018. Crop productivity changes in 1.5 °C and 2 °C worlds under climate sensitivity uncertainty. Environmental Research Letters, 13(6). https://doi.org/10.1088/1748-9326/aab63b

Shin, Y., Lee, E.J., Im, E.S, Jung, I.W., 2017. Spatially distinct response of rice yield to autonomous adaptation under the CMIP5 multi-model projections. Asia-Pacific Journal of Atmospheric Sciences, 53(1): 21-30. https://doi.org/10.1007/s13143-017-0001-z

Soil Data Center, N.E.S.S.D.S.I., National Science and Technology Infrastructure of China. http://soil.geodata.cn

Sumberg, J., 2012. Mind the (yield) gap(s). Food Security, 4(4): 509-518. https://doi.org/10.1007/s12571-012-0213-0

Tahir, I.S.A., Nakata, N., Yamaguchi, T., Nakano, J., Ali, A.M., 2010. Influence of high shoot and root-zone temperatures on growth of three wheat genotypes during early vegetative stages. Journal of Agronomy and Crop Science, 194(2): 141-151. https://doi.org/10.1111/j.1439-037X.2008.00298.x

Tan, K., Zhou, G., Lv, X., Guo, J., Ren, S., 2018. Combined effects of elevated temperature and CO_2 enhance threat from low temperature hazard to winter wheat growth in North China. Scientific Reports, 8(1): 4336. https://doi.org/10.1038/s41598-018-22559-4

Tao, F. et al., 2017a. Contribution of crop model structure, parameters and climate projections to uncertainty in climate change impact assessments. Global Change Biology, 24(3): 1291-1307. https://doi.org/10.1111/gcb.14019

Tao, F., Xiao, D., Zhang, S., Zhang, Z., Rötter, R.P., 2017b. Wheat yield benefited from increases in minimum temperature in the Huang-Huai-Hai Plain of China in the past three decades. Agricultural and Forest Meteorology, 239: 1-14. https://doi.org/10.1016/j.agrformet.2017.02.033

Tao, F., Zhang, S., Zhang, Z., 2012. Spatiotemporal changes of wheat phenology in China under the effects of temperature, day length and cultivar thermal characteristics. European Journal of Agronomy, 43(43): 201-212. https://doi.org/10.1016/j.eja.2012.07.005

Tao, F., Zhang, Z., Liu, J., Yokozawa, M., 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection. Agricultural and Forest Meteorology, 149(8): 1266-1278.

https://doi.org/10.1016/j.agrformet.2009.02.015

Tao, F. et al., 2014. Responses of wheat growth and yield to climate change in different climate zones of China, 1981–2009. Agricultural and Forest Meteorology, 189-190(189): 91-104. https://doi.org/10.1016/j.agrformet.2014.01.013

Tian, Y. et al., 2012. Warming impacts on winter wheat phenophase and grain yield under field conditions in Yangtze Delta Plain, China. Field Crops Research, 134(3): 193-199. https://doi.org/10.1016/j.fcr.2012.05.013

Tian, Y. et al., 2014. Climatic warming increases winter wheat yield but reduces grain nitrogen concentration in east China. PLoS One, 9(4): e95108. https://doi.org/10.1371/journal.pone.0095108

UNFCCC, 2016. Adoption of the Paris Agreement. 32pp. available at: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf, United Nations Framework Convention on Climate Change.

Urban, D.W., Sheffield, J., Lobell, D.B., 2015. The impacts of future climate and carbon dioxide changes on the average and variability of US maize yields under two emission scenarios. Environmental Research Letters, 10(4): 45003-45011. https://doi.org/10.1088/1748-9326/10/4/045003

van Bussel, L.G.J. et al., 2015. From field to atlas: Upscaling of location-specific yield gap estimates. Field Crops Research, 177: 98-108. https://doi.org/10.1016/j.fcr.2015.03.005

van Ittersum, M.K. et al., 2013. Yield gap analysis with local to global relevance—A review. Field Crops Research, 143(1): 4-17. https://doi.org/10.1016/j.fcr.2012.09.009

Verrillo, F. et al., 2017. Elevated field atmospheric CO_2 concentrations affect the characteristics of winter wheat (cv. Bologna) grains. Crop and Pasture Science, 68(2017): 713-725. https://doi.org/10.1071/CP17156

Wall, G.W., Kimball, B.A., White, J.W., Ottman, M.J., 2011. Gas exchange and water relations of spring wheat under full-season infrared warming. Global Change Biology, 17(6): 2113–2133. https://doi.org/10.1111/j.1365-2486.2011.02399.x

Wallach, D. et al., 2018. Multimodel ensembles improve predictions of crop–environment–management interactions. Global Change Biology, 24(11): 5072-5083. https://doi.org/10.1111/gcb.14411

Wang, B. et al., 2019. Variable effects of 2°C air warming on yield formation under elevated [CO_2] in a Chinese double rice cropping system. Agricultural and Forest Meteorology, 278: 107662. https://doi.org/10.1016/j.agrformet.2019.107662

Wang, B. et al., 2017a. Spatiotemporal changes in wheat phenology, yield and water use efficiency under the CMIP5 multimodel ensemble projections in eastern Australia. Climate Research, 72(2): 83-99. https://doi.org/10.3354/cr01458

Wang, B., Liu, D.L., Asseng, S., Macadam, I., Yu, Q., 2015. Impact of climate change on wheat flowering time in eastern Australia. Agricultural and Forest Meteorology, 209–210: 11-21. https://doi.org/10.1016/j.agrformet.2015.04.028

Wang, B. et al., 2017b. Australian wheat production expected to decrease by the late 21st century. Global Change Biology, 24(6): 2403-2415. https://doi.org/10.1111/gcb.14034

Wang, E. et al., 2017. The uncertainty of crop yield projections is reduced by improved temperature response functions. Nature Plants, 3: 17102. https://doi.org/10.1038/nplants.2017.102

Wang, J., Wang, E., Feng, L., Hong, Y., Yu, W., 2013. Phenological trends of winter wheat in response to varietal and temperature changes in the North China Plain. Field Crops Research, 144(6): 135-144. https://doi.org/10.1016/j.fcr.2012.12.020

White, J.W., Kimball, B.A., Wall, G.W., Ottman, M.J., 2012. Cardinal temperatures for wheat leaf appearance as assessed from varied sowing dates and infrared warming. Field Crops Research, 137(137): 213-220. https://doi.org/10.1016/j.fcr.2012.08.013

Xiao, L. et al., 2018. Estimating spring frost and its impact on yield across winter wheat in China. Agricultural and Forest Meteorology, 260-261: 154-164. https://doi.org/10.1016/j.agrformet.2018.06.006

Xu, H. et al., 2020. Impacts of spatial zonation schemes on yield potential estimates at the regional scale. Agronomy, 10(5): 631-646. https://doi.org/10.3390/agronomy10050631

Yan, M., Cao, W., Luo, W., Jiang, H., 2000. A mechanistic model of phasic and phenological development of wheat. I. Assumption and description of the model. Chinese Journal of Applied Ecology, 11(3): 355-359. (In Chinese with English abstract)

Yang, X. et al., 2015. Potential benefits of climate change for crop productivity in China. Agricultural and Forest Meteorology, 208: 76-84. https://doi.org/10.1016/j.agrformet.2015.04.024

Yang, Z.H., 2004. Simulation on nitrogen uptake and partitioning in crops. System Sciences and Comprehensive Studies in Agriculture, 20(1): 5-11. (In Chinese with English abstract)

Zhang, T., Huang, Y., Yang, X., 2013. Climate warming over the past three decades has shortened rice growth duration in China and cultivar shifts have further accelerated the process for late rice. Global Change Biology, 19(2): 563–570. https://doi.org/10.1111/gcb.12057

Zhao, C. et al., 2017. Temperature increase reduces global yields of major crops in four independent estimates. Proceedings of the National Academy of Sciences of the United States of America, 114(35): 9326-9331. https://doi.org/10.1073/pnas.1701762114

Zhao, G. et al., 2016. Evaluating the precision of eight spatial sampling schemes in estimating regional means of simulated yield for two crops. Environmental Modelling & Software, 80: 100-112. https://doi.org/10.1016/j.envsoft.2016.02.022

Zhao, G. et al., 2015. Demand for multi-scale weather data for regional crop modeling. Agricultural and Forest Meteorology, 200: 156-171. https://doi.org/10.1016/j.agrformet.2014.09.026

Figure legend

Figure 1. (a) Wheat planting area of China. Red lines indicated study region. **(b) Study region, eco-zones and agro-meteorological stations.** Blue lines indicated the four main subregions of winter wheat production in China, and the colorful blocks indicated the 10 eco-zones. Red points were the 129 agro-meteorological stations.

Figure 2. Stations used for calibration of genetic parameters for representative cultivars. 1 to 3 commonly used cultivars were selected for each eco-zone as representative cultivars, based on the planting times.

Figure 3. Comparison of simulated and observed anthesis date (a-d), maturity date (e-h), and grain yield (i-l) in model evaluation for CERES-Wheat (a, e and i), Nwheat (b, f and j), WheatGrow (c, g, and k) and APSIM-Wheat (d, h, and l). Red lines are linear regression lines and black lines are 1 to 1 lines. DOY: day of year.

Figure 4. Spatial distribution of ensemble mean of growing season temperature (GST, °C), under baseline (a, d and g) and changes of growing season temperature under 1.5°C (b, e and h) and 2.0°C (c, f and i) scenarios. GST during vegetative (GST-v, °C), reproductive (GST-r, °C), and whole growing season (GST-w, °C) periods were the average temperatures from sowing to anthesis, from anthesis to maturity, and from sowing to maturity, respectively. GST for 1.5°C and 2.0°C scenarios was the mean value of four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1.

Figure 5. Spatial distribution of ensemble mean value of simulated growing season duration (GSD, days) under baseline (a, d and g) and changes of simulated GSD under 1.5ºC (b, e and h) and 2.0ºC (c, f and i) scenarios. Vegetative (GSD-v), reproductive (GSD-r), and whole growing season (GSD-w) duration were days from sowing to anthesis, from anthesis to maturity, and from sowing to maturity, respectively. The simulated GSD for 1.5ºC and 2.0ºC scenarios was the mean value of four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1.

Figure 6. Spatial distribution of simulated potential yield under baseline (a-e) and relative changes of potential yield under 1.5ºC (f-j) and 2.0ºC (k-o) scenarios for CERES-Wheat (a, f, k), Nwheat (b, g, l), WheatGrow (c, h, m), APSIM-Wheat (d, i, n) and the ensemble (e, j, o) mean value of four models with CO_2 fertilization effects. The potential yield changes for 1.5ºC and 2.0ºC scenarios were the mean value of simulated potential yield changes from four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1. CO_2 concentration was 390ppm, 423ppm and 487ppm for Baseline, 1.5ºC and 2.0ºC scenarios, respectively.

Figure 7. The boxplot of ensemble mean changes of potential wheat yield under 1.5ºC and 2.0ºC scenarios without (a, c) and with (b, d) CO_2 effect from four crop models including CERES-Wheat, Nwheat, WheatGrow, and APSIM-Wheat. CO_2 concentration was 390ppm, 423ppm and 487ppm for baseline, 1.5ºC and 2.0ºC scenarios, respectively. (a) and (b) indicated the absolute changes of potential yield, (c) and (d) indicated the relative changes of potential yield. NS: the

North Subregion; HHS: the Huang-Huai Subregion; MYS: the Middle-Lower Researches of Yangzi River Subregion; SWS: the Southwest Subregion.

Figure 8. Relationship between growing season temperature (GST-w, ºC) under baseline and relative changes of potential yield under 1.5ºC (a) and 2.0ºC (b) scenarios at 129 stations. The potential yield changes for 1.5ºC and 2.0ºC scenarios were the mean of four crop models and four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1. CO_2 concentration was 390ppm, 423ppm and 487ppm for Baseline, 1.5ºC and 2.0ºC scenarios, respectively.

Figure 9. Projected absolute (a, b) and relative (c, d) changes of regional potential wheat production in different subregions of winter wheat planting area of China under 1.5ºC and 2.0ºC scenarios without (a, c) and with (b, d) CO_2 effects. The regional wheat productions for 1.5ºC and 2.0ºC scenarios were the mean of four crop models and four global climate models (GCMs), including CanAM4, CAM4, MIROC5, and NorESM1. CO_2 concentration was 390ppm, 423ppm and 487ppm for Baseline, 1.5ºC and 2.0ºC scenarios, respectively. NS: the North Subregion; HHS: the Huang-Huai Subregion; MYS: the Middle-Lower Researches of Yangzi River Subregion; SWS: the Southwest Subregion.