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ORIGINAL PAPER

Identifying the optimum irrigation strategies to maximize canola yield and profitability under climate change in Guanzhong Plain, China

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Abstract

Climate change has a substantial impact on Chinese canola production, introducing a high level of uncertainty regarding future climatic conditions and their potential impact on canola production and gross margins. This study focused on identifying the optimal irrigation strategy to enhance the profitability of canola production in the Guanzhong Plain under future climate change conditions. In this study, we used the calibrated Agricultural Production Systems sIMulator (APSIM)-Canola model with the downscaled daily climate projections from 27 general circulation models (GCMs). These simulations were conducted under two Shared Socio-economic Pathways scenarios (SSP245 and SSP585) to assess the impact of climate change on canola phenology, rainfed and irrigated crop yield. We also conducted a gross margin analysis to assess the profitability dynamics of supplying irrigation to rainfed canola crop. An increase in rainfed canola yield was observed for all simulation periods, with an average increase of 11%, 15%, and 17% for the 2030s, 2060s, and 2090s, respectively. Supplementary irrigation using a threshold of 10–60% of plant available water capacity (PAWC) was found to be effective. Overall, it led to a 28% increase in yield for rainfed and an 85% improvement in gross margin. Beyond the threshold of 60% PAWC, additional irrigation did not result in statistically significant increases in yield and gross margin. We identified the optimal amount of irrigation for achieving maximum water productivity (WP) ranges from 85 to 150 millimeters. By avoiding irrigation when the soil's plant available water capacity (PAWC) is over 60%, up to 44% of water can be saved. These findings could be useful for policymakers and farmers in planning for sustainable and enhanced canola production in the region.

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Introduction

Climate change driven by global warming and characterized by increased global temperature and shifts in precipitation patterns, has become a megatrend that will generate significant global shifts in the future (IPCC 2018, 2023). China has experienced significant temperature and precipitation changes over the last 20 to 30 years, with notable higher temperatures of 1.3–3.3 °C and inconsistent intra-annual precipitation distribution (Chen 2020; NIC 2009; Zhang and Zhou 2019). These changes have both positive and negative impacts on Chinese agriculture production, affecting crops such as wheat, maize, and oilseed crops. For instanceSaddique et al. (2020a); Xie et al. (2020) reported the adverse effects of changing climate conditions on China's maize yield, which declined by 33%, and wheat yield, which reduced by 4.3%. Liu et al. (2021) observed similar detrimental impacts on regional oilseed crops, specifically indicating a negative influence on canola yield, with a decline of 800 kg/ha. In contrast, Guo et al. (2022) and Tian et al. (2018) reported that climate change can lead to a positive impact on canola yield, with 11.3% increase in yield and projected increases of 0.34–1.64 million tons by 2050, respectively.

China is among the major producers and consumers of canola oil in the world, and it produces nearly 18% of the world's canola seed (FAO 2019). The canola yield in regions of China impacted by climate change continues to exhibit notable variability compared with other crops (Cui et al. 2022). This variability has made it challenging to meet the growing demand for canola in China (Jannat et al. 2022). The increasing demand for canola has attracted renewed management practices and efforts to improve yield under future climate change (Liu et al. 2021). These management practices include better irrigation scheduling and the modification in the planting date to mitigate the adverse effects of climate change (Mandryk et al. 2017; Lobell 2014). He et al. (2015) found that irrigation could effectively sustain and increase canola production amid future climate variability. For instance, in regions where water is scarce, cultivated grain crops that receive proper irrigation produce a higher yield per unit of land than rainfed crops (Muleke et al. 2022; Saddique et al., 2020a, b). Considerable yield gain due to irrigation application also improves the overall profitability in Canola production (Meier et al. 2020).

In general, crop gross margins vary across farms and years due to fluctuations in commodity prices, yields, water usage, and variable costs, including fertilizer, fuel, transportation, repairs, maintenance, labor, etc. Especially, in drought-prone regions such as Guanzhong Plain in China (Wu et al. 2017), the provision of irrigation in terms of both time and quantity can be pivotal to have profitable crop yields. A good cropping season with ample water supply, whether through sufficient precipitation or irrigation, play a pivotal role in mitigating the variability of input costs. In addition to optimal yields, higher commodity prices help sustain profitability. Moreover, this provides a strong rationale for investing in infrastructural enhancements to improve on-farm water management (Ali et al. 2017; Zou et al. 2021). Climate change and seasonal variability can increase the volatility of crop-related profits in Guanzhong Plain by disrupting the irrigation supply demand ratio during drought periods (Wang et al. 2019; Wu et al. 2017; Zhang et al. 2021). Droughts can lead to increased demand for irrigation water, potentially impacting the water prices in Guanzhong Plain (Shen et al. 2020; Tang et al. 2015). The increase in demand for water leads to a considerable increase in the prices of water (Chen et al. 2014; Wang et al. 2016; Wen et al. 2023; Zhong et al. 2015). Considering the increasing water price and occurrence of extreme events like droughts, farmers have to consistently adjust their farm management strategies to ensure reasonable farm profits (FAO 2015). For instance, optimized irrigation strategies can maintain the farmer the profit, as suggested by Tang et al. (2020).

Crop modeling is an effective approach for simulating crop interactions with climate, water, soil conditions, and management practices (Xing et al. 2017), and can be further linked to input costs and net income from farm-produced commodities. A modelling approach can identify strategies for improving productivity and resource efficiency in various environments, seasons, and management scenarios (Wang et al. 2022). Several previous crop modeling studies have focused on different crops (maize and wheat) to assess the climate change impacts on crop phenology, crop ideotypes, planting date, and irrigation scheduling (Lin et al. 2017; Saddique et al. 2019; Xiao et al. 2020). However, the impact of climate change on canola production and its profitability under different irrigation scenarios has not been studied in Guanzhong region. Some existing modeling work on canola in China Xia et al. (2022), who used APSIM model to identify the optimal planting date for canola in Inner Mongolia under varying precipitation years and investigated the suitability of canola planting under wet and dry years. He et al. (2017) investigated genotype, environment and management interactions for canola yield in China using APSIM, and highlighted the favorable impacts of improved radiation use efficiency in wet regions and enhanced transpiration efficiency in dry region.

In this study, we calibrated the APSIM model for canola with three-year field experimental datasets on crop phenology, crop yield, biomass, and crop management. The calibrated model was used to assess the impacts of climate change on canola production and its profitability with future climate data statistically downscaled from 27 global climate models (GCM) from Coupled Model Intercomparison Project phase 6 (CMIP6). Such coupling of climate change focused crop modeling and profitability of canola production in Guanzhong Plain fill the gap in knowledge for the producers, agriculture education, planning and policy makers. Unlike most of the crop modeling studies that overlook the economic element of crop production, this study provided a novel insight into the canola production's adaptability in the region in connection with variation in future profit margins, which has not been previously explored.

The objectives of this study were to (1) Evaluate the APSIM-Canola performance using three years of field experiment data in Guanzhong Plain; (2) Predict how altering climatic conditions will impact the phenology and production of canola in the future; (3) Determine the most effective irrigation strategy approaches for optimizing canola production, water productivity, and gross margin under future climate.

Materials and methods

Study area

In this study, the crop data was extracted from experimental work conducted by Gu et al. 2019 at Key Laboratory of Agricultural Soil and Water Engineering, Northwest A&F University, Shaanxi Province, China. The specific location is illustrated in Fig. 1 (Coordinates: 34°18′N, 108°24′E, Elevation: 506 m above sea level). The study area falls within a sub-humid to semi-arid climate zone, characterized by an average annual temperature of 12.9 °C. The mean annual maximum and minimum air temperatures recorded are 40 °C and −8.4 °C, respectively. The total annual growing degree unit is 2544 GDU, and the annual precipitation amounts to 548 mm. Daily measurements of maximum and minimum air temperature (°C), precipitation (mm per day), and solar radiation for the years 2014–2017 were obtained from the Yangling meteorological station, which is conveniently located adjacent to the open field experimental site. The data can be accessed at http://data.cma.cn. The details of the experiment can be found in the supplementary file.

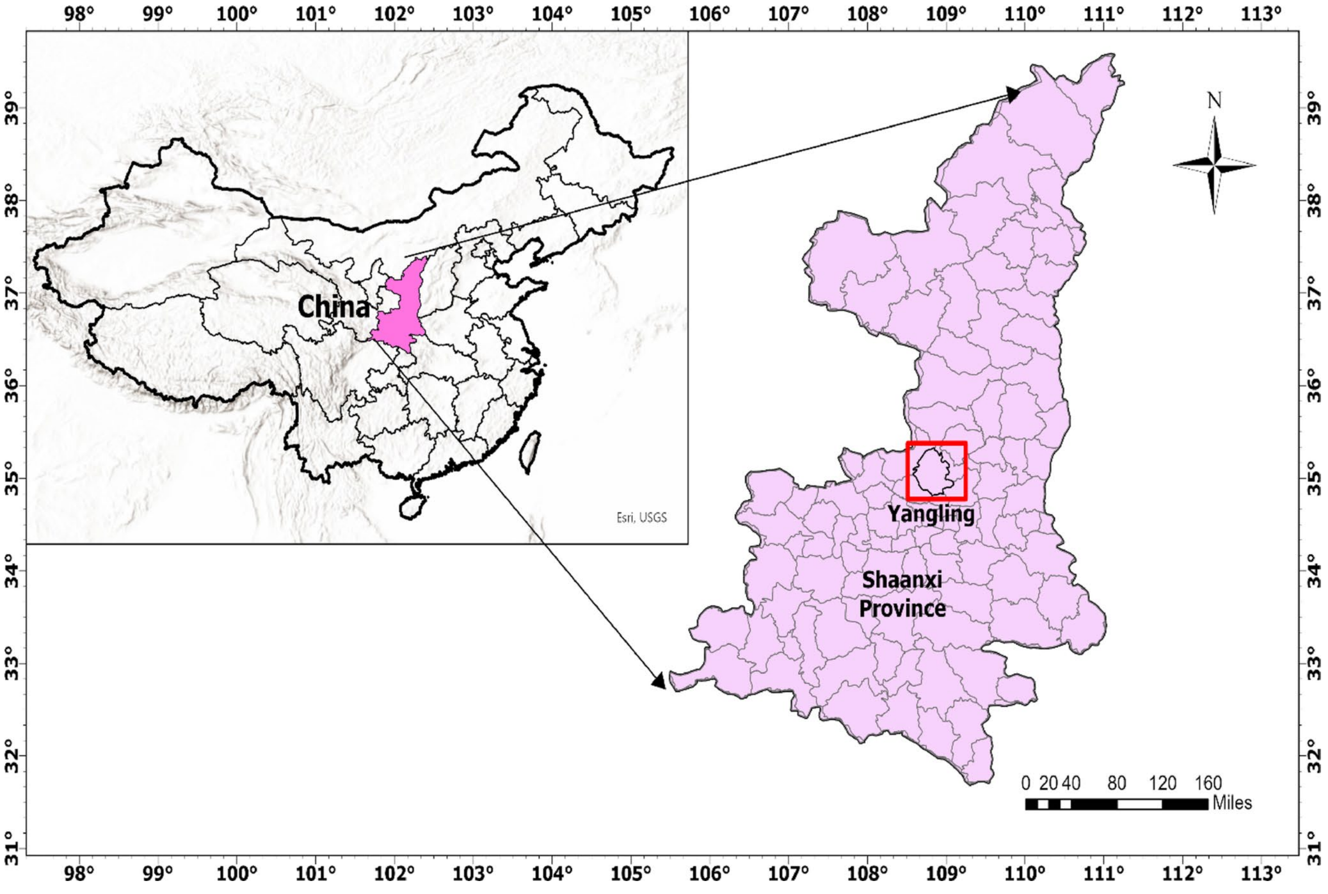

Fig. 1 Study area location: Yangling, located in the Guanzhong Plain, Northwest China

Climate data

Historical climate data

Over a 50-year span from 1961 to 2010, historical climate data was collected from the Chinese meteorological administration's weather station near the Wugong experimental site in Shaanxi province, specifically located in Yangling (34°18′N, 108°24′E). The historical climate data included maximum and minimum temperatures (°C), precipitation (mm) and solar radiation (MJ m^{-2}).

Future climate data

Future monthly gridded climate data from 27 GCMs employed in the Coupled Model Intercomparison Project Phase 6 of the Intergovernmental Panel on Climate Change (CMIP6 IPCC AR6) were obtained from https://pcmdi.llnl.gov/CMIP6/. Table 1 provides detailed information about the GCMs. The climate data included maximum and minimum temperature, precipitation and solar radiation.

Table 1 List of 27 CMIP6 global climate models (GCMs) under SSP245 and SSP585 climate scenarios used in the study

Model ID	Name of GCM	Institute ID [a]	Country
01	ACCESS-CM2	BoM	Australia
02	ACCESS-ESM1-5	BoM	Australia
03	BCC-CSM2-MR	BCC	China
04	CIESM	THU	China
05	CMCC-CM2-SR5	CMCC	Europe
06	FGOALS-g3	FGOALS	China
07	NESM3	NUIST	China
08	CanESM5	CCCMA	Canada
09	CanESM5-CanOE	CCCMA	Canada
10	CNRM-CM	CNRM	France
11	CNRM-CM6-1-HR	CNRM	France
12	CNRM-ESM	CNRM	France
13	EC-Earth3	EC-EARTH	Europe
14	EC-Earth3-Veg	EC-EARTH	Europe
15	GFDL-ESM4	NOAA GFDL	USA
16	GFDL-CM4	NOAA GFDL	USA
17	GISS-E2-1-G	NASA GISS	USA
18	HadGEM3-GC31-LL	MOHC	UK
19	INM-CM4-8	INM	Russia
20	INM-CM5-0	INM	Russia
21	IPSL-CM	IPSL	France
22	MIROC6	MIROC	Japan
23	MIROC-ES2L	MIROC	Japan
24	MRI-ESM2-0	MRI	Japan
25	MPI-ESM1-2-HR	MPI-M	Germany
26	MPI-ESM1-2-LR	MPI-M	Germany
27	UKESM1-0-LL	Met Office	UK

a: For full institution names corresponding to each Institute ID, please refer to the official CMIP6 institution list: https://wcrp-cmip.github.io/CMIP6_CVs/docs/CMIP6_institution_id.html

The IPCC AR6 has recently developed climate projections based on atmospheric CO_2 concentration, known as Shared Socio-economic Pathways scenarios (SSP), which encompass a range of plausible forcing scenarios using CMIP6 data. For this study, SSP245 and SSP585 were selected due to their more accurate representation of current radiative forcing and emissions conditions, as indicated by He et al. (2022). Additionally, these SSPs were chosen for statistical downscaling as they provide raw monthly GCMs simulated temperature data.

For future daily climate projections data, a statistical downscaling method based on a weather generator developed by the New South Wales Department of Primary Industries at Wagga Wagga Agricultural Institute (NWAI-WG) was employed, as detailed by Liu and Zuo (2012). This method involves first spatially downscales the GCM simulations specific to the site through inverse distance-weighted interpolation, followed by a bias correction using the observed historical climate data. Finally, the bias-corrected monthly GCM projections were downscaled to the daily temperature time series using a modified stochastic weather generator (Richardson and Wright 1984). This downscaling method has been widely utilized in other climate change research projects (Liu et al. 2014; He et al. 2022; Wang et al. 2015). Importantly, the NWAI-WG approach also considers interannual variations of precipitation, radiation, and temperature (Liu and Zuo 2012; Anwar et al. 2015), enhancing the accuracy of predictions for future climate conditions. In this study, we compared climatic parameters between the baseline period of 1961–2010 and three future periods: 2030s (2020–2039), 2060s (2050–2069) and 2090s (2080–2099).

APSIM model

In our study, we employed the Agricultural Production Systems sIMulator (APSIM) to simulate how canola grows and develops at our research site. APSIM has proven to be successful in predicting crop yield at the field level (Holzworth et al. 2014). APSIM incorporates key components including water balance, crop simulation, cropping system analysis, intercropping, and soil water interactions with crops, adaptive cropping systems, and land use models (Keating et al. 2003). This commonly used crop model has been widely applied to simulate various crops, including maize in Guanzhong Plain, Northwest China (Xu et al. 2021), and its process-based modeling framework allows simulating canola as well. APSIM-Canola, has been applied to numerous canola cultivars globally under different management and climate (Wang et al. 2022). We used APSIM-Canola model Version 7.7 for our study, because it has been validated using field trial data sets under similar environmental conditions and therefore provides consistent research with previous studies. Xu et al. (2021) also applied APSIM 7.7 in Northwest China, validating its applicability and reliability in this region and for more detailed information, interested individuals can visit the APSIM model website at https://www.apsim.info/ APSIM-model.

Model evaluation

The model was calibrated using soil data (loamy soil), weather data and crop data (such as phenology, grain yield, biomass, evapotranspiration, WP, and oil production) obtained from the full irrigation treatment in the experiment conducted over three growing seasons (2014–2017) as documented by Gu et al. (2019). This approach is similar to the methods employed by Kothari et al. (2019). The APSIM-Canola model was used to estimate the cultivar coefficients for the winter canola crop based on these data. Additionally, the genetic coefficients for the winter canola cultivar (Shaanyou No. 107) in the APSIM model were determined through a trial and error approach to achieve comparable simulation results with the observed values, as described by Mavromatis et al. (2001). The simulations were terminated once they met the statistical requirements between the observed and simulated data, as outlined by Hunt and Boote (1998). The resulting genetic coefficients for the APSIM model are presented in Table 2. The model evaluation was evaluated using statistical analyses such as d-index (Willmott 1982) (Eq. 1), coefficient of determination (R^2), and normalized root mean square error (nRMSE) (Eq. 2) between the simulated and observed data. The model evaluation indicated good agreement between the simulated and observed ET, indicating that the model is capable of reproducing crop water use. Similarly, simulated water productivity was consistently comparable to observed values. Furthermore, crop yield and biomass were calibrated and validated in the model, demonstrating strong agreement with observed data. As soil moisture content is essential for ET, water productivity and biomass accumulation, we also evaluated its accuracy. Simulated soil moisture content was similar to observed data, further validating the capabilities of the model to simulate soil water balance. (detailed results are provided in the supplementary material).

Table 2 Genetic coefficients for APSIM Canola cultivar 'shaanyou 107 _' calibrated with data from the experiments of 2014–2015, 2015–2016 and 2016–2017

Parameters	Values	Description
tt_emergence	650	Thermal time from emergence to end juvenile stage (∘d)
tt_end_of_juvenile	580	Maximum thermal time required to complete the juvenile process at no vernalisation
tt_start_grain_fill	750	Cumulative thermal time required for grain-filling
tt_flowering	200	
hi_max_pot	0.30	Harvest index

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} \left(\left| P_i' \right| + \left| O_i' \right| \right)^2} \right], 0 \leq d \leq 1 \tag{1}$$

Whrere n = number of observations, $P_i =$ predicted and $O_i =$ observed values of ith measurement and $P_i' = P_i - \bar{O}$; $O_i' = O_i - \bar{O}$, mean of observed values are represented by $\bar{O}$. Higher d-index value means better fit between simulated and observed data. The nRMSE was calculated by using Eq. (2).

$$nRMSE = \frac{RMSE \times 100}{\bar{O}} \tag{2}$$

Root mean square error (RMSE) was determined by Eq. (3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (P_i - O_i)^2}{n}} \tag{3}$$

For the comparison of simulated and observed values, the nRMSE criteria is classified into excellent (nRMSE < 10%), good (10% ≤ nRMSE < 20%), fair (20% ≤ nRMSE < 30%), and poor (nRMSE ≥ 30%).

Gross margin calculation

The gross margin (GM) was calculated as outlined by Li et al. (2017).

$$GM = (1 - T) \times P \times Y \times -C_S - C_I - C_O - C_f - C_{pc} - C_t - C_h \tag{4}$$

Where T represents the government levy, P stands for the grain price in Chinese Renminbi per hectare (RMB kg^{-1}), Y denotes the crop grain yield in kilograms per hectare (kg ha^{-1}), and C_s, C_I, C_O,, C_f, C_{pc}, C_t, and C_h correspond to the costs associated with sowing, irrigation, canola oil price, fertilizer, pest control, tillage, and harvest, respectively, all measured in Chinese Renminbi per hectare (RMB ha^{-1}), respectively. The economic cost associated with field management practices were detailed and provided in Table 3.

Configuring the model for future simulations

The canola planting window for our study was determined to be from 10 September to 25 September, as this timeframe aligns with the typical canola sowing dates in the region

Table 3 Canola cultivation cost analysis in the field experiment

Sr No.	Parameters	Cost (rmb)	Remarks
1	Labor	300	6 people/mu[a]
2	Machine cultivation (tillage)	50	
3	Seed for sowing	36	120RMB/kg, 0.3Kg needed/mu
4	Fertilizers	130	50 kg/mu
5	Pest Control	30	twice,15Rmb/mu
6	Irrigation	0.27/m^3	0.27/m^3
7	Local price of canola grain yield	4.8	4.8/kg, recent 3 years average
8	Canola Oil Price	10	/kg
9	Harvest	80	/mu
10	government levy%	0	tax free

a: One mu is equivalent to approximately 666.67 square meters or 0.0667 hectares

(Secchi et al. 2023). Each year, canola was sown when the cumulative precipitation over a 4-day period exceeded 20 mm or upon reaching the end of the sowing timeframe. Additionally, 180 kg/ha of nitrogen fertilizers was used at the time of sowing. The model simulated baseline canola yield, phenology, irrigation amount, water productivity and gross margin with baseline climate data from 1961 to 2010 and a CO_2 concentration of 350 ppm. For future projections, we simulated canola yield, phenology, irrigation amount, water productivity, and gross margin from the 2030s to 2090s under two climate change scenarios (SSP245 and SSP585). The CO2 concentrations for SSP245 and SSP585 were calculated using the approach outlined by Bai et al. 2022.

To prevent emergence failure and the effects of abnormal residual soil water carrying-over from previous year in the simulations, the initial soil water content was reset to 50% of the plant available water capacity (PAWC) two weeks prior to sowing. PAWC is defined as the difference between the water content at field capacity (FC) and that at the wilting point (LL). The simulation was conducted for the Yangling site, using soil parameters identical to those reported by Xu et al. (2021). The soil depth used for simulations in this region was 1.0 m, aligning with the actual root depth of annual crops such as canola. Our investigation focused on assessing the future irrigation requirements for winter canola, specifically targeting the period from the 2030s to the 2090s. For this, we examined nine distinct irrigation strategies, each representing a varying percentage of the PAWC, ranging from 10 to 90%. These strategies were designed to assess the response of winter canola under different irrigation conditions and to pinpoint an optimal approach for irrigation. The nine strategies were denoted as ARR1, ARR2, and so on, up to ARR9, with ARR0 denoting the rainfed condition. For instance, ARR1 denoted that when the soil water content dropped to 10% of the PAWC, an appropriate amount of irrigation water was applied to restore the soil moisture to field capacity (FC).

Results and discussion

Predicted climate conditions in future climate scenarios

The maximum and minimum temperatures during the baseline seasonal period (September to May) from 1961 to 2010 in Yangling were 18.9 °C and 8.7 °C, respectively. Figure 2a and b illustrate the projected changes in seasonal maximum and minimum temperatures during the winter canola growing season (September to May) at Yangling, based on downscaled data from an ensemble of 27 Global Climate Models (GCMs) under the SSP245 and SSP585 scenarios, relative to the baseline period (1961–2010). Both scenarios indicate an increase in maximum temperature of 1.7 °C and minimum temperature of 1.3 °C by the 2030s. In the 2060s, seasonal maximum temperature is projected to rise by 2.7 °C (SSP245) and 3.7 °C (SSP585), while seasonal minimum temperature is projected to rise by 2.1 °C (SSP245) and 2.9 °C (SSP585). By the 2090s, the seasonal maximum temperature is expected to increase by 3.5 °C (SSP245) and 5.5 °C (SSP585), and the seasonal minimum temperature is projected to increase by 2.8 °C (SSP245) and 4.8 °C (SSP585).

The projected changes in seasonal precipitation varied among the GCMs. Some GCMs predicted a decrease in precipitation for the 2030s and 2060s (Fig. 2c), while others indicated the opposite trend. However, an overall maximum increase in precipitation was observed for the 2090s. The multi-GCM ensemble predicted increased precipitation for both scenarios compared to the baseline. In the 2030s, precipitation increased by 6.1% under SSP245 and 4.6% under SSP585. For the 2060s and 2090s, it was projected to rise between 9.9% and 24.7% for both scenarios.

These climate change results from the ensemble of 27 GCMs under both scenarios for the Guanzhong plain region generally align with the findings of Wu et al. (2022), who reported a gradual increase in both temperature and precipitation for this study area. Regarding mean seasonal daily radiation, the baseline value from 1961 to 2010 at Yangling was 13.0 MJm^{-2}. The multi-GCM ensemble projected a decrease in radiation by -2.35% under SSP245 and −1.1% under SSP585 for the 2030s. However, by the 2060s and 2090s, radiation was projected to increase by 2 to 4.76% (Fig. 2d). Additionally, it was observed that the projected radiation of SSP585 increased more than SSP245 for both the 2060s and 2090s.

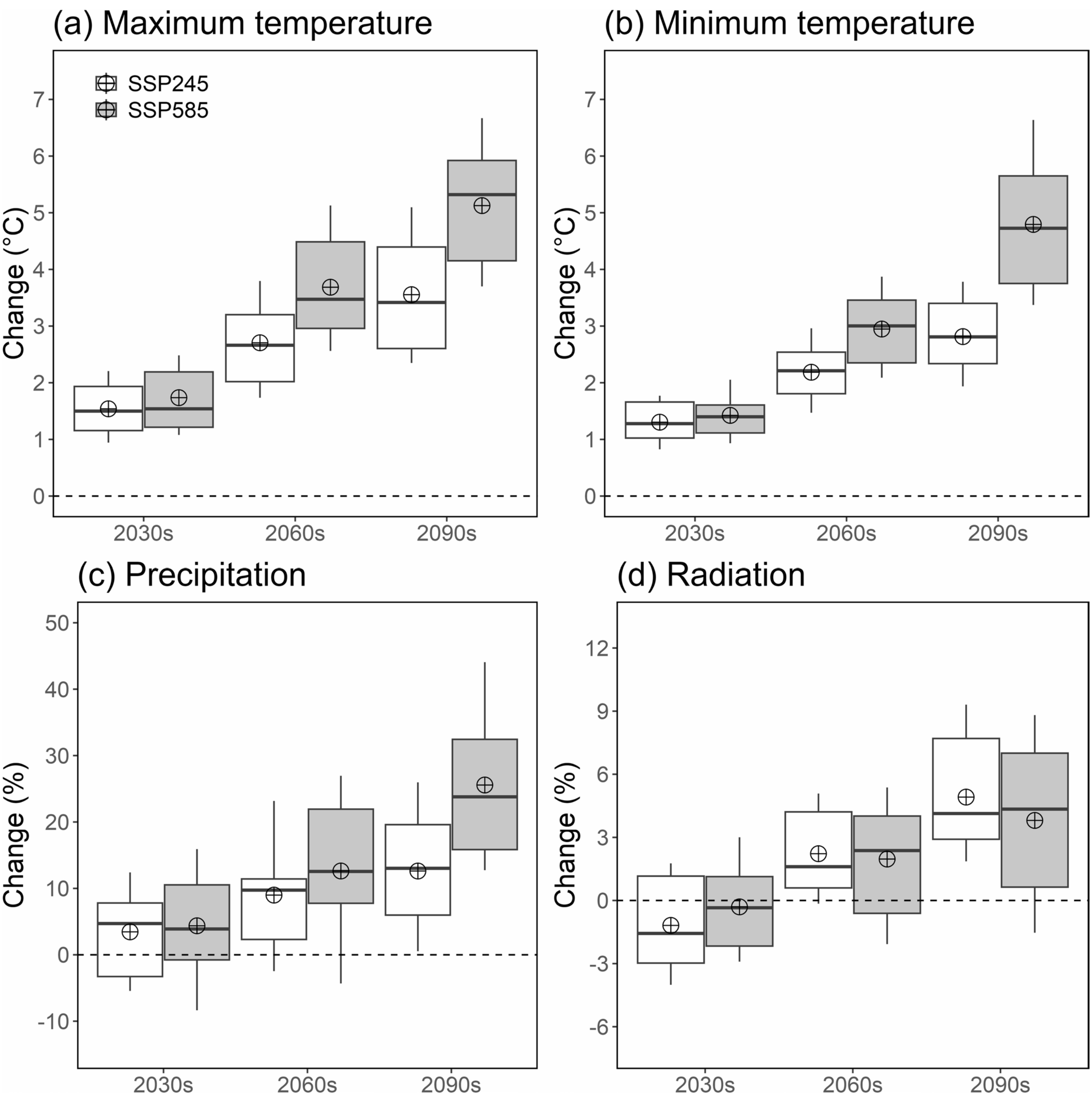

Fig. 2 Projected changes in growing season (Sep.-May), maximum and minimum temperature, mean radiation and precipitation under SSP245 and SSP585 at the station. Data were presented as changes between 1961–2010 and three future time periods (2030s, 2060s and 2090s) based on the 27 downscaled GCMs. Each box consists of 27 values. Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

Crop phenology changes

The findings indicate that the future climate is expected to significantly impact the flowering and maturity period of canola. As shown in Fig. 3, the projected results demonstrate that the flowering and maturity dates are predicted to occur earlier across all irrigation strategies in the 2030s, 2060s, and 2090s under both the SSP245 and SSP585 scenarios. As flowering and maturity are predominantly governed by temperature, the projected changes in temperature most likely would have a significant impact on these growth stages (Qian et al. 2018; Asseng et al. 2015). In general, when considering the ensemble mean of multiple GCMs (Fig. 3a), the flowering period is projected to advance by 9–25 days and

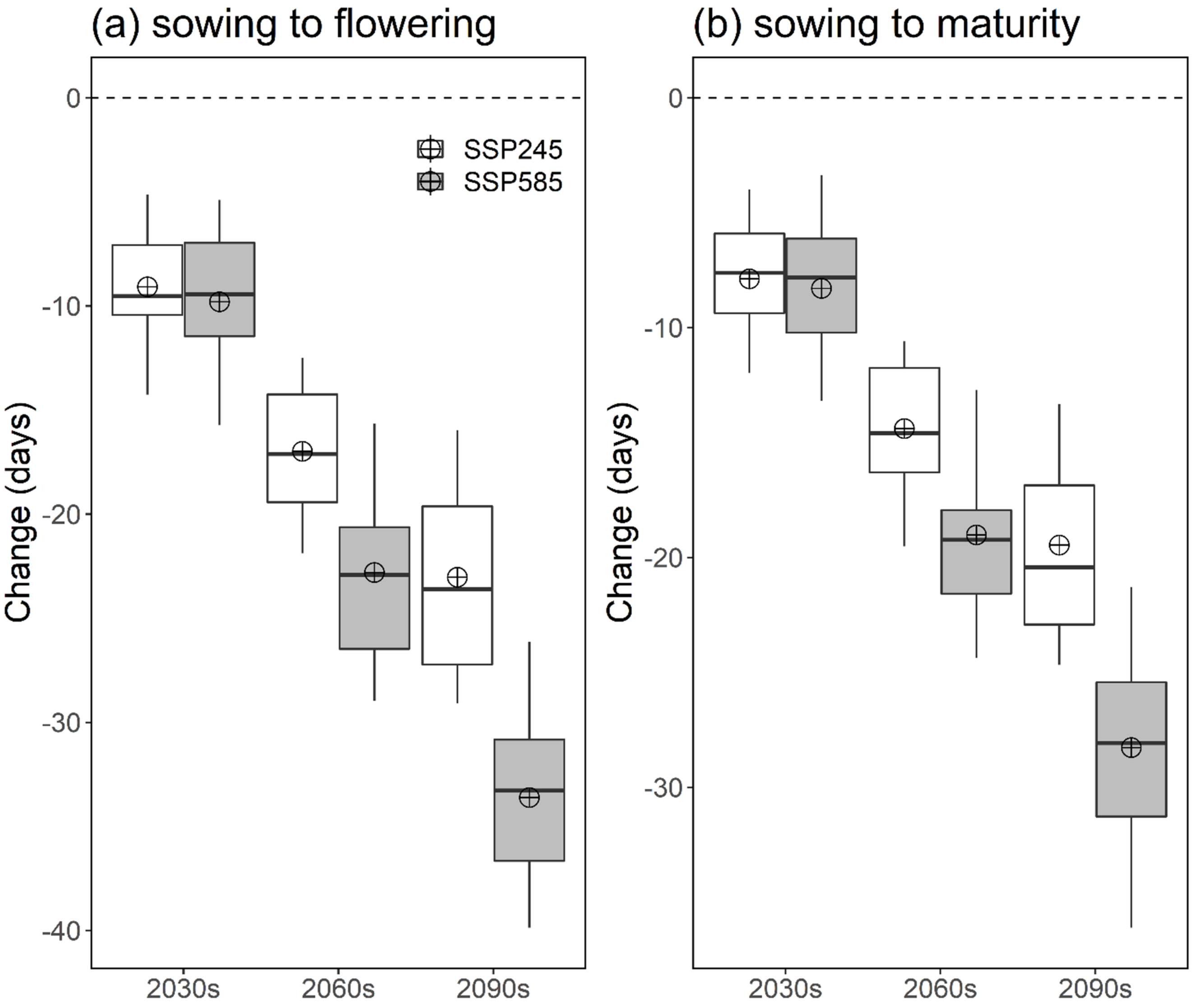

Fig. 3 Simulated flowering and maturity days change (compared with baseline 1961–2010) in the 2030s, 2060s, and 2090s under SSP245 and SSP585 using 27 downscaled GCMs for 10 irrigation strategies at the station. Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

9–34 days during the three periods (the 2030s, 2060s, and 2090s) under the SSP245 and SSP585 scenarios, respectively. Similarly, the maturity stage is expected to be 8–21 days and 7–25 days early under the SSP245 and SSP585 scenarios, respectively (Fig. 3b). These results suggest a likely negative correlation between the rise in growing season temperature and the timing of flowering and maturity. The increased variation in phenology observed under SSP585 in the 2090s is primarily attributed to the intensified warming associated with this high-emission scenario. Projections indicate that maximum temperatures could rise by approximately 5.5 °C under SSP585 by the 2090s (Fig. 2). This considerable rise in temperature accelerates the accumulation of growing degree days (GDD), leading to earlier and more pronounced phenological shifts. These findings suggest that, overall, the canola growth period is expected to be reduced due to projected warming conditions in the future, which is consistent with the findings of He et al. (2017) and Wang et al. (2022).

Impacts of climate change on rainfed and irrigated Canola yield

Under future climate change scenarios, the projected yields for both rainfed and irrigated conditions show an overall increase compared to baseline levels (Fig. 4). According to the multi-GCM ensemble mean, the rainfed yield ARR0 is expected to increase by 10%, 14%, and 15% in the 2030s,

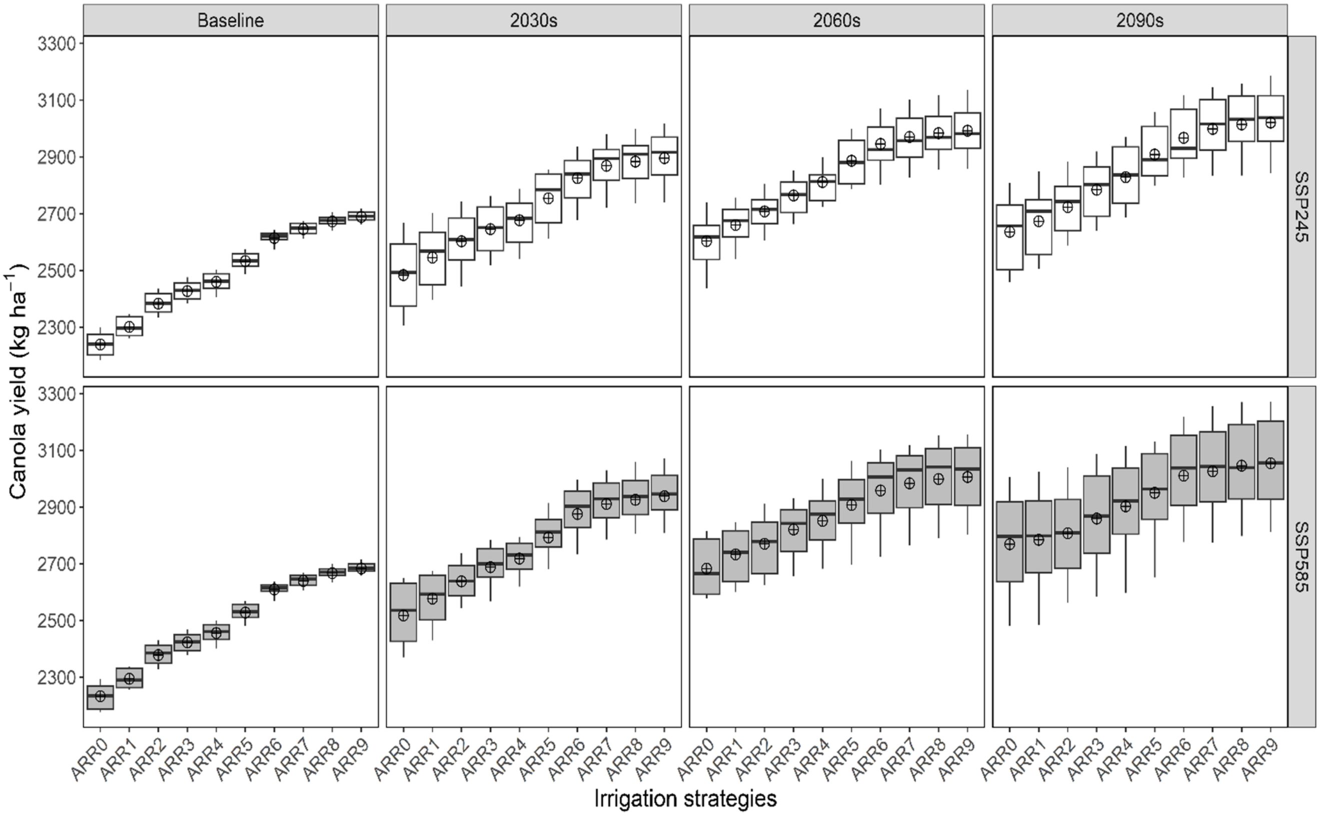

Fig. 4 Simulated canola yield during baseline (1961–2010), 2030s, 2060s, and 2090s under SSP245 and SSP585 using 27 downscaled GCMs for 10 irrigation strategies (ARR0: Rainfed, ARR1–ARR9: Irrigation strategies). Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

2060s, and 2090s, respectively, under the SSP245 scenario. Likewise, in the case of the SSP585 scenario, the rainfed yield ARR0 is projected to increase by 11.3%, 16.7%, and 19% in the corresponding periods. Under irrigation, the maximum change was observed in the ARR1 treatment compared to other irrigation strategies. The increases in irrigated yield for the 2030s, 2060s, and 2090s were 8.8%, 13%, and 14% under the SSP245 scenario, and 11%, 16%, and 18% under the SSP585 scenario, respectively, relative to baseline yield. The mean yield of the other irrigation treatments (ARR2-ARR9) showed a small difference. The increase in yield for these treatments relative to the baseline was less than 12% in the 2030s. However, in the 2060s and 2090s, the increase exceeded 12% under both the SSP245 and SSP585 scenarios. In terms of yield variation, there was slightly higher variability in the projected yield for the 2090s under the SSP585 scenario compared to the other two time periods and the SSP245 scenario across all irrigation strategies (ARR1-ARR9). This could be attributed to the larger variation in growing season precipitation during the 2090s under the high emission scenario (Fig. 2c). This study's results indicated increase in simulated rainfed and irrigated yields in both SSP scenarios. Similar trends were observed in certain regions of China by Tian et al. (2018) who reported a potential increase in canola yield of 10–16% under future climate change. Furthermore, it was observed that the increase in rainfed yield was higher in the 2090s under the SSP585 scenario. It could be mainly because of the elevated CO_2 fertilization effect observed under SSP585. This effect compensates for potential adverse effects of increased temperatures and improvements the probability of enhanced photosynthesis for C3 plants (Chavas et al. 2009; Kheir et al. 2019). Regression analyses in this study also indicate that elevated CO_2 levels significantly contribute to crop yield (Table 4).

In addition, rainfed yield variability was influenced by projected variations in precipitation, which varied 5–25% among the 27 GCMs. In addition, the inter-annual variations in precipitation resulted differences in soil moisture availability, a crucial constraint for crop production in dryland farming. The variation in soil moisture will likely exert a significant impact on projected rainfed canola yields. Our findings point to the importance of implementing adaptive irrigation strategies compensating for deficiencies in soil moisture to sustain canola yield under shifting climate conditions. Supplementary irrigation strategies, specifically

Table 4 Coefficients of multiple linear regression for APSIM-simulated yield change as a function of climate variables and irrigation

Treatment	a	b	c	D	e	R^2
ARR0	1.40	-38.69	-0.38	145.49***	-	0.83
ARR1	1.02	-44.14	-0.60	153.48***	-1.02*	0.83
ARR2	6.93***	9.12	-2.80	75.17**	3.17**	0.83
ARR3	11.76***	42.69	2.77	52.87*	5.96***	0.87
ARR4	11.54***	47.10*	-0.52	57.35**	6.27***	0.90
ARR5	10.94***	66.52**	2.43	53.61**	5.76***	0.88
ARR6	12.70***	83.82***	5.96	31.91	7.45***	0.91
ARR7	12.88***	83.47***	3.78	36.30*	7.20***	0.90
ARR8	13.20***	86.05***	4.64	23.56*	8.67***	0.92
ARR9	13.24***	81.03***	6.46*	21.74	9.69***	0.92

Note: The multiple linear regression model describes APSIM-simulated yield change (ΔY, kg ha^{-1}) as a function of changes in growing season precipitation (ΔPrcp, %), mean temperature (ΔTmean, °C), solar radiation (ΔRad, %), CO_2 concentration (ΔCO_2, 100 ppm), and irrigation amount (ΔIrri, %). The model follows the form: $\Delta Y = a\Delta Prcp + b\Delta Tmean + c\Delta Rad + d\Delta CO_2 + e\Delta Irri$. *, *, and *** indicate significance levels at $P = 0.05$, $P = 0.01$, and $P = 0.001$, respectively

ARR1-ARR6, demonstrated that growers could potentially elevate the rainfed yield potential by adopting a deficit irrigation approach from 85 to 150 mm. Similarly, Wang et al. (2023) found that optimizing irrigation regimes could maintain and enhance crop yields in changing climates conditions. Moreover, our findings mirror the observations in previous literature, where climate change has shown positive influence on canola yield, particularly in rainfed scenarios (Tian et al. 2018). The increase in the crop yield relative to the baseline in our study reinforces this argument.

Impacts of climate change on irrigation amount and water productivity

To determine the most effective irrigation strategy for maximizing canola yield under future climate change scenarios, we simulated nine distinct irrigation treatments (Fig. 5). It was observed that the irrigation amounts decreased across all climate change scenarios and projected time periods. The most significant reduction in irrigation, 30%, occurred in the 2090s under the SSP585 scenario, while the least was in 2030 under SSP245. This decrease can be attributed to the predicted increase in precipitation in future periods under both climate change scenarios (Fig. 2c) and also our regression model exhibited that 1% increase in canola growing season precipitation led to a 1.4% increase in canola yield (Table 4). Furthermore, the projected increase in CO_2 concentration and the shortening of crop growth duration as a result of rising temperatures under future climate change are both factors that contribute to a decreased necessity for irrigation (Tian et al. 2023). Moreover, the projected increase in atmospheric CO_2 levels under future climate scenarios demonstrated a positive effect on canola water productivity. This could be linked to increased water productivity in canola at the leaf level where net photosynthetic assimilation rate increases and stomatal conductance decreases under higher CO_2 concentration as reported by Uddin et al. (2018). In the 2090s, there is a slightly higher water productivity (8%) of rainfed crop for SSP585 compared to SSP245. This finding is consistent with the research conducted by Xing et al. (2019) and Qian et al. (2019) who reported that canola's water productivity (WP) is expected to improve in future climate change scenarios due to increased CO_2 fertilization.

Applying 85–150 mm of irrigation (ARR1-ARR6) resulted in an improvement of rainfed yield by 12–28% across the three-time periods under both SSP scenarios (Fig. 4). Similarly, when applying 160–210 mm of irrigation (ARR7- ARR9), the rainfed yield showed an improvement of 13–14% in the same time periods. This indicates that irrigation strategies from ARR1-ARR6 can be used as optimal supplemental irrigation range to enhance yields. This finding suggests that canola requires supplementary irrigation to achieve reasonable yields in semi-arid regions since precipitation alone is insufficient for growth and production (George et al. 2018; Zhang et al. 2019). Additionally, the irrigated yield remained largely unchanged after the irrigation treatment ARR6. It is important to note that if an irrigation treatment with additional water has a similar trend to a lower irrigation amount, it can be disregarded (Mpanga and Idowu 2021; Zou et al. 2021). However, this may not be accurate for all study cases or environment. The decision to ignore an irrigation treatment should be based on various factors, such as the type of crop being grown, the soil type, and the climate conditions (Pereira et al. 2002). Also, Hergert et al. (2016) found that by applying 50–67% of full irrigation canola yield reached 93–100% and 60–75% of potential yield during wet and dry years, respectively. Moreover, in this study the ARR1 irrigation treatment showed high water savings ranging from 2.2 to 80% compared to other irrigation strategies (ARR2-ARR9) across the three time periods under both SSP scenarios as depicted in Fig. 6. Based on this observation, it may be beneficial to consider

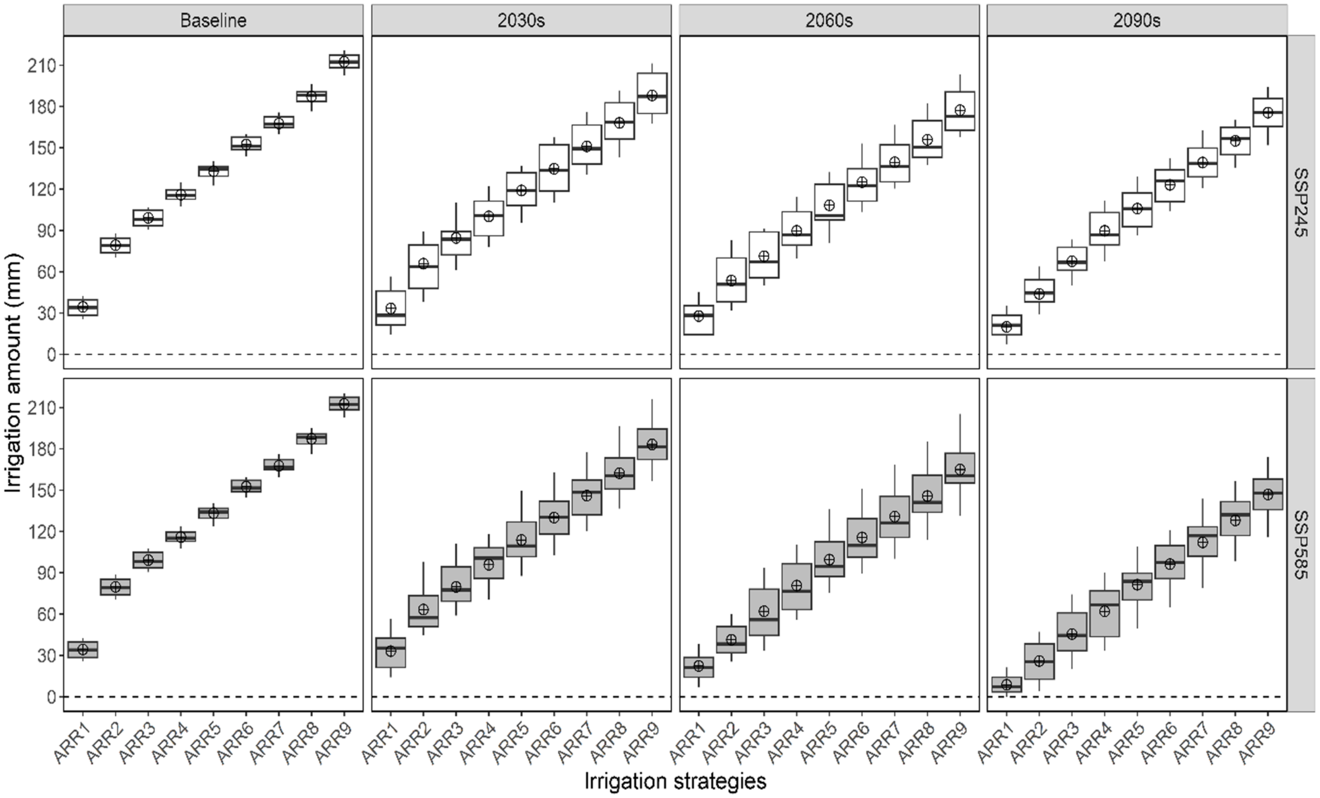

Fig. 5 Simulated irrigation amount during baseline (1961–2010), 2030s, 2060s, and 2090s under SSP245 and SSP585 using 27 downscaled GCMs for 10 irrigation strategies (ARR0: Rainfed, ARR1–ARR9: Irrigation strategies). Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

deficit irrigation for Canola cultivation, in areas where water availability is shrinking due to competition with other sectors or during drought years (Katuwal et al. 2020). According to this study and field practices, the amount of irrigation needed for deficit irrigation (ARR1) during each period would be between 20 and 40 mm. This demonstrates significant potential for water conservation when compared to the current irrigation practices, which range from 85 to 100 mm in Guanzhong Plain. These results are consistent with findings of Saddique et al. (2020a, b), who reported that agricultural practices, such as adjusting planting dates and irrigation schedules, can effectively enhance water productivity and combat climate challenges. Canola is generally considered a plant that can grow in arid climates. However, it has been observed that providing irrigation during the plant's rapid growth stages can considerably impact both the yield and yield components (Dogan et al. 2011). This effect is particularly noticeable during drought years. Therefore, it is recommended that supplementary irrigation be applied if water is available to ensure that the canola can develop and yield economically viable crops.

Impacts of climate change on Canola gross margin

Our simulation results indicate that the impact of climate change on the gross margin differs significantly between rainfed and irrigation scenarios. In the rainfed gross margin, all climate change scenarios showed an improvement of up to 38% relative to the baseline gross margin (Fig. 7). The results suggest that the yield of canola crops is likely to increase in regions where climate change is favorable, leading to higher profits for rainfed canola growers. These findings are consistent with a study conducted by Tian et al. in 2018, who reported that future climate change indicated positive impact on canola yield in Shaanxi region. It is evident that the overall profitability of rainfed canola would be affected by climate change. This impact depends on the balance between climate change's positive and negative effects, as well as the adaptation and mitigation strategies employed by canola growers (He et al. 2022).

Irrigated canola profitability varied under future climate scenarios, with strategies AAR1 to AAR9 positively impacting gross margins. AAR1 is the most beneficial irrigation strategy, yielding a 58% gross margin. The finding suggests that optimizing irrigation strategies can improve

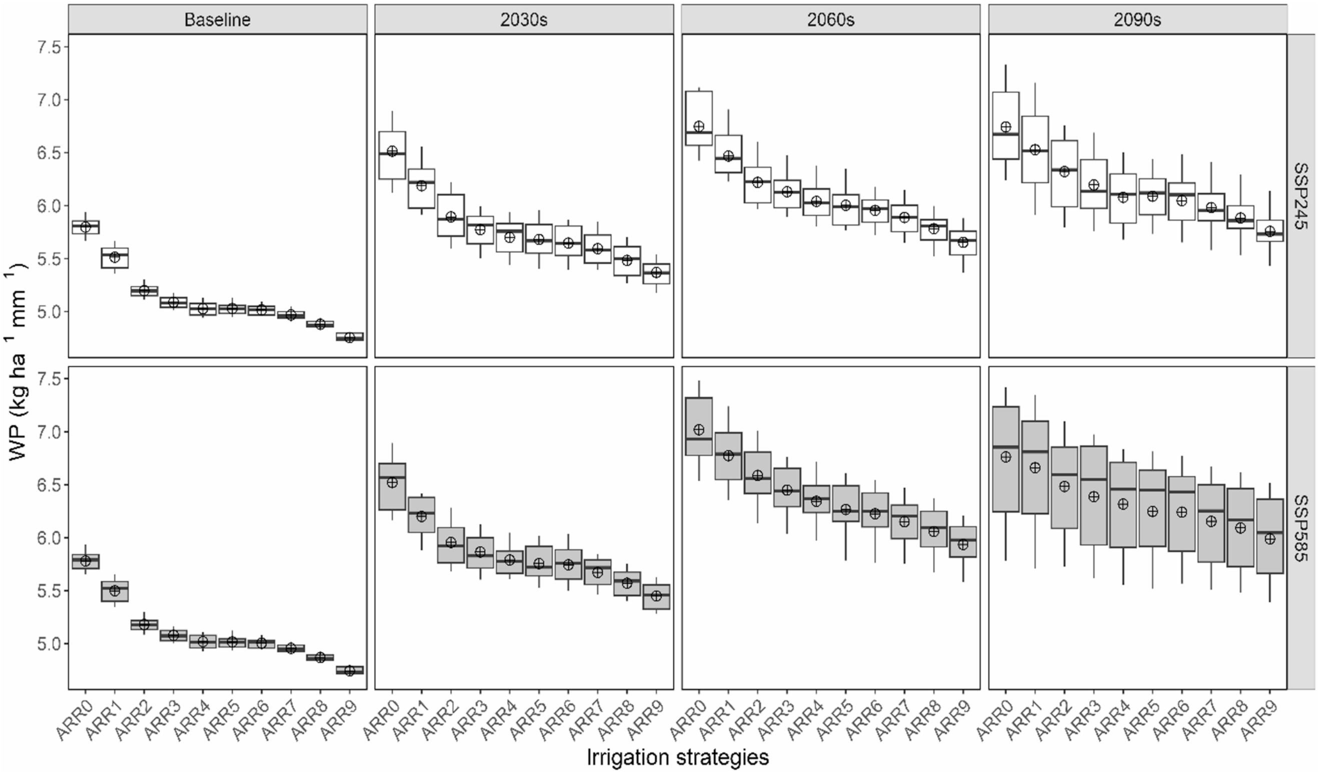

Fig. 6 Simulated Water productivity (WP) during baseline (1961–2010), 2030s, 2060s, and 2090s under SSP245 and SSP585 using 27 downscaled GCMs for 10 irrigation strategies (ARR0: Rainfed, ARR1–ARR9: Irrigation strategies). Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

the profitability of irrigated canola crops (Nielsen et al. 2012). Furthermore, the gross margin of AAR6 is not significantly different from AAR7-AAR9, which are higher in irrigation amount, indicating that water-related cost can be saved while still achieving similar profits (Mandryk et al. 2017). This implies that adopting optimized irrigation strategies can help save water and buffer the volatility of water prices, leading to reduced water costs compared to full irrigation strategies (Chen 2023; Tang et al. 2020; Toan 2016; Yazdi et al. 2016). Higher yields may not guarantee enhanced profitability when water prices are subject to increase. The interplay between water costs and canola margins underscores the need for growers to have access to decision support systems to better understand the governing factors of profitability related to water price and other variable costs (Muleke et al. 2022). Therefore, it is crucial for canola growers to consider water price volatility as a critical factor in canola production. To mitigate the risks and take advantage of water price opportunities, growers need to monitor and manage water price in their local water use scenario, considering their water price tolerance for both grain and cash crops (Huang et al. 2023). The decision of buying costly water to produce high yield crop may be linked to market price fluctuation of canola that could be based on the dynamics of international trade. For example, restrictions imposed by China on Canadian canola imports caused canola prices to ramp up nationally (Wang 2019; Cardwell and Brewin 2019). Such scenario may provide justification for supplying additional expense water to crop.

Limitation and uncertainties

Our research assumed fixed thresholds of PAWC for irrigation under consistent sowing dates, cultivar, and fertilizer quantities for historical and future timeframes. This can be considered as a limitation of this study as different cultivars would interact differently with varying PAWC thresholds, sowing dates and fertilizer application under future climate change in the Guanzhong Plain, China. Uncertainties associated with APSIM-Canola also adds to the limitations of this study. For example, He at al. (2017) reported the issues related to parameter optimization due to lack of granularity in the APSIM-Canola to differentiate between vernalization and photoperiod sensitive phases. In addition, APSIM-Canola utilizes radiation use efficiency-based approach (developed for other C3 crops) to simulate growth response to CO_2, which in comparison to other models who use generic C3 photosynthesis model could be less accurate

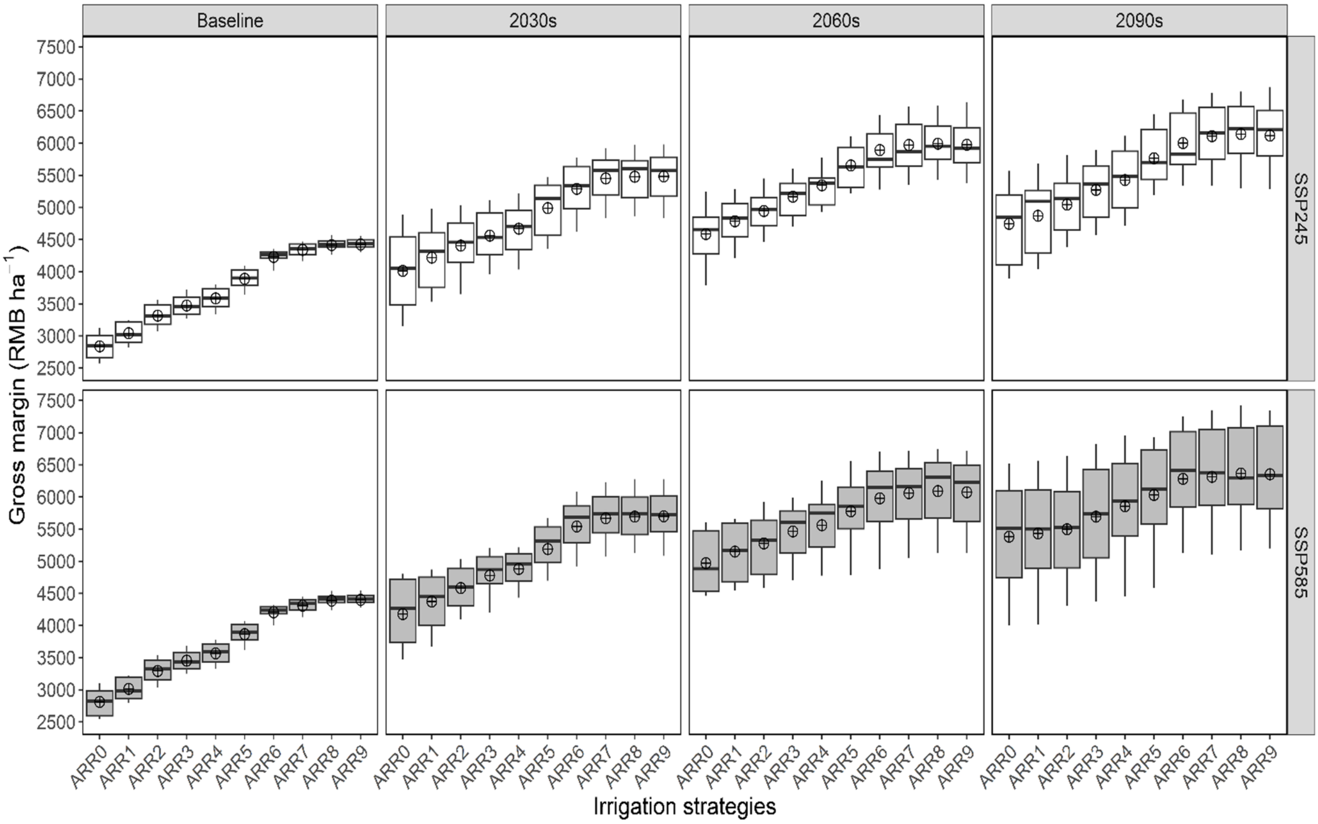

Fig. 7 Simulated Gross margin during baseline (1961–2010), 2030s, 2060s, and 2090s under SSP245 and SSP585 using 27 downscaled GCMs for 10 irrigation strategies (ARR0: Rainfed, ARR1–ARR9: irrigation strategies). Box boundaries indicate the 25th and 75th percentiles across GCMs, whiskers below and above the box indicate the 10th and 90th percentiles. The black lines and crosshairs within each box indicate the multi-model median and mean respectively

(Wang et al. 2022) especially for studying specific environmental interactions.

Conclusion

This study results showed that calibrated APSIM-Canola can be reliably used in the region for predicting role of irrigation in enhancing rainfed canola yield under different climate change scenarios in 2030s, 2060s and 2090s. The changes in climate are expected to influence the phenology of canola, with early flowering and maturity dates projected across all irrigation strategies. For both rainfed and irrigated canola production, positive impact on yield was noted in future climate scenarios. The rainfed yield improved up to 19%, whereas the deficit irrigation strategies (ARR1-ARR6) emerged as optimal strategies to further enhance canola yields, with growing season irrigation application ranging between 85 and 150 mm. Impacts on gross margins for rainfed and irrigated scenarios varied. Rainfed canola showed increased profitability (up to 38%), while the profitability of irrigated canola was highest for ARR1 (58%), highlighting the need for growers to adapt to changing water availability and prices. The study underscores the importance of considering water price volatility in decision-making processes to optimize both yield and profitability. Moreover, future research should explore potential impacts of other factors on canola productivity and profitability, such as soil nutrients and salinity, groundwater depletion, and water quality.

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Author contributions QS: manuscript text, study concept, model calibration and evaluation; DLL: Climate data, simulation, AA and BW: Review and edit, XG: Experiment data, MA: Review and edit, PF: Figures, YW: Review and edit, YZ: Data collection, HC: Funding and supervisionanalysis.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

References

Ali S, Xu Y, Ma X, Ahmad I, Kamran M, Zhaoyun, Dong Z, Tie C, Qianmin J, Xiaolong R, Zhang P, Zhikuan J (2017) Planting patterns and deficit irrigation strategies to improve wheat production and water productivity under simulated rainfall conditions. Front Plant Sci 8:1408

Anwar MR, Liu DL, Farquharson R, Macadam I, Abadi A, Finlayson J, Wang B, Ramilan T (2015) Climate change impacts on phenology and yields of five broadacre crops at four climatologically distinct locations in Australia. J Agric Food Syst Community Dev 13:133–144

Asseng S, Ewert F, Martre P, Rotter RP, Lobell DB, Cammarano D, Kimball BA, Ottman MJ, Wall GW, White JW, Reynolds MP, Alderman PD, Prasad PVV, Aggarwal PK, Anothai J, Basso B, Biernath C, Challinor AG, DeSanctis G, Doltra J, Fereres E, Garcia-vila M, Gayler S, Hoogenboom G, Hunt LA, Izaurralde RC, Jabloun M, Jones CD, Kersebaum KC, Koehler AK, Muller C, Nareshkumar S, Nendel C, O'Leary G, Olesen JE, Palosuo T, Priesack E, Eyshirezaei E, Ruane AC, Semenov MA, Shcherbak I, Stockle C, Stratonovitch P, Streck T, Supit I, Tao F, Thorburn PJ, Waha K, Wang E, Wallach D, Wolf J, Zhao Z, Zhu Y (2015) Rising temperatures reduce global wheat production. Nat Clim Chang 5:143–147

Bai H, Xiao D, Wang B, Liu DL, Tang S J (2022) Simulation of wheat response to future climate change based on coupled model intercomparison project phase 6 multi-model ensemble projections in the North China plain. Front Plant Sci 13:829580

Cardwell R, Brewin DG (2019) Blackleg or blackmail? Economics of the Canada–China Canola trade dispute. Can J Agr Econ 67:251–260

Chavas DR, Izaurralde RC, Thomson AM, Gao XJ (2009) Long-term climate change impacts on agricultural productivity in Eastern China. Agric Meteorol 149:1118–1128

Chen Y (2020) Increasingly uneven intra-seasonal distribution of daily and hourly precipitation over Eastern China. Environ Res Lett 15:104068

Chen Z (2023) Management of surface flow allocation in rice cultivation by maximization of water use and economic efficiency. Water Supply 24:133–140

Chen S, Wang Y, Zhu T (2014) Exploring china's farmer-level water-saving mechanisms: analysis of an experiment conducted in Taocheng district, Hebei Province. Water 6:547–573

Cui Q, Ali T, Xie W (2022) The uncertainty of climate change impacts on china's agricultural economy based on an integrated assessment approach. Mitig Adapt Strateg Glob Chang 27:25

Dogan E, Copur O, Kahraman A, Kirnak H, Guldur ME (2011) Supplemental irrigation effect on Canola yield components under semiarid Climatic conditions. Agric Water Manage 98:1403–1408

FAO (Food and Agriculture Organization) (2015) Climate change and food security: risks and responses. FAO. https://openknowledge.fao.org/server/api/core/bitstreams/a4fd8ac5-4582-4a66-91b0-55abf642a400/content. Accessed 1 Nov 2023

FAO (Food and Agriculture Organization) (2019) FAOSTAT: FAO Statistical Databases. http://www.fao.org/faostat/. Accessed 1 Jan 2024

George N, Thompson SE, Hollingsworth J, Orloff S, Kaffka S (2018) Measurement and simulation of water-use by Canola and camelina under cool-season conditions in California. Agric Water Manag 196:15–23

Gu XB, Cai HJ, Zhang ZT, Fang H, Chen PP, Huang P, Li YP, Li YN, Zhang L, Zhou JM, Du YD (2019) Ridge-furrow full film mulching: an adaptive management strategy to reduce irrigation of dryland winter rapeseed (Brassica Napus L.) in Northwest China. Agric Meteorol 266–267:119–128

Guo C, Bai Z, Wang X, Zhang W, Chen X, Prakash L, Ma L, Lu J, Liu B, Shi X (2022) Spatio-temporal assessment of greenhouse gas emission from rapeseed production in China by coupling nutrient flows model with LCA approach. Food Energy Secur 11

He D, Wang J, Wang E (2015) Modelling the impact of climate variability and irrigation on winter Canola yield and yield gap in Southwest China. 21st Congress on modelling and simulation. Gold Coast, Australia

He D, Wang E, Wang J, Lilley JM (2017) Genotype × environment × management interactions of Canola across china: a simulation study. Agric Meteorol 247:424–433

He Q, Liu DL, Wang B, Li L, Cowie A, Simmons A, Zhou H, Tian Q, Li S, Li Y, Liu K, Yan H, Harrison MT, Feng P, Waters C, Li GD, Voil PD, Yu Q (2022) Identifying effective agricultural management practices for climate change adaptation and mitigation: A win-win strategy in South-Eastern Australia. Agric Syst 203:103527

Hergert GW, Margheim JF, Pavlista AD, Martin DL, Supalla RJ, Isbell TA (2016) Yield, irrigation response, and water productivity of deficit to fully irrigated spring Canola. Agric Water Manag 168:96–103

Holzworth DP, Huth NI, Zurcher EJ, Herrmann NI, McLean G, Chenu K, van Oosterom EJ, Snow V, Murphy C, Moore AD (2014) APSIM–evolution towards a new generation of agricultural systems simulation. Environ Model Softw 62:327–350

Huang Y, Wang S, Li X, Cheng D, Wang Z, He B, Fan Y (2023) Agricultural irrigation water price apportionment and sharing. Water Policy 25:429–445

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. Systems approaches for sustainable agricultural development. Kluwer Academic, Dordrecht

IPCC, Geneva, Switzerland IPCC (2018) Global warming of 1.5°C An IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.https://archive.ipcc.ch/report/sr15/pdf/sr15_citation.pdf

IPCC (2023). Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II, and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva, Switzerland

Jannat A, Ishikawa-Ishiwata Y, Furuya J (2022) Does climate change affect rapeseed production in exporting and importing countries?? Evidence from market dynamics syntheses. Sust 14:6051

Katuwal KB, Cho Y, Singh S, Angadi VS, Begna S, Stamm M (2020) Soil water extraction pattern and water use efficiency of spring Canola under growth-stage-based irrigation management. Agric Water Manag 239:106232

Keating BA, Carberry PS, Hammer GL, Probert ME, Robertson MJ, Holzworth D, Huth NI, Hargreaves JN, Meinke H, Hochman Z (2003) An overview of APSIM, a model designed for farming systems simulation. Eur J Agron 18:267–288

Kheir AMS, El Baroudy A, Aiad MA, Zoghdan MG, Abd El-Aziz MA, Ali MGM et al (2019) Impacts of rising temperature, carbon dioxide concentration and sea level on wheat production in North nile delta. Sci Total Environ 651:3161–3173

Kothari K, Alea S, Bordovsky JP, Thorp KR, Porter DO, Munster CL (2019) Simulation of efficient irrigation management strategies for grain sorghum production over different climate variability classes. J Agric Food Syst Community Dev 170:49–62

Li Y, Liu DL, Schwenke G et al (2017) Responses of nitrous oxide emissions from crop rotation systems to four projected future climate change scenarios on a black vertosol in subtropical Australia. Clim Change 142:545–558

Lin Y, Feng Z, Wu W, Yang Y, Zhou Y, Xu C (2017) Potential impacts of climate change and adaptation on maize in Northeast China. Agron J 109:1476–1490

Liu DL, Zuo H (2012) Statistical downscaling of daily climate variables for climate change impact assessment over new South wales, Australia. Clim Chang 115:629–666

Liu DL, Anwar MR, O'Leary GJ, Conyers MK (2014) Managing wheat stubble as an effective approach to sequester soil carbon in a semi-arid environment: spatial modelling. Geoderma 214–215:50–61

Liu Q, Niu J, Sivakumar B, Ding R, Li S (2021) Accessing future crop yield and crop water productivity over the Heihe river basin in Northwest China under a changing climate. Geosci Lett 8:2

Lobell DB (2014) Climate change adaptation in crop production: beware of illusions. Global Food Sect. 3:72–76

Mandryk M, Reidsma PM, van Ittersum KM (2017) Crop and farm level adaptation under future climate challenges: an exploratory study considering multiple objectives for flevoland, the Netherlands. Agric Syst 152:154–164

Mavromatis T, Boote K, Jones J, Irmak A, Shinde D, Hoogenboom G (2001) Developing genetic coefficients for crop simulation models with data from crop performance trials. Crop Sci 41:40–51

Meier E, Lilley J, Kirkegaard J, Whish J, McBeath T (2020) Management practices that maximise gross margins in Australian Canola (Brassica Napus L). Field Crop Res 252:107803

Mpanga IK, Idowu OJ (2021) A decade of irrigation water use trends in Southwestern USA: the role of irrigation technology, best management practices, and outreach education programs. Agric Water Manag 243:106438

Muleke A, Harrison MT, Eisner R, de Voil P, Yanotti M, Liu K, Yin X, Wang W, Monjardino M, Zhao J, Zhang F, Fahad S, Zhang Y (2022) Whole farm planning raises profit despite burgeoning climate crisis. Sci Rep 12:17188

NIC (2009) China: impact of climate change to 2030. A Commissioned Research Report

Nielsen DC, Saseendran SA, Ma L, Ahuja LR (2012) Simulating the production potential of dryland spring Canola in the central great plains. Agric Meteorol 104:853–969

Pereira LS, Oweis T, Zairi A (2002) Irrigation management under water scarcity. Agric Water Manag 57:175–206

Qian B, Jing Q, Bélanger G, Shang J, Huffman T, Liu J, Hoogenboom G (2018) Simulated Canola yield responses to climate change and adaptation in Canada. Agron J 110:133–146

Qian B, Zhang X, Smith W, Grant B, Jing Q, Cannon AJ, Neilsen D, McConkey B, Li G, Bonsal B (2019) Climate change impacts on Canadian yields of spring wheat, Canola and maize for global warming levels of 1.5°C, 2.0°C, 2.5°C and 3.0°C. Environ Res Lett 14:1–13

Richardson CW, Wright DA (1984) WGEN: A model for generating daily weather variables. U.S. Department of Agriculture, Agricultural Research Service, Washington, DC

Saddique Q, Cai H, Ishaque W, Chen H, Chau HW, Chattha MU, Hassan MU, Khan MI, He J (2019) Optimizing the sowing date and irrigation strategy to improve maize yield by using CERES-Maize model. Agronomy 9:109

Saddique Q, Cai HJ, Xu JT, Ajaz A, He JQ, Yu Q, Wang YF, Chen H, Khan MI, Liu DL (2020a) Analyzing adaptation strategies for maize production under future climate change in Guanzhong plain, China. Mitig Adapt Strateg Glob Chang 25:1523–1543

Saddique Q, Liu DL, Wang B, Feng P, He J, Ajaz A, Ji J, Xu J, Zhang C, Cai H (2020b) Modelling future climate change impacts on winter wheat yield and water use: A case study in Guanzhong plain, Northwestern China. Eur J Agron 119:126113

Secchi MA, Fernandez JA, Stamm MJ, Durrett T, Prasad PVV, Messina CD, Ciampitti IA (2023) Effects of heat and drought on Canola (Brassica Napus L.) yield, oil, and protein: A meta-analysis. Field Crop Res 293:108848

Shen H, Chen Y, Wang Y, Xing X, Ma X (2020) Evaluation of the potential effects of drought on summer maize yield in the Western Guanzhong plain, China. Agronomy 10:1095

Tang K, Hailu A (2020) Smallholder farms' adaptation to the impacts of climate change: evidence from china's loess plateau. Land Use Policy 91:104353

Tang J, Folmer H, Xue J (2015) Technical and allocative efficiency of irrigation water use in the Guanzhong plain, China. Food Policy 50:43–52

Tian Z, Ji YH, Sun LX, Xu XL, Fan DL, Zhong HL, Liang ZR, Fischer G (2018) Changes in production potentials of rapeseed in the Yangtze river basin of China under climate change: Multi-model ensemble approach. J Geogr Sci 28:1700–1714

Tian X, Dong J, Jin S, Zhang X, Zhao Y, Li L, Li L, Du Y, Zhang W, Chen J (2023) Climate change impacts on regional agricultural irrigation water use in semi-arid environments. Agric Water Manag 281:108239

Toan TD (2016) Water pricing policy and subsidies to irrigation: a review. Environ Process 3:1081–1098

Uddin S, Löw M, Parvin S, Fitzgerald GJ, Tausz-Posch S, Armstrong R, Michael T (2018) Yield of Canola (Brassica Napus L.) benefits more from elevated CO2 when access to deeper soil water is improved. Environ Exp Bot 155:518–528

Wang Z (2019) Canola disputes in Canada-China agricultural trade: a Chinese policy perspective. Canadian Agri-Food Policy Institute. https://capi-icpa.ca/

Wang B, Liu DL, Asseng S, Macadam I, Yu Q (2015) Impact of climate change on wheat flowering time in Eastern Australia. Agric Meteorol 209:11–21

Wang J, Zhang L, Huang J (2016) How could we realize a win-win strategy on irrigation price policy? Evaluation of a pilot reform project in Hebei province, China. J Hydrol 539:379–391

Wang J, Yang Y, Huang J, Adhikari B (2019) Adaptive irrigation measures in response to extreme weather events: empirical evidence from the North China plain. Reg Environ Change 19:1009–1022

Wang EL, He D, Wang J, Lilley JM, Christy B, Hofmann MP, Leary G, Hatfield JL, Ledda L, Deligios PA, Grant B, Jing Q, Nendel

C, Kage H, Qian BD, Rezaei EE, Smith W, Weymann W, Ewert F (2022) How reliable are current crop models for simulating growth and seed yield of Canola across global sites and under future climate change? Clim Chang 172:20

Wang B, Dam JV, Yang X, Ritsema C, Du T, Kang S (2023) Reducing water productivity gap by optimizing irrigation regime for winter wheat-summer maize system in the North China plain. Agric Water Manag 280:108229

Wen F, Fang X, Khanal R, An M (2023) The effect of sectoral differentiated water tariff adjustment on the water saving from water footprint perspective: A case study of Henan Province in China. J Clean Prod 393:136152

Willmott CJ (1982) Some comments on the evaluation of model performance. Bull Am Meteorol Soc 63:1309–1313

Wu H, Qian H, Chen J (2017) Assessment of agricultural drought vulnerability in the Guanzhong plain, China. Water Resour Manage 31:1557–1574

Wu B, Quan Q, Huang X, Deng J (2022) Response of extreme precipitation to Climatic warming in the Weihe river basin, China and its mechanism. Open Geosci 14:853–862

Xia XL, Yang L, Jing W, Xia MH, Rui B, Yang S, Qi HU, Ying ZJ, Wei CR (2022) Adaptability evaluation of staple crops under different precipitation year types in four ecological regions of inner Mongolia based on APSIM. (**in Chinese**)

Xiao D, Liu DL, Wang B, Feng P, Waters C (2020) Designing high-yielding maize ideotypes to adapt to changing climate in the North China plain. Agric Syst 181:102805

Xie W, Huang J, Wang J, Cui Q, Robertson R, Chen K (2020) Climate change impacts on china's agriculture: the responses from market and trade. China Eco Rev 62:101256

Xing H, Liu DL, Li G et al (2017) Incorporating grain legumes in cereal-based cropping systems to improve profitability in Southern new South wales, Australia. Agric Syst 154:112–123

Xing H, Brill R, Li G, Liu DL, Blake A, Slinger D (2019) Future climate change increases canola productivity and water productivity in the rainfed cropping systems of Southern Australia. Proceedings of the 2019 Agronomy Australia Conference, 25–29. Available at: www.agronomyaustralia.org/conference-proceedings

Xu F, Wang B, He C, Liu DL, Feng P, Yao N, Zhang R, Xu S, Xue J, Feng H (2021) Optimizing sowing date and planting density can mitigate the impacts of future climate on maize yield: A case study in the Guanzhong plain of China. Agronomy 11:1452

Yazdi M, Khalilzadeh M, Asgari H (2016) Design and evaluation of irrigation water pricing policies for enhanced water use efficiency. Water Resour Manage 30:1689–1702

Zhang W, Zhou T (2019) Significant increases in extreme precipitation and the associations with global warming over the global land monsoon regions. J Clim 32:8465–8488

Zhang H, Han K, Gu S, Wang D (2019) Effects of supplementary irrigation on the accumulation, distribution, and transportation of 13 C-photosynthate, yield, and water use efficiency of winter wheat. Agric Water Manag 214:1–8

Zhang Z, Chen Z, Li F (2021) Appropriate management scale of farmland and regional differences under different objectives in Shaanxi Province. China Land 10:314

Zhong S, Shen L, Sha J, Okiyama M, Tokunaga S, Liu L, Yan J (2015) Assessing the water parallel pricing system against drought in china: A study based on a CGE model with multi-provincial irrigation water. Water 7:3431–3465

Zou Y, Saddique Q, Ajaz A, Xu J, Khan MI, Qing M, Siddique KHM (2021) Deficit irrigation improves maize yield and water productivity in a semi-arid environment. Agric Water Manag 243:106483