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Climate change impacts and adaptation strategies on rainfed and irrigated maize in the agro-pastoral ecotone of Northwestern China

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ABSTRACT: The agro-pastoral ecotone of Northwestern China (APENC) is one of the major agricultural production areas in China and a region where climate change is evident. Maize is a widely cultivated crop in the APENC, but the potential impact of climate change on maize, and potential adaptation strategies in response to this, are poorly understood. In this study, we used the Cropping System Model (CSM)-CERES-Maize to evaluate the impacts of climate change on maize yield, as well as the feasibility of 2 adaptation strategies; namely, adjusting the planting date and supplying irrigation. CSM-CERES-Maize was driven by an ensemble of 20 global climate models under 2 Representative Concentration Pathways (RCPs: RCP4.5 and RCP8.5) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). CSM-CERES-Maize performed well in simulating phenology, leaf area index (LAI), maize yield, and soil water dynamics. The results showed that irrigated maize yield would change by +3.9, −16.3, and −20.4% under the RCP4.5 scenario and +0.1, −31.2, and −53.1% under the RCP8.5 scenario in the 2030s, 2060s, and 2090s, respectively. Rainfed maize yield during the 2030s, 2060s, and 2090s would change by +21.7, +16.4, and +12.6% under the RCP4.5 scenario and +25.1, +4.8, and −12.3% under the RCP8.5 scenario, respectively. Evaluation of adaptation strategies suggests that delaying planting dates and supplying irrigation at the tasseling and grain filling stages are the best strategies to increase maize yield under climate change. These results will provide comprehensive information for local policymakers to combat the adverse impacts of climate change.

KEY WORDS: GCM-CERES-Maize · Climate change · Adaptation strategies · Maize yield

1. INTRODUCTION

The impacts of climate change on agriculture is one of the most important challenges that threatens the sustainability of food production systems (Asseng et al. 2015, Kadiyala et al. 2015). Climate change over the past decades has severely affected many agricultural regions in China and will cause more issues in the future (Tao et al. 2003, 2012, Guo et al. 2010). Therefore, assessing the impacts of climate change on crops and implementing adaptation measures are essential for local agricultural sustainability.

Adaptation strategies can greatly reduce the negative impacts of climate change on crops (Y. Yang et al. 2014, Boonwichai et al. 2019, Ahmad et al. 2020). Traditionally, assessments of climate change impacts and adaptation strategies have primarily relied on statistical analysis (Li et al. 2014, Verón et al. 2015) or field experiments (Tao et al. 2012). However, these methods are time-consuming and costly due to the

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complicated interaction between crops and the environment (Bhatia et al. 2008). In recent years, crop models have been widely used to investigate the impacts of climate change on crops and adaptation strategies (White et al. 2011), including Decision Support System for Agro-technology Transfer (DSSAT; Boonwichai et al. 2019, Zhang et al. 2019), Agricultural Production Systems Simulator (APSIM; Y. Yang et al. 2014, Deihimfard et al. 2018), AquaCrop (Yang et al. 2017), and others. Such models have the capacity to simulate interactions among multiple climate factors and can also reveal and quantify the impacts of climate, soil, and management on crop growth and development (Asseng et al. 2015, Zhang et al. 2019). Currently, combining outputs of global climate models (GCMs) with crop models is a powerful and effective method to investigate the impacts of future climate change on crops (Y. Yang et al. 2014, Adhikari et al. 2016, Yang et al. 2017). However, these studies are subject to a range of uncertainties from both future climate change scenarios and model uncertainties. Therefore, it is necessary to quantify the range of uncertainties from climate change scenarios and their effects on crop yield to prepare for climate change adaptations (Zhang et al. 2019). Thus, in this study, we used the ensemble simulation method (Collins 2007), which is an effective means of addressing assessment uncertainty.

Many studies have addressed the impacts of climate change on crop production in China (Tao et al. 2006, W. Wang et al. 2014, Zhang et al. 2019), but few have provided adaptation strategies to offset the potential negative impacts of climate change. Maize is the world's third-largest crop after wheat and rice, and its planting area is the largest of all crops in China (FAO 2018). The agro-pastoral transitional zone (APTZ) of North China is one of the world's largest ecotones, and is highly sensitive to changes in climate conditions and surface physical properties (Cao et al. 2015). The agro-pastoral ecotone of Northwestern China (APENC) is an essential part of the APTZ, and serves as a key ecological shelter in preventing desertification and ensuring ecosystem services and food production in China (Zhou et al. 2007, Xue & Tang 2018, Wang et al. 2020), with nearly 80% of the population engaged in agricultural production (Hou et al. 2018). Maize is a staple crop in the APENC, accounting for >50% of the total sown crop area. Therefore, maize production in the APENC plays an important role in maintaining local food security. However, little is currently known about the effects of climate change on maize production and adaptation strategies in the APENC. Adjusting planting dates and supplying irrigation water are effective adaptation strategies to offset the negative impacts of climate change.

In this study, we used the Cropping System Model (CSM)-CERES-Maize (Jones et al. 2003), driven by future daily resolution climate data from 20 GCMs calculated for the Coupled Model Intercomparison Project Phase 5 (CMIP5) under 2 Representative Concentration Pathway scenarios (RCP4.5 and RCP8.5), to evaluate the impacts of future climate change on 2 typical maize crops (rainfed maize and irrigated maize) in the APENC, and to assess 2 potential adaptation strategies. Therefore, the objectives of this study were to (1) evaluate the performance of the CSM-CERES-Maize using reported trial data in the APENC, (2) investigate the effects of future climate change on maize yield, and (3) identify specific adaptation strategies.

2. MATERIALS AND METHODS

2.1. Study area

For this study, we selected 6 sites across the APENC to investigate the impacts of climate change on maize and identify specific adaptation strategies (Fig. 1). Detailed information about each site is shown in Table 1. The study area is located in a semiarid to arid climate zone with a mean annual temperature of 8.6°C and annual precipitation of 311 mm. Maize is the dominant crop in the region (Zhou et al. 2019) and is planted from the end of April to early May and harvested at the end of September by local farmers. In this area, maize is usually irrigated by groundwater. Long-term maize irrigation has caused a continuous decline in groundwater in the APENC (Tang et al. 2019). Hence, rainfed maize also plays an important role in some insufficiently irrigated areas of the APENC.

2.2. Data collection

2.2.1. Climate data

Daily maximum temperature (°C), minimum temperature (°C), precipitation (mm), and sunshine hours (h) during the historical period from 1986–2005 (baseline) were obtained from the Chinese Meteorological Data Service Center (CMDC; http://data.cma.cn/en). Daily solar radiation (MJ m^{-2}) was calcu-

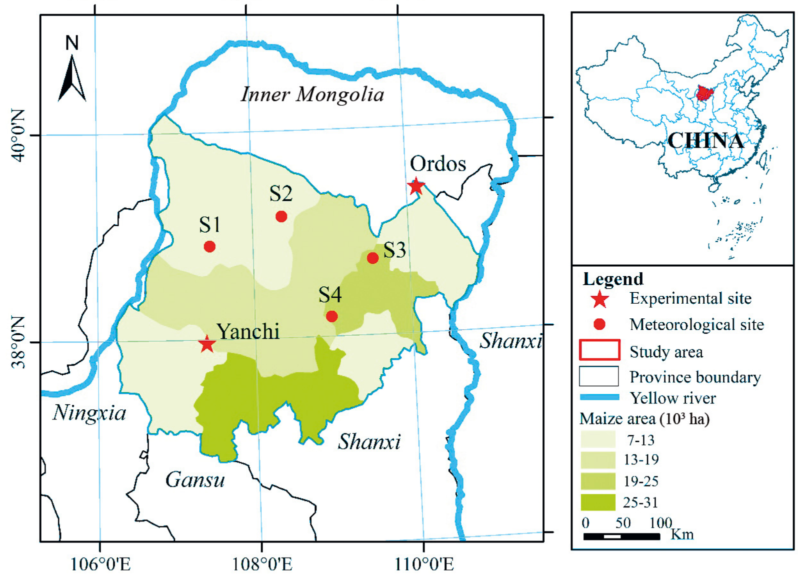

Fig. 1. The agro-pastoral ecotone of Northwestern China (APENC) and the distribution of study sites

lated from the recorded daily sunshine hours using the Angstrom empirical formula (Angstrom 1924). We set up an automatic meteorological station in the 2 experimental sites to observe meteorological data. The measurement period was from 1 January 2017 to 30 December 2018.

For the future climate, we selected daily climate data from 20 GCMs CMIP5 (source: https://esgf-node.llnl.gov/search/cmip5/) simulations (Table 2) under 2 scenarios (RCP4.5 and RCP8.5), covering 3 time periods of the 21st century: the 2030s (2021–2040), the 2060s (2051–2070), and the 2090s (2081–2100). The RCP4.5 scenario is an intermediate stabilization pathway in which CO_2 concentration falls between 580 and 720 ppm, while the RCP8.5 scenario presents very high greenhouse gas concentrations, with CO_2 concentrations >1000 ppm (Taylor et al. 2012). In the RCP4.5 and RCP8.5 scenarios, the CO_2 concentration for each year during the period 2021–2100 was input into the DSSAT model. GCM outputs are generally biased and require correction before they can be used for crop modeling. In this study, an inverse distance-weighted interpolation method (Liu & Zuo 2012) was used to downscale daily GCM projections from daily GCM grid cells to daily values for each site. Then we used the quantile mapping method (QM) to correct the data, which can reduce biases in daily temperature and precipitation by roughly one order of magnitude (Themeßl et al. 2012). QM provides a mapping between 2 cumulative distribution functions (CDFs): GCM data and observed data. It has been widely used in many studies and can effectively correct the historical climate model data with observed data using the mean, standard deviation, and magnitude (Fang et al. 2015, Boonwichai et al. 2019). QM can be expressed in terms of ecdf:

$$\mathrm{Pcorr} = \mathrm{ecdf}_{\mathrm{obs}}^{-1}(\mathrm{ecdf}_{\mathrm{GCM}}(P_{\mathrm{GCM}})) \quad (1)$$

where P_{GCM} is the GCM data, ecdf is the CDF, ecdf^{-1} is the inverse CDF, and P_{corr} is the corrected GCM data.

2.2.2. Soil data

The soil database of the DSSAT model included soil texture, hydraulic conductivity, bulk density, pH, organic carbon, and total nitrogen, which were required to run the model. In this study, soil samples at 2 experimental sites (Yanchi and Ordos) were collected using a metal cylinder (with a height and internal diameter of 5 cm) at 5 depths (0–10, 10–20, 20–30, 30–50, and 50–70 cm) and transported to the Key Laboratory of West China's Environment System (Ministry of Education) at Lanzhou University to determine physical and chemical parameters (Table 3). Detailed descriptions of measurement methods are provided in Tian et al. (2017).

Table 1. Detailed information at all 6 representative sites in the agro-pastoral ecotone of Northwestern China (APENC)

Sites	Yanchi	Ordos	S1	S2	S3	S4
Province	Ningxia	Inner Mongolia	Inner Mongolia	Inner Mongolia	Shanxi	Shanxi
Latitude (°N)	37.97	39.48	38.9	39.17	38.74	38.19
Longitude (°E)	107.37	110.2	107.44	108.38	109.53	108.97
Elevation (m)	1318	1296	1226	1401	1270	1190
Soil texture	Loamy sand	Sand	Loam	Sand	Clay	Sand

Table 2. Information on the 20 global climate models (GCMs) selected in this study

ID	GCM	Country
1	ACCESS1-0	Australia
2	ACCESS1-3	Australia
3	CanESM2	Canada
4	CCSM4	USA
5	CESM1-BGC	USA
6	CESM1-CAM5	USA
7	CMCC-CM	Europe
8	CMCC-CMS	Europe
9	CNRM-CM5	France
10	GFDL-CM3	USA
11	GFDL-ESM2G	USA
12	HadGEM2-AO	Korea
13	HadGEM2-ES	UK
14	INM-CM4	Russia
15	MIROC5	Japan
16	MIROC-ESM	Japan
17	MIROC-ESM-CHEM	Japan
18	MPI-ESM-LR	Germany
19	MRI-CGCM3	Japan
20	NorESM1-M	Norway

The other 4 soil profile data sets were obtained from the Harmonized World Soil Database version 1.2 (Wieder et al. 2014).

2.2.3. Field experiments for model calibration

Field experiments were conducted in 2017 and 2018 at the Yanchi and Ordos sites, located at the Southwestern and Northeast of the APENC, respectively (Fig. 1). Data from the 2 sites were used to calibrate and validate simulations of the 'WG568' maize cultivar at the Yanchi site and the 'ZJ308' cultivar at the Ordos site.

The planting dates at Yanchi and Ordos were 25 and 28 April, respectively. The maize was sown in rows at a depth of 5 cm, with a row spacing of approximately 50 cm and plant spacing of 30 cm. The same spacings were maintained in 2017 and 2018 for the 2 sites. Fertilizer was applied 3 times during the maize growth period, with 250 kg ha^{-1} of ammonium polyphosphate applied on 1 May, 200 kg ha^{-1} of ammonium polyphosphate on 25 June, and 75 kg ha^{-1} of urea on 20 July. The flood irrigation method was used in this study. We selected the Yanchi site as the full irrigation treatment site and the Ordos site as the rainfed treatment site. The key phenological stages, including planting, emergence, anthesis, and maturity, were recorded (days after planting). The leaf area index (LAI) was measured by the Plant Canopy Analyzer (Model: LAI-2200) 20 d after emergence. At maize maturity, 50 plants site^{-1} were randomly selected and harvested. All plants from each site were air dried and threshed to obtain the grain yield. Soil moisture was determined by ECH2O 5TE sensors (Decagon Devices) installed at various soil depths from 0–70 cm. We summarized these field records to build a crop management database in the DSSAT model. Specifically, data from 2017 was used to calibrate the CSM-CERES-Maize for simulating LAI, soil water content, phenology, and maize yield. Data from 2018 was used as independent data to evaluate the model.

2.3. CSM-CERES-Maize and its parameterization

The CSM-CERES-Maize used in this study was included in DSSAT version 4.7.5 (Hoogenboom et al. 2019). CSM-CERES-Maize is a biophysical process-oriented crop model that has been successfully

Table 3. Physical and chemical parameter values at different soil layers for the soil profile in the Yanchi and Ordos sites

	Soil depth (cm)	Bulk density (g cm^{-3})	Hydraulic conductivity (cm h^{-1})	Sand content (%)	Silt content (%)	Clay content (%)	pH	Organic carbon (%)	Total nitrogen (%)
Yanchi	0–10	1.51	3.05	89.1	9.7	1.2	7.8	0.17	0.05
	10–20	1.7	1.19	88.4	9.9	1.7	8	0.18	0.04
	20–30	1.67	1.58	88.2	10.4	1.4	8.1	0.16	0.08
	30–50	1.31	0.41	91.4	7.6	1	8.1	0.15	0.04
	50–70	1.58	4.52	92.7	6.7	0.6	7.9	0.15	0.05
Ordos	0–10	1.81	6.78	94.1	5.5	0.4	7.4	0.07	0.12
	10–20	1.83	1.63	91.9	7.3	0.8	7.3	0.28	0.16
	20–30	1.85	4.69	89.4	9.4	1.2	7.3	0.35	0.12
	30–50	1.79	6.43	96.8	3.1	0.1	7.2	0.12	0.04
	50–70	1.74	7.89	93.4	6.1	0.5	7.2	0.29	0.06

adapted for simulating maize growth and yield at locations such as Gansu in Northwestern China (Jiang et al. 2016), Gongzhulin and Hailun in Northeastern China (Liu et al. 2013, Yang et al. 2013), and the Hebei Plain in North China (Yang et al. 2010). However, it has not yet been evaluated in the APENC.

Crop genotype parameters are required to simulate variables such as crop growth rates and stages, biomass production, and grain yield (Liu et al. 2013). There are 6 genotype parameters included in the CSM-CERES-Maize; we used the generalized likelihood uncertainty estimation (GLUE) method (He et al. 2010) to estimate the genotype parameters based on field trial data (Table 4) until a close match was found between the simulated and measured yield, phenology, and LAI.

2.4. Modeling impacts of adaptation measures on maize yield

Long-term simulations under 2 scenarios (RCP4.5 and RCP8.5) for 3 future periods (the 2030s, 2060s, and 2090s) were designed to investigate the impact of climate change on maize yield in the APENC. Adaptation measures could reduce the negative effects of climate change on maize production. In this study, a shift in planting date and supplemental irrigation for rainfed maize were selected for performance evaluation.

Planting date scenarios: the local normal planting date was 25 April. In the CSM-CERES-Maize, planting dates were set at an interval of 5 d from 5 April to 25 May. Six runs of the simulation were conducted to investigate the effects of planting date on maize yield. The optimal planting date was determined according to the simulated average highest yield during the 3 periods.

Supplemental irrigation scenarios: in the CSM-CERES-Maize, different irrigation amounts and times were used for the long-term simulations during the 3 periods with the local normal planting date (25 April). We selected 6 irrigation regimes under different combinations of phenological phases (planting, emergence, jointing, tasseling, and grain filling) to be simulated: rainfed (no irrigation), 1 irrigation, 2 irrigations, 3 irrigations, 4 irrigations, and 5 irrigations (Table 5). Based on what local farmers usually used, each irrigation consisted of 50 mm of water. We set 32 irrigation combinations in total and explored the optimal timing of supplemental irrigation.

2.5. Statistical analysis

The performance of the CSM-CERES-Maize in simulating phenology, LAI, soil water content, and maize yield was evaluated based on the following statistical parameters, which were recommended by J. Yang et al. (2014): the coefficient of determination (R^2), Eq. (2); the root mean square error (RMSE), Eq. (3); the normalized root mean square error (nRMSE), Eq. (4); and the mean error (ME), Eq. (5). These statistics are defined as follows:

$$R^2 = \frac{[\Sigma_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})]^2}{\Sigma_{i=1}^{n}(O_i - \bar{O})^2\,\Sigma_{i=1}^{n}(S_i - \bar{S})^2} \quad (2)$$

$$\mathrm{RMSE} = \sqrt{\tfrac{1}{n}\Sigma_{i=1}^{n}(S_i - O_i)^2} \quad (3)$$

$$\mathrm{nRMSE} = \frac{\mathrm{RMSE}}{\bar{O}} \times 100 \quad (4)$$

$$\mathrm{ME} = \tfrac{1}{n}\Sigma_{i=1}^{n}(S_i - O_i) \quad (5)$$

where n is the number of values, S_i and O_i are the i^{th} simulation and observation, and $\bar{O}$ and $\bar{S}$ are the average of the observation and simulation, respectively. R^2 was used to explain how well the simulated data fit the observed data. The R^2 value was between 1 and 0, where 0 indicates no fit and

Table 4. Genetic coefficient result of cultivars adjusted during CERES-Maize model calibration

Parameters	Cultivar coefficients description	Test range	Calibrated value Yanchi	Calibrated value Ordos
P1	Degree days (base 8°C) from emergence to end of juvenile phase	100–400	307.7	352.2
P2	Photoperiod sensitivity coefficient	0.1–0.8	0.58	0.55
P5	Degree days (base 8°C) from silking to physiological maturity	600–1000	790.2	822.2
G2	Potential kernel number	560–850	701.0	809.0
G3	Potential kernel growth rate (mg d^{-1})	5–12	7.05	8.42
PINT	Degree days required for a leaf tip to emerge (phyllochron interval) (°C d)	35–55	50	50

Table 5. Irrigation strategies scenario (1–32) simulation with the CERES-Maize model. Stages: P: planting; E: emergence; J: jointing; T: tasseling; G: grain filling. Superscript numbers: irrigation treatment

Irrigation frequency	Irrigation amount (mm)	Irrigation at key phenological phase
0 (Rainfed)	0	None^{1}
1	50	P^{2}, E^{3}, J^{4}, T^{5}, G^{6}
2	100	PE^{7}, PJ^{8}, PT^{9}, PG^{10}, EJ^{11}, ET^{12}, EG^{13}, JT^{14}, JG^{15}, TG^{16}
3	150	PEJ^{17}, PET^{18}, PEG^{19}, PJT^{20}, PJG^{21}, PTG^{22}, EJT^{23}, EJG^{24}, ETG^{25}, JTG^{26}
4	200	$PEJT^{27}$, $PEJG^{28}$, $PETG^{29}$, $PJTG^{30}$, $EJTG^{31}$
5	250	$PEJTG^{32}$

1 indicates a perfect fit between simulated and observed data. For the nRMSE (0 ≤ nRMSE ≤ 100%), we generally considered nRMSE ≤ 10% as 'excellent' agreement, 10–20% as 'good' agreement, 20–30% as 'fair' agreement, and ≥30% as 'poor' agreement (Bannayan & Hoogenboom 2009). We used RMSE to evaluate the goodness of fit for soil water content, with lower RMSE values indicating a good fit between the simulated and observed data. ME was used to indicate average simulated data bias, that is, over-prediction and under-prediction.

We used boxplots to show the scatter of the maize yield. The difference in maize yield under different climate scenarios and planting dates was examined using a 1-way ANOVA with the post hoc Bonferroni test when the normality and homogeneity of variance of the data sets were satisfied. If these conditions were not satisfied, we used Kruskal-Wallis ANOVA with a post hoc Dunn's test. All statistical tests used a 0.05 significance level.

3. RESULTS

3.1. CSM-CERES-Maize performance

The CSM-CERES-Maize was used to investigate the effect of climate change on maize yield and evaluate the impact of adaptation strategies on maize production in the APENC. We used observations from the experimental sites in 2017 to calibrate the model and those from 2018 to evaluate the model performance. CSM-CERES-Maize was calibrated based on 6 crop genetic coefficients parameters, as shown in Table 4. Table 6 shows the differences between the observed and simulated results, including harvest yield, maximum LAI, emergence, anthesis, and maturity dates. The nRMSE values of simulated and observed maize were 2.37 and 2.84 for the calibration and validation periods, respectively, which falls within a satisfactory range. In addition, the simulated maximum LAI and dates of emergence, anthesis, and maturity fell within the very good range during both calibration and validation periods. Thus, CSM-CERES-Maize performed well for simulating the growth processes of maize after calibration and is suitable for simulating future maize production under changing climate conditions in the study area. Additionally, one purpose of this study was to evaluate the effect of supplemental irrigation on maize yield, so it was important to evaluate the performance of the CSM-CERES-Maize in simulating the soil water content. As shown in Fig. 2, the CSM-CERES-Maize accurately simulated the soil water content at different soil depths. The results showed that the R^2, RMSE, and nRMSE values of the whole data set between the simulated and measured soil water content were in the range of 0.57–0.91, 0.016–0.038, and 16.5–41.7%, respectively, for each of the soil layers. The ME values were 0.006–0.012

Table 6. Performance evaluation of the GCM-CERES-Maize model. DAP: day after planting; LAI: leaf area index

Period		Yanchi				Ordos			
		Observed	Simulated	nRMSE (%)	ME	Observed	Simulated	nRMSE(%)	ME
Calibration (2017)	Emergence (DAP)	12	12	0	0	12	13	8.33	1
	Anthesis (DAP)	91	91	0	0	95	95	0	0
	Maturity (DAP)	160	160	0	0	160	162	1.25	2
	Maximum LAI	2.03	2.23	9.85	0.2	2.17	2.18	0.46	0.01
	Yield (kg ha^{-1})	6108	6253	2.37	145	3110	3262	4.89	152
Validation (2018)	Emergence (DAP)	11	11	0	0	11	11	0	0
	Anthesis (DAP)	93	92	1.07	−1	97	97	0	0
	Maturity (DAP)	159	161	1.26	2	158	156	1.27	−2
	Maximum LAI	2.19	2.26	3.1	0.07	2.21	2.27	2.71	0.06
	Yield (kg ha^{-1})	6578	6765	2.84	187	3795	3687	2.84	−108

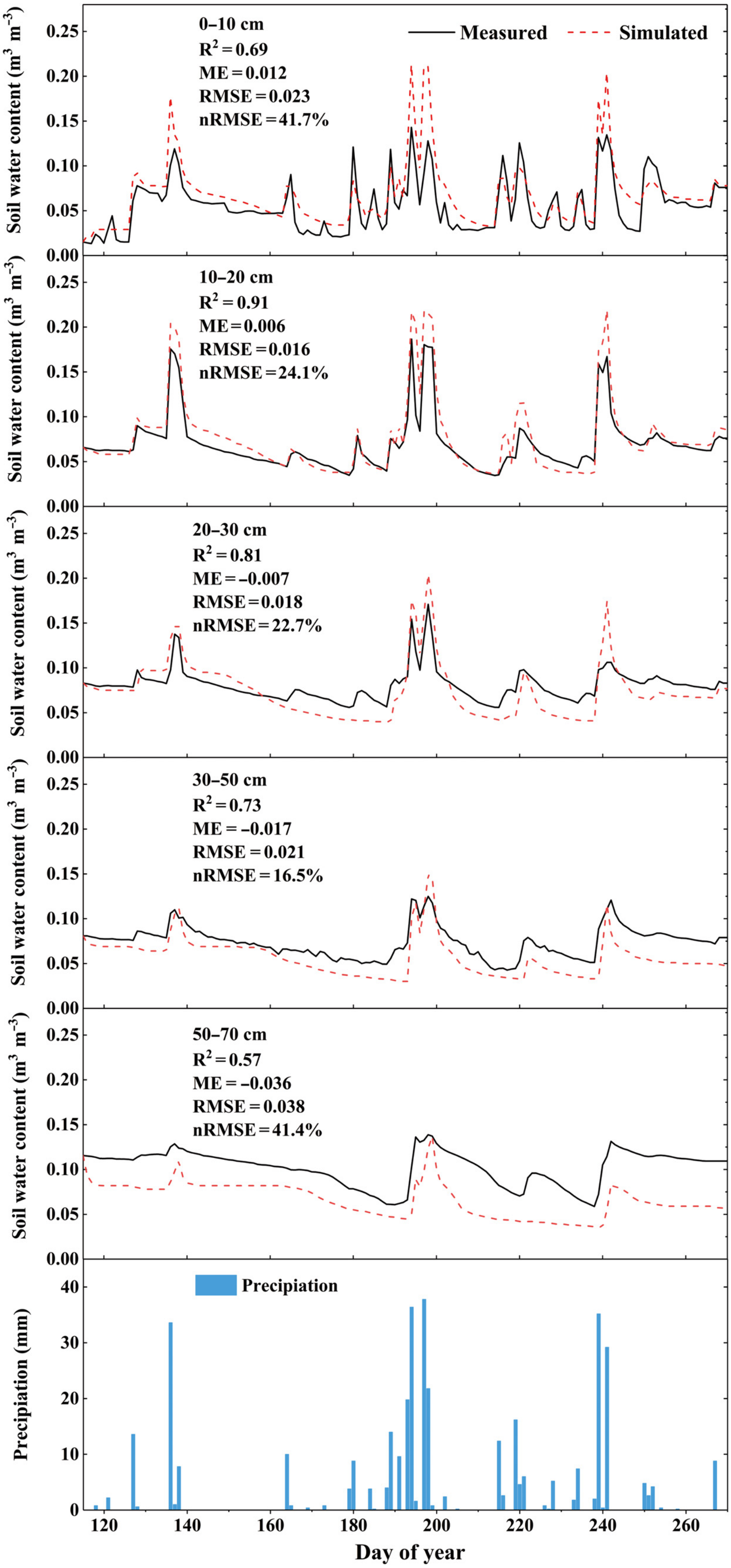

Fig. 2. Comparison between the simulated and measured soil water content at different depths for the 2018 growing season in the Ordos site

for the top soil depth and −0.036 to −0.007 for lower soil depth. Moreover, the model accurately simulated the effects of precipitation on the change in soil water content. Overall, the CSM-CERES-Maize can accurately simulate soil water content and maize yield in the study area.

3.2. Future climate trends

The multi-model projections for the APENC generally depict a warming trend. The average annual maximum temperature is expected to increase by up to 1.7, 2.6, and 3.2°C under the RCP4.5 scenario and by 2.3, 3.9, and 5.5°C under the RCP8.5 scenario for the 2030s, 2060s, and 2090s, respectively. Minimum temperature is also expected to increase by up to 2.4, 3.4, and 4.1°C under the RCP4.5 scenario and 2.7, 4.6, and 6.7°C under the RCP8.5 scenario for the 2030s, 2060s, 2090s, respectively, as shown in Table 7. This indicates that the high emission scenario (RCP8.5) will increase air temperature significantly compared to the medium stabilization emission scenario (RCP4.5). The monthly maximum and minimum temperatures are projected to be higher throughout the maize growth period (Fig. 3). The projected temperature would increase significantly compared to the baseline in July, August, and September.

The projected precipitation shows a slight increase during both scenarios. Specifically, future precipitation may increase by up to 4, 28, and 62 mm under the RCP4.5 scenario and by up to 8, 47, and 124 mm under the RCP8.5 scenario for the 2030s, 2060s, and 2090s, respectively. The monthly rainfall pattern will change in the

Table 7. Historical and projected annual maximum temperature, minimum temperature, precipitation, and solar radiation under RCP4.5 and RCP8.5 scenarios

Period	Scenario	T_{max} (°C)	T_{min} (°C)	Precipitation (mm)	Solar radiation (MJ m^{-2})
Baseline	1986–2005	14.96	1.47	311.5	16.81
2030s	RCP4.5	16.67	3.86	314.6	17.42
	RCP8.5	17.22	4.12	318.8	17.43
2060s	RCP4.5	17.62	4.87	339.5	17.63
	RCP8.5	18.83	6.09	357.7	17.49
2090s	RCP4.5	18.13	5.59	373.3	17.57
	RCP8.5	20.49	8.12	435.5	17.38

future, with a possible increase during April–June and September and a decrease during July–August, as shown in Fig. 3.

The projected annual solar radiation shows no significant change. Compared to the baseline, it only increases slightly, and there is no significant difference in both scenarios and all periods. The monthly solar radiation may increase during April–May and decrease during June–September.

3.3. Impact of climate change on maize

Future rainfed and irrigated maize yields were projected under 2 climate scenarios for 3 future periods. The study assumed that crop management practices will not change in the future, making climate the only variable. The baseline rainfed and irrigated maize yields were 3652 and 6681 kg ha^{-1}, respectively. Average future rainfed maize yield is expected to increase by 21.7, 16.4, and 12.6% under the RCP4.5 scenario for the 2030s, 2060s, and 2090s, respectively (Fig. 4a). Under the RCP8.5 scenario, the average rainfed maize yield is expected to increase by 25.1 and 4.8% for the 2030s and 2060s, respectively, and decrease by 12.3% in the 2090s (Fig. 4a). It appears that future climate change may be beneficial to rainfed maize production, except in the 2090s under the RCP8.5 scenario.

The future average irrigated maize yield is expected to increase by 3.9% under the RCP4.5 scenario and by 0.1% under the RCP8.5 for the 2030s and to decrease by 16.3 and 20.4% under the RCP4.5 scenario and by 31.2 and 53.1% under the RCP8.5 scenario for the 2060s and 2090s, respectively (Fig. 4b). Under the 2 RCP scenarios, maize yields for the 2030s show no significant difference. However, maize yields for the 2060s and 2090s under the RCP8.5 scenario are significantly reduced compared to those for the RCP4.5 scenario.

3.4. Adaptation strategies

Based on the simulation results, the irrigated maize yield without adaptation strategies would decrease under both climate change scenarios. Adaptation strategies could offset some negative impacts of climate change, for either irrigated maize or rainfed maize. Two adaptation strategies, changing the planting date and supplying irrigation water, were evaluated to mitigate the effects of climate change on maize yield.

3.4.1. Changing planting date

The results of shifting the planting date on irrigated and rainfed maize yield are shown in Fig. 5. The optimal planting date of rainfed maize was consistent with the local normal planting date under both RCP scenarios for the 2030s. The optimal planting dates for rainfed maize were shown to be 15 and 25 May under both RCP scenarios for the 2060s and 2090s, respectively. Compared with the local normal planting date, by using optimal planting dates, the rainfed maize yield could be enhanced by 3.5 and 19.8% under the RCP4.5 scenario and 7.5 and 22.5% for the 2060s and 2090s, respectively.

Planting 10 d late would produce at least a 4% increase in irrigated maize yield under both RCP scenarios. Comparing the 2 RCP scenarios, later planting produces a greater yield increase under the RCP4.5 scenario. The optimal planting dates for irrigated maize are suggested to be 5 May, 5 May, and 15 May under the RCP4.5 scenario and 5 May, 5 May, and 25 May under the RCP8.5 scenario for the 2030s, 2060s, and 2090s, respectively. Shifting the planting date would increase irrigated maize yield by 14.4, 34.1, and 31.4% under the RCP4.5 scenario and by 17.9, 39.2, and 51.1% under the RCP8.5 scenarios for the 2030s, 2060s, and 2090s, respectively, compared with no shift in planting date.

3.4.2. Supplying irrigation water

Because the water requirement for maize is different at different growth stages and future precipitation will change unevenly, the effects of different

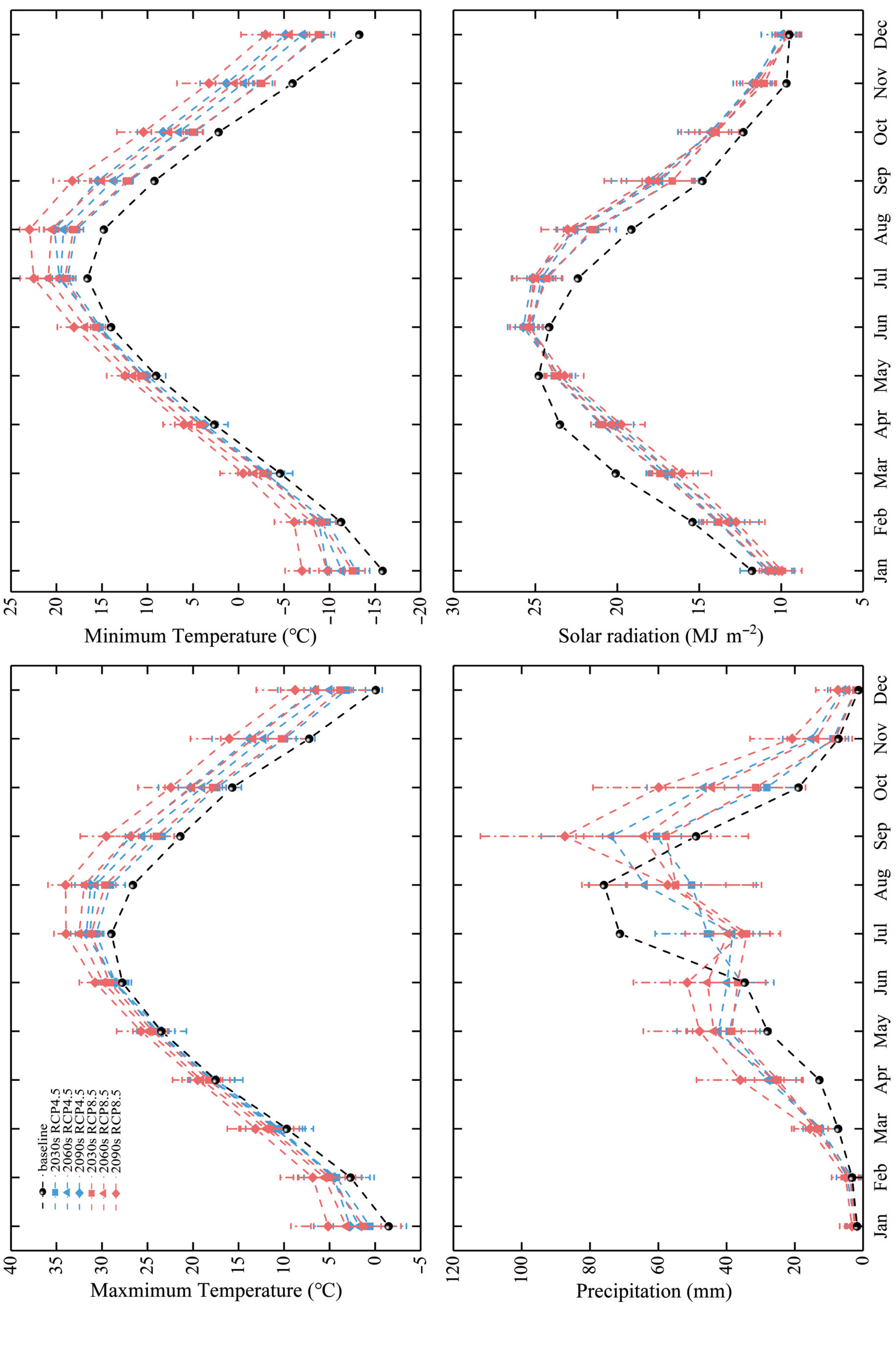

Fig. 3. Projected monthly maximum temperature, minimum temperature, precipitation, and solar radiation under RCP4.5 and RCP8.5 scenarios using 20 global climate models (GCMs) in the study area

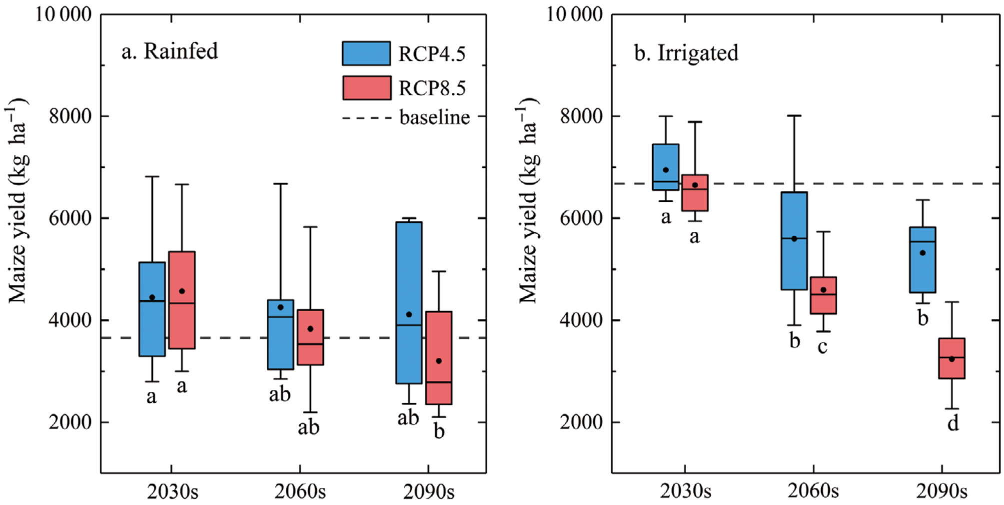

Fig. 4. Simulation of (a) rainfed and (b) irrigated maize yields during 3 periods under the RCP4.5 and RCP8.5 scenarios. Box boundaries: 25th and 75th percentiles; black line and dot within the box: median and mean value, respectively; whiskers below and above the box: minimum and maximum values, respectively. Different lowercase letters below the box plot indicate significant difference ($p < 0.05$)

irrigation combinations on the final yield varied. In the CSM-CERES-Maize, we set 32 irrigation combinations in 5 key growth stages (planting, emergence, jointing, tasseling, and grain filling) with 0, 1, 2, 3, 4, and 5 irrigations (Table 5). In contrast to other adaptation strategies, the supply of irrigation water resulted in higher rainfed maize yield. As shown in Fig. 6, the average maize yield under the RCP4.5 and RCP8.5 scenarios reached the maximum at Treatment 16, which was the combination of the tasseling and grain filling stages. After that, the maize yield increment with increasing irrigation frequency and amount was relatively small. The optimal treatment combination of irrigation frequency and amount under the RCP4.5 and RCP8.5 scenarios for the 2030s, 2060s, and 2090s is shown in Table 8. Comprehensive consideration of the simulation results suggests that supplying irrigation at the tasseling and grain filling stages may be optimal and economical.

4. DISCUSSION

4.1. Performance of CSM-CERES-Maize

The performance of GCM-CERES-Mazie needs to be validated before applying it in the APENC. We tested CSM-CERES-Maize at our 2 experimental sites and found that it simulated maize growth well. Statistical analysis comparing the simulated and observed data showed that CSM-CERES-Maize performed well in maize phenology, LAI, grain yield, and soil water dynamics (Table 6, Fig. 2). Similar statistical values were found in the literature for maize phenology, LAI, and grain yield using CSM-CERES-Maize (Jiang et al. 2016, Kaur & Arora 2018) and APSIM-maize (J. Wang et al. 2014). As a result, we conclude that the validated GCM-CERES-Maize has an acceptable error rate and is therefore suitable for further use.

4.2. Yield change under future climate change

Assessment of the effects of future climate change on crops has shown that meteorological factors are not the only factors impacting future crops: enhanced CO_2 concentration will also affect crop growth (Wang et al. 2017). The potential effects of atmospheric CO_2 fertilization on maize physiological processes are taken into consideration by the CSM-CERES-Maize, which is based on radiation-use efficiency, and it uses an externally prescribed CO_2 response modifier based on observed CO_2 response data (Hoogenboom et al. 2019).

Climate change predicted by the multi-model showed significant increases in temperature in the APENC. For irrigated maize, water is not the main factor limiting its growth. Thus, increasing temperature has potentially large impacts on irrigated maize production. Our simulation projected that, compared with the baseline across the 6 sites, multi-model mean irrigated maize yield would decrease by 20.4 % under

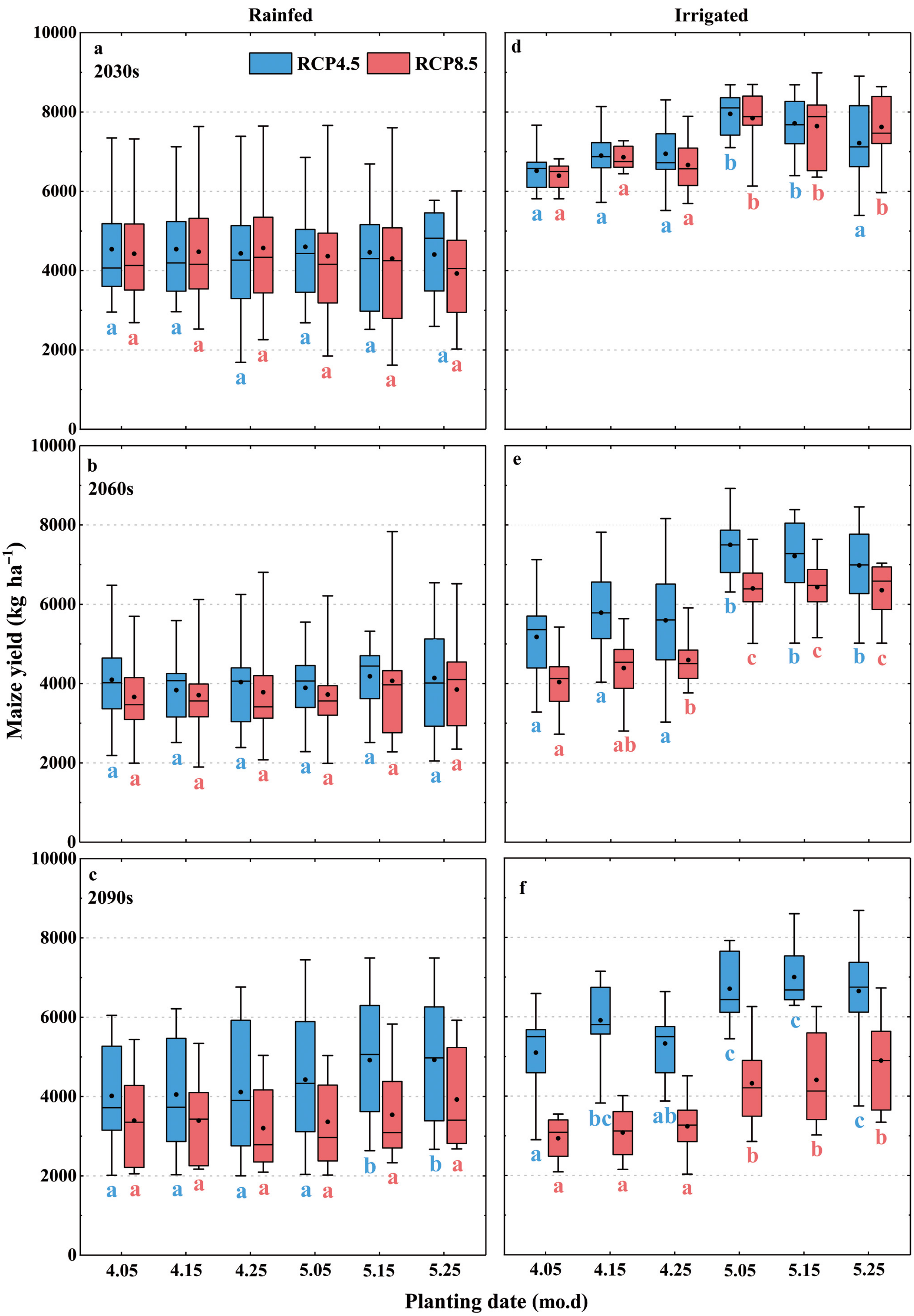

Fig. 5. Simulated irrigated and rainfed maize yields for the adaptation strategies of changing planting dates under RCP4.5 and RCP8.5 scenarios for the (a,d) 2030s, (b,e) 2060s, and (c,f) 2090s. Box boundaries: 25th and 75th percentiles; black line and dot within the box: median and mean, respectively; whiskers below and above the box: minimum and maximum values, respectively. Different lowercase letters below the box plot indicate significant difference ($p < 0.05$)

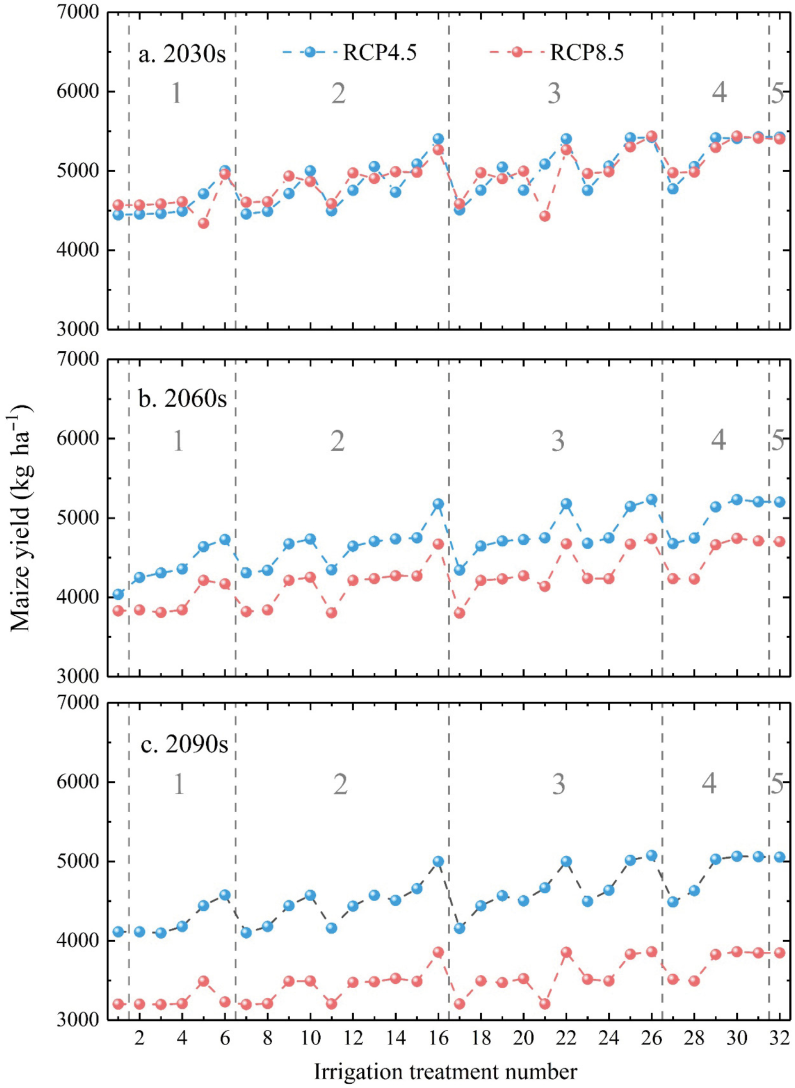

Fig. 6. Simulated maize yield under different scenarios at different irrigation treatments from the 2030s to the 2090s; gray numbers represent the irrigation frequency. For irrigation treatment number see Table 5 for detailed combinations

Table 8. Summary of the maize yield (kg ha^{-1}) of supplying irrigation under RCP4.5 and RCP8.5 scenarios for the 2030s, 2060s, and 2090s. Numbers in left column: irrigation treatment number (see Table 5 for detailed combinations)

Irrigation frequency and amounts	Optimal treatment	RCP4.5 2030s	RCP4.5 2060s	RCP4.5 2090s	RCP8.5 2030s	RCP8.5 2060s	RCP8.5 2090s
0 (baseline, no irrigation)	1	4446	4038	4112	4569	3830	3202
1 (50 mm)	6	5003	4730	4578	4959	4169	3229
2 (100 mm)	16	5404	5178	5001	5266	4672	3857
3 (150 mm)	22	5405	5179	5001	5266	4674	3855
4 (200 mm)	30	5409	5232	5066	5437	4743	3861
5 (250 mm)	32	5426	5202	5055	5402	4702	3847

RCP4.5 and by 53.1 % under RCP8.5 at the end of the 21st century (2090s). Previous findings showed that higher temperatures would lead to earlier maturation and a shorter period for the formation and accumulation of dry matter, causing less accumulation and thus reduced grain yield (Tubiello & Ewert 2002, Asseng et al. 2015, Yang et al. 2017, Huang et al. 2018). Our simulation results (Fig. 7) were consistent with previous findings and showed that the number of days to maturity will decline in the future, especially for irrigated maize (Fig. 7b). However, in the early 21st century (2030s), the projections suggest a slight upward trend in irrigated maize yield, probably because the enhanced CO_2 concentration and a small increase in temperature will likely have a positive effect on maize yield. A previous study found that elevated CO_2 concentrations only had a small fertilizing effect with regard to biomass accumulation on maize as a C4 crop (Kellner et al. 2019). Boote et al. (2010) discussed the CO_2 response in C4 crops simulated by the CERES-based models in DSSAT and found that double CO_2 (350–700 ppm) would cause a 4.2% grain yield increase. Hence, as the temperature exceeds the suitable maize growing temperature, the mean maize yield will decline.

Overall, future climate change will have a positive effect on rainfed maize yield, which can be attributed to rising precipitation. Precipitation is the main limitation for rainfed maize yield in arid and semi-arid areas. Two soil water stress factors in the CSM-CERES-Mazie model are implemented as a crop growth module (Qi et al. 2016). One is primarily responsible for photosynthesis and dry matter accumulation, called SWFAC. The expansion of leaf growth is reduced somewhat sooner by a similar factor called TURFAC. We calculated 2 soil water stress factors for rainfed maize during 3 periods under the RCP4.5 and RCP8.5 scenarios (Fig. 8). This calculation showed that the increase in projected precipitation can significantly reduce rainfed maize water stress, which will have a positive effect on photosynthesis and expansion growth. Our simulation results showed that the positive effect of

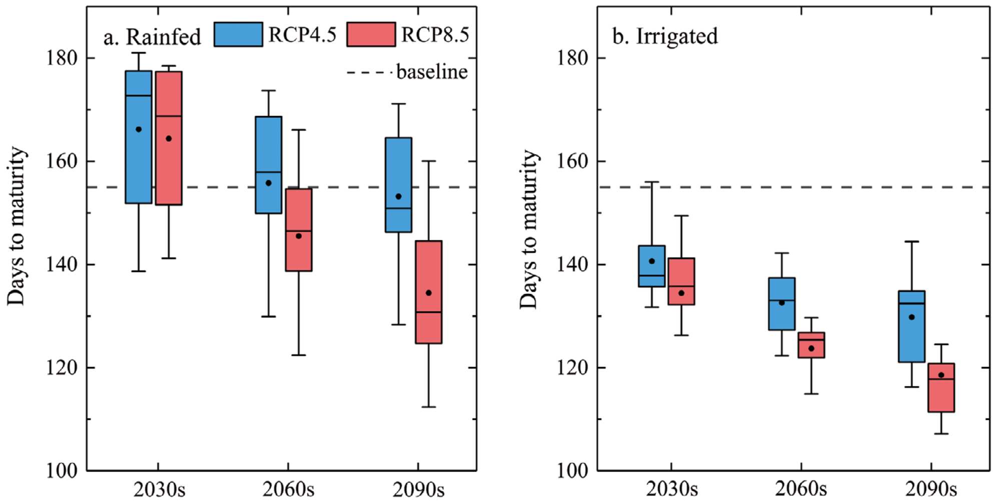

Fig. 7. Simulated number of days to maturity of (a) rainfed and (b) irrigated maize during 3 periods under the RCP4.5 and RCP8.5 scenarios. Box boundaries indicate the 25th and 75th percentiles; black line and dot within the box: median and mean, respectively; whiskers below and above the box: minimum and maximum values, respectively

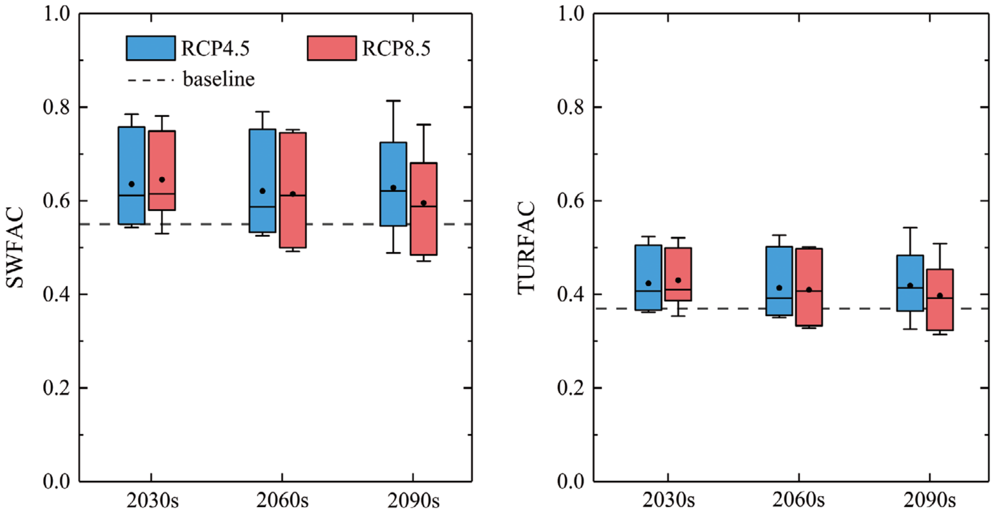

Fig. 8. Soil water stress factors for rainfed maize during 3 periods under the RCP4.5 and RCP8.5 scenarios. Box boundaries: 25th and 75th percentiles; black line and dot within the box: median and mean, respectively; whiskers below and above the box: minimum and maximum values, respectively. SWFAC represents the effect of soil water stress on photosynthesis; TURFAC represents water stress for maize expansion growth, where 1.0 = no stress; 0.0 = max. stress

increased precipitation is greater than the negative effect of air warming, but when the temperature increases too much, the rainfed maize yield will decrease, such as in the 2090s under the RCP8.5 scenario.

4.3. Performance of adaptation strategies

As the APENC faces the implications of climate change and its varied potential impacts on maize agriculture, adaptation measures are urgently needed. Shifting planting dates is a popular and easy way to mitigate the negative effects of climate change on crop yield in arid and semi-arid regions (Li et al. 2015, Saddique et al. 2019). In the APENC, there is much potential in the crop growth season for a single cropping system to adapt to yearly climate variations (Tang et al. 2018). Based on the simulation results, our study indicates that planting 10 or 20 d later than the normal planting date could significantly increase both rainfed and irrigated maize yield. Solar radiation is an essential source of energy for maize growth, development, and biomass accumulation. Previous research showed that maize yield was significantly correlated with solar radiation (Chen et al. 2013). Future solar radiation will be lower than the baseline from January–May and higher than the baseline from June–December (Fig. 3); hence, shifting planting to a later date would accumulate more solar radiation during the maize-growing season and avoid the decrease in the photosynthesis rate. This is the primary reason why a delayed plating date would increase maize yield. The delayed planting adaptation strategy is consistent with Li et al. (2015), who used semi-structured interviews and questionnaire survey data to show that farmers in the APENC have already delayed maize sowing dates to adapt to the changing climate. These results were also consistent with previous studies in other regions of China (Lv et al. 2019, Xiao et al. 2020).

Water is an important contributing factor in limiting rainfed maize growth and yield. Applying supplemental irrigation is therefore regarded as another effective adaptive strategy to respond to climate change in the APENC. Our simulation results showed that applying supplemental irrigation at critical stages of maize growth could significantly increase the rainfed maize yield. Although more irrigation could increase maize yield, there is not enough water for local farmers to irrigate maize, especially in arid and semi-arid areas. In the study region, rainwater harvesting has been an effective way to guarantee the application of supplemental irrigation (Pan et al. 2007). As rainwater harvesting efficiency is approximately 20% depending on collection environments (Tang et al. 2018), supplemental irrigation at the critical stage is important for maize water use efficiency. Therefore, applying supplemental irrigation 2 times, at the tasseling and grain filling stages, is recommended.

4.4. Uncertainty and limitations of the study

As different climate change projections may generate different results, we used a number of climate models to determine the range of uncertainty for the climate projections in this study. However, there are still uncertainties in the maize simulations. Although crop models are powerful and effective tools for predicting the effects of future climate change on crop yields and determining the best adaptation strategies, we applied a single model to simulate crop yields in this study, and we did not consider the uncertainty in simulating the response of maize to altered climate that can be attributed to differences in the structure and parameters of crop models (Asseng et al. 2013). Thus, multi-model comparison and ensemble modeling are proposed to be more reliable than a single model because multi-model ensembles provide more information from all selected models (Martre et al. 2015, Tao et al. 2018). Future studies should consider multi-crop models to reduce uncertainties.

Some limitations of our study need to be discussed. The study assumed that field management practices, fertilization, soil type, and maize cultivars will not change in the future, and the simulations do not sufficiently take into account yield reduction due to diseases, pests, weeds, or extreme weather events. Policymakers and resource managers need to be aware of these limitations when making management decisions to adapt to and alleviate the negative effects of future climate change. In our study, the only adaptation strategies for maize yield considered were adjusting the planting date and applying supplemental irrigation. Other adaptation strategies, such as changes in fertilizer application date and dose (Boonwichai et al. 2019) and identifying the optimum cultivar parameters (Tao et al. 2017, Xiao et al. 2020), could also contribute to improving crop yields. In future studies, these methods should be considered together to provide a comprehensive and reasonable scheme for adapting to climate change.

5. CONCLUSIONS

The CSM-CERES-Maize was applied for climate change impact assessment and adaptation measurement evaluation in this study. The future climatic variables were projected by an ensemble of 20 GCMs used in CMIP5 to address uncertainty. Two adaptation strategies, changing the planting date and supplying irrigation water, were evaluated for the 2030s, 2060s, and 2090s. After calibration, the CSM-CERES-Maize simulated phenology, LAI, and maize yield with reasonable accuracy. Simulation results showed that future climate change will have negative and positive effects on irrigated and rainfed maize, respectively. Higher temperatures will lead to earlier maize maturation, causing less accumulation and thus reduced irrigated maize grain yield. However, increased precipitation can reduce water stress and would be favorable to rainfed maize. Two adaptation strategies could enhance maize yield significantly. Both irrigated and rainfed maize could benefit from shifting the planting date later. However, applying supplemental irrigation is a more effective way to enhance rainfed maize yield than adjusting the planting date. Our study also revealed that supplying irrigation at the critical stages of maize growth would be optimal and economical. However, the feasibility of adaptation actions would depend on available water sources and farmers. Further work is warranted to explore a combination of adaptation strategies for local policymakers.

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