CrossMark

ORIGINAL ARTICLE

Simulating climate change impacts and potential adaptations on rice yields in the Sichuan Basin, China

Che-Chen Xu [1,2,3] · Wen-Xiang Wu [1,3] · Quan-Sheng Ge [1,3] ·
Yang Zhou [1,3] · Yu-Mei Lin [1,3] · Ya-Mei Li [1,3]

Abstract Rice (*Oryza*) is a staple food in China, and rice yield is inherently sensitive to climate change. It is of great regional and global importance to understand how and to what degree climate change will impact rice yields and to determine the adaptation options effectiveness for mitigating possible adverse impacts or for taking advantage of beneficial changes. The objectives of this study are to assess the climate change impact, the carbon dioxide (CO_2) fertilization effect, and the adaptation strategy effectiveness on rice yields during future periods (2011–2099) under the newly released Representative Concentration Pathway (RCP) 4.5 scenario in the Sichuan Basin, one of the most important rice production areas of China. For this purpose, the Crop Estimation through Resource and Environment Synthesis (CERES)-Rice model was applied to conduct simulation, based on high-quality meteorological, soil and agricultural experimental data. The modeling results indicated a continuing rice reduction in the future periods. Compared to that without incorporating of increased CO_2 concentration, a CO_2 fertilization effect could mitigate but still not totally offset the negative climate change impacts on rice yields. Three adaptive measures, including advancing planting dates, switching to current high temperature tolerant varieties, and breeding new varieties, could effectively offset the negative climate change impacts with various degrees. Our results will not only contribute to inform regional future agricultural adaptation decisions in the Sichuan Basin but also gain insight into the mechanism of regional rice yield response to global climate change and the effectiveness of widely practiced global thereby assisting with appropriate adaptive strategies.

✉ Wen-Xiang Wu
   wuwx@igsnrr.ac.cn

[1]   Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

[2]   Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

[3]   University of Chinese Academy of Sciences, Beijing 100049, China

⌁ Springer

1 Introduction

Increasing atmospheric carbon dioxide (CO_2) concentrations, temperature, and associated uncertainties in rainfall patterns can generate serious direct and indirect consequences on crop production and thus on regional and global food security (Houghton et al. 2001; IPCC et al. 2013; Piao et al. 2010; Tao et al. 2008; Wheeler and Braun 2013; Xiong et al. 2008). Chinese grain production is critical to the global food security (Yao et al. 2007) and rice (Oryza) is a staple food in China, which accounts for 33.8 % of Chinese grain production and 18.4 % of China's cultivated area (National Bureau of Statistics of China, http://data.stats.gov.cn/index). The Sichuan Basin is one of the primary rice producing areas in China, and the rice production encompasses nearly 46 % of its own total grain production in this region (National Bureau of Statistics of China, http://data.stats.gov.cn/index). Rice (Oryza) yield is very sensitive to climate change (Tao et al. 2013); therefore, food security in the Sichuan Basin and beyond will be challenged by climate change impacts in the context of likely future increases in food demand from population growth and changes in consumption patterns. Exploring the nature and degree of climate change impacts on rice yields in the Sichuan Basin are thus of great significance for regional or national food security.

Adaptation is one of the key factors that will determine the severity of climate change impacts on crop production in the future (Porter et al. 2014; Tao and Zhang 2010). During the past few decades, adaptation in agricultural system has been gaining recognitions at both international and regional levels. One good example is continuous emphasis of IPCC on the various adaptation measures in mitigating climate change impacts including cultivar adjustment, planting date adjustment, irrigation optimization, and fertilizer optimization (Porter et al. 2014). These adaptive options have been simulated widely at both global (Challinor et al. 2014; Deryng et al. 2011; Rosenzweig et al. 2013) and local regional levels (Babel et al. 2011; Kim et al. 2013; Krishnan et al. 2007; Moore and Lobell 2014; Tao et al. 2014). However, how to effectively apply adaptive measures is still a major global challenge, and many researches have been exploring suitable adaptive measures for different regions, e.g., various adaptive strategies have been assessed by the inter-comparison of different crop models (Rosenzweig et al. 2014) and integrated into relevant and existing policies, programs, and activities (Raj et al. 2014). In addition, indigenous knowledge is an effective tool for the optimum adaptive options in each region (Lashkari et al. 2011). Challinor et al. (2009) and Tao and Zhang (2010) have conducted such works and concluded that the most optimal adaptation strategies should be the region-specific and variety-specific. Therefore, assessing how climate change will affect crop yields and what adaptation options should be taken in the Sichuan Basin is necessary and helpful for the development of global adaptive strategies.

Crop models can serve as a surrogate laboratory (Challinor et al. 2009) to simulate the complex interactions between a range of factors that affect crop performance, including weather, soil properties, and management practices; consequently, they are one of the most useful tools for evaluating the potential impacts of climate change (van Ittersum et al. 2013) and the effectiveness of adaptation options (Jones et al. 2003; Rosenzweig and Hillel 1998). During the past few decades, the application of crop models has rapidly expanded in climate change research (White et al. 2011) and was a major data source for the last four Intergovernmental

Panel on Climate Change (IPCC) assessments of agriculture (Easterling et al. 2007; Gitay et al. 2001; Porter et al. 2014; Reilly et al. 1996).

The Crop Estimation through Resource and Environment Synthesis (CERES)-Rice model, embedded in the Decision Support System for Agro-technology Transfer (DSSAT), is one of the most successful models used to simulate the combined effects of plant genetics, management practices, weather, and soil conditions on the growth, development, and yield of rice plants (Timsina and Humphreys 2006). Like other similar models, such computer-based tools also require high-quality and sufficient input data to run the model and to simulate precise and reliable predicted results (Hoogenboom et al. 2012). However, the application of the CERES-Rice model is usually limited by the unavailability of necessary inputs (Hoogenboom et al. 2012; Hunt and Boote 1998; Timsina and Humphreys 2006). As a traditional agriculturally based country with long-term history of crop cultivation, China's local, regional, and national governments have all been paying great attention to the observation, collection, and documentation of crop development at various stages, which provides detailed and precise records on weather, crop phenology, and management. These data have been valuable for facilitating model calibration, validation, and evaluation, thereby enhancing model performance and facilitating its application in China. With these and other data, some researchers have used the CERES-Rice model to assess climate change impacts on crop yields in China. Among these researchers, Jin et al. (1995) was one of the few early researchers to introduce the CERES-Rice model into China and to conduct early impact studies; Lin et al. (2005) used the CERES-Rice v3.0 model, coupled with a regional climate change model (PRECIS), to simulate climate change impacts on crop yields and the CO_2 fertilization effect in China at a national scale; Yao et al. (2007) used data from eight representative sites to evaluate climate change impacts and CO_2 fertilization effects on rice yields in the main rice ecological zones of China with the CERES-Rice v3.5 model under the B2 climate change scenario from the Regional Climate Model (RCM); Xiong et al (2009) used the same crop model version and regional climate model to assess climate change impacts and direct CO_2 fertilization effects on rice yields in China on 50 km×50 km grids instead of at a plot scale.

However, in spite of their extensive and innovative attempts, previous studies may not make full use of high-resolution data due to the fact that they were conducted at a large-scale level with a limited number of stations (Lin et al. 2005; Xiong et al. 2009; Yao et al. 2007). Furthermore, previous studies have mainly focused their attempts on climate change impacts and atmospheric CO_2 fertilizer effects on rice yields, without much consideration of simulating adaptation options (Lin et al. 2005; Xiong et al. 2001; Yao et al. 2007); the latter has been gaining increasing attention by the IPCC (Easterling et al. 2007; Gitay et al. 2001; Porter et al. 2014) and others in the scientific community (Reilly et al. 1996). Furthermore, previous studies have mainly used the Special Report on Emissions Scenarios (SRES) from the IPCC in climate change research (Lobell et al. 2006; Tao and Zhang 2010; Yao et al. 2007); however, this approach was unable to indicate the stabilizing concentrations of greenhouse gases by the United Nations Framework Convention on Climate Change (UNFCCC) and the risks of human-induced climate change, as well as policy actions for mitigating the impacts of climate change on crop production (IPCC 2000; Moss et al. 2010). A well-validated, location-specific management option for climate change adaptation

in rice production systems under new scenarios at a regional scale in China is still lacking. Such research is necessary because location-specific cultivars, planting time, and management adaptations will be effective for mitigating climate change impacts on local rice production.

This study aims to simulate climate change impacts and atmospheric CO_2 fertilizer effects on rice yields, as well as the effectiveness of three widely practiced adaptation options under Representative Concentration Pathway (RCP) 4.5 scenario conditions in the Sichuan Basin. To achieve this object, we first simulated climate change impacts on rice yields, and on the basis of this impact assessment, we selected three globally widely practiced adaptation options: altering the planting dates, switching to high temperature tolerant rice cultivars, and breeding new rice cultivars; these adaptation strategies were evaluated with the aim of providing an understanding of how future rice yields will respond to differences in local climate changes, soil characteristics, crop management practices, and crop genetics and how to cope with future climate change risks.

2 Materials and methods

2.1 Study area and stations

The Sichuan Basin is located in the eastern Sichuan province and Chongqing province in China, covering an area of 19×10^4 km^2 (Wu et al. 2013). It lies in the subtropical humid climate zone, with an annual average temperature ranging from 14 to 19 °C, which is 1 °C higher than that at the equivalent latitudes (Shao et al. 2012). Annual cumulative daily average temperatures greater than or equal to 10 °C range from 4200 to 6100 °C, and annual sunshine hours vary from 900 to 1600 h. Rainfall is abundant, with annual precipitation ranging from 900 to 1200 mm, and is mainly concentrated in the rice-growing season (March to September). The main soil type of the experimental field is loamy clay soil with pH 6.0–8.0, containing an abundant total N of 0.059–0.210 % (http://www.soil.csdb.cn/); therefore, it is suitable for rice cultivation. According to the planting division in China (Cheng and Li 2007), the annual single-crop rice cropping system, which means that rice cultivar is planted in a region once a year, is applied in the Sichuan Basin. The favorable climate, abundant water resources, and proper cropping system make this region one of the most important areas for commercial crop production in China.

As indicated in an earlier chapter, the key data inputs, such as agricultural experimental data (including management practices, crop phenology, and crop yield), in the CERES-Rice model simulations were derived from Chinese agro-meteorological experimental stations. However, not all sites in the Sichuan Basin can provide qualified data. To ensure the simulation precision and reliability, we chose suitable sites that could provide the required fine-quality data. Twelve typical sites (Table 1) were carefully selected, which contained both agricultural experimental data and climate data, based on three criteria: (1) it was during 1995–2010 that agricultural and climate data existed; (2) the same representative rice variety was cultivated in a given site for at least 3 years during the study periods; and 93) there were no anomalous yield records associated with pest disease or extreme climate disasters and yields that increased during these 3 years. Figure 1 shows the geographical locations of the selected sites for this study.

Table 1 Information for each selected site in the Sichuan Basin

Site	Latitude (N)	Longitude (E)	Altitude (m)	Rice cultivar	Rice cropping system	Calibrated and validated years
Chengdu	30° 42′	103° 54′	506.1	Gangyou22	mid-maturation	1997–1999[a]
Dazhu	30° 48′	107° 12′	398.4	Shanyouduoxi1	mid-maturation	1995, 1999, 2000[a]
Dujiangyan	31° 00′	103° 36′	698.5	Gangyou6	mid-maturation	1997–1999[a]
Hanyuan	29° 59′	103° 00′	628	Yixiang1577	mid-maturation	2006, 2007, 2009[a]
Leshan	29° 36′	103° 48′	424.2	Dyou63	mid-maturation	1995, 1996, 1998[a]
Liangshan	27° 54′	102° 18′	1590.9	IIyou838	mid-maturation	2003, 2004, 2010[a]
Miyi	26° 48′	102° 06′	1099.2	Dyou68	mid-maturation	1998, 2000, 2006[a]
Mingshan	30° 06′	103° 06′	691.3	Gangyou527	mid-maturation	1999, 2002, 2007[a]
Neijiang	29° 36′	105° 06′	347.1	Iyou838	mid-maturation	2001, 2002[a], 2003
Yibin	29° 48′	104° 36′	340.8	Gangyou22	mid-maturation	1995, 1996[a], 1998
Jiangjin	29° 35′	106° 28′	259	IIyou6078	late-maturation	1999[a], 2000, 2001
Youyang	28° 50′	108° 46′	664	IIyou58	mid-maturation	2001[a], 2002, 2003

[a] The records of these years were used to calibrate the CERES-Rice crop model, and the others were used to validate the CERES-Rice crop model

2.2 CERES-Rice crop model

The DSSAT model, developed by the International Benchmark Sites Network for Agrotechnology Transfer at the University of Hawaii (Jones et al. 2003; Tsuji and Balas 1993), is a process-based, dynamic, and mechanistic model series to simulate crop growth and development over time, as well as the soil carbon, nitrogen, and water processes and crop managements for agricultural production forecasts and risk assessments. It is also a variety-specific and site-specific model operating on a daily time step. Since its appearance, this model has been continuously being refined and modified. Compared with a former version, the latest developed DSSAT v4.5 has improvements in bug fixes, model structure, and new capabilities
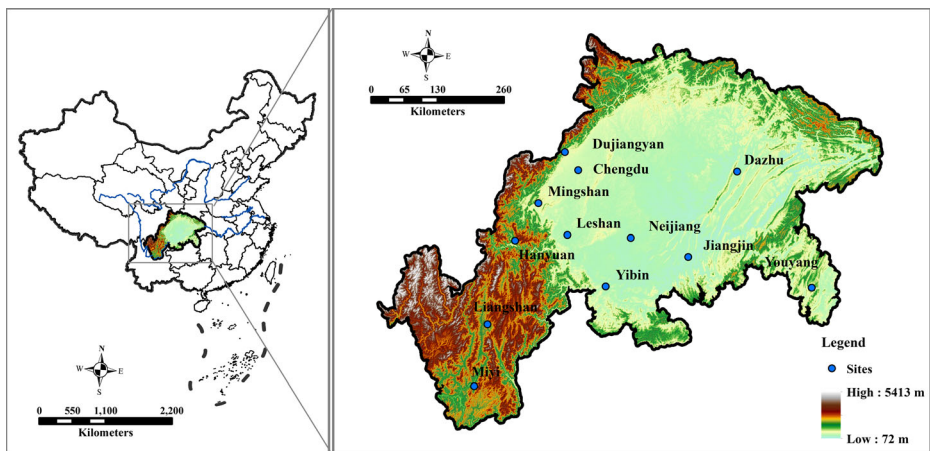

Fig. 1 Map indicating the site locations providing high-resolution data for crop model applications in the Sichuan Basin. The *colored area* of the figure *at the left* represents the Sichuan Basin. The *blue dots in the right* figure represent the selected site for simulations in the Sichuan Basin

(Hoogenboom et al. 2010). DSSAT v4.5 reads the atmospheric CO_2 concentrations from external files, and a new soil evaporation routine and soil layer distribution method was added. Currently, the DSSAT v4.5 software program comprises over 28 crop models, including the CERES-Rice model (Jones et al. 2003). In the CERES-Rice model, the major crop growth, consisting of phasic and morphological development, includes juvenile, floral, heading, flowering, grain filling, maturing, and harvesting data (Sudharsan et al. 2012), which were divided by the accumulation of growing degree-days (GDD):

$$GDD = \begin{cases} T - T_{\text{base}} & for \quad T_{\text{base}} < T < T_{\text{opt}} \\ T_{\text{high}} - T & for \quad T_{\text{opt}} < T < T_{\text{high}} \\ 0 & for \quad T < T_{\text{base}} \ or \ T \geq T_{\text{high}} \end{cases} \tag{1}$$

T_{base}, T_{high}, and T_{opt} are the base temperature, critical high temperature, and optimum temperature for rice growth, respectively. The GDD values decreased linearly towards zero when T reached T_{opt} and approached T_{high}, whereas it was zero when T reached T_{high}. In this model, crop yields are considered to be a fraction of the total biomass partitioned to grain, whereas the total crop biomass is determined by the growth duration and average growth rate (Ritchie et al. 1998), which was governed by thermal time, or GDD (Hoogenboom et al. 2010).

Because it is one of the oldest, most advanced, and thus most widely used crop simulation models (Jones et al. 2003) and has been validated in a wide variety of environments, ranging from temperate to tropical regions across the world (Timsina and Humphreys 2006; Vaghefi et al. 2013; Zhang and Tao 2013), the CERES-Rice v4.5 model was selected to conduct simulations in this study.

2.3 Input data for the CERES-Rice model

To minimize errors in predictions and enhance model performance, the CERES-Rice model requires high-quality and specified input data for rigorous model calibration, validation, and evaluation (Hunt et al. 2001). The required basic input data include daily weather data, soil data, and crop management data (Hoogenboom et al. 2012; Hunt and Boote 1998; Mahmood et al. 2004). More detailed input data requirement and data processing are described in the following sections.

2.3.1 Climate scenario data

Climate scenarios represent plausible future climate conditions (Moss et al. 2010). They contain daily solar radiation, daily maximum and minimum air temperature, and precipitation. Such projected weather data were used to drive the model to simulate complex interactions among climate change, environments, soil, crop genotype, and human adaptation options.

In the Fifth Assessment Report of the IPCC, the RCPs containing four RCP radiative forcing levels (RCP8.5, RCP6.0, RCP4.5, and RCP2.6) were announced. In terms of energy and industry CO_2 emissions, RCP2.6 (van Vuuren et al. 2011) represents the pathway below the 10th percentile of mitigation scenarios and is too optimistic to achieve; RCP8.5 (Riahi et al. 2011) represents the 90th percentile of the reference emissions range, not considering major new improvements in agricultural efficiencies; RCP4.5 (Thomson et al. 2011) and RCP6.0 (Masui

et al. 2011) are both medium stabilization scenarios, but RCP6.0 could not be achieved unless the developed world cuts 50 % of the per capita meat consumption from 1980 levels, which seems unlikely under current cultural trends. Therefore, RCP4.5 was selected to generate climate projections for this study and to explore the long-term climate system responses to stabilizing anthropogenic components of radiative forcing. Future CO_2 emissions and concentrations for each forcing level are presented in Fig. 2.

In this study, future climate variables were obtained from climate projections of the HadGEM2 Earth System Model (HadGEM2-ES), provided by the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) at the Potsdam Institute for Climate Impact Research. HadGEM2-ES is a coupled atmospheric-ocean general circulation model (AOGCM) and was provided in phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Jones et al. 2011). In this study, HadGEM2-ES was bias-corrected with a quantile mapping method (Hempel et al. 2013) and downscaled with an atmospheric resolution of 0.5°×0.5° with 38 vertical levels.

Table 2 and Figs. 3 and 4 present the changes in the future critical climate variable values in Sichuan Basin, including the average change in daily maximum and minimum air temperature, precipitation and solar radiation, annual extreme high temperature days, and an effective cumulative temperature greater than or equal to 10 °C. For the daily average temperature, the general circulation model (GCM) projected a continuous increase in the future periods with a main increase occurring in summer (July to August). Therefore, incidences of extreme high temperature events in terms of daily maximum air temperature more than 35 °C (Xie et al. 2009; Zhang et al. 2010) increased obviously during the rice-growing season (March to September). The annual precipitation was also projected to increase and concentrate from May to September and peak in July, coinciding with the rice-growing seasons (Fig. 5).

2.3.2 Meteorological data

The minimum weather inputs required to calibrate and validate the CERES-Rice model included the daily precipitation, daily maximum and minimum air temperature, and daily solar radiation. The observed weather data in the selected years, including the maximum and minimum air temperature, precipitation, and hours of sunshine, were downloaded from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/) that is collected and operated by the China Meteorological Administration (CMA). The observed weather data for the five selected stations (Chengdu, Dujiangyan, Leshan, Yibin, and Youyang) were from
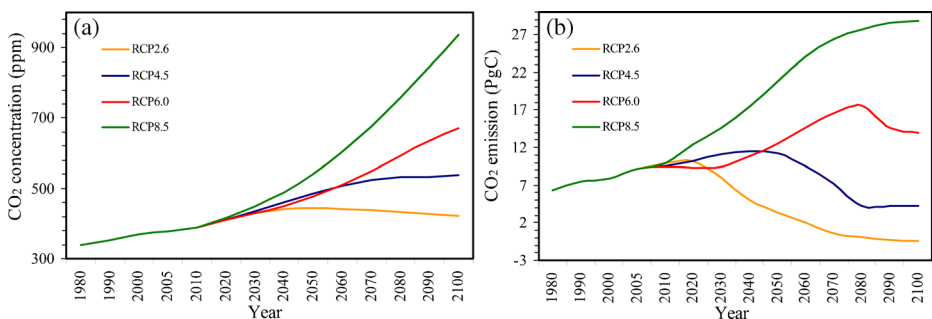

Fig. 2 Changes of the global **a** carbon dioxide (CO_2) concentration and **b** emission for each Representative Concentration Pathway (RCP) scenario (2.6, 4.5, 6.0, and 8.5) during 1980–2100

Table 2 Changes for temperature, precipitation and solar radiation in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099), projected by selected the Regional Climate Model (RCM) under the Representative Concentration Pathway (RCP) 4.5 scenario

Periods	Temperature (°C)	Extreme high temperature (d·a^{-1})	Precipitation (mm·day^{-1})	Solar radiation (MJ·m^{-2}·d^{-1})
2020s	+1.1	+6.7	−4.9 %	+0.5
2050s	+2.3	+19.3	−2.7 %	+2.4
2080s	+3.0	+26.6	+1.1 %	+3.0
Average	+2.1	+17.5	−2.2 %	+2.0
Baseline	20.0	132.8	7.9	15.4

the local meteorological stations, whereas the weather data from the other stations (Dazhu, Hanyuan, Liangshan, Miyi, Mingshan, Neijiang, and Jiangjin) were derived from their closest meteorological station (the latitude and longitude difference between them did not exceed 1°) due to the absence of records. Daily solar radiation for each station was calculated by the Angstrom equation (Wang et al. 2008) based on the daily sunshine hours. The projected weather data, including historic climate data (1981–2010) and the future climate data (2020s (2011–2040), 2050s (2041–2070s), and 2080s (2071–2099)), were derived from the HadGEM2-ES model and from the closet grid data for each station.

2.3.3 Soil data

Crop model inputs related to soil properties for each station included general surface information and characteristics for each soil layer (Wilkens et al. 2004). For general surface information, the inputs included color, drainage, slope, runoff potential, and a fertility factor. For the characteristics of each soil layer, the inputs contained organic carbon, water pH, cation exchange capacity, total nitrogen, and the percentage of the soil grain diameter. It assumed that the percentage of stones was 100 % minus the percentages of clay and silt (Tsuji et al. 1994). A soil characteristics database (including color, water pH, cation exchange capacity, total nitrogen, and the percentage of calculated/edited soil grain diameter) was obtained from
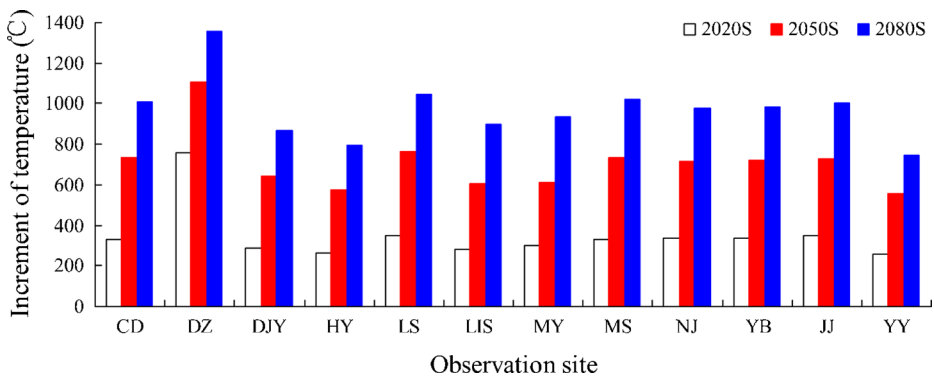

Fig. 3 Changes of annual cumulative daily average air temperatures that are greater than or equal to 10 °C in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099) under the Representative Concentration Pathway (RCP) 4.5 scenario in the Sichuan Basin. *CD* Chengdu, *DZ* Dazhu, *DJY* Dujiangyan, *HY* Hanyuan, *LS* Leshan, *LIS* Liangshan, *MY* Miyi, *MS* Mingshan, *NJ* Neijiang, *YB* Yibin, *JJ* Jiangjin, *YY* Youyang
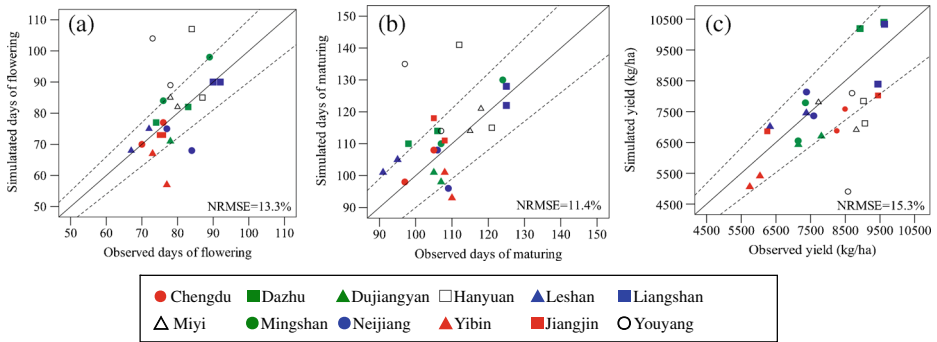
Fig. 4 Simulation vs. observation values of **a** flowering duration **b** maturing duration and **c** rice yields for the selected experimental data set. The *solid lines* represent the 1:1 relationship and the *broken lines* refer the error with ±15 %

the Chinese Soil Scientific Database (http://www.soil.csdb.cn/) and the Sichuan Soil Genus Records (Meng et al. 1994). The soil properties for each site in the Sichuan Basin were presented as Appendix.

2.3.4 Field agricultural experimental data

The field agricultural experimental data were obtained from the Chinese agro-meteorological experimental stations, which were maintained by the CMA (Tao et al. 2014). They were observed and collected from rice field experiments by well-trained agricultural technicians based on a standardized observation criterion and a prescribed method (China Meteorological Administration 1993). The observations were generally conducted every other day in the afternoon but every day in the morning during flowering periods. These experimental data included detailed and precise information about rice physiological data (e.g., sowing, emergence, transplanting, panicle initiation, flowering, and physiological maturity dates), management practices (e.g., plant population, planting and harvesting dates, row spacing, fertilizer application amounts and dates, and pesticide use), and rice yields and yield components (e.g.,

Fig. 5 The monthly precipitation's temporal distribution during rice-growing season in the Sichuan Basin under baseline periods and future climate scenario
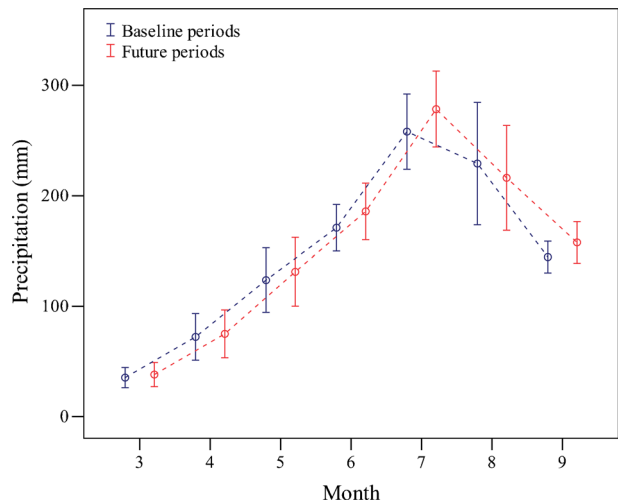
biomass, byproduct dry weight, pod per panicle, grain unit dry weight). Every phonological event has a clear definition, and each variable related to growth stages and yield was rigorously measured and calculated (China Meteorological Administration 1993).

Crop management practices at these experimental stations were generally better than those of local farmers. Adequate water supplies, nitrogen, and the application of pesticides and herbicides protected these crops from the effects of drought, insects, diseases, and weeds; the management practices at most stations did not change much during the study period, except for a change in varieties (Tao et al. 2006). Therefore, these long-term and high-quality data, in conjunction with other data (flowering dates, maturing dates and yield), could provide high-quality data for the rigorous calibration and verification of a CERES-Rice model, which would enhance modeling performance and the reliability of simulated results.

2.3.5 Genetic coefficients

The genetic coefficients are sets of adjustable parameters that describe the interaction between a genotype and environment and characterize the growth and development of crop varieties or hybrids differing in maturity dates (Tsuji and Balas 1993). They are mathematically used in quantity to summarize how a particular cultivar responds to external factors, including climate change, variations in CO_2 concentrations, and management practices such as adaptation options (Román-Paoli et al. 2000).

The genotype coefficients used for the growth and development of rice cultivars were presented in Table 3. The P coefficients enable the model to predict events such as flowering and maturity dates, and the G coefficients predict the potential grain yield of a specific cultivar (Tsuji and Balas 1993).

2.4 Model calibration, validation, and evaluation

For credible results, all crop models should be rigorously calibrated, validated, and evaluated for the varieties and environments of interest (Timsina and Humphreys 2006). Model calibration is a process of adjusting a set of model parameters to the local experimental field conditions (Wajid et al. 2013). In this study, the final coefficient values for a specific cultivar were necessary, and they were obtained until close matches were achieved between the

Table 3 The genetic coefficients for rice cultivar and their definitions in the Crop Estimation through Resource and Environment Synthesis (CERES)-Rice model

Coefficients	Definitions
P1	The growing degree-days (°C-days) above a base temperature of 9 °C in basic vegetative phase
P20	The critical photoperiod or the longest day length measured in hours, during which development occurred at a maximum rate
P2R	The extent of delay in panicle initiation, expressed in °C-days
P5	The time period in °C-days from the beginning of grain filling to physiological maturity with a base temperature of 9 °C in grain filling phase
G1	The potential spikelet numbers per panicle
G2	The single grain weight
G3	The tillering coefficients relative to IR64 cultivars
G4	The temperature tolerance coefficient

simulated and observed phenology and yield. Such a calibration process is also the model parameterization process. Model validation assesses the ability of a successfully calibrated model to simulate the selected cultivars through a comparison between the simulation and observed data at plot scale (Wilkens et al. 2004). Evaluation is an overall assessment of crop model performance in a study region, which depends largely on the great confidence in model capacity for estimating the results that agree well with the observed ones.

One year of observed data from each site were used to calibrate, and two other years of independent data (Table 1) were used to validate the crop model, both of which included the anthesis and maturity duration for the development coefficients and the final grain yield for the growth coefficients. When calibrated and validated, 100 kg/ha N were incorporated into soil at the depth of 15 mm as the basal manure and 200 kg/ha N were applied as topdressing. For irrigated regions, 100 mm water were applied before and after transplanting periods divided into two times. In addition, rice cultivars were transplanted at the depth of 1.5 cm, and the row spacing was 25×25 cm. To ensure simulation precision, the selected cultivars should be planted for at least 3 years at one site during the selected years, and there must be a yield increment and no apparent impact from diseases and extreme climate during these years.

Parameterization or calibration was conducted using the Generalized Likelihood Uncertainty Estimation (GLUE), a Bayesian Monte Carlo parameter estimation technique (He et al. 2010), to closely match the simulated and observed data. The estimation process of the GLUE program is fast and can be used with any number of genetic coefficients. In contrast, estimating coefficients with filed experiments and measurements is time-consuming and is restricted to the parameter number (Román-Paoli et al. 2000). In this study, approximately 10,000 runs were conducted using GLUE with the following summarized steps: (1) initializing the rice genetic coefficients of a specific cultivar; (2) running the GLUE module with original genetic coefficients and producing parameter values (anthesis duration, maturity duration, and yield), as well as a set of new genetic coefficient values; and (3) calculating the deviation between the simulated and observed values. If the error was acceptable, then the process was complete; if not, step 3 was repeated.

During calibration and validation, the errors between the simulated values for rice anthesis duration, maturity duration, and the observed ones were estimated using the predicted deviation (PD) to evaluate the model performance for each station. For evaluation, we use the normalized root mean square error (NRMSE) to assess the model performance for the Sichuan Basin.

$$\text{PD} = (S_i - O_i)/O_i \tag{2}$$

$$\text{NRMSE} = \left[\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2 \right]^{1/2} / \overline{O_i} \tag{3}$$

Here, S_i and O_i are the predicted and observed parameter values, respectively; $\overline{O_i}$ is the observed mean value, n is the validated year number, and i is each observation. The simulation is considered perfect when the NRMSE is less than 10 %, good with an NRMSE between 10 and 20 %, fair with an NRMSE between 20 and 30 % and poor with an NRMSE more than 30 % (Rinaldia et al. 2003).

2.5 Model application

The simulation of rice yields is generally based on calibration of the model parameters of the selected cultivars under current weather conditions and its subsequent application under future climate change scenarios. In an agricultural system, plant growth and development depend on the integrated responses of various eco-physiological processes with a combination of environmental conditions, such as temperature, CO_2 concentrations, nutrients, water, and agronomic management. It is impossible, however, to accurately examine all of these variables and their interactions and to assess their respective potential effects on agricultural production. Therefore, the evaluation of climate change impacts and adaptation options in this study were conducted based on the general assumption that all variables, such as cultivar varieties, soil, and agricultural management, were held constant while leaving each of these three factors, i.e., climate change, CO_2 concentrations, and adaptation options, as the only independent variables. This approach has been widely adopted in crop simulation research (IPCC 2001).

2.5.1 Evaluation of climate change impacts

Assuming that the rice area, agro-technology level, cultivar, crop management, and irrigation conditions remain the same as in the present, the impacts of climate change on rice phenologies and yields were evaluated by comparing the CERES-Rice model outputs (rice phenologies and yields) over three time periods (2020s, 2050s, and 2080s) under the RCP4.5 scenario with those under the baseline (1981–2010). To eliminate the mutual effect among different dependent climate variables on rice yields, the stepwise multiple regression method, which is helpful to identify the major variables affecting the dependent variables and in ranking them for importance (Armstrong and Hilton 2010), was applied in the latter analysis. In this study, temperature and CO_2 concentrations were mainly taken into account to simulate climate change impacts on rice growth. Considering the sensitivity of rice growth to high temperatures, the daily average air temperature and maximum air temperature were analyzed to evaluate the relationship between temperature and rice yields. The impact of increased atmospheric CO_2 concentrations on rice yields was simulated by running the crop model for all stations with different CO_2 concentrations of the baseline and three future periods (2020s, 2050s, and 2080s) under RCP4.5 scenario, which were derived from the RCP Database v2.0.5 (http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=compare).

2.5.2 Evaluation of adaptation options

The Fifth Assessment Report of the IPCC (IPCC 2014) suggested several adaptation strategies to address projected climatic change; these included altering the planting dates, switching to more suitable current available crop varieties, breeding new cultivars, irrigating, increasing the effectiveness of pest and disease control, and improving crop management practices. However, some of the adaptation strategies are beyond the capacity of the CERES-Rice model to simulate, and it is also beyond the scope of this paper to simulate all of the adaptation strategies. In this study, we selected the three most commonly practiced adaptation measures

to evaluate their effectiveness in mitigating the negative impacts of climate change on rice production, i.e., changing the planting date, switching to high temperature tolerant rice cultivars, and breeding new rice cultivars. The former two measures represent a typical household-level autonomous adaptation measure, whereas the latter usually represents a typical planned adaptation sponsored mainly by governments and research communities (Porter et al. 2014).

To adjust rice planting dates, we assessed the effectiveness of shifting planting dates on rice yields by advancing and delaying the planting date by 40 days at a 5-day interval and compared the simulated results with those of the current planting dates for the selected stations. The best planting date was then determined for each rice cultivar as the one with an increased rice yield and the minimum yield stability (ΔSD) value, which is an important indicator of rice production and is affected by climate change (Jiang et al. 2013).

$$\Delta SD = \left| \frac{\mu_c \pm \sigma_{\mu c}}{\mu_a} \right| \tag{4}$$

$$\sigma_{\mu c} = \sqrt{\sigma_{\mu c}^2 + \sigma_{\mu b}^2} \tag{5}$$

$$\sigma_{\mu c} = \frac{\sigma_a}{\sqrt{n_a}}, \sigma_{\mu b} = \frac{\sigma_b}{\sqrt{n_b}} \tag{6}$$

Here, σ_a and σ_b are the standard deviations of the annual rice yield in the baseline and future climate periods, respectively, and μ_a and μ_b are the average values of annual rice yield in the baseline and future climate periods, respectively. $\mu_c = \mu_b - \mu_a$ is the difference in the annual rice yield between the baseline and future climate periods. n_a and n_b are the lengths of the computed years.

Switching rice cultivars from other stations to the selected ones, a similar condition in temperature and solar radiation between them needed to be guaranteed for successful adaptation (Cheng and Li 2007). Therefore, high-yielding rice cultivars with a high temperature tolerance at other sites that were located in the same climate as the selected sites were imported to simulate this approach's effectiveness in mitigating the impacts of high temperature on rice yields.

For breeding new cultivars at the selected stations based on current rice varieties, a sensitivity one-factor-at-a-time (OAT) method (Morris 1991) was first used to select the most sensitive genetic coefficients for each rice variety. The relative sensitivity (RS) (Liu et al. 2008) was estimated and used to evaluate the relative degree between each coefficient and rice yield.

$$RS = \left| \left(\left(y(x = \Delta x) - y(x) \right) \Big/ y(x) \right) \Big/ \left(\Delta x \Big/ x \right) \right| \tag{7}$$

Here, x is a rice genetic coefficient, Δx is the increment of a genetic coefficient, and $y(x)$ and $y(x + \Delta x)$ are rice yields before and after altering the coefficients, respectively. The most sensitive coefficient obtained by the OAT method was then used for improving the current available rice cultivars at the selected stations by changing their values in a relative fixed step size while keeping other variables constant.

3 Results and discussion

3.1 Model performance

Table 4 shows the estimated genetic coefficients for each rice cultivar, and Fig. 4 presents an evaluation of the model performance. It shows that the NRMSE of flowering duration (13.3 %), maturity duration (11.4 %), and grain yields (15.3 %) were all greater than 10 % but less than 20 %, indicating good model performance based on the evaluation standard of model simulation (Rinaldia et al. 2003). Moreover, the simulated and observed values distributed relatively uniformly around a one-to-one line within ±15 % PD for most values in validation (Fig. 4), suggesting that the CERES-Rice model performed well and could be applied in the Sichuan Basin.

3.2 Impacts of climate change on rice production

The following evaluation was based on a comparison between RCP4.5 climate change scenario data (2011–2099) and baseline (1981–2010) data.

3.2.1 Impacts of climate change on rice phenologies

The predicted results indicated in Fig. 6 showed that the average flowering duration would be shortened by 6.6 days during 2011–2099, with a maximum decrease of 12.1 days occurring at the Liangshan site and a minimum decrease of 1.7 days at the Neijiang site. At the same time, the average duration to maturation would decrease by 14.4 days during 2011–2099, with a maximum decrease of 34.1 days at the Hanyuan site and a minimum decrease of 3.6 days at the Jiangjin site. For all future periods, the average shortened flowering period was 3.9, 6.1, and 9.9 days in the 2020s, 2050s, and 2080s, respectively, whereas the maturity dates advanced by 8.6, 14.9, and 19.7 days in the 2020s, 2050s, and 2080s compared to those of the baseline, respectively.

Table 4 The calculated genetic coefficient values for each rice variety using the Crop Estimation through Resource and Environment Synthesis (CERES)-Rice crop model in the Sichuan Basin

| Sites	Cultivar	P1	P2R	P5	P20	G1	G2	G3	G4
Chengdu	Gangyou22	646.1	56.2	365.9	11.9	59.6	0.0220	0.82	1.022
Dazhu	Shanyouduoxi1	230.3	192.7	496.6	11.6	73.4	0.0250	0.77	1.077
Dujiangyan	Gangyou6	624.2	74.2	373.3	14.0	57.0	0.0201	0.81	0.986
Hanyuan	Yixiang1577	608.4	70.8	396.4	13.2	120.0	0.0300	0.73	1.222
Leshan	Dyou63	400.1	99.0	471.2	13.3	60.7	0.0230	0.84	1.003
Liangshan	IIyou838	546.2	59.4	410.6	11.6	81.1	0.0180	0.68	1.228
Miyi	Dyou68	451.4	32.9	337.9	11.3	118.6	0.0240	0.60	1.030
Mingshan	Gangyou527	615.6	123.5	337.8	12.2	59.7	0.0190	0.97	0.917
Neijiang	Iyou838	224.1	216.3	464.4	12.3	68.4	0.0210	0.43	0.926
Yibin	Gangyou22	508.2	30.4	552.5	13.3	50.5	0.0190	0.69	1.090
Jiangjin	IIyou6078	457.2	94.0	367.0	11.8	117.4	0.0300	0.57	1.190
Youyang	IIyou58	460.4	63.3	566.2	12.9	77.8	0.0240	0.33	0.884
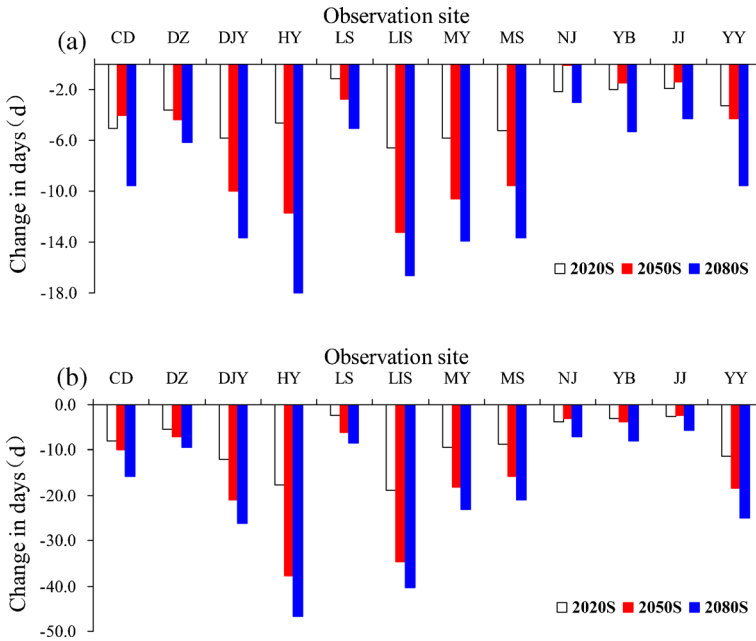
Fig. 6 Changes of rice **a** flowering duration and **b** maturing duration compared with those of baseline in the 2020s (2011–2040), 2050s (2041–2070) and 2080s (2071–2099) under RCP 4.5 scenario in the Sichuan Basin

Generally, the physiological maturity of rice could be determined by leaf senescence, grain color, and grain weight (Shi et al. 2015). However, these traits could not contain the specific physiological status of heat stress during physiological maturity at the same time. Therefore, the GDD has been incorporated into the CERES-Rice model to divide the rice growth stages into different phases, e.g., the anthesis and maturity phase. In this study, rice anthesis and maturity duration shortened during future climate change from increased temperature stress, which was in accordance with the conclusion of Challinor et al. (2007), Rani et al. (2013), Zhang et al. (2013) and Shi et al. (2015). Zhang et al. (2013) simulated the impacts of climate change and variability on rice phenology by using five crop models (CERES-Rice, ORYZA2000, RCM, Beta Model, and SIMRIW), concluding that the rice-growing season was shortened by about 0.45–5.78 days in most of study regions except northeastern China where rice-growing season prolonged due to the impacts of increased extreme temperature; Shi et al. (2015) found an obvious advance in physiological maturity for rice under post-anthesis heat stress by using the original RiceGrow model. A plausible mechanism was that the phenological stages of rice were completed earlier with a prescriptive accumulated GDD from increasing high temperatures, therefore, leading to a decrease in the growth duration (Jones et al. 2003; Rani and Maragatham 2013).

3.2.2 Impacts of temperature, precipitation, and solar radiation on rice yields

Predicted changes in rice yields not considering the direct CO_2 fertilizer effect between baseline and future climate periods for all the stations are shown in Fig. 7. The rice yield across all sites indicated a continually decreasing trend during all periods. The lowest and highest reduction occurred at the Liangshan and Jiangjin site, respectively, with decreases of
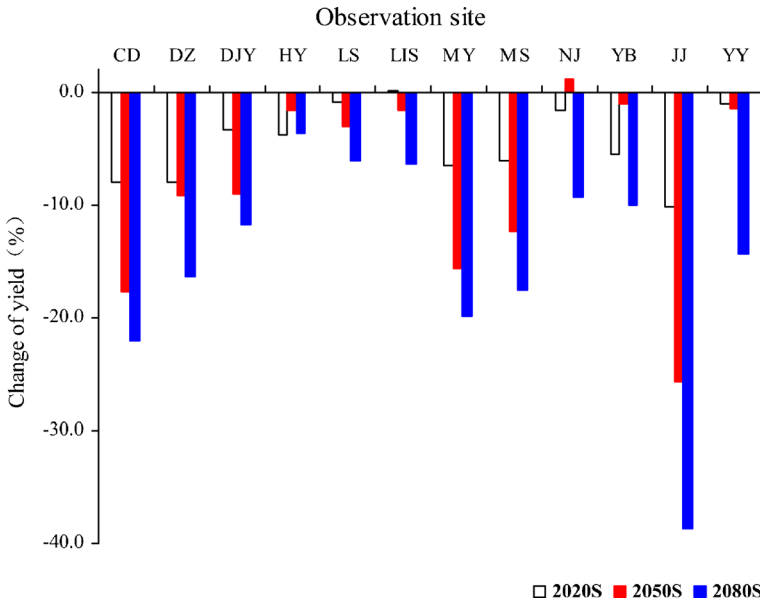
Fig. 7 Changes of rice yields compared with those under baseline in the 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2099) under the Representative Concentration Pathway (RCP) 4.5 scenario in the Sichuan Basin

2.6 and 24.8 %. The reductions in rice yields over all the future periods were projected to be 4.4, 7.9, and 14.2 % in the 2020s, 2050s, and 2080s, respectively, with the most serious decrease occurring in the 2080s. However, not all the stations would experience yield reductions in the future. The Liangshan and Neijiang sites are such exceptions; they exhibited a 0.1 and 1.1 % increase in yield in the 2020s and 2050s, respectively.

The mechanism behind the relative contributions of various climatic variables to changes in rice phenology and yield could be further explored based on stepwise multiple regression analysis between climate impact factors (daily average air temperatures, solar radiation, and precipitation) and rice yields (yield$=-338.86$Tav-0.98Prec$+15885.869$, $P=0.00<0.01$, Tav, Prec: the daily average air temperature and precipitation, respectively). The daily average air temperature was the most dominant factor that influenced rice yields negatively to a large extent, which is consistent with findings by Kim et al. (2013) and Krishnan et al.(2007). In contrast, precipitation and solar radiation at a regional scale exhibited no discernible impact on rice yields, probably as a combined result of the abundant rainfall during the rice-growing season and the insensitivity of mid-season rice to light (Cheng and Li 2007).

Temperature can influence rice yields mainly by affecting the average growth rates and growth durations through the two following pathways (Ritchie et al. 1998): (1) the average growth rates are decided by rice net photosynthesis (difference between photosynthesis and respiration), which would change depending on the current temperature relative to an optimum (Chartzoulakis and Psarras 2005; Fredeen and Sage 1999), whereas high temperatures at nighttime would increase respiration and then biomass consumption (Hatfield et al. 2011; Lobell and Gourdji 2012) without any benefit for photosynthesis. Furthermore, a warming climate would lead to spikelet sterility, lower yields, and even the risk of complete crop failure when the temperature was close to an extreme high temperature, especially for the time period

before and during the flowering stage (Jagadish et al. 2014; Lansigan et al. 2000; Lobell and Gourdji 2012). Therefore, an increase in the average air temperature and annual extreme high temperature days during rice-growing season would reduce the rice growth rates by decreasing the net photosynthesis; (2) growth durations, which determine the time of biomass accumulation, include anthesis and maturity, which decreased in duration during high temperatures under future climate change according to previous conclusions about anthesis and maturity, as shown in Fig. 6. Therefore, rice yields in the study region would decline due to a decrease in the growth rate and shortening of the growth durations, both of which resulted from the elevated temperatures under a future warming climate. This conclusion was consistent with that by Krishnan et al. (2007) and Bocchiola et al. (2015). Krishnan et al. (2007) predicted a reduction of 7.2 and 6.7 %, for every 1 °C increase in temperature by using ORYZA1 and INFOCROP rice models, respectively; Bocchiola et al. (2015) suggested that the decrease in rice yields projected by PolyCrop model under most future climate scenarios in the Po valley of Italy was mainly due to increasing summer temperature through the crop model.

In contrast to the obtained results of most other stations, rice yields at the Liangshan site in the 2020s and at the Neijiang site in the 2050s increased. According to a stepwise multiple regression analysis between rice yields and climate data at the Liangshan and Neijiang site on a plot level, the main effective factor of both stations was precipitation ($P=0.004<0.01$; $P=0.005<0.01$), leading to negative impacts on rice yields. Therefore, yields at the two sites increased from a precipitation decrease by 7.2 % during the 2020s at the Liangshan site and 1.1 % during the 2050s at the Neijiang site during future climate periods. Two reasons may account for this negative relationship. The first was probably that the amount of precipitation (904 mm) during rice growth in the Sichuan Basin exceeded the requirement of single-crop rice cultivars (Fang et al. 1998); therefore, excessive precipitation would damage rice development and result in reductions in rice yields. The second may be related to high temporal variability in the precipitation distribution, which indicated that more than 50 % of the rainfall was concentrated during flowering periods and 10 % or less occurred during the periods between planting and heading duration (Fig. 5). Therefore, flooding during the flowering periods would easily occur, which would exert negative impacts on rice yields. Therefore, a decrease in the precipitation by less than 10 % may not affect the rice water requirements significantly; in contrast, a decrease in precipitation may increase rice yields by reducing the risk of excess rainfall to rice production in the 2020s and 2080s at these two sites. Such a negative relationship between precipitation and rice yields is consistent with the conclusion obtained by Buan et al. (1996), who indicated that the predicted rain-fed rice yield declined by 10 % in response to precipitation increases, probably due to the already abundant seasonal rainfall there.

3.2.3 Impacts of the CO_2 fertilization effect on rice yield

An increase in ambient CO_2 concentrations, causing high temperature and radiation variance, would also impact the rice yield through a direct fertilizer effect, as indicated by variations in rice yields in Table 5. When considering the CO_2 fertilizer effect, the margin of rice reduction decreased by 2.1, 5.8, and 6.9 % in the 2020s, 2050s, and 2080s, respectively, compared with those of the baseline. However, the average rice yield across all stations still declined by 2.3, 2.1, and 7.3 % in the 2020s, 2050s, and 2080s, respectively. Therefore, this indicated that the increase in CO_2 concentration under future climate scenarios was able to mitigate the reduction in rice yields to some extent but was still not able to offset the negative effect of climate change

Table 5 Relative changes (in %) of future rice yields simulated with and without the carbon dioxide (CO_2) fertilization effect for each site in the Sichuan Basin

Site	2020s			2050s			2080s		
	Without	With	CO_2 fertilizer effect	Without	With	CO_2 fertilizer effect	Without	With	CO_2 fertilizer effect
Chengdu	−7.9	−6.3	1.7	−17.7	−5.0	12.7	−22.1	1.4	23.5
Dazhu	−7.9	−5.8	2.1	−9.2	4.7	13.9	−16.4	−1.0	15.4
Dujiangyan	−0.9	0.5	1.5	−3.1	2.4	5.5	−6.1	3.0	9.1
Hanyuan	0.1	3.2	3.0	−1.6	4.9	6.5	−6.5	4.1	10.6
Leshan	−6.0	−4.0	2.0	−12.3	−1.2	11.1	−17.5	1.9	19.4
Liangshan	−1.6	0.4	2.0	1.1	9.1	8.1	−9.3	−2.3	7.1
Miyi	−5.5	−3.9	1.6	−1.0	43.5	44.5	−10.0	21.3	31.3
Mingshan	−10.1	−8.5	1.6	−25.7	−11.7	14.0	−38.6	−11.4	27.3
Neijiang	−3.3	−0.9	2.4	−9.0	−0.3	8.7	−11.7	4.2	15.9
Yibin	−3.8	−1.7	2.0	−1.6	8.4	9.9	−3.7	5.7	9.4
Jiangjin	−6.5	−3.5	2.9	−15.7	−1.3	14.4	−19.9	6.9	26.8
Youyang	−1.0	1.2	2.2	−1.5	5.5	7.0	−14.3	−9.0	5.3
All	−4.4	−2.3	2.1	−7.9	−2.1	5.8	−14.2	−7.3	6.9

on rice yields. This finding was consistent with the conclusion by Lin et al. (2005), Xiong et al. (2009), and Krishnan et al. (2007). Krishnan et al. (2007) used INFOCROP and ORYZA1 rice models and projected an increase in rice yields by 25.92 and 18.57 %, respectively, when considering the effects of increased CO_2 concentration alone. However, rice yields would decrease when the temperature increase was more than 3 °C.

Three plausible interpretations based on plant physiology for rice yield increases were that elevated CO_2 concentrations could: (1) enhance photosynthesis by constraining photorespiration (Widodo et al. 2003) and advancing light use efficiency due to a greater leaf area index (Ewert 2004); (2) increase the utilization rate of water by reducing the stomata conduction and consequent transpiration (Tubiello and Ewert 2002), and thus contribute to biomass accumulation and tillering consequently (Bazzaz et al. 1989).

3.3 Adaptation options simulation

As the impacts simulation indicated earlier, the risk of rice production due to elevated temperatures would occur under the RCP4.5 scenario, and the most adversely impacted rice yields of 22.1 and 38.6 % occurred at the Chengdu and Jiangjin sites, respectively, during the 2080s. Therefore, these two sites were selected to investigate the effectiveness of three adaptation options in the 2080s, including adjusting the planting date, switching to high temperature tolerant varieties, and breeding new rice cultivars.

3.3.1 Adjusting rice planting dates

The predicted yields and stabilities at the Chengdu and Jiangjin sites in the 2080s are presented in Fig. 8, indicating non-linear variation. Rice yields increased when planting dates advanced earlier than current dates at the Chengdu and Jiangjin sites, as did the yield stability, which
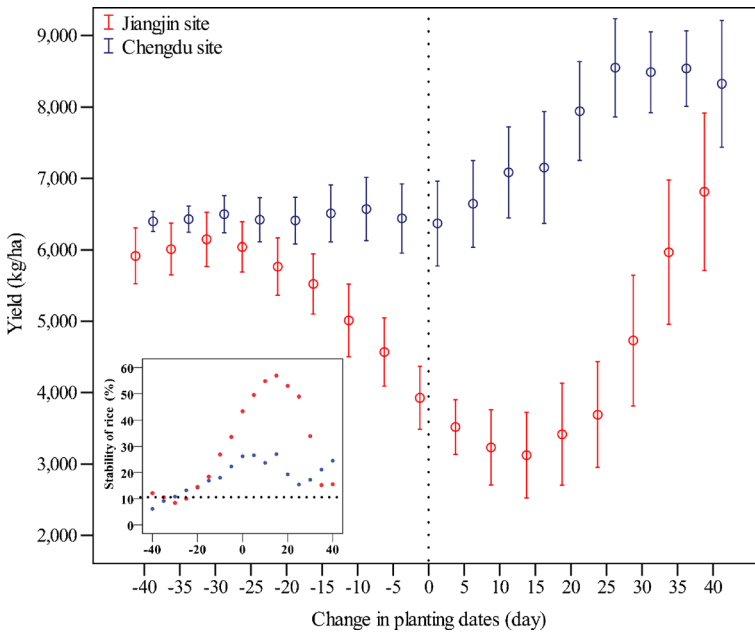
Fig. 8 Change of rice yields and stabilities in the 2080s (2071–2099) under the Representative Concentration Pathway (RCP) 4.5 scenario at the Chengdu and Jiangjin site. The *plus and minus in horizontal ordinate* represent earlier and later days than current planting dates, respectively

exhibited a steady level. Considering the integrated effect of advancing the planting date on rice yields and its stabilities, the optimum planting date for rice cultivars would be to advance the planting date 40 days earlier at the Chengdu site and 30 days earlier at the Jiangjin site with the most significant yield increases of 24.3 and 56.5 %, respectively, compared with those of current planting dates.

High temperatures during rice flowering would easily cause rice reduction but would have less impact on rice production during other stages of rice growth (Lansigan et al. 2000). Before adjustment, the flowering date was July 30th at the Chengdu site and July 15th at the Jiangjin site. Both of these sites were expected to experience extreme high temperatures during flowering periods because their maximum daily air temperatures were 35.1 and 35.4 °C, respectively. After advancing the planting dates by 40 days at the Chengdu site and 30 days at the Jiangjin site, their flowering dates were set to July 12th and June 20th. Then, the maximum air temperature was 33.4 and 33.5 °C (Fig. 9), respectively, and the rice cultivar could avoid extreme high temperatures during its flowering periods. Furthermore, the lengthened maturity duration (19.6 % at the Chengdu site and 6.3 % at the Jiangjin site) would increase the rice yields as a result of the extended cumulative time for dry matter (Saseendran et al. 2000). Therefore, the initiative of avoiding extreme high temperatures during flowering periods and prolonged growth durations resulting from planting date advancement would increase rice yields and improve its stability at selected stations in the 2080s.

Adjusting rice planting dates has been widely evaluated and identified around the world (Byjesh et al. 2010; Deryng et al. 2011; Kapetanaki and Rosenzweig 1997; Lashkari et al.

Fig. 9 Changes of maximum air temperature during flowering periods in the 2080s (2071–2099) under the Representative Concentration Pathway (RCP 4.5) scenario at the Chengdu and Jiangjin sites
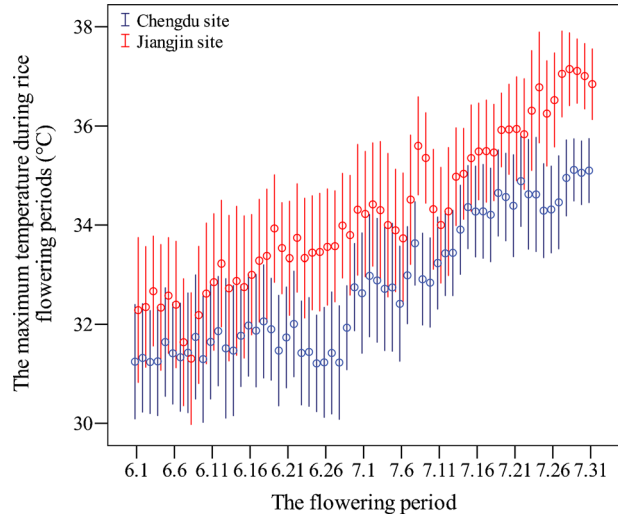
2011; Mati 2000; Moradi et al. 2013; Moriondo et al. 2010; Singh et al. 2013; Srivastava et al. 2015; Tingem and Rivington 2008; Travasso et al. 2009). The predictions obtained above, indicating that early planting increased rice yields in the mid-season cultivars under future climate change in the RCP4.5 scenario during the 2080s, are consistent with many previous studies. Kim et al. (2013) simulated rice yields with planting dates at 30, 20, and 10 days before and after current planting dates in a temperate climate in Asia and concluded that yields would reach a peak at 30 days earlier than planting for the mid-season cultivar in 2050 and 2100. Krishnan et al. (2007) examined rice yield changes by adjusting the planting date to June 1, June 15, July 1, July 15, and August 1, compared to the typical planting date of June 15, at two stations (Cuttack and Jorhat) with ORYZA1 and INFOCROP models under the GFDL, GISS, and UKMO scenarios in eastern India. They indicated that planting 30 days earlier could increase rice yields to the maximum extent at all stations and under all scenarios. Babel et al. (2011) explored rice yields in northeast Thailand by gradually shifting planting dates at an interval of 10 days from 30 days before and after the original planting dates in the 2020s, 2050s and 2080s under the regional climate model. They showed that delaying the planting date by 30 days during the 2020s and 2050s, 20 days during 2080s was optimal for three sites, which was in contrast with the predictions in this paper. However, it was consistent in that the adjustment of planting dates could contribute to avoiding high temperatures during the critical growth stage of rice. Therefore, either advancing or delaying the planting date would both increase rice yields during the key growth stage of rice, which would be completed before the onset of extreme high temperatures.

3.3.2 Switching to high temperature tolerant rice cultivars

The impact simulation indicated that the rice cultivar "Iyou838" has a shorter growing season and a lower yield decrease compared with other cultivars. We further simulated the effects of transplanting the Iyou838 cultivar from the Neijiang site to the Chengdu and Jiangjin sites while holding fertilizer, irrigation, and planting dates constant for the current simulations. The predicted yields of new cultivars at the Chengdu and Jiangjin sites were 7776 and 4486 kg/ha,

respectively, increasing by 22.1 and 14.2 % compared to that of current varieties (6369 and 3927 kg/ha). It indicated that such an adaptive measure can effectively mitigate the high temperature impacts on rice yields. Krishnan et al. (2007), Wassmann et al. (2009), and Challinor et al.(2009) obtained a similar result. A possible reason explaining such increases in rice yield is that switching to the selected Iyou838 rice cultivar with a shorter growing season can avoid the extreme high temperatures during the flowering period (Fig. 10). This trait is also a reflection of high temperature tolerance in rice cultivars (Wassmann et al. 2009). The maximum air temperature during flowering periods at the Chengdu and Jiangjin sites were 34.9 and 33.6 °C, respectively, lower than those of former rice varieties (35.1 and 35.0 °C); switching to more high temperature tolerant varieties can thus attribute to rice yield increases. Therefore, the Iyou838 rice variety could be planted at the Chengdu and Jiangjin sites to convert higher temperature stress to favorable thermal resources for rice growth, thereby increasing rice yields under future climate scenarios.

3.3.3 Breeding new rice cultivars

In the CERES-Rice model, genotype coefficients were used as an important input to simulate the growth and development of rice cultivars; thus, it was generally assumed that we can simulate the adaptive effectiveness of breeding new rice cultivars by a way of altering the genotype coefficient values of a simulated rice variety. Table 6 indicates the sensitivities of rice yields to different genetic coefficients at the Chengdu and Jiangjin sites. The most sensitive coefficients were P1 (the GDD above a base temperature of 9 °C) at the Chengdu site and P1, G1 (the potential spikelet numbers per panicle), and G2 (the single grain weight) at the Jiangjin site. Therefore, these parameters of interest were altered by 5 % from their current values within the given value ranges in the CERES-Rice model under a condition of holding other coefficient values constant. Then, the changed parameter values were used to simulate rice yields of improved cultivars in the 2080s with the CERES-Rice model.

Fig. 10 Distributions of the maximum air temperature during rice flowering periods for each rice cultivar at the Chengdu and Jiangjin sites
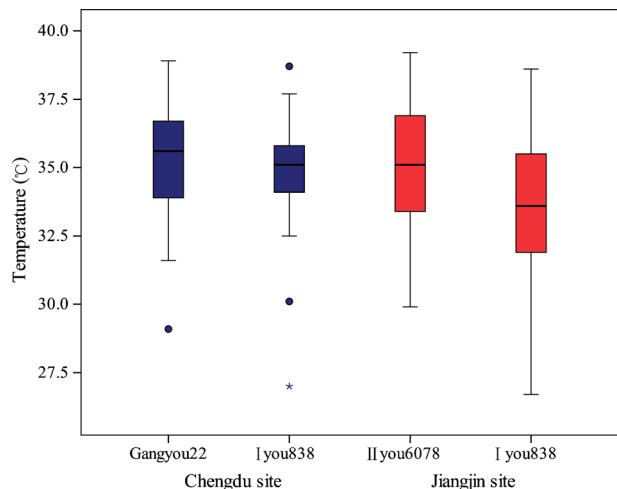
Table 6 The sensitivity of rice yields to genetic coefficients for each rice variety at the Chengdu and Jiangjin sites

Sites	Cultivars	P1	P2R	P5	P20	G1	G2	G3	G4
Chengdu	Gangyou22	0.78	0.4	0.14	0.76	0.68	0.68	0.19	0.03
Jiangjin	Eryou6078	0.49	0.08	0.07	0.02	0.49	0.49	0.16	0.32

Yields as a function of changing cultivar coefficients indicated a continuous increasing trend for the new cultivar in the 2080s at the Chengdu and Jiangjin sites (Fig. 11). Rice yields peaked by an increase of 21.5 % at the Chengdu site when P1 was 839.9 and 25.4 % at the Jiangjin site when P1 was 868.7. Furthermore, rice yields already reached a peak when G1 and G2 were at current values at the Jiangjin site. In conclusion, increasing the requirement of rice cultivars for thermal resources during its basic vegetative growth could effectively contribute to yield increases, which is similar to the results obtained by Krishnan et al. (2007) and Wassmann et al. (2009). Furthermore, improving cultivar tolerance to high temperatures is continuously identified as an adaptation strategy for many crops globally (Porter et al. 2014).
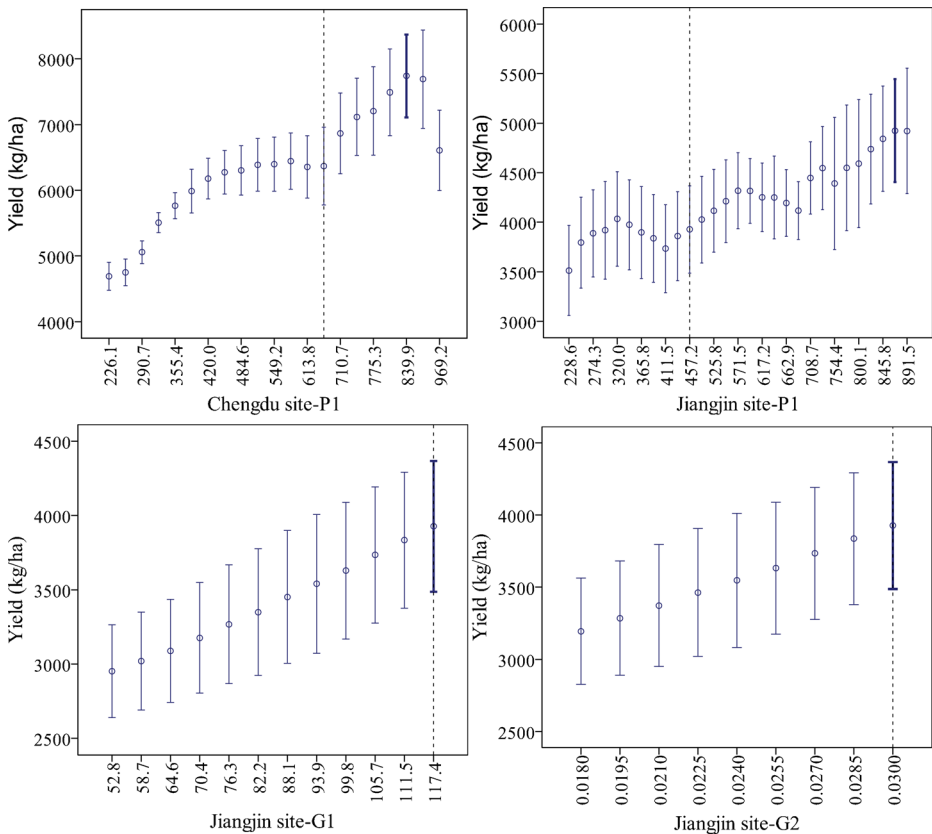

Fig. 11 Yields of four new rice cultivars as a function of cultivar parameter changes in the 2080s (2071–2099) under the Representative Concentration Pathway (RCP) 4.5 scenario at the Chengdu and Jiangjin sites. Treatment 14 at the Chengdu site and treatment 11, 12, and 9 at the Jiangjin site are based on current coefficient values. The rice yield peaked in treatment 20 at the Chengdu site and in treatment 29, 12, and 9 at the Jiangjin site

Therefore, breeding high temperature tolerant cultivars is an effective measure that can reduce the negative impacts of climate change on rice yields and should be widely applied under future climate warming conditions.

Except for these three globally widely practiced adaptive measures, sufficient irrigation and altering cropping systems may also be effective methods for adapting rice cultivars to future climate change. For irrigation, the obvious temporal differences of precipitation presented in Fig. 5 would easily cause drought during the early growth stage of rice cultivars. Therefore, irrigation should be adopted as a useful adaptation strategy to mitigate the adverse effects of high temperatures on rice production. For changing cropping systems, the annual cumulative temperature of greater than or equal to 10 °C, which is crucial for rice growth (Liu et al. 2010), increased by 1007 and 1001 °C at the Chengdu and Jiangjin sites, respectively, in the 2080s (Fig. 3). Therefore, elevating the multiple-crop index to sufficiently utilize thermal resources was another effective measure to increase yields and reduce the negative impacts of high temperatures on rice production for a single rice cropping system.

4 Uncertainties and limitations

Like other studies simulating climate change impacts and adaptive measures using crop models, this study also suffers from several potential uncertainties and limitations due to multiple sources (Asseng 2013); these include the climate assessment in climate models, variations in different crop models, and the discrepancy in scale between the climate model outputs and the crop model inputs.

The first uncertainty, resulting from the climate assessment, was due to different emission scenarios and climate models. The plausible emission scenarios, which were raised to project future climate change through climate models, embodied the uncertainty of climate change impacts on yields due to the uncertainty of government policy, new technology, and energy development impacts on greenhouse gas emissions. Furthermore, different climate models (Masutomi et al. 2009) would also produce different climate change outcomes. The impacts of climate change on yields depend on the numbers of general circulation models (GCMs) used to a large extent, and the uncertainties could be evaluated by using projections from multiple climate models (Collins 2007; Masutomi et al. 2009).

The second uncertainty from crop models was mainly due to the structure of crop models, the calibration of genetic coefficients, and the responses of crops to climate change. (1) Process-based crop models are the most common and powerful tool to estimate the impact of climate change on crop production while considering the interaction among soil, water, crop, climate, and managements. However, interactions between these climate and non-climate factors confounded the evaluated results and also contained uncertainties due to man-made factors. Some researchers have assessed the uncertainty of crop models by using more than one crop model, and they performed well (Challinor and Wheeler 2008; Matthews and Wassmann 2003). (2) The localization of models was the premise of model application. However, crop models could not account for all of the factors in the field that may influence crop yield. Without considering crop diseases, weeds, the spatial variability of soils and management implementation, large differences in yields would occur when comparing the simulations with observation. (3) Furthermore, the CO_2 fertilization effect, high stress, and high-temperature-by-CO_2 interactions also still remain uncertain in the crop model simulations. Leakey et al. (2009) concluded that crop models overestimated the impact of the CO_2 fertilization effect on

crop yields, whereas others held the opposite views (Tubiello et al. 2007). Porter et al. (2014) concluded that temperature responses were well analyzed for temperatures up to the optimum temperature for crop growth, but the impacts of high temperature beyond the optimum temperature on development were not clear. Therefore, further theoretical and experimental research to qualify and reduce uncertainties in the CO_2 fertilization effect and high stress is necessary. Furthermore, the effect of technological developments on crops was not considered in the simulations; nevertheless, it had a positive effect on yields that was greater than the negative impacts from climate change (Ewert et al. 2005), which is also an uncertainty.

The third uncertainty derives from a discrepancy in scale between the climate model outputs and crop models inputs. Generally, the impacts of climate change on crop production at a regional level were assessed by simulating at the plot scale first, using downscaled climate models and crop models. However, the latest research has shown that significant factors of crop production at the plot level include soil properties and management measures, whereas it was the climate factor that significantly affect crop production at a regional level (Bakker et al. 2005; Challinor et al. 2009). Therefore, some uncertainties in the cultivars and management measures would exist when a crop model is applied from the plot scale to regional simulations. Some methods, e.g., sampling input variability in geographic or probability space (Hansen and Jones 2000) and developing crop models that match the GCM grids (Challinor et al. 2004), were determined to have good performance in mitigating the uncertainties of scale.

5 Conclusions

The simulation results indicated that high temperatures would shorten rice growth durations and reduce rice yields significantly. The CO_2 fertilization effect could lead to an overall increase in rice yields but could not offset the negative impacts of elevated temperatures. To cope up with the adverse impacts of climate change on rice yields, three most widely practiced adaptive strategies, i.e., changing planting dates, switching to higher temperature tolerant varieties, and breeding new rice varieties, were evaluated, and the results indicated that they are all effective in mitigating the negative climate impacts, though with various degrees.

However, some uncertainties inherently exist in the model simulations, easily causing an inconsistency between the predicted variables and observed data in the study region. Therefore, some measures, such as improving the temperature and CO_2 relationships and incorporating multi-model ensembles into the simulations, were recommended to be further researched to reduce and quantify the uncertainties of simulations, respectively.

In spite of these uncertainties, the CERES-Rice model demonstrated a promising potential to investigate the effect of climate change on rice yields under future periods, and our simulation results could aid policymaking at the regional level and global adaptation strategy development. To mitigate the climate change impacts more efficiently, planting dates advance and rice varieties that tolerating high temperature and requiring more thermal resources were recommended for farmers in coping with climatic risks, and further researches about more global adaptive measures and their integrations are also expected.

Appendix

Table 7 The soil characteristics for the Crop Estimation through Resource and Environment Synthesis (CERES)-Rice model inputs in the Sichuan Basin

Sites	General surface information					Characteristics for each soil layer							
	Color	Drainage	Slope	Runoff potential	Fertility factor	Soil layer code	Thickness (cm)	The percentage of the soil grain diameter (%)			Organic carbon (%)	Water pH	Total nitrogen (%)
								<0.002 mm	0.02–0.002 mm	>2 mm			
Chengdu	Gray	Well	8	Moderately low	1	Aa	16	23.00	54.07	22.93	1.57	7.3	0.21
						Ap	8	22.90	54.37	22.73	1.17	7.6	0.15
						P	51	23.50	41.29	35.21	0.59	7.8	0.08
Dazhu	Gray	Moderately well	8	Moderately high	1	A'	20	28.80	41.65	29.54	1.16	5.3	0.15
						Pb	10	23.20	46.85	29.95	0.77	6.2	0.11
						Wa2b2	70	37.50	41.53	20.94	0.12	7.2	0.05
Dujiangyan	Gray	Well	8	q	1	Aa	23	16.60	39.51	43.89	1.83	7.5	0.16
						Ap	11	16.70	39.31	43.99	1.59	7.9	0.13
						G	62	14.80	47.82	37.38	1.57	7.9	0.16
Hanyuan	Brown	q	8	Moderately low	1	A'	16	18.10	28.50	53.40	1.10	8.0	0.06
						Pb	5	17.20	28.50	54.30	0.92	8.1	0.05
						P	59	16.30	29.20	54.60	0.72	8.1	0.03
Leshan	Brown	Moderately well	8	Moderately high	1	Aa	18	41.00	33.00	26.00	1.83	6.7	0.16
						Ap	8	44.50	32.30	23.20	1.55	6.5	0.15
						W1	21	44.00	31.50	24.50	0.95	6.6	0.10
						W2	28	34.00	35.50	30.50	0.38	6.9	0.04
Liangshan	Yellow	Well	8	Moderately low	1	Aa	19	22.40	35.90	41.70	1.68	5.5	0.14
						Ap	10	22.30	35.94	41.76	1.44	5.8	0.13

Table 7 (continued)

Sites	Color	Drainage	Slope	Runoff potential	Fertility factor	Soil layer code	Thickness (cm)	<0.002 mm	0.02–0.002 mm	>2 mm	Organic carbon (%)	Water pH	Total nitrogen (%)
Miyi	Yellow	Well	8	Moderately low	1	C	60	19.30	30.94	49.76	0.69	5.8	0.06
						A'	14	18.60	33.69	47.71	2.49	6.8	0.21
						Pb	8	24.16	27.37	48.47	1.89	7.0	0.15
						P	58	23.00	25.57	51.43	0.44	6.9	0.04
Mingshan	Yellow	Moderately well	8	Moderately high	1	Aa	15	40.50	52.50	7.00	1.58	5.0	0.15
						Ap	7	37.00	53.80	9.20	1.42	5.1	0.13
						E1	12	40.50	53.50	6.00	0.93	5.2	0.09
Neijiang	Yellow	well	8	Moderately low	1	E2	46	42.00	48.50	9.50	0.30	5.2	0.04
						Aa	14	22.10	42.10	35.80	1.79	5.3	0.14
						Ap	9	21.00	37.09	41.91	1.15	5.9	0.12
Yibin	Brown	Moderately well	8	Moderately high	1	P	38	28.00	27.18	44.82	0.23	7.0	0.03
						Aa	20	28.80	41.65	29.55	1.16	5.3	0.15
						Ap	10	23.20	46.85	29.95	0.77	6.2	0.11
Jiangjin	Brown	Moderately well	8	Moderately high	1	W	48	37.50	46.85	15.65	0.12	6.2	0.05
						Aa	25	26.70	29.80	43.50	0.12	6.7	0.10
						Ap	11	26.10	29.60	44.29	0.50	7.1	0.09
						C	44	23.70	29.30	46.99	0.41	7.3	0.06
Youyang	Gray	Moderately well	8	Moderately high	1	A'	20	26.80	34.60	38.65	1.57	6.0	0.16
						Pb	10	26.30	37.20	36.50	0.73	6.1	0.09
						Wa1b2	44	26.10	27.80	46.14	0.84	6.3	0.10

References

Armstrong R A, Hilton A C (2010) Stepwise multiple regression. In: Armstrong R A, Hilton A C (eds) Statistical Analysis in Microbiology: Statnotes, 1st edn. Hoboken, NJ

Asseng S (2013) Uncertainty in simulating wheat yields under climate change. Nat Clim Chang 3:827–832

Babel MS, Agarwal A, Swain DK et al (2011) Evaluation of climate change impacts and adaptation measures for rice cultivation in Northeast Thailand. Clim Res 46:137–146

Bakker MM, Govers G, Ewert F et al (2005) Variability in regional wheat yields as a function of climate, soil and economic variables: assessing the risk of confounding. Agric Ecosyst Environ 110:195–209

Bazzaz FA, Garbutt K, Reekie EG et al (1989) Using growth analysis to interpret competition between a C3 and a C4 annual under ambient and elevated CO_2. Oecologia 79:223–235

Bocchiola D (2015) Impact of potential climate change on crop yield and water footprint of rice in the Po valley of Italy. Agric Syst 139:223–237

Buan RD, Maglinao AR, Evangelista PP et al (1996) Vulnerability of rice and corn to climate change in the Philippines. Water Air Soil Pollut 92:41–51

Byjesh K, Kumar SN, Aggarwal PK (2010) Simulating impacts, potential adaptation and vulnerability of maize to climate change in India. Mitig Adapt Strateg Glob Chang 15:413–431

Challinor AJ, Ewert F, Arnold S et al (2009) Crops and climate change: progress, trends, and challenges in simulating impacts and informing adaptation. J Exp Bot 60:2775–2789

Challinor AJ, Watson J, Lobell DB et al (2014) A meta-analysis of crop yield under climate change and adaptation. Nat Clim Chang 4:287–291

Challinor AJ, Wheeler TR (2008) Use of a crop model ensemble to quantify CO_2 stimulation of water-stressed and well-watered crops. Agric For Meteorol 148:1062–1077

Challinor AJ, Wheeler TR, Craufurd PQ et al (2007) Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures. Agric Ecosyst Environ 119:190–204

Challinor AJ, Wheeler TR, Craufurd PQ et al (2004) Design and optimisation of a large-area process-based model for annual crops. Agric For Meteorol 124:99–120

Chartzoulakis K, Psarras G (2005) Global change effects on crop photosynthesis and production in Mediterranean: the case of Crete, Greece. Agric Ecosyst Environ 106:147–157

Cheng S, Li J (2007) Contemperary rice in China. Beijing, China

China Meteorological Administration (1993) Agro-meteorological observation standard. Beijing, China

Collins M (2007) Ensembles and probabilities: a new era in the prediction of climate change. Phil Trans R Soc A 365:1957–1970

Deryng D, Sacks WJ, Barford CC et al (2011) Simulating the effects of climate and agricultural management practices on global crop yield. Glob Biogeochem Cycles 25:1–18

Easterling WE, Aggarwal PK, Batima P et al (2007) Food, fibre and forest products coordinating. In: Parry ML, Canziani OF, Palutikof JP (eds) Climate change 2007: impacts, adaptation and vulnerability, 1st edn. Cambridge University Press, Cambridge

Ewert F (2004) Modelling plant responses to elevated CO_2: how important is leaf area index? Ann Bot 93:619–627

Ewert F, Rounsevell MDA, Reginster I et al (2005) Future scenarios of European agricultural land use I. Estimating changes in crop productivity. Agric Ecosyst Environ 107:101–116

Fang X, Zhang W, Zhang L (1998) The land use arrangement of China in the Holocene megathermal period and its significance. J Nat Resour 13:16–22

Fredeen AL, Sage RF (1999) Temperature and humidity effects on branchlet gas-exchange in white spruce: an explanation for the increase in transpiration with branchlet temperature. Trees 14:161–168

Gitay H, Brown S, Easterling W et al (2001) Ecosystems and their goods and services. In: Fischlin Diaz S (ed) Climate change 2001: impacts, adaptation, and vulnerability, 1st edn. Cambridge University Press, Cambridge

Hansen JW, Jones JW (2000) Scaling-up crop models for climate variability application. Agric Syst 65:43–72

Hatfield JL, Boote KJ, Kimball BA et al (2011) Climate impacts on agriculture implications for crop production. Agron J 103:351–370

He J, Jones JW, Graham WD et al (2010) Influence of likelihood function choice for estimating crop model parameters using the generalized likelihood uncertainty estimation method. Agric Syst 103:256–264

Hempel S, Frieler K, Warszawski L et al (2013) A trend-preserving bias correction-the ISI-MIP approach. Earth Syst Dyn 4:219–236

Hoogenboom G, Jones J W, Porter C et al (eds) (2010) Decision Support System for Agrotechnology Transfer Version 4.5. Volume 1: Overview. Honolulu, HI

Hoogenboom G, Jones JW, Traore PCS et al (2012) Experiments and data for model evaluation and application. In: Kihara J, Fatondji D, Hoogenboom G et al (eds) Improving soil fertility recommendations in Africa using the decision support system for agrotechnology transfer (DSSAT), 1st edn. Springer Science, Business Media, Dordrecht

Houghton J T, Ding Y, Griggs D J et al (2001) The scientific basis: contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Climate Change 525-582

Hunt LA, Boote KJ (1998) Data for model operation, calibration, and evaluation. In: Tsuji GY, Hoogenboom G, Thornton PK (eds) Understanding options for agricultural production, 1st edn. Kluwer Academic Publishers, Kluwer

Hunt LA, White JW, Hoogenboom G (2001) Agronomic data: advances in documentation and protocols for exchange and use. Agric Syst 7:477–492

IPCC (2000) Emissions scenarios: a special report working group III of the Intergovernmental Panel on Climate Change. England, Cambridge

IPCC (2001) Climate change 2001: impacts, adaptation, and vulnerability. England, Cambridge

IPCC (2014) Climate change 2014: impacts, adaptation, and vulnerability. England, Cambridge

IPCC, Stocker T, Dahe Q et al (2013) Climate change 2013: the physical science basis. Cambridge, England

Jagadish SVK, Murty MVR, Quick WP (2014) Rice responses to rising temperatures: challenges, perspectives and future directions. Plant Cell Environ 38:1686–1698

Jiang M, Jin Z, Shi C et al (2013) Response of rice production based on self-adaption to climate change in Fujian province. Acta Agron Sin 38:2246–2257

Jin Z, Ge D, Chen H et al (1995) Effects of climate change on rice production and strategies for adaptation in Southern China. In: Rosenzweig C, Allen LH, Harper LA (eds) Climate change and agriculture: analysis of potential international impacts, 1st edn. American Society of Agronomy, Madison

Jones CD, Hughes JK, Bellouin N et al (2011) The HadGEM2-ES implementation of CMIP5 centennial simulations. Geosci Model Dev 4:543–570

Jones JW, Hoogenboom G, Porter H et al (2003) The DSSAT cropping system model. Eur J Agron 18:235–265

Kapetanaki G, Rosenzweig C (1997) Impact of climate change on maize yield in central and northern Greece: a simulation study with ceres-maize. Mitig Adapt Strateg Glob Chang 1:251–271

Kim H-Y, Ko J, Kang S et al (2013) Impacts of climate change on paddy rice yield in a temperate climate. Glob Chang Biol 19:548–562

Krishnan P, Swain DK, Bhaskar BC et al (2007) Impact of elevated CO_2 and temperature on rice yield and methods of adaptation as evaluated by crop simulation studies. Agric Ecosyst Environ 122:233–242

Lansigan FP, Santos WLdl, Coladilla JO (2000) Agronomic impacts of climate variability on rice production in the Philippines. Agric Ecosyst Environ 82:129–137

Lashkari A, Alizadeh A, Rezaei EE et al (2011) Mitigation of climate change impacts on maize productivity in northeast of Iran: a simulation study. Mitig Adapt Strateg Glob Chang 17:1–16

Leakey ADB, Ainsworth EA, Bernacchi CJ et al (2009) Elevated CO_2 effects on plant carbon, nitrogen, and water relations: six important lessons from FACE. J Exp Bot 60:2859–2876

Lin E, Xiong W, Ju H et al (2005) Climate change impacts on crop yield and quality with CO_2 fertilization in China. Philos Trans R Soc B 360:2149–2154

Liu G, Xie Y, Gao X et al (2008) Sensitivity analysis on parameters of ALMANAC crop model. Chin J Agrometeorol 29:259–263

Liu S, Wang Y, Miao Q et al (2010) Variation characteristics of thermal resources in northeast China in recent 50 years. J Appl Meteorol Sci 21:267–278

Lobell DB, Field CB, Cahill KN et al (2006) Impacts of future climate change on California perennial crop yields: model projections with climate and crop uncertainties. Agric For Meteorol 141:208–218

Lobell DB, Gourdji SM (2012) The influence of climate change on global crop productivity. Plant Physiol 160: 1686–1697

Mahmood R, Legates DR, Meo M (2004) The role of soil water availability in potential rainfed rice productivity in Bangladesh: applications of the CERES-Rice model. Appl Geogr 24:139–159

Masui T, Matsumoto K, Hijioka Y et al (2011) An emission pathway for stabilization at 6 Wm^{-2} radiative forcing. Clim Chang 109:59–76

Masutomi Y, Takahashi K, Harasawa H et al (2009) Impact assessment of climate change on rice production in Asia in comprehensive consideration of process/parameter uncertainty in general circulation models. Agric Ecosyst Environ 131:281–291

Mati BM (2000) The influence of climate change on maize production in the semi-humid–semi-arid areas of Kenya. J Arid Environ 46:333–344

Matthews R, Wassmann R (2003) Modelling the impacts of climate change and methane emission reductions on rice production: a review. Eur J Agron 19:573–598

Meng N, Sichuan Provincial Agriculture Department, Sichuan Provincial Soil Survey Office (1994) Sichuan soil genus records. Chengdu, China

Moore FC, Lobell DB (2014) Adaptation potential of European agriculture in response to climate change. Nat Clim Chang 4:610–614

Moradi R, Koocheki A, Mahallati MN (2013) Adaptation of maize to climate change impacts in Iran. Mitig Adapt Strateg Glob Chang 19:1223–1238

Moriondo M, Bindi M, Kundzewicz ZW et al (2010) Impact and adaptation opportunities for European agriculture in response to climatic change and variability. Mitig Adapt Strateg Glob Chang 15:657–679

Morris MD (1991) Factorial sampling plans for preliminary computational. Technometrics 33:161–174

Moss RH, Edmonds JA, Hibbard KA et al (2010) The next generation of scenarios for climate change research and assessment. Nature 463:747–756

Piao S, Ciais P, Huang Y et al (2010) The impacts of climate change on water resources and agriculture in China. Nature 467:43–51

Porter JR, Xie L, Challinor AJ et al (2014) Food security and food production systems. In: Field CB, Barros VR, Dokken DJ (eds) Climate change 2014: impacts, adaptation, and vulnerability, 1st edn. Cambridge University Press, Cambridge, and New York

Raj RB, Cassandra S, Walter LF (2014) Effectiveness of the local adaptation plan of action to support climate change adaptation in Nepal. Mitig Adapt Strateg Glob Chang. doi:10.1007/s11027-014-9610-3

Rani BA, Maragatham N (2013) Effect of elevated temperature on rice phenology and yield. Indian J Sci Technol 6:5095–5097

Reilly J, Baethgen W, Chege FE et al (1996) Agriculture in a changing climate: impacts and adaptation. In: Watson RT, Zinyowera MC, Moss RH (eds) Climate change 1995: impacts, adaptations and mitigation of climate change: scientific-technical analyses, 1st edn. Cambridge university press, Cambridge

Riahi K, Rao S, Krey V et al (2011) RCP8.5: a scenario of comparatively high greenhouse gas emissions. Clim Chang 109:33–57

Rinaldia M, Losavioa N, Flagellab Z (2003) Evaluation and application of the OILCROP-SUN model for sunflower in southern Italy. Agric Syst 78:17–30

Ritchie JT, Singh U, Godwin DC et al (1998) Cereal growth, development and yield. In: Tsuji GY, Hoogenboom G, Thornto PK (eds) Understanding options for agricultural production, 1st edn. Kluwer Academic Publishers, Dordrecht

Román-Paoli E, Welch SM, Vanderlip RL (2000) Comparing genetic coefficient estimation methods using the CERES-Maize model. Agric Syst 65:29–41

Rosenzweig C, Elliott J, Deryng D et al (2014) Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. PNAS 111:3268–3273

Rosenzweig C, Hillel D (1998) Climate change and the global harvest. New York, America

Rosenzweig C, Jones JW, Hatfield JL et al (2013) The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric For Meteorol 170:166–182

Saseendran SA, Singh KK, Rathore LS et al (2000) Effects of climate change on rice production in the tropical humid climate of Kerala, India. Clim Chang 44:495–514

Shao J, Li Y, Ni J (2012) The characteristics of temperature variability with terrain, latitude and longitude in Sichuan-Chongqing region. J Geogr Sci 22:223–244

Shi P, Tang L, Lin C et al (2015) Modeling the effects of post-anthesis heat stress on rice phenology. Field Crop Res 177:26–36

Singh P, Nedumaran S, Ntare BR et al (2013) Potential benefits of drought and heat tolerance in groundnut for adaptation to climate change in India and West Africa. Mitig Adapt Strateg Glob Chang 19:509–529

Srivastava AK, Gaiser T, Ewert F (2015) Climate change impact and potential adaptation strategies under alternate climate scenarios for yam production in the sub-humid savannah zone of West Africa. Mitig Adapt Strateg Glob Chang. doi:10.1007/s11027-015-9639-y

Sudharsan D, Adinarayana J, Reddy DR et al (2012) Evaluation of weather-based rice yield models in India. Int J Biometeorol 57:107–123

Tao F, Hayashi Y, Zhang Z et al (2008) Global warming, rice production, and water use in China: developing a probabilistic assessment. Agric For Meteorol 148:94–110

Tao F, Yokozawa M, Xu Y et al (2006) Climate changes and trends in phenology and yields of field crops in China, 1981–2000. Agric For Meteorol 138:82–92

Tao F, Zhang S, Zhang Z et al (2014) Maize growing duration was prolonged across China in the past three decades under the combined effects of temperature, agronomic management, and cultivar shift. Glob Chang Biol 20:3686–3699

Tao F, Zhang Z (2010) Adaptation of maize production to climate change in North China Plain: quantify the relative contributions of adaptation options. Eur J Agron 33:103–116

Tao F, Zhang Z, Shi W et al (2013) Single rice growth period was prolonged by cultivars shifts, but yield was damaged by climate change during 1981-2009 in China, and late rice was just opposite. Glob Chang Biol 19:3200–3209

Thomson AM, Calvin KV, Smith SJ et al (2011) RCP4.5: a pathway for stabilization of radiative forcing by 2100. Clim Chang 109:77–94

Timsina J, Humphreys E (2006) Applications of CERES-Rice and CERES-Wheat in research, policy and climate change studies in Asia: a review. Int J Agric Res 1:202–225

Tingem M, Rivington M (2008) Adaptation for crop agriculture to climate change in Cameroon: Turning on the heat. Mitig Adapt Strateg Glob Chang 14:153–168

Travasso MI, Magrin GO, Rodriguez GR et al (2009) Climate change impacts on regional maize yields and possible adaptation measures in Argentina. Int J Global Warming 1:201–213

Tsuji G Y, Balas S (1993) The IBSNAT decade. Honolulu, America

Tsuji G Y, Uehara G, Balas S (eds) (1994) Decision support system for Agrotechnology Transfer Version 3. Volumn 2. Honolulu, Hawaii

Tubiello FN, Amthorb JS, Boote KJ et al (2007) Crop response to elevated CO_2 and world food supply. Eur J Agron 26:215–223

Tubiello FN, Ewert F (2002) Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. Eur J Agron 18:57–74

Vaghefi N, Shamsudin MN, Radam A et al (2013) Modelling the impact of climate change on rice production: an overview. J Appl Sci 13:5649–5660

van Ittersum MK, Cassman KG, Grassini P et al (2013) Yield gap analysis with local to global relevance: a review. Field Crop Res 143:4–17

van Vuuren DP, Stehfest E, Elzen MGJd et al (2011) RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C. Clim Chang 109:95–116

Wajid A, Rahman MHU, Ahmad A et al (2013) Simulating the interactive impact of nitrogen and promising cultivars on yield of lentil (lens culinaris) using CROPGRO-legume model. Int J Agric Biol 15:1331–1336

Wang E, Yu Q, Wu D (2008) Climate, agricultural production and hydrological balance in the North China Plain. Int J Climatol 28:1959–1970

Wassmann R, Jagadish SVK, Heuer S et al (2009) Climate change affecting rice production: the physiological and agronomic basis for possible adaptation stragies. Adv Agron 101:59–122

Wheeler T, Braun J v (2013) Climate change impacts on global food security. Science 341:508–513

White JW, Hoogenboom G,A, Kimball B et al (2011) Methodologies for simulating impacts of climate change on crop production. Field Crop Res 124:357–368

Widodo W, Vu JCV, Boote KJ et al (2003) Elevated growth CO_2 delays drought stress and accelerates recovery of rice leaf photosynthesis. Environ Exp Bot 49:259–272

Wilkens P W, Hoogenboom G, Porter C H et al (eds) (2004) Decision Support System for Agrotechnology Transfer Version 4.0. Volume 2: Data management and analysis tools. Honolulu, HI

Wu X, Dai J, Liao F et al (2013) Origin and source of CO_2 in natural gas from the eastern Sichuan Basin. Sci China Earth Sci 56:1308–1317

Xie X, Li B, Li Y et al (2009) High temperature harm at flowering in Yangtze River Basin in recent 55 years. Jiangsu J Agric Sci 25:28–32

Xiong W, Conway D, Holman I et al (2008) Evaluation of CERES-Wheat simulation of wheat production in China. Agron J 100:1720

Xiong W, Conway D, Lin E et al (2009) Potential impacts of climate change and climate variability on China's rice yield and production. Clim Res 40:23–35

Xiong W, Tao F, Xu Y et al (2001) Simulation of rice yields under climate changes in future in China. Chin J Agrometeorol 22:1–5

Yao F, Xu Y, Lin E et al (2007) Assessing the impacts of climate change on rice yields in the main rice areas of China. Clim Chang 80:395–409

Zhang S, Tao F (2013) Modeling the response of rice phenology to climate change and variability in different climatic zones: comparisons of five models. Eur J Agron 45:165–176

Zhang T, Zhu J, Wassmann R (2010) Responses of rice yields to recent climate change in China: an empirical assessment based on long-term observations at different spatial scales (1981–2005). Agric For Meteorol 150: 1128–1137