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ORIGINAL PAPER

Projective analysis of staple food crop productivity in adaptation to future climate change in China

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Abstract Climate change continually affects our capabilities to feed the increasing population. Rising temperatures have the potential to shorten the crop growth duration and therefore reduce crop yields. In the past decades, China has successfully improved crop cultivars to stabilize, and even lengthen, the crop growth duration to make use of increasing heat resources. However, because of the complex cropping systems in the different regions of China, the possibility and the effectiveness of regulating crop growth duration to reduce the negative impacts of future climate change remain questionable. Here, we performed a projective analysis of the staple food crop productivity in double-rice, wheat-rice, wheat-maize, single-rice, and single-maize cropping systems in China using modeling approaches. The results indicated that from the present to the 2040s, the warming climate would shorten the growth duration of the current rice, wheat, and maize cultivars by 2–24, 11–13, and 9–29 days, respectively. The most significant shortening of the crop growth duration would be in Northeast China, where single-rice and single-maize cropping dominates the croplands. The shortened crop growth duration would consequently reduce crop productivity. The most significant decreases would be 27–31, 6–20, and 7–22% for the late crop in the double-rice rotation, wheat in the winter wheat-rice rotation, and single maize, respectively. However, our projection analysis also showed that the negative effects of the warming climate could be compensated for by stabilizing the growth duration of the crops via improvement in crop cultivars. In this case, the productivity of rice, wheat, and maize in the 2040s would increase by 4–16, 31–38, and 11–12%, respectively. Our modeling results implied that the possibility of securing future food production exists by adopting proper adaptation options in China.

Keywords Model projection · Climate change · Crop productivity · Adaptation

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Introduction

Global warming has continued for more than 200 years as a result of an accelerated increase in atmospheric greenhouse gases (GHGs). Projections of global circulation models (GCMs) have shown that temperature will continue to rise in the next 100 years, with the amplitude depending on the amount of anthropogenic GHG emissions (IPCC 2013). The warming climate will have fundamental impacts on global environments and ecosystems. In the agricultural sector, reducing the possible negative effects of global warming on crop productivity is extremely important to meet the increasing need for agricultural products from the expanding population (Ortiz et al. 2008).

China is a nation of multiple climate zones that support diverse cropping systems. In the past decades, increases in crop productivity were achieved mainly by fertilizer application, progress in agronomic techniques, and improved crop cultivars. These advances have played a vital role in guaranteeing the food security of the nation and the world (Piao et al. 2010). However, excessive mineral fertilizer application has resulted in severe environmental problems (Ju et al. 2009). Further increases in crop productivity are therefore subject to the ability of crops to adapt to the warming climate (Lobell et al. 2008; Challinor et al. 2014).

Crops accumulate biomass via photosynthesis during the period of crop growth; therefore, the longer the period, the more the biomass accumulates (Yang et al. 2007). Physiologically, the growth duration (GD, the period between the sowing and harvesting dates) of a given cultivar is intrinsically controlled by its effective accumulated temperature (EAT, the sum of the positive differences between the daily temperature and a cultivar-specific threshold temperature). Therefore, warmer temperatures usually shorten the growth duration of a given crop (Liu et al. 2010; Zhang et al. 2013), reducing crop biomass accumulation (Asseng et al. 2014; Field et al. 2014).

In the past three decades, the annual mean air temperature has risen by 0.45 ± 0.13 °C per decade in China (Li et al. 2010). This warming is thought to have led to a shortened crop GD and decreased crop productivity (Liu et al. 2010, 2012). However, observations have shown that warming has not always shortened crop GD but has more likely stabilized or even extended it in the past decades (Liu et al. 2010, 2012), owing to adaptations in agronomic management (Meza et al. 2008; Liu et al. 2013) and cultivar renewal (Lobell et al. 2008; Wang et al. 2012). In southern China, where rice dominates the croplands, although warming shortened the GD of rice, the negative impacts of the shortened GD have been compensated for by cultivar improvement with a magnitude of 0.5–0.6 days °C^{-1} (Zhang et al. 2013). In Northeast China, the GD of maize was even lengthened by approximately 3 days per decade during 1961–2007 (Liu et al. 2013).

The observed changes in crop GD suggest that the EAT of the crops has been augmented by cultivar improvement. In Northern China, the EAT of winter wheat has shown the most significant increase (Sun et al. 2014). Adaptation strategies, such as improving the photosynthetic efficiency of crops and appropriately manipulating sowing/harvesting dates, have had the greatest effect on compensating the negative effects of climate warming and have furthermore enhanced crop productivity (Tao and Zhang 2010; Wang et al. 2012). In consideration of projected future climate warming, Lin et al. (2015) reported that replacing a maize cultivar with those having a longer growth period could compensate for the negative impacts of climate warming in northeastern China. In comparison to the scenario of a shortened GD caused by rising temperature, maize yield would increase by 9.9–15.2% if the GD remained unchanged (Tao and Zhang 2010). On the national scale, Xiong et al. (2009) estimated with the CERES-Rice model that even with CO_2 fertilization effects, the rice yield in China would decrease by up to 26.2% during the 2080s without adaptation. Lv et al. (2013) reported that under rainfed conditions, the wheat yield would decrease in the northern regions but would increase in the southern regions of China.

While observational and modeling studies have shown that the impacts of the warming climate on crop production differ among crops, it is important to analyze how the productivity of the staple food crops of rice, wheat, and maize will vary with climate change in different cropping systems in China. Although improvements in technology and management have increased crop yields in China, model simulations can isolate the climate signal by holding all inputs and management constant, with the exception of climate information. In the present study, we attempted to evaluate the potential productivity of rice, wheat, and maize in China and its spatial variation. As the first step, the crop model Agro-C (Huang et al. 2009) was re-calibrated to make the model consistent with up-to-date cultivars. Afterward, the crop productivities under different crop calendar scenarios that are directly correlated with climate change were simulated.

Materials and methods

The modeling approach

The Agro-C model (Huang et al. 2009) is a process-based model for simulating crop photosynthesis, respiration, and other processes involved in crop growth and carbon/nitrogen dynamics in soils. It takes climatic, edaphic, atmospheric CO_2 concentration; crop calendar; and field management data as inputs. The outputs of the model include crop biomass, leaf area index (LAI), gross primary productivity (GPP), crop respiration, and net primary productivity (NPP). The model used in the present study has two functional modules to simulate crop photosynthesis and respiration. These modules incorporate impacts of the environmental variables of temperature, solar radiation, soil moisture, and atmospheric CO_2 concentration on crop growing. The effect of air temperature on photosynthesis is expressed by a piecewise function and is determined by the lower and upper temperature limits and optimum temperature subject to specific crop varieties. The optimum temperatures for the photosynthesis of rice, wheat, and maize are 29, 18, and 30 °C, respectively (Huang et al. 2009). Additional details of the model can be found in Huang et al. (2009).

Model calibration and validation

Field observations

Crop improvement efforts have resulted in rapid crop cultivar renewal in China (Zhou et al. 2007; Liu et al. 2010; Yu et al. 2012). To re-calibrate the model, we used field observations from 16 agricultural stations within the Chinese Ecosystem Research Network (CERN) (Appendix Table 7). The observations spanned the period from 2004 to 2010 and covered the representative cropping systems in China. The observations included crop calendar (sowing, heading, harvesting, etc.), LAI, leaf weight, and aboveground and belowground biomass. The methods of irrigation and synthetic fertilizer application and the amounts of organic manure and residue retention were also recorded. The soil properties relevant to crop growth, i.e., the total soil nitrogen and organic carbon, bulk density, pH, and sand/clay fractions, were site-specific. The meteorological data, including the daily maximum and minimum temperature, solar radiation, and precipitation from 2004 to 2010, were measured simultaneously at the stations along with the crop growth measurements.

Calibration of model parameters

The parameters of the Agro-C model that were re-calibrated included specific leaf area (SLA), the fraction of photosynthesis allocated to leaves (PL), and the photosynthetic efficiency (α) of the crops. The three parameters were calibrated with a priori values from the literature (Huang et al. 2009), and the posterior values were determined by minimizing the deviation (see Eq. 2) of the simulated crop aboveground biomass (AGB) and the LAI from the observed values. The posterior values of SLA, PL, and α are shown in Appendix Table 8.

Validating the model performance

Three statistical indexes (Brisson et al. 2002), the root mean square error (RMSE), the relative mean deviation (RMD), and the model efficiency (EF), were used to evaluate the model performance. The RMSE was computed to measure the coincidence between the observed and the simulated results. The RMD was computed to evaluate the systematic bias of the model. The EF was calculated to estimate model performance in relation to the observed mean. A higher positive EF indicates better model performance, while a negative EF indicates that the model is worse than simply averaging the observations (Smith et al. 1997).

$$\mathrm{RMSE} = \frac{100}{\overline{O}}\sqrt{\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}} \tag{1}$$

$$\mathrm{RMD} = \frac{100}{\overline{O}}\sum_{i=1}^{n}\frac{(P_i-O_i)}{n} \tag{2}$$

$$\mathrm{EF} = 1-\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{\sum_{i=1}^{n}\left(\overline{O}-O_i\right)^2} \tag{3}$$

where P_i and O_i represent the simulated and observed values, respectively. $\overline{O}$ and n are the mean of the observed values and the number of observations, respectively.

To obtain more details regarding the composition of the modeling error, we decomposed the mean square error into three components (Allen and Raktoe 1981; Smith and Rose 1995):

$$\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2 = \left(\overline{P}-\overline{O}\right)^2 + \left(S_p-rS_O\right)^2 + \left(1-r^2\right)S_O{}^2 \tag{4}$$

where $\overline{P}$ is the mean of the simulated data

and

$$S_P{}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(P_i-\overline{P}\right)^2 \tag{5}$$

$$S_O{}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(O_i-\overline{O}\right)^2 \tag{6}$$

$$r = \frac{\sum_{i=1}^{n}\left(P_i-\overline{P}\right)\left(O_i-\overline{O}\right)}{\left\{\sum\left(P_i-\overline{P}\right)^2\sum\left(O_i-\overline{O}\right)^2\right\}^{1/2}} \tag{7}$$

The first component $\left(\overline{P}-\overline{O}\right)^2$ represents the bias in the modeling procedure. The value will be large if a model underestimates or overestimates the simulated values relative to the observed data and will be zero if the mean of the observed data is equal to that of the simulated results. The second component $S_p - rS_O$ was the error due to the imperfection of the regression between the simulated values and the observations, which will be close to zero when the regression between the observed and the simulated data is close to the line of 1:1. The third component $(1 - r^2)S_O{}^2$ was a measure of pure random noise and will be zero if either $r = \pm 1$ or if $S_O{}^2 = 0$. The above three components can be normalized by dividing each component by $\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2$. The three proportions of error were thus defined as

$$U_\mathrm{M} = \frac{\left(\overline{P}-\overline{O}\right)^2}{\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2} \tag{8}$$

$$U_\mathrm{R} = \frac{(S_P-rS_O)^2}{\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2} \tag{9}$$

$$U_\mathrm{E} = \frac{(1-r^2)S_O{}^2}{\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2} \tag{10}$$

and hence

$$U_\mathrm{M} + U_\mathrm{R} + U_\mathrm{E} = 1 \tag{11}$$

where U_M, U_R, and U_E represent the modeling bias, the regression bias, and the random error, respectively. One would expect U_M and U_R to account for a small fraction of the total error and hence for U_E to be large (Allen and Raktoe 1981). If either U_M or U_R (or both) were large, the parameters of the model should be further adjusted.

To perform the model re-calibration and validation, the measured crop LAI and ABG between the crop durations were assumed independent here, though the environmental factors, e.g., the soil properties (i.e., the total soil nitrogen and organic carbon, bulk density, pH, and sand/clay fractions), were nearly the same from one crop to the other at a location. Owing to the complexity of the dependence among the measured values, it is hard to specifically quantify the impacts of the dependence on the statistical analysis. Here, we split the observations during the period from 2004 to 2010 into two parts. Those from the odd years were used for model calibration and the rest for model validation. When there was only 1 year available at a station, the observation was used for model validation.

Modeling changes in crop productivity

With the re-calibrated Agro-C model, the productivity of rice, wheat, and maize at five sites in China was simulated for a 5-year baseline historical climate (2006–2010) and an alternative future climate period (2011–2050). The five sites, Changshu (31.53° N, 120.68° E) with a winter wheat-rice rotation, Taoyuan (28.92° N, 111.45° E) with a double-rice rotation, Fengqiu (35° N, 114.4° E) with a winter wheat-maize rotation, Sanjiang (47.58° N, 113.52° E) with single-rice cultivation, and Hailun (47.43° N, 126.63° E) with single-maize cultivation, represent the typical cropping systems of the main cultivation regions of China (Fig. 1).

Observed meteorological data and climate change scenarios

The observed meteorological data (daily maximum and minimum temperatures, precipitation, and solar radiation) and the atmospheric CO_2 concentration of the baseline period (2006–2010) were taken from the CERN. To fill the data gap in the observed solar radiation at the CERN stations, we estimated the solar radiation with the method utilized in Zhang et al. (2007).

The future climate change scenario used in this study was the Representative Concentration Pathway (RCP) 4.5 of the Intergovernmental Panel on Climate Change fifth assessment report (IPCC AR5) over the next four decades (2011–2050), which was projected by the Flexible Global Ocean-Atmosphere-Land System (FGOALS) climate model (Yu et al. 2004). The FGOALS is a GCM with a spatial resolution of 1.65° in latitude and 2.8° in longitude and a temporal step of daily output. The projected data of FGOALS was provided by the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG) within the Institute of Atmospheric Physics (IAP) of the Chinese Academy of Sciences (CAS). The outputs of FGOALS were spatially downscaled to the five sites using the delta change method (Hay et al. 2000; Prudhomme et al. 2002; Beldring et al. 2008).

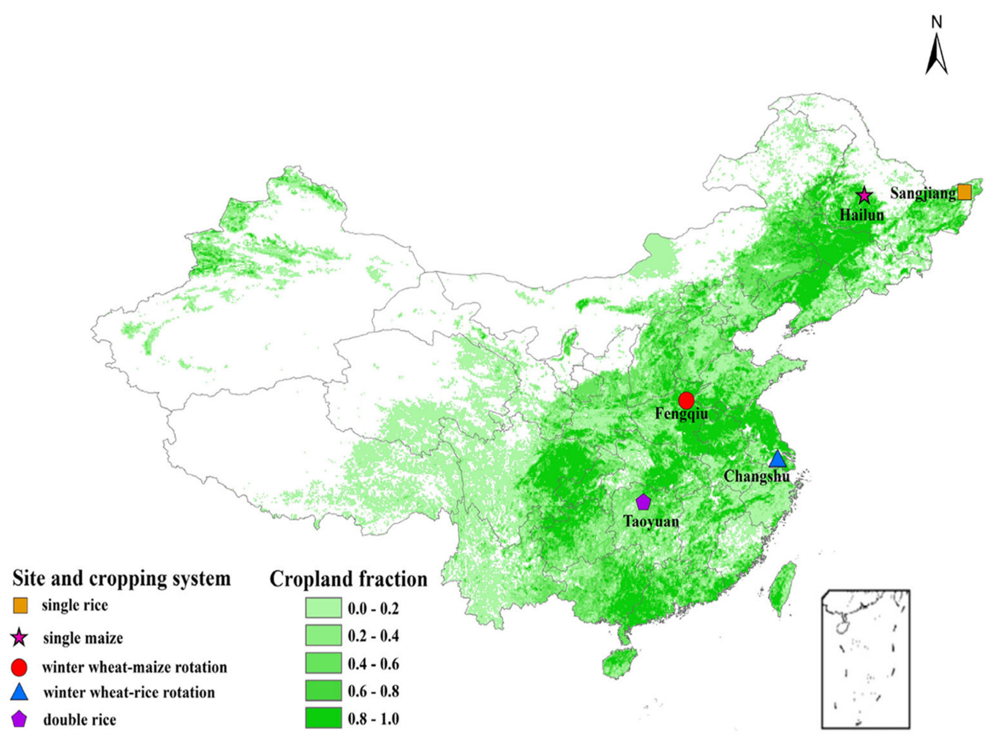

Fig. 1 Location of the five stations for future adaptive analysis in relation to the cropping systems

Scenarios of crop calendar changes

To evaluate the impacts of crop improvement on productivity in the future, we assigned two crop GD scenarios in comparison to the baseline scenario. The baseline scenario, S0 (2006–2010), was simulated using the dataset from the CERN, including the meteorological data, field management data, cultivar data, and crop phenology data (transplanting, heading, harvesting dates). The two scenarios, S1 and S2, were designed to distinguish the different responses of crop productivity to different GD scenarios from 2011 to 2050. In scenario S1, the EAT of crops was held constant over the next four decades and, therefore, the crop GD varied with the changing climate. The EAT of a given crop in S1 was calculated according to the crop phenology data from the CERN stations during the period from 2006 to 2010. In scenario S2, the crop calendar and the crop GD were fixed to be the same as those in S0, which means the crop EAT varied with the changing climate to reflect the capacity for crop adaptation.

Results

Model performance

Figure 2 compares the LAI and AGB of rice, wheat, and maize before and after the model calibration. The re-calibration significantly improved the model performance in terms of the regression between the model simulation and the field observations (Fig. 2), which suggested the necessity of the model re-calibration before being used to project future crop biomass. After re-calibration, 80% of the observed variation in crop AGB was accounted for by the model output at all 16 sites (Fig. 2b, d, f). Against the observations, the RMSE, RMD, and EF for the modeled AGB were 32.52%, −0.95%, and 0.87, respectively, and U_M, U_R, and U_E were 0.1, 0.9, and 99%, respectively (Table 1).

The simulated LAI and AGB of rice at different sites were close to field observations (Fig. 2a, b). After model calibration, the regression of the simulated values against the observed rice AGB showed an R^2 of 0.87 (n = 138, $p < 0.001$). The RMSE, RMD, and EF of the model simulation were 31.96%, −6.23%, and 0.87, respectively. Of the estimation error (RMSE), 93.8% was the random error (U_E), with U_M and U_R accounting for only 3.8 and 2.4%, respectively (Table 1). The performance of the model in simulating wheat growth was similar to that in rice. The regression of the simulated values against the observed wheat AGB showed an R^2 of 0.81, and the RMSE, RMD, and EF were 41.33%, −0.77%, and 0.79, respectively. The error components of U_M, U_R, and U_E were 0.03, 9.5, 90.47%, respectively. When modeling maize, the RMSE, RMD, and EF were 22.41%, 6.29%, and 0.94, respectively. Within locations, the simulated AGB for different crop species were close to the field observations. We presented the comparison of the simulated and observed AGB for different crop species at the five locations chosen for the future scenario analysis (Fig. 3). The RMSE, RMD, and EF of the modeling results were 32.52%, −0.95%, and 0.87, respectively (Table 1).

Responses of crop growth to climate change

Responses of crop growth to scenarios of unchanged EAT

In scenario S1, the EAT of the cultivars remained unchanged, and therefore, warming would lead to a shortened crop GD (Tables 2 and 3), and the shortened GD would result in a decrease in AGB for all crops (Table 4, Fig. 4).

In Northeast China, where rice is planted singly in summer (Sanjiang site), its GD would shorten by 18.5% in response to significant rises in temperature through the 2040s, and the AGB would thus decrease by 5.1%. In the region where rice rotates with winter wheat within a single year (Changshu site), the GD was expected to shorten (by 8.7%); however, this resulted in a minimal decrease in AGB. Southward to the warm temperate region (Taoyuan site) where the double cropping of rice dominates, the GD of the late rice would shorten by 15.7% in the 2040s (Table 3), with the AGB decreasing by approximately 30% because of the shrink in GD (Table 4). For early rice, the impacts of rising temperature would be minor, and the GD would shorten by only 2.6% with the AGB decreasing by 8.3% (Table 4).

In North China (Fengqiu site), where a wheat-maize rotation is the main cropping system, the GD of the wheat would shorten by 4.7%, accompanied by the AGB decreasing by 1.4% by the 2040s. In the region where wheat rotates with rice year-round (Changshu site), the GD and AGB of wheat would decrease by 5.9 and 6.1%, respectively, with rising temperature. It should be noted that the AGB of the wheat might alternate between −6.1 and −20.4% from the 2010s to the 2040s (Table 4).

In Northeast China, the GD of the singly planted maize (Hailun site) would shorten by 21.9% in the 2040s, and the shortened GD would then result in a decrease in crop AGB by 22.4%. In the wheat-maize rotation, the GD and AGB of maize would decrease by 8.8 and 13.8%, respectively (Tables 3 and 4).

As a whole, the crop AGB of different cropping systems showed more or less a decrease under scenario S1 (Fig. 4). For the double-rice rotation and the single-maize systems, the crop AGB would obviously decrease by 18.4 and 22.4%, respectively, by the 2040s. The crop AGB of the single-rice and winter wheat-rice rotation systems showed a slight decrease, with the crop AGB decreasing by only 5.1 and 3.0% by the 2040s, respectively. For the winter wheat-maize rotation system, the crop AGB would decrease by 8.2% in the 2040s (Fig. 4).

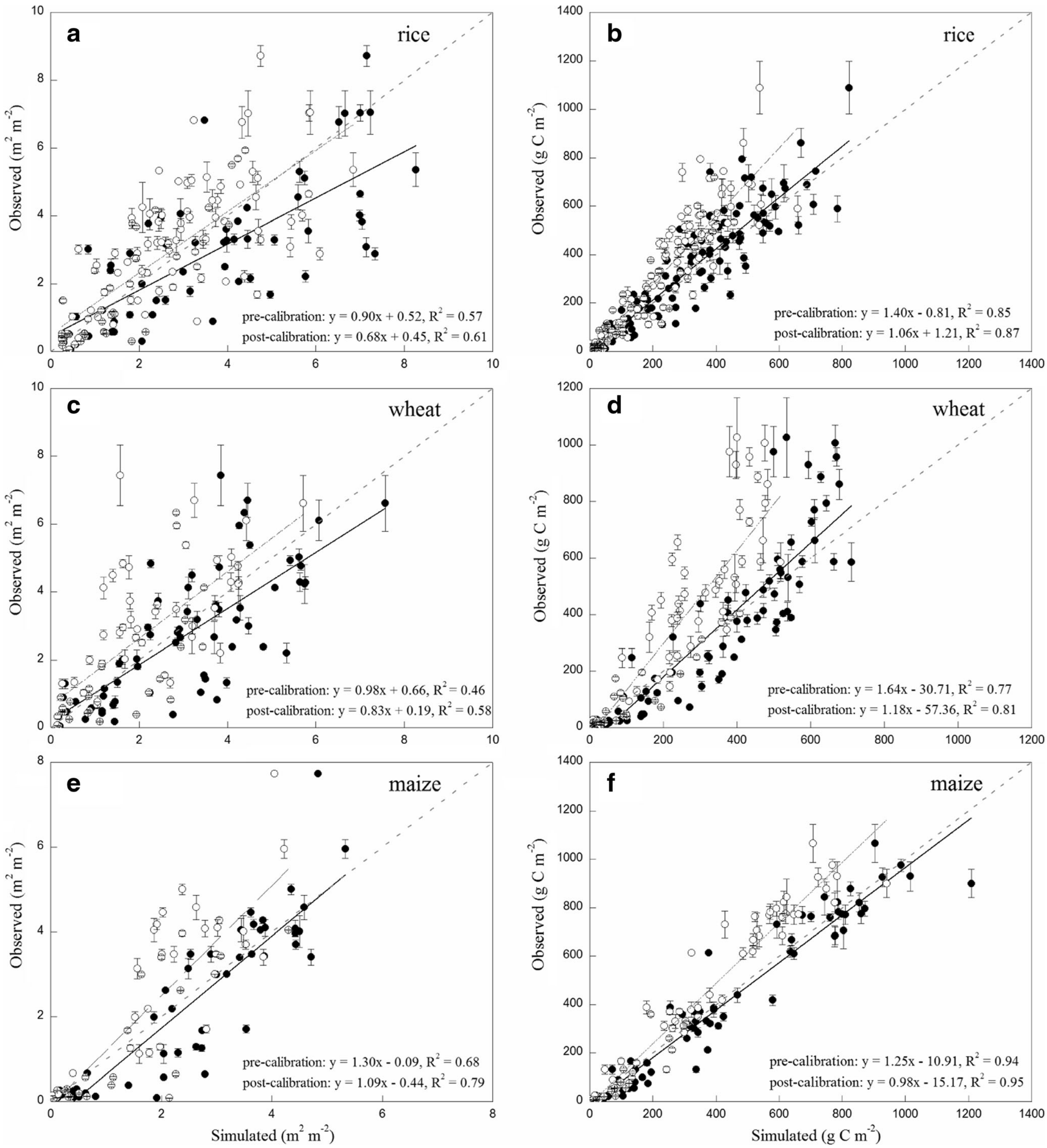

Fig. 2 Modeled vs. observed LAI (**a**, **c**, **e**) and AGB (**b**, **d**, **f**) for rice (**a**, **b**), wheat (**c**, **d**), and maize (**e**, **f**) at different sites. *Black dashed lines* and *hollow circles* for model pre-calibration. *Black solid lines* and *solid circles* for model post calibration. The *vertical bars* are standard errors from four to six fields in each site. *Gray dashed lines* are 1:1. The measurements of LAI and AGB were assumed independent for simplicity, and this undermines the model validity owing to the unquantified correlations between the measurements in a time series (Fig. 3)

Response of crop growth to scenarios of unchanged GD

In scenario S2, the crops' GDs were held constant, and the crop EAT would consequently rise along with climate warming by 4.6 to 24.5% (Tables 2 and 3). The AGB of rice, wheat, and maize would increase by 4.4–16.4, 30.9–37.6, and 11.4–11.7%, respectively, by the 2040s (Table 4, Fig. 4), by making full use of the resource of increased EAT.

From the 2010s to the 2040s, the EAT of the single-rice crop in Northeast China would increase by 24.5% in response to the

Table 1 Statistical characteristics of model performance for AGB

	RMSE%	RMD%	EF	U_M (%)	U_R (%)	U_E (%)
Rice	31.96	−6.23	0.87	3.80	2.40	93.80
Wheat	41.33	−0.77	0.79	0.03	9.50	90.47
Maize	22.41	6.29	0.94	7.86	0.61	91.53
All	32.52	−0.95	0.87	0.10	0.90	99.00

significant temperature rise in the region (Appendix Table 9). With the stabilized GD in the warm temperate region of South China where double rice dominates, the EAT of the early and late rice would increase by 4.6 and 14.5% (Table 3), respectively. In the wheat-rice cropping system in East China, the increase in rice EAT would be 6.5% (Table 3), comparable to that of early rice in the double-rice rotation. Along with the increased EAT, the AGB of the rice in the single-crop, double-rice, and wheat-rice

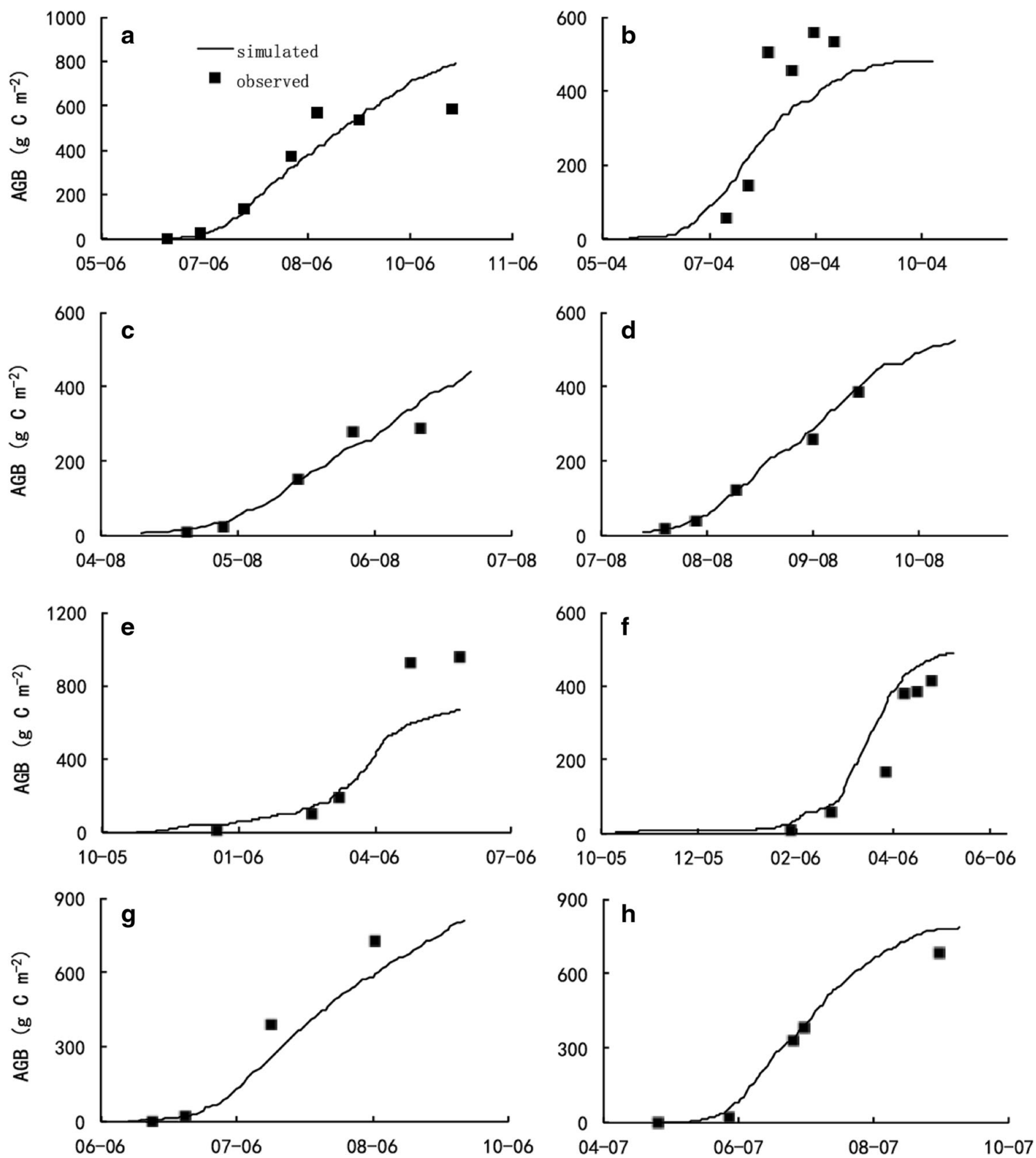

Fig. 3 Comparison of the simulated and observed AGB for different crop species. **a** Single rice (Changshu, Jiangsu Province). **b** Single rice (Sanjiang, Heilongjiang Province). **c** Early rice (Taoyuan, Hunan Province). **d** Late rice (Taoyuan, Hunan Province). **e** Winter wheat (Changshu, Jiangsu Province). **f** Winter wheat (Fengqiu, Henan Province). **g** Maize (Fengqiu, Henan Province). **h** Maize (Hailun, Heilongjiang Province)

Table 2 The average effective accumulative temperature and phenology information of crops during 2006 to 2010

Sites	Crops	EAT (°C day^{-1})[a]		Phenology (MM/DD)		
		Emergence/transplanting-heading	Heading-harvesting	Emergence/transplanting	Heading	Harvesting
Changshu (Jiangsu)	Single rice	1451	2163	6/14	8/28	10/22
	Winter wheat	778	1587	10/28	4/15	5/29
Sanjiang (Heilongjiang)	Single rice	521	1038	5/17	7/29	9/25
Taoyuan (Hunan)	Early rice	594	1068	4/26	6/15	7/10
	Late rice	866	1364	7/14	9/2	10/10
Fengqiu (Henan)	Winter wheat	727	1567	10/24	4/20	6/8
	Summer maize	975	1818	6/12	8/7	9/25
Hailun (Heilongjiang)	Spring maize	755	1430	5/22	7/24	10/3

[a] The average effective accumulative temperature of crops: rice (≥12 °C), winter wheat (≥3 °C), and maize (≥9 °C)

cropping systems would increase by 16.4, 4.4, 6.0, and 14.2%, respectively (Table 4).

In the wheat-rice cropping system that dominates in East China, the EAT and AGB of wheat would increase by 20.5 and 37.6%, respectively, which was higher than the increases expected in the wheat-maize cropping system in North China, which were 10.0 and 30.9%, respectively (Tables 3 and 4). Among the three major crops, the increase in the AGB of winter wheat would be the most significant.

In Northeast China, the EAT of the single crop maize would increase by 18.6%, which would result in an 11.4% increase in the maize AGB (Table 4). In the wheat-maize rotation of Northern China, the EAT of maize would increase less, by only 6.6%, but the increase in maize AGB would be 11.7%, which was comparable to the single crop maize (Tables 3 and 4).

In general, under scenario S2, the crop AGB of the different cropping systems would increase in the future (Fig. 4). For the winter wheat-rice rotation and the winter wheat-maize rotation systems, the crop AGB would obviously increase by 25.1 and 21.0% in the 2040s, respectively, while the crop AGB of the double-rice rotation system would increase by only 4.7% in the 2040s and would even decrease before the 2030s. For the single-maize and single-rice systems in Northeast China, the crop AGB would increase by 11.4 and 16.4% in the 2040s, respectively (Fig. 4).

Table 3 Changes of growth duration and effective accumulative temperature in two scenarios

Sites	Crops	Change of GD in scenario S1[a]					Change of EAT in scenario S2[b]				
		Baseline[c] (days)	2010s (%)[d]	2020s (%)	2030s (%)	2040s (%)	Baseline (°C·d)	2010s (%)	2020s (%)	2030s (%)	2040s (%)
Changshu (Jiangsu)	Single rice	130	−0.8	−6.6	−5.5	−8.7	2163	3.1	3.6	4.0	6.5
	Winter wheat	213	−4.3	−3.1	−5.9	−5.9	1587	16.7	11.2	19.2	20.5
Sanjiang (Heilongjiang)	Single rice	131	−2.4	−12.7	−12.7	−18.5	1038	3.7	11.7	9.8	24.5
Taoyuan (Hunan)	Early rice	76	−0.8	−0.5	−1.6	−2.6	1068	1.5	1.8	3.5	4.6
	Late rice	88	−14.0	−12.7	−14.3	−15.7	1364	11.4	9.6	11.1	14.5
Fengqiu (Henan)	Winter wheat	227	−3.2	−3.0	−4.5	−4.7	1567	5.4	0.2	9.5	10.0
	Summer maize	105	−1.1	−5.8	−4.7	−8.8	1818	2.0	5.3	3.0	6.6
Hailun (Heilongjiang)	Spring maize	134	−7.8	−16.8	−12.6	−21.9	1430	4.0	10.9	9.1	18.6

[a] S1 is the scenario with fixed effective accumulative temperature

[b] S2 is the scenario with fixed growth duration

[c] Baseline is the period from 2006 to 2010

[d] The relative change to the value of baseline

Table 4 Changes of crops aboveground biomass in two scenarios

Sites	Crops	Present AGB ($g\ C\ m^{-2}$) 2006–2010	Change of AGB in scenario S1[a] (%)[b]				Change of AGB in scenario S2[c] (%)[b]			
			2010s	2020s	2030s	2040s	2010s	2020s	2030s	2040s
Changshu (Jiangsu)	Single rice	615	−4.3	−8.0	−1.1	−0.2	3.2	1.6	10.2	14.2
	Winter wheat	540	−17.2	−7.2	−20.4	−6.1	23.5	18.9	22.8	37.6
Sanjiang (Heilongjiang)	Single rice	794	−3.7	−6.0	−4.1	−5.1	6.6	9.9	8.9	16.4
Taoyuan (Hunan)	Early rice	493	−2.6	−8.8	−10.6	−8.3	1.8	−0.4	1.5	4.4
	Late rice	547	−29.0	−30.3	−30.9	−27.4	−9.2	−5.8	0.3	6.0
Fengqiu (Henan)	Winter wheat	647	8.0	−4.8	−9.2	−1.4	13.5	4.5	21.5	30.9
	Summer maize	796	−3.5	−13.9	−5.3	−13.8	2.5	0.6	9.6	11.7
Hailun (Heilongjiang)	Spring maize	965	−7.2	−13.8	−12.7	−22.4	1.3	6.9	9.0	11.4

[a] S1 is the scenario with fixed effective accumulative temperature

[b] The relative change to the average value from 2006 to 2010

[c] S2 is the scenario with fixed growth duration

Discussion

The improvement in crop photosynthetic efficiency

Crop productivity is linearly related to the photosynthetically active radiation (PAR) absorbed by the crop canopy and the efficiency with which this radiation resource is transformed into crop biomass through net photosynthesis (Madani et al. 2014). The photosynthetic efficiency also varies with the environment. Over the past few decades, the photosynthetic efficiency of crops has been greatly improved through cultivar renewal to make use of increased light and thermal resources (Brady and Provart 2007). Since the 1980s, the photosynthetic rates of rice cultivars have improved by more than 20% in North China (Cao et al. 2001) and South China (Wu et al. 2009), with an increased annual growth rate of 0.5–1.5% in

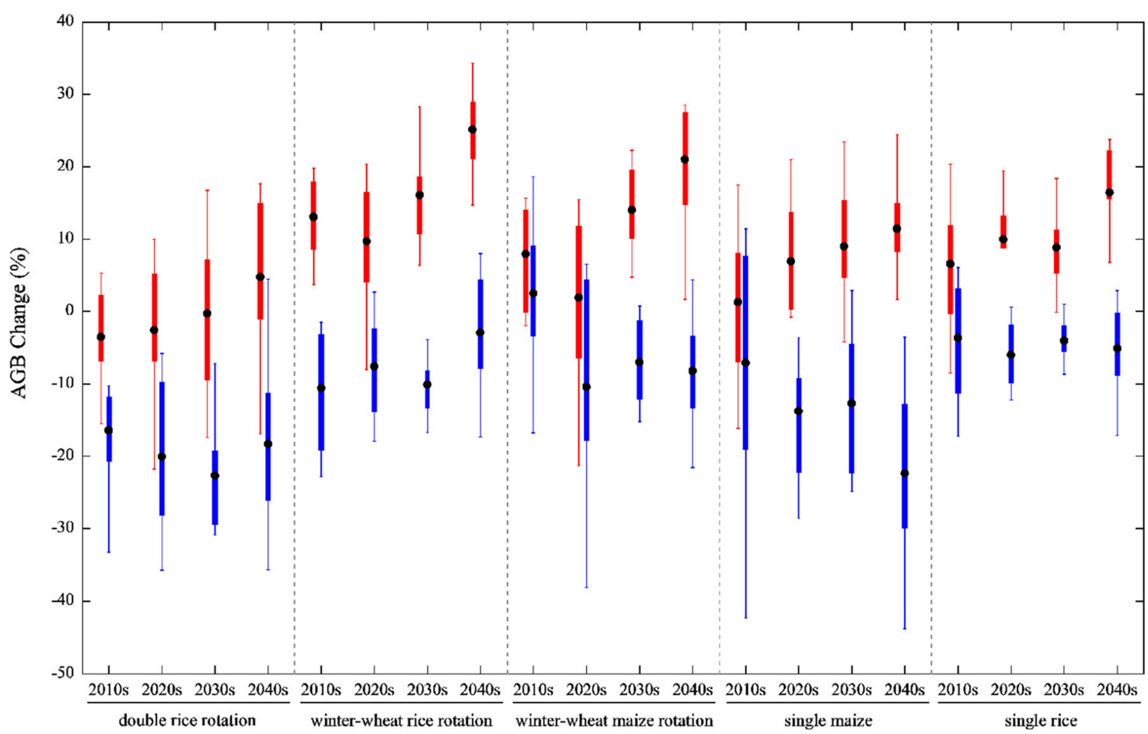

Fig. 4 Box plot of future AGB change (%) (relative to the baseline period) in the typical cropping systems in the main cultivation regions of China, with the *red* (*blue*) representing the AGB change under unchanged GD (EAT). The *upper and lower hinges of the box* indicate the 75th percentile and 25th percentile of the dataset, respectively. The *black spots inside the boxes* indicate the median values for each 10-year analysis period

Table 5 Comparisons of projected impacts for crops in China with CO_2 fertilization (without cultivar renewal)

Region	Yield/productivity impacts	Study period	Climate change scenario	Crop model	Baseline	Reference
Rice cultivation areas across China	Rice, −10~3.3, −16.1~2.5, and −19.3~0.18%	+1, +2, and +3 °C higher than the global mean temperature	Probabilistic climate scenarios generated by a Monte Carlo technique	CERES-Rice	1961–1990	Tao et al. (2008)
Yangtze River	IRice*, −3.3% RRice*, −4.1%	2021–2050	PRECIS; B2	ORYZA2000	1961–1990	Shen et al. (2011)
Eastern China	Rice, 6.5% Wheat, 24.9% Maize, 18.6%	2071–2100	RegCM3; A2	EPIC	1961–1990	Chavas et al. (2009)
Southern China	Rice, 5~20%	2071–2090	PRECIS; B2	CERES-Rice	1961–1990	Yao et al. (2007)
Nanjing/Luancheng	Wheat, −4~−1 and −8~−4%/−4~−1 and −12~−8%	+2 and +4 °C higher than the series of climate data from 1981 to 2010	+2 and +4 °C above the climate data from 1981 to 2010	Ensemble of 30 crop models	1981–2010	Asseng et al. (2014)
Huang-Huai-Hai Plain	Wheat, 0.2 and 0.8 Mg/ha	2015–2045; 2070–2099	HadCM3; A2, B2	EPIC	1961–1990	Thomson et al. (2006)
Rice, wheat, and maize cultivation areas across China	IRice*, 3.8, 6.2, and 7.8% (A2)/−0.4, −1.2%, and −4.9% (B2) IWheat*, 13.3, 25.1, and 40.3% (A2)/11.0, 14.2, and 25.5% (B2) IMaize*, −0.6, −2.2, and −2.8% (A2)/−0.1, −1.3, and −2.2% (B2)	2010–2019; 2040–2049; 2070–2079	PRECIS; A2, B2	CERES	1961–1990	Lin et al. (2005)
Rice cultivation areas across China	Rice, 15.8, 8.0, and −5.6% (A2)/3.4, 0.02, and −0.9% (B2)	2011–2040; 2041–2070; 2071–2100	PRECIS; A2, B2	CERES	1961–1990	Xiong et al. (2009)
North China Plain	Maize, −9.7~−9.1, −19.0~−15.7, and −25.5~−24.7%	2011–2040; 2041–2070; 2071–2100	Ensemble of 5 GCMs; A1F1, B1	MCWLA-Maize	1961–1990	Tao et al. (2009)
Maize cultivation areas across China	IMaize*, 1.0, −2.8, and −6.6% (A2)/−2.0, −1.9, and −4.8% (B2)	2011–2040; 2041–2070; 2071–2100	PRECIS; A2, B2	CERES-Maize	1961–1990	Xiong et al. (2007)
Main production areas of rice, wheat, and maize	Rice, −0.2~−27.4% Wheat, −1.4~−6.1% Maize, −13.8~−22.4%	2041–2050	FGOALS; RCP4.5	Agro-C	2006–2010	This study

**I* irrigated, *R* rainfed

different areas (Peng et al. 2008). This is part of the reason for the increase in rice yield from 3.98 t ha^{-1} in 1980 to 6.99 t ha^{-1} in 2009 (Yu et al. 2012).

In the Agro-C model we used in the current study, the crop photosynthetic efficiency was defined by the model parameter α (Huang et al. 2009). We re-calibrated the model parameters including α (Appendix Table 8) to keep up with up-to-date crop cultivars. Compared to the average α of the crop cultivars over the past few decades, from 1980 to 2006, current cultivars have improved photosynthetic efficiency, with α increasing by 8% (single rice) to 50% (spring wheat). Apart from maintaining a stabilized crop GD, improving crop photosynthetic efficiency may also be one of the most effective options in mitigating the negative impacts of climate change on crop production. In the current study, however, the possible further increase in crop photosynthetic efficiency was not assumed because our emphasis was on the impacts of changes in crop GD and EAT, which are directly associated with climate change.

Impact assessments and adaptive options

Although many studies have been carried out using crop models with different climate change scenarios (Tables 5 and 6), estimates of the potential impact of future climate change on agricultural productivity remain highly uncertain (Piao et al. 2010; Field et al. 2014). Owing to the differences in study areas, time duration, climate change scenarios, and crop models used, and whether adaptive adjustments have been taken into account (Tables 5 and 6), direct comparisons between the studies are quite difficult. A greater proportion of the uncertainty in climate change impact projections is due to a variation among crop models than to a variation among downscaled general circulation models (Asseng et al. 2013). In China, the majority of staple food production is from well-irrigated and fertilized croplands, and the adaptive adjustment of the crop calendar may be the main option to mitigate impacts of climate change.

The modeling results for rice showed mixed estimates in different studies (Tables 5 and 6) and in different cropping systems (Table 4). For single rice at the Sanjiang site, the current temperature is lower than the optimum for rice growing. Therefore, rising temperatures would promote the growth of rice and would compensate for the negative impact on rice growth caused by the shortening of GD. The loss of rice AGB, which was estimated to be −5.1% in scenario S1, was much less than the projected maize loss of −22.4% (Table 4). Also benefiting from rising temperatures, the mid/late-maturing rice cultivars may move northward in northeastern China, with a 46% rice yield increase in the 2080s under the Special Report on Emissions Scenarios (SRES) B2 scenario of climate change (Wu et al. 2014). In East China, the warm climate supports double cropping, mainly of winter wheat and rice. Crop productivity might decrease by 2.5–12% with a flexible crop calendar (Chavas et al. 2009; Yu et al. 2014), analogous to scenario S1 in the current study. However, the CO_2 fertilization effect could reverse the decrease in rice and enhance the rice productivity by 6.5–20.9% (Table 5). However, whether the CO_2 fertilization effect overrides the negative impacts of rising temperature depends also on the magnitude of atmospheric CO_2 and the temperature increase in the climate change projections. The temperatures in the SRES A2/B2 scenarios were projected to increase by approximately 1 °C in China, and the CO_2 concentration was projected to be as high as 550–600 ppm in the 2040s, which resulted in greater CO_2 fertilization effects on rice productivity in Yu's simulation (Table 6, Yu et al.

Table 6 Comparisons of projected impacts for crops in China with CO_2 fertilization (with cultivar renewal)

Regions	Yield/productivity impacts (%)	Periods	GCMs/RCMs; scenarios	Crop model	Baseline	Reference
Rice cultivation areas across China	Rice, 28.6%	2041–2050	PRECIS; A2, B2	Agro-C	2000–2009	Yu et al. (2014)
Eastern China	Rice, +7.5~17.5, 0~25, and −10~25%	2011–2040; 2041–2070; 2071–2100	Ensemble of 5 GCMs; A1F1, B1	MCWLA-Rice	1961–1990	Tao et al. (2013a)
North China Plain	Wheat, 37.7, 67.8, and 87.2%	2011–2040; 2041–2070; 2071–2100	Ensemble of 5 GCMs; A1F1, B1	MCWLA-Wheat	1961–1990	Tao et al. (2013b)
North China Plain	Maize, −2.4~45.6%	2011–2040; 2041–2070; 2071–2100	Ensemble of 5 GCMs; A1F1, B1	MCWLA-Maize	1961–1990	Tao et al. (2010)
Main production areas of rice, wheat, and maize	Rice, 4.4~16.4% Wheat, 30.9~37.6% Maize, 11.4~11.7%	2041–2050	FGOALS; RCP4.5	Agro-C	2006–2010	This study

2014). The RCP 4.5 used in the current study produced a 1.0–1.6 °C rise in temperature at different locations in China (Appendix Table 9). Rice productivity would therefore decrease without cultivar renewal (Table 4), even with the CO_2 fertilization effect. In southern China, where the current temperature is near the critical point for rice physiology (Wassmann et al. 2009), a slight increase in the air temperature would bring an obvious decrease in productivity (Gammulla et al. 2010; Lanning et al. 2011). This is the reason why late rice in Taoyuan would be the most negatively affected when no adaptive option was adopted (Table 4), which indicated the urgent need to improve the heat tolerance of late rice.

Global wheat production was estimated to fall by 6% for each 1.0 °C of additional temperature increase without adaption (Asseng et al. 2014), and the medians of 30 crop models demonstrated that expected declines in wheat yield in response to temperature impacts were likely to be larger than previously thought and should be expected earlier and became more variable over space and time. For wheat, most previous studies showed a positive effect of warming under different scenarios, even without cultivar improvement (Table 5). Our results here also showed a declining trend in future wheat productivity in the absence of cultivar change.

Most of the projected maize productivity decreased when no adaptive adjustment was included, even with the benefits from CO_2 fertilization and increasing rainfall (Table 5). In the North China Plain, maize productivity might decrease by 9.7–9.1% (during the period from 2011 to 2040) if crop cultivars and management practices were assumed to be the same as the level during the baseline period from 1961 to 1990 (Tao et al. 2009). Even in consideration of CO_2 fertilization, maize productivity would decrease by 1.2–2.2% in well-irrigated lands, and the productivity drop could be 0.4–11.9% if there was no CO_2 fertilization (Lin et al. 2005). It also decreased in the 2040s without cultivar renewal in this study (Table 3). It seems generally inevitable that maize productivity would decrease along with the rise in temperature if no adaptive option was taken, as shown in previous studies (Table 5) and in the current study (Table 3). However, improving maize cultivars to maintain a stable GD had the effect of guaranteeing maize productivity in single or double cropping systems (Table 4).

Over the past few decades, there have been many changes in agronomic activities, such as renewed cultivars (Zhou et al. 2007; Liu et al. 2010), optimized fertilizers (Reilly and Schimmelpfennig 1999; Huang et al. 2007), and expanded irrigation (Wang et al. 2009). These non-climatic factors all contributed to the observed changes in crop productivity over the past decades (Liu et al. 2010; Yu et al. 2012; Song et al. 2014). The IPCC AR5 suggested locally appropriate adaptive strategies for crops to address climate change (Challinor et al. 2014; Field et al. 2014). Improvement in cultivars may be an effective option to address the problems, even there are uncertainties in specific breeding technologies. Limits may be also found in facilitating the compensatory changes of GD modeled here. With the experiences in the past (Liu et al. 2013; Tao and Zhang 2010; Zhang et al. 2013), there are possibilities that the crop GD would be retained/lengthened in the future by crop renewal and/or agronomic improvement. The modeling results (Table 6) provided suggestions to alleviate the negative impacts of climate change on crop production. However, adaptive options are variable in time and space, and potential crop productivity may also have other possibilities differing from known findings (Zhang et al. 2015).

The effects of climate change in the future will be highly uncertain, and the choice of a specific projection from one or an ensemble of climate models may add to the overall uncertainty in impact assessments by crop modeling (Lobell et al. 2008; Masutomi et al. 2009; Asseng et al. 2013; Vanuytrecht et al. 2014). Here, we provided a possible trend in crop productivity based on one climatic scenario, RCP 4.5 of FGOALS. However, the possible increases in extreme weather events caused by global warming, which may pose an increasing risk to global crop production (Lesk et al. 2016; Wang et al. 2015), are not sufficiently addressed in the climate projections. Crop productivity may also be affected by other factors, such as the occurrence of pests and diseases, which are closely associated with climate change (Reidsma et al. 2010).

Conclusions

China is one of the largest nations for crop production in the world and is facing the challenge of future crop productivity loss with climate change. Our modeling showed that the GD of the current cultivars of the staple food crops of rice, wheat, and maize would be shortened by the warming climate in all of the main crop cultivation regions. Crop productivity would also be substantially reduced if no cultivar improvement occurs. However, the negative effects of climate change on crops in China could be compensated for if new cultivars could stabilize the crop GD to make full use of this increased thermal resource. In this case, the demands of the crop EAT of different crops would increase by 5 to 25%, and the productivity of winter wheat in China would increase significantly, followed by maize, while the productivity of rice in South China showed only a minor increase.

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Appendix 1

Table 7 General information for the stations selected for model parameterization

Site (province)	Latitude	Longitude	Altitude (m)	Crop system	Crop data period
Changshu (Jiangsu)	31° 32′ N	120° 41′ E	1.3	Winter wheat-rice	2005–2010
Qianyanzhou (Jiangxi)	26° 45′ N	115° 04′ E	100	Double-rice	2004–2010
Sanjiang (Heilongjiang)	47° 35′ N	133° 31′ E	56.2	Single-rice	2004, 2006, 2007, 2009
Shenyang (Liaoning)	41° 31′ N	123° 24′ E	31	Rice, maize	2005–2010
Taoyuan (Hunan)	28° 55′ N	111° 27′ E	77.5	Double-rice	2005–2010
Yanting (Sichuan)	31° 16′ N	105° 27′ E	460	Rice, winter wheat-maize	2005–2007
Yingtan (Jiangxi)	28° 15′ N	116° 55′ E	35.6	Late rice	2005–2010
Changwu (Shaanxi)	35° 12′ N	107° 40′ E	1120	Winter wheat-maize	2004–2010
Fengqiu (Henan)	35° 00′ N	114° 24′ E	67.5	Winter wheat-maize	2005–2010
Luancheng (Hebei)	37° 53′ N	114° 41′ E	50.1	Winter wheat-maize	2005–2010
Linze (Gansu)	39° 04′ N	99° 35′ E	1120	Spring wheat-maize	2005–2010
Lasa (Xizang)	29° 40′ N	91° 20′ E	3668	Winter wheat	2005, 2009, 2010
Naiman (Neimenggu)	43° 55′ N	120° 42′ E	358	Spring wheat	2006
Yucheng (Shandong)	36° 40′ N	116° 22′ E	21	Winter wheat-maize	2005–2009
Ansai (Shaanxi)	36° 51′ N	109° 19′ E	1189	Spring maize	2005–2009
Hailun (Heilongjiang)	47° 26′ N	126° 38′ E	240	Spring maize	2005, 2007, 2009

Appendix 2

Table 8 Key calibrated parameters of Crop-C for rice, wheat, and maize

DVI	Rice		Spring wheat		Winter wheat		Spring maize		Summer maize	
	SLA	PL	SLA	PL	SLA	PL	SLA	PL	SLA	PL
0.0	35 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.50 (0.47)	20 (22)	0.50 (0.47)
0.1	33 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.50 (0.47)	20 (22)	0.50 (0.47)
0.2	31 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.50 (0.47)	20 (22)	0.50 (0.47)
0.3	30 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.50 (0.47)	20 (22)	0.50 (0.47)
0.4	29 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.50 (0.44)	20 (22)	0.50 (0.44)
0.5	28 (25)	0.42	18 (22)	0.43 (0.5)	20 (24)	0.43 (0.5)	16 (22)	0.46 (0.40)	20 (22)	0.46 (0.40)
0.6	27 (25)	0.34	18 (22)	0.34 (0.4)	20 (24)	0.34 (0.4)	16 (22)	0.40 (0.35)	20 (22)	0.40 (0.35)
0.7	26 (25)	0.26	18 (22)	0.26 (0.3)	20 (24)	0.26 (0.3)	16 (22)	0.32 (0.28)	20 (22)	0.32 (0.28)
0.8	25 (25)	0.17	18 (22)	0.17 (0.2)	20 (24)	0.17 (0.2)	16 (22)	0.23 (0.19)	20 (22)	0.23 (0.19)
0.9	24 (25)	0.09	18 (22)	0.09 (0.1)	20 (24)	0.09 (0.1)	16 (22)	0.11 (0.10)	20 (22)	0.11 (0.10)
1.0	23 (25)	0.00	18 (22)	0.00 (0.0)	20 (24)	0.00 (0.0)	16 (22)	0.00 (0.00)	20 (22)	0.00 (0.00)
	Crop	Single rice	Single rice	Early rice	Late rice	Winter wheat	Spring wheat	Spring maize	Summer maize	
	α	13 (12)	13 (12)	15 (12)	16 (12)	16 (12)	18 (12)	17 (18)	21 (18)	

The values in (out) the parentheses represent a priori (*posterior*) values of the parameters

Appendix 3

Table 9 Projected future temperature, precipitation and CO_2 change under RCP4.5 for different sites in FGOALS

	Changshu			Taoyuan			Fengqiu			Hailun			Sanjiang			CO_2 (ppmv)
	ΔT_{max} (°C)	ΔT_{min} (°C)	ΔPre (%)	ΔT_{max} (°C)	ΔT_{min} (°C)	ΔPre (%)	ΔT_{max} (°C)	ΔT_{min} (°C)	ΔPre (%)	ΔT_{max} (°C)	ΔT_{min} (°C)	ΔPre (%)	ΔT_{max} (°C)	ΔT_{min} (°C)	ΔPre (%)	
2010s	0.6	0.7	8.4	0.7	0.6	3.6	0.5	0.5	−0.5	0.7	0.5	5.8	0.5	0.3	10.1	391–411
2020s	0.4	0.4	5.0	0.1	0.1	5.8	0.3	0.3	−3.4	1.1	1.3	4.7	1.1	1.1	6.7	413–435
2030s	0.9	0.8	7.6	1.0	0.8	3.7	0.8	0.7	4.1	0.8	0.8	10.5	0.8	0.8	7.0	438–461
2040s	1.3	1.1	1.0	1.3	1.0	6.1	1.2	1.1	2.6	1.3	1.5	16.9	1.5	1.6	7.1	463–487

The Δ symbol represents the projected changes for 2010s, 2020s, 2030s, and 2040s relative to those for 2006–2010

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