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ORIGINAL PAPER

Evaluating rice yield and adaptation strategies under climate change based on the CSM-CERES-Rice model: a case study for northern Iran

Dorsa Darikandeh[1] · Ali Shahnazari[2] · Mojtaba Khoshravesh[2] · Gerrit Hoogenboom[3,4]

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Abstract

The goal of this simulation study was to explore how rice yield for different water supply levels will respond to climate change at a field scale in northern Iran. The CSM-CERES-Rice model was used in combination with downscaled outputs of a General Circulation Model. Three representative concentration pathways (RCP2.6, RCP4.5, RCP8.5) and seven irrigation treatments (FI (full irrigation), PRD10, PRD30, PRD60 (partial root drying in different rates), RDI10, RDI30, RDI60 (regulated deficit irrigation in different rates)) were used in this study. Moreover, three adaptation strategies were evaluated to mitigate the vulnerability of yield to climate change. The results showed that irrigated rice yield will decrease for climate change projections for 2026–2047, but the reduction was insignificant for all RCPs. Our findings confirm the hypothesis that adaptations can significantly increase the irrigated rice yield under climate change. Shifting transplanting date 2 weeks earlier with FI, RDI10, PRD10, RDI30, and PRD30 showed a higher average yield between 4.67 and 5.03 ton/ha relative to RDI60 and PRD60 reference irrigation treatments for all RCPs. Shifting nitrogen fertilizer application date 1 week earlier under RCP2.6 and RCP8.5 and 2 weeks earlier under RCP4.5 with FI resulted in the highest yield ranging from 3.13 and 4.33 ton/ha. By adjusting the amount of nitrogen fertilizer applied, the highest yield was obtained for 2.5 times the application of the current application amount with FI for all RCPs. The evaluation of these adaptation scenarios suggests that shifting transplanting date is the best strategy compared to the other two adaptations, which resulted in a higher yield with the same amount of water for all RCPs.

1 Introduction

Today, climate change and global warming are considered the most important issues in the world (Bates and Kundzewicz 2008; Yadav et al. 2015; Feliciano et al. 2022). Understanding the impact of change in precipitation patterns and magnitudes coupled with rise in temperature during the growing season is a necessity for formulating adaptation strategies to climate change (Zhang et. al.2022; Ahmed et al. 2021; Shi et al. 2020). Compared to 1995–2014, global surface temperature averaged over 2081–2100 is very likely to be higher by 0.15 to 0.95 °C under the very low GHG emission scenario and by 2.45 to 4.85 °C under the very high GHG emission scenario. In addition, the average annual global land precipitation is projected to increase by 0–5% under the very low GHG emissions scenario and 1–13% under the very high GHG emissions scenario (IPCC 2021).

Several studies in Iran have illustrated that the projected minimum and maximum temperatures will increase by the end of this century, while future precipitation may either increase or decrease depending on the region in Iran (Darand and Hamidi. 2021; Lotfirad et al. 2021; Doulabian et al. 2021).

Climate change as a global phenomenon is one of the most critical factors threatening food security, and it is expected to make food and nutrition security more challenging in the future (Rutten et al. 2014; Palazzo et al. 2017; Carpena 2019). The agricultural system is very vulnerable to climate change due to its close relationship with weather and

✉ Ali Shahnazari
aliponh@yahoo.com

1 Water Engineering Department, Sari Agricultural Sciences and Natural Resources University, Sari, Iran

2 Faculty of Agriculture, Water Engineering Department, Sari Agricultural Sciences and Natural Resources University, P.O. Box 578, Sari, Iran

3 Department of Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611-0570, USA

4 Food Systems Institute, University of Florida, Gainesville, FL 32611-0570, USA

thus climate conditions, and it is one of the first sectors to be affected by this phenomenon (Chen and Gong 2020). Climate change can affect crop yield, as well as water demand by changing the rate of crop evapotranspiration depending on the intensity and time duration of precipitation (Ashraf Vaghefi et al. 2014; Ahiablame et al. 2017; Yarmohammadi et al. 2017).

Since developing countries are heavily dependent on agriculture, the effects of climate change and global warming will pose serious food security risks for them (Allen et al. 2014; Emediegwu et al. 2022). Following wheat and maize, rice is the third most important crop in the world (Mekonnen and Hoekstra 2011; Bajus et al. 2019; Kapela et al. 2020). Drought is the most important limiting factor in rice production in the world, which has been exacerbated under the effects of climate change in recent years (Prasad et al. 2012; Dien et al. 2019; Sakoda et al. 2021).

Based on USDA 2021 statistics, the area under rice cultivation in Iran is 560 thousand hectares in this year, and the total amount of rice production is 1.9 M ton. The average yield of paddy rice in Iran is 5.14 ton per hectare (USDA 2021). Mazandaran Province located on the southern coast of the Caspian Sea in the north of Iran, with over 300 thousand hectares land area under rice cultivation, has the highest amount of rice production (Rezaei and Asadi 2013; Yousefian 2018).

Rice is considered one of the most drought-susceptible crops and, thus, is strongly affected by climate change (Sahebi et al. 2018). The occurrence of water shortages and droughts has raised concerns about the sustainability of rice production, including the main rice cultivation production region of Mazandaran in Iran (Yousefian 2018). Most studies have reported that rice production will decrease in the future due to a projected increase in temperature and a projected decrease in precipitation) Basak et al. 2010; Boonwichai et al. 2018; Nasir et al. 2020; Nicolas et al. 2020). Sheidaeian et al. (2015) found that climate change due to a decrease in precipitation and an increase in potential evapotranspiration slightly decreased yield and increased net irrigation water requirements for the Tajan river basin suited mostly in Mazandaran province in northern Iran.

Although farmers are unable to control climatic conditions, field-level management can reduce the potential negative effect of climate change on crop growth and development and ultimately yield. Management factors that can be modified include planting date, fertilizer application rate, fertilizer application date, timing and amount of irrigation applications, and various others. Darzi-Naftchali and Karandish (2016 and 2017) suggested that late transplanting dates relative to the current transplanting date can increase the irrigation water requirement and decrease the yield of rice in Mazandaran province.

Because of the numerous variations in environmental conditions and many different rice cultivars, there is no standard method for irrigation of rice in Iran (Yousefian 2018). Mismanagement or fear of drought during the rice growing season can lead to excessive water use. Furthermore, providing suitable irrigation systems and controlling irrigation are not easy and practical. Evidence shows that in Iran, permanent flooding, which is a conventional method for rice cultivation, causes problems during the growing season, such as a lack of aeration and accumulation of toxins in the root environment, plant susceptibility to pests and diseases, as well as water and soil pollutants (Yousefian 2018).

Experiences in different parts of the world have shown the efficiency of deficit irrigation in optimal use of each unit of water use and in increasing of net profit (Hasheminia 2004; Belder et al. 2004; Zhang et al. 2008; Maneepitak et al. 2019; Cheng et al. 2022). Regulated deficit irrigation (RDI) and partial root drying (PRD) are two methods of deficit irrigation that reduce water use compared to permanent flooding known as full irrigation (FI). Deficit irrigation is usually without yield reduction and sometimes with a slight reduction in yield, resulting in an increase in water productivity (Engelish et al. 1990).

Although many farmers, particularly in Iran, feel that permanent flooding conditions for rice farming are inevitable, climate change forces the use of water-saving technologies to ensure the long-term viability of irrigated rice production in paddy fields (Yousefian 2018; Mirfendereski 2021). Accordingly, it seems necessary to find new methods for rice cultivation that reduce water use and make optimal use of available water while maintaining yield due to the impact of climate change.

Many studies illustrated the impacts of climate change on rice yield in Iran, but only a few of them have considered adaptation strategies that can reduce the potential negative impact of climate change. Our hypothesis is that evaluating alternate adaptation strategies using crop simulation model can provide guidance for increasing irrigated rice production under climate change conditions. The challenge of this study is to understand the impact of climate change on rice yield for cultivation under partial root drying and regulated deficit irrigation (PRD and RDI) as water saving techniques, compared to permanent flooding as full irrigation (FI) along with adaptation strategies.

To respond to this challenge, the main focus is to explore the possibility of employing adaptation strategies including (1) change in the transplanting date, (2) change in the nitrogen fertilizer application date, and (3) change in the nitrogen fertilizer application amount, to reduce vulnerability of paddy cultivation to the potential negative effect of climate change.

2 Materials and methods

2.1 Description of experimental site

A 2-year experiment was conducted from May to August in 2015 and 2016 at the experimental field of the Iranian Rice Research Institute (36° 28′ N, 52° 27′ E; 29.8 m above sea level) in Amol, a city in the north of Iran, in Mazandaran province (Fig. 1). The site is categorized as warm temperate climate with a long-term mean annual precipitation of 800 mm and temperature of 16° C (Yousefian 2018).

The dominant soil type at the experimental site is silty clay loam with an organic carbon concentration of 1.36%, a pH of 7.1, a total neutralizing value (TNV) of 5%, and an electrical conductivity of the saturated paste extract (ECe) of 0.962 ds/m. The available phosphorus was 10 (gr soil/kg), and the available potassium was 180 (gr soil/kg). The water source for irrigation consists of a deep well located in the vicinity of the experimental field. The water quality is suitable for rice cultivation with an average salinity of 0.848 ds/m and a pH between 7.1 and 7.6 (Yousefian 2018).

2.2 Data collection

2.2.1 Meteorological data

The long-term baseline (1984–2005) observation data that included daily minimum, maximum temperature, and total

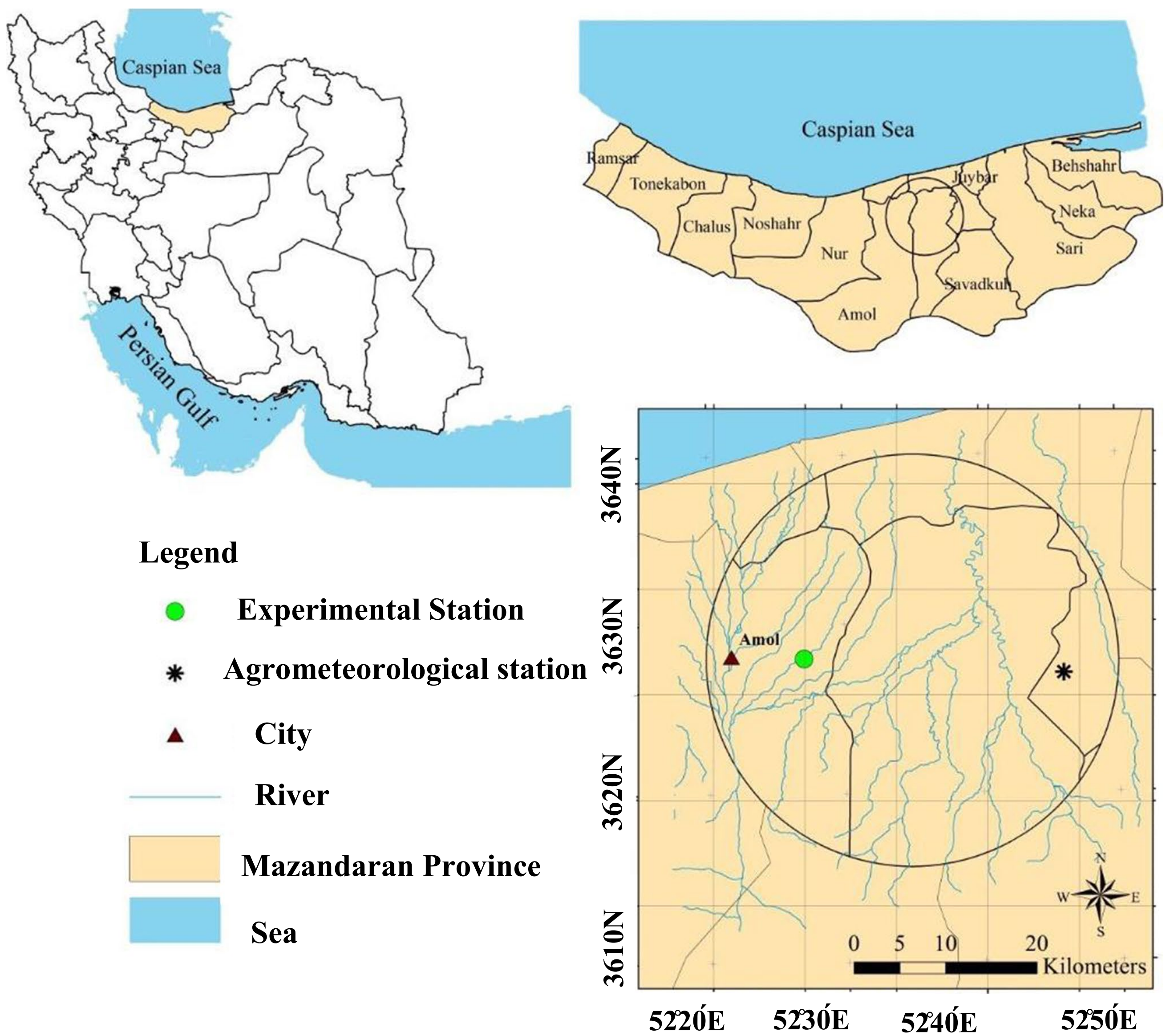


Fig. 1 Location of the study site

Table 1 GCM feature to project the future climate in this study

General Circulation Model (GCM)	Representative concentration pathway (RCP)	Resolution (latitude × longitude)	Modeling center	Reference
CanESM2	RCP2.6 RCP4.5 RCP8.5	2.79° × 2.81°	Canadian Center for Climate Modelling and Analysis (CCCma)	Chylek et al. (2011)

Table 2 Experimental details and observations for the 2015 and 2016 experiments

Year	Primary tillage	Harrowing	Transplanting	Anthesis (flowering)	Physiological maturity (harvesting)	Grain yield (ton/ha)	Planting density (m^{-2})
2015	28th April	17th May	24th May	9th July	27th August	3.71	20
2016	1st May	20th May	27th May	6th July	28th August	3.76	20

Source: Yousefian (2018)

precipitation and sunshine hours were obtained from the Gharakheil agrometeorological station (36° 27′ N, 52° 46′ E) located at a distance of 27 km from the experimental field.

Total precipitation for 2015 was 99.6 mm and for 2016 was 113.2 mm, while the average maximum temperature for 2015 was 31.48 °C and for 2016 was 31.1 °C, and the average minimum temperature for 2015 was 22.04 °C and for 2016 was 21.8 °C during rice-growing season (May to August).

2.2.2 General Circulation Model (GCM)

The climate variables including precipitation, maximum and minimum temperature, and solar radiation for the future scenarios were obtained from Second Generation Canadian Center for Climate Modelling and Analysis Earth System Model (CanESM2) General Circulation Model (GCM), developed by the National Center for Atmospheric Research, Canada (http://climatescenrios.canads.ca/page=pred-canesm2) (Table 1).

This GCM was selected based on its performance, and it has been widely used in Iran for projecting future climate (Doulabian et al. 2021; Lotfirad et al. 2021; Nikbakht Shahbazi 2019). It is a member of the Coupled Model Intercomparison Project Phase 5 (CMIP5) that is based on climate change projections under Representative Concentration Pathways (RCP2.6, RCP8.5, and RCP4.5 scenarios). RCP2.6 is the most optimistic scenario that assumes a CO_2 concentration of 421 ppm which is a low concentration pathway with a radiative forcing of approximately 2.6 Wm^{-2} by the year 2100. In contrast, RCP8.5 is the most pessimistic scenario that assumes a CO_2 concentration of more than 900 ppm; this is a high concentration pathway with a radiative forcing of approximately 8.5 Wm^{-2} by the end of year 2100. The RCP 4.5 scenario projects development in between the two extremes and assumes a CO_2 concentration between 580 and 720 ppm, which is an intermediate stabilization pathway with a radiative forcing of approximately 4.5 Wm^{-2} by the year 2100 (Moss et al. 2010; Meinshausen et al. 2011). In this study, all three RCP2.6, RCP4.5, and RCP8.5 scenarios were considered for the projection of future climate conditions.

Table 3 Morphological and qualitative traits for the rice cultivar *Hashami*

Traits	Name of rice cultivar
	Hashami
Average plant height (cm)	140
Average panicle length (cm)	27
Grain type	Long
Average number of grains per panicle	101
Average weight of 1000 grains (g)	28.10
Average yield (kg/ha)	3850–4150
Duration of germination period from seed soaking to harvest (day)	118
Duration of transplanting to harvest (day)	90–98
Leaf position	Angular
Maturity group	Early-maturing
White rice protein content (%)	8.8

Source: Rice Research Institute, Amol, Mazandaran

2.2.3 Rice crop and agronomic management practices

Experimental data were collected for the rice cultivar *Hashami*, which is one of the local cultivars and has had the highest area under cultivation in the region during the past few years (Yousefian 2018). In Table 2, the detailed observations that were collected from the field experiments conducted for 2015 and 2016 are presented.

According to the soil analysis of experimental site performed in the water and soil laboratory at rice research institute, 150 kg of N per hectare along with 100 kg of P per hectare was applied in a three-stage split application: 40% before transplanting (one week before transplanting), 30% in the middle of tillering (four weeks after transplanting), and 30% at the time of the maximum tillering (six weeks after transplanting). In addition, 100 kg of K per hectare was given to the soil in one stage (one week before transplanting) (Yousefian 2018).

Table 3 represents some morphological and qualitative characteristics of rice cultivar (*Hashami*) considered in this study.

Seven irrigation treatments were arranged in the randomized complete block design replicated three times. The irrigation treatments included permanent flooding as a control treatment)FI(, irrigation at a matric potential of − 10 kPa (PRD10, RDI10), irrigation at a matric potential of − 30 kPa (PRD30, RDI30), and irrigation at a matric potential of − 60 kPa (PRD60, RDI60) (Yousefian 2018).

RDI10 and PRD10 irrigation treatments with a total application rate of 659 and 564 mm were applied every 2 days in June and every other day in July. RDI30 and PRD30 irrigation treatments with a total application rate of 588 and 503 mm were applied every 4 days in June and every 2 days in July. RDI60 and PRD60 irrigation treatments with a total application rate of 528 and 473 mm were applied once a week in June and every 4 days in July. For the FI treatment with a total application rate of 827 mm, during each irrigation, the water height was equal to 5 cm, which was applied once a week in June and twice a week in July (Yousefian 2018).

Each experiment plot contained 7 blocked-end furrows with a length of 8 m. Irrigation was applied with plastic hoses attached to the end of a PVC pipes. The amount of water used in each treatment was measured with a volumetric water meter. In order to determine the irrigation scheduling, the soil moisture was measured using a tensiometer installed inside the ridges at a depth of 10 cm. Once the moisture reached the intended range, irrigation was performed (Yousefian 2018). According to Alizadeh (1999), a recording of 10 with a tensiometer (matric suction of − 0.1 atm) is considered a permanent saturation of root zoon, a recording of 30 with a tensiometer (matric suction of − 0.3 atm) is considered a field capacity, and a recording of 60 with a tensiometer (matric suction of − 0.6 atm) is considered a severe water stress in the rice crop.

2.3 Generation of climate change scenarios

The data sets for 1984–2005 of Gharakheil agrometeorological station acquired from the Iran Meteorological Organization were applied as the baseline data for the evaluation of the CanESM2 model. Near future (2026–2047) climate variables under three emission scenarios (RCP 2.6, RCP4.5, and RCP8.5) (Taylor et al. 2009; Moss et al. 2010) were created using CanESM2 model based on the baseline daily climate variables.

The climate variables of the CanESM2 model have a coarse spatial resolution (Table 1), and, hence, it is unsuitable to use the outputs for the local scale study. It is, therefore, necessary to downscale the climate variables to a local level for impact studies (Giorgi and Mearns 1991). Therefore, the Statistical Down Scaling Model (SDSM version 4.2.9) was used to downscale the climate variables at the geographical location of the study area. According to Wilby (1999), SDSM has the ability to capture the inter-annual variability better than other statistical downscaling approaches, such as weather generators. Ahmadi and Ghermezcheshmeh (2020) reported the high performance of SDSM in climate change studies in some stations in northern Iran in Mazandaran province.

SDSM is a combination of regressions and stochastic weather generators. The regression component of SDSM allows for establishing statistical relationship between the predictor(s) and the predictand(s). The stochastic component of SDSM allows for performing many simulations in a weather generator (Wilby 1999). SDSM needs two types of daily data. The first type corresponds to local predictands of interest, e.g., temperature, precipitation, and the second type corresponds to the data of large-scale predictors (NCEP and GCM) of a grid box closest to the study area (Wilby 1999).

The National Centre for Environmental Prediction (NCEP) regional scale predictor variables were screened using correlation analysis in order to choose the appropriate downscaling predictor variables, the predictors that were highly correlated with the predictands. To find the best correlation among the predictors and predictands, the confidence level of 95% with p-value of 0.05 was selected. The predictor variables that were highly correlated with predictands were used for calibration and evaluation of SDSM model (Wilby and Dawson 2007; Shrestha et al. 2014).

The performance of the SDSM model during the calibration and evaluation was assessed by using Percent Bias (PBIAB) and Normalized Root Mean Square Error (NRMSE) which were calculated according to Eqs. (1) and (2) respectively.

$$PBIAS = \frac{\sum_{i=1}^{n} |O_i - S_i|}{\sum_{i=1}^{n} O_i} \quad (1)$$

PBIAS values $< \pm 10$, $\pm 10 \leq$ PBIAS $< \pm 15$, $\pm 15 \leq$ PBIAS $< \pm 25$, and PBIAS $\geq \pm 25$ were classified as very good, good, satisfactory, and unsatisfactory, respectively (Moraisi et al. 2007; Thiemig et al. 2013).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - S_i\right)^2}$$

$$NRMSE(\%) = \frac{RMSE}{\overline{O_i}} \times 100 \qquad (2)$$

where n is the number of observations, S_i simulated variable for ith time, O_i observed variable for ith time, and $\overline{O_i}$ average of the observed variable for ith time.

NRMSE values 0–10%, 10–20%, 20–30%, and > 30% were classified as excellent, good, fair, and poor, respectively (Soler et al. 2007).

Downscaled weather data (under RCP scenarios) were used as inputs for CERES-Rice model of the DSSAT v.4.7.5 software for climate change impact study on rice yield.

2.4 Crop simulation model

The Crop Estimation through Resource and Environment Synthesis (CERES) crop model within the Decision Support System for Agrotechnology Transfer Cropping Systems Model (DSSAT-CSM) is a process-based dynamic crop simulation module (Jones et al. 2003; Hoogenboom et al 2019a, b). CSM simulates growth and development of daily biomass and yield for over 42 crops grown on a uniform land area based upon four sets of input data: (1) weather data (maximum and minimum temperatures, precipitation, solar radiation), (2) soil data (soil texture, organic matter, total nitrogen, etc.), (3) crop management data (planting date, irrigation application rates and dates, fertilizer application rates and dates, etc.), and (4) genotype coefficients (cultivar).

The genetic coefficients in genotype input file are mostly on the basis of photoperiod sensitivity, grain filling duration, gain weight, temperature tolerant, etc. (Boonwichai et al. 2019).

In this study, daily solar radiation was estimated based on sunshine hours per day and Angstrom–Prescott equation (Prescott 1940). The development phases of CSM-CERES-Rice are controlled by growing degree days (GDD). Main growth and development stages include juvenile, heading, anthesis (flowering), grain filling, maturity, and harvest (Yan et al. 2006; Nicolas et al. 2020). In CSM-CERES-Rice, the highest production occurs when the temperature is between the baseline and optimal temperatures (Guo et al. 2019). In order to simulate reference evapotranspiration (ET0), two methods are embedded in the model, including FAO-56 (Allen et al. 1998) (requires solar radiation, maximum and minimum temperatures, wind speed, and relative humidity data) and Priestley–Taylor (Priestley and Taylor 1972) (requires solar radiation, maximum and minimum temperature data). In our study, the Priestley–Taylor method was applied because the available climate data were suitable for this approach. The study assumes that the experimental field management practices are the same and the soil for paddy field is homogeneous and uniform during the early twenty-first century.

2.5 Calibration and evaluation of CERES-Rice

The CERES-Rice model was calibrated with the observed data obtained from the field experiment in 2015 for the treatment that consisted of full irrigation (FI) as it did not experience any drought stress. Model calibration was performed by adjusting the cultivar coefficients in order to reduce the difference between simulated and observed values for the main growth and development stages using Genotype Coefficient Calculator, GENCALC software embedded in the DSSAT v.4.7.5 software. GENCALC estimates the coefficients for a genotype by iteratively running the crop model within the approximate range of the coefficients concerned (Hunt et al. 1993; Buddhaboon et al. 2018). It compares model outputs with measured values and then automatically alters the coefficients until the simulated and measured values match or be close together (Hunt et al. 1993). The experimental data obtained from 2016 were used for independent model evaluation. The percent of deviation (d) (Eq. (3)) and the coefficient of determination (R^2) (Eq. (4)) were the goodness of indicators to evaluate the model performance by estimating the errors between simulated and observed values.

$$d = \left[\frac{S_i - O_i}{O_i}\right] \times 100 \qquad (3)$$

where d is the percent of deviation; the lower percent of deviation indicates good model performance (Araya et al. 2017).

$$R^2 = \frac{\sum S_{i\times} O_i - \sum S_i \times \sum O_i}{\sqrt{\sum S_i^2 - (\sum S_i)^2} \times \sqrt{\sum O_i^2 - (\sum O_i)^2}} \qquad (4)$$

where S_i is the simulated value and O_i observed value.

R^2 values $0.75 < R^2 \leq 1$, $0.65 < R^2 \leq 0.75$, $0.5 < R^2 \leq 0.65$, and ≤ 0.5 were classified as very good, good, satisfactory, and unsatisfactory, respectively (Moraisi et al. 2007; Thiemig et al. 2013).

2.6 Adaptation strategies

Three adaptation strategies were evaluated to reduce potential harmful effects of climate change on irrigated rice yield. These strategies include transplanting date, nitrogen fertilizer application date, and nitrogen fertilizer application rate. The simulations were conducted with the rice cultivar *Hashami* at different transplanting dates including shifting both forward and backward 1 and 2 weeks from the current (baseline) transplanting date. Additionally, simulations were run for the future climate with shifting forward and backward 1 and 2 weeks from current nitrogen fertilizer application date. The influence of changing nitrogen fertilizer application amounts of 0.5, 1.5, 2, and 2.5 times the application of the recommended amount was also evaluated.

The positive changes (increasing rice yield) compared to the baseline rice production were worth taking into consideration as adaptation strategies, while negative changes (decreasing rice yield) demonstrated inefficiency, which is not recommended for the region based on the future climate conditions.

However, the conflicting results of this study with the study of others could be related to some factors such as different crop simulation models, rice cultivars, crop management practices, and environmental conditions.

The flowchart for the workflow of this study is presented in Fig. 2. The methodology is briefly divided into three main stages. First, the RCP climate scenarios were created using CanESM2 based on the baseline daily climate data by employing Statistical Down Scaling Model (SDSM) to project future maximum and minimum temperatures and precipitation. Second, the CSM-CERES-Rice model was calibrated with the experimental data obtained from field experiment in 2015 and then evaluated with the experimental data obtained from 2016 to simulate climate change impact on irrigated rice yield for the future time period (2026–2047) through the application of seasonal analysis embedded in DSSAT v.4.7.5 software. Finally, different adaptation strategies were evaluated to determine the potential offset for the impact of climate change on rice production at a field scale.

3 Results and discussion

3.1 CERES-Rice model calibration and evaluation

The CERES-Rice model of DSSAT v.4.7.5 was used to determine the climate change impact on rice yield and to evaluate potential adaptation strategies on rice yield at a field scale. The model was calibrated with experimental data collected during the 2015 rice-growing season. The genetic

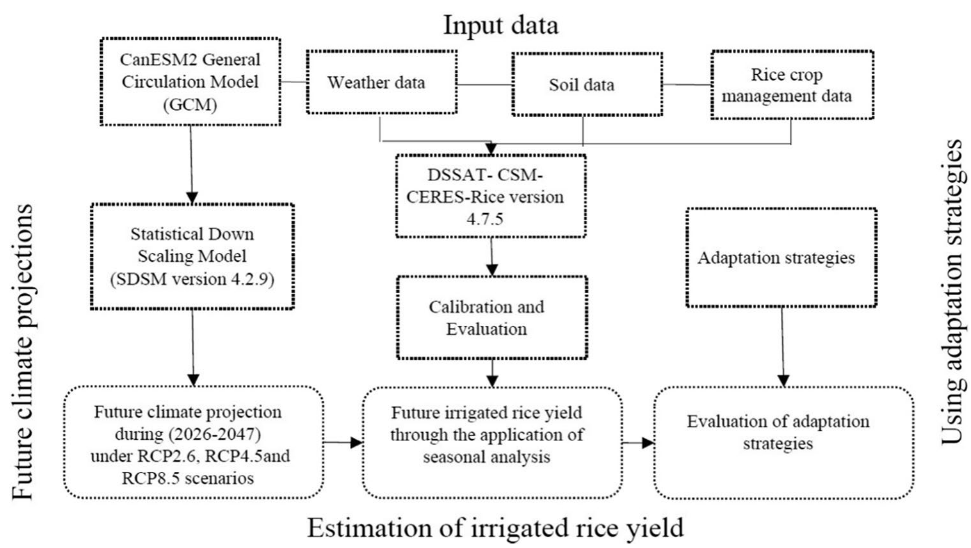


Fig. 2 Workflow used in this study

Table 4 Genetic coefficients for the rice cultivar *Hashami*

Genetic coefficient	Description	Range of values	Calibrated values
P1	Basic vegetative phase of the plant	100–880	100
P2R	Photoperiod sensitivity in panicle initiation	5–300	36.20
P5	Grain filling duration	150–850	695.00
P2O	Critical photoperiod of development occurring at a maximum rate	10–13	12.50
G1	Potential spikelet number coefficient	37–77.8	77.80
G2	Single grain weight	0.01–0.03	0.03
G3	Tillering coefficient	0.53–1.30	1.16
G4	Temperature tolerant coefficient	0.7–1.25	1.00

coefficients of *Hashemi* were estimated through combination of GENCALC (Genotype Coefficient Calculator) and trial and error. The calibrated values for the eight genetic coefficients including parameters related to vegetative (P1, P2R, and P5) and reproductive (P2O, G1, G2, G3, and G4) growth and development of rice are presented in Table 4.

The PBIAS values were 6.52%, 0%, and 16.8% for the calibration data sets which fell within the very good to satisfactory range. The *d* values were 6.5%, 0%, and – 16.8% which indicated good performance of the model during calibration period. The NRMSE values showed 6.5%, 0%, and 17.3% during calibration within the performance rating from excellent to good (Table 5).

Comparison between simulated and observed yield under different irrigation treatments shows very good performance of CERES-Rice model in the DSSAT v.4.7.5 software during calibration (Fig. 3).

The PBIAS values were 18.6%, 5.4%, and 24% for the evaluation data sets which fell within the excellent to satisfactory range. The *d* values were 18.6%, 3.2%, and – 24.4% which indicated good performance of the model during calibration period. The NRMSE values showed 18.6%, 5.4%, and 25.9% during evaluation within the performance rating from excellent to fair (Table 6).

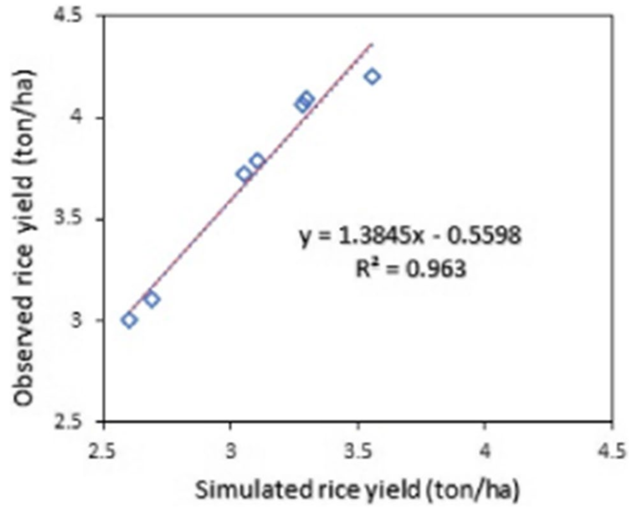


Fig. 3 Comparison between observed and simulated irrigated rice yield during calibration

3.2 SDSM calibration and evaluation

The SDSM model was calibrated using daily maximum and minimum temperature and precipitation data for the period of 1984–1999, whereas the evaluation was performed using data for the period of 2000–2005 with data recorded at the Gharakheil agrometeorological station. After calibration and evaluation, daily maximum and minimum temperatures and daily precipitation were downscaled for this agrometeorological station for assessment of climate change impacts.

The main step for calibration is to screen the local scale predictor variables (Wilby and Dawson 2007; Shrestha et al. 2014). Table 7 shows the predictors that have a significant influence on the predictands.

It is apparent that for minimum temperature, the geopotential height at 500 hpa has a very good correlation (partial *r*-value > 0.75). In addition, the divergence at 500 hpa of true wind has a significant correlation with minimum temperature (partial *r*-value > 0.25). It can also be observed that the air temperature at 2 m and the geopotential height at 500 hpa have a significant correlation with maximum temperature (partial *r*-value > 0.25). However, for precipitation, the predictor-predictand relationships are poor, and the predictors of p1-zgl (1000 hpa zonal velocity) and p8_zgl (850 hpa zonal velocity) were considered the best predictors because they had the highest partial correlation coefficient and the lowest probability value compared to the other predictor variables. Therefore, they were used for the calibration and evaluation process.

The calibration and evaluation of the SDSM model with the screened predictors indicates that the model can simulate the observed variables with a good agreement (Table 8).

Table 5 Calibration goodness of fit indicators of CERES-Rice model in the DSSAT v.4.7.5 software for the cultivar (*Hashami*)

Goodness of indicators	Anthesis (day)	Physiological maturity (day)	Rice yield (t ha^{-1})
	Oi Si	Oi Si	Oi Si
	46 49	95 95	3.71 3.14
NRMSE (%)	6.5	0	17.3
d (%)	6.5	0	– 16.8
PBIAS (%)	6.52	0	16.8

Oi observed variable

Si simulated variable

Table 6 Evaluation goodness of fit indicators of CERES-Rice model in the DSSAT v.4.7.5 software for the cultivar (*Hashami*)

Goodness of indicators	Anthesis (day)	Physiological maturity (day)	Rice yield (t ha^{-1})
	Oi Si	Oi Si	Oi Si
	43 51	92 97	3.76 2.84
NRMSE (%)	18.6	5.4	25.9
d (%)	18.6	3.2	– 24.4
PBIAS (%)	18.6	5.4	24

Oi observed variable

Si simulated variable

Table 7 Summary of selected predictor variables and their respective predictands for the Gharakheil agrometeorological station

Predictand	Predictor variables	Partial ***r***-value	Partial ***p***-value
Maximum temperature	Air temperature at 2 m (tempgl)	0.33	0
	500 hpa geopotential height (p500gl)	0.28	0
Minimum temperature	500 hpa geopotential height (p500gl)	0.78	0
	500 hpa divergence of true wind (p500zhgl)	0.26	0
Precipitation	850 hpa zonal velocity (p8_zgl)	−0.09	0
	1000 hpa zonal velocity (p1-zgl)	0.09	0

Table 8 SDSM model performance during the calibration and evaluation period

Period	Predictands	NRMSE (%)	PBIAS (%)
Calibration (1984–1999)	Maximum temperature	1.36	1.11
	Minimum temperature	1.97	1.52
	Precipitation	12.26	9.11
Evaluation (2000–2005)	Maximum temperature	1.51	1.18
	Minimum temperature	1.90	1.58
	Precipitation	8.17	6.21

Table 9 The statistical analysis t-test of the change in maximum and minimum temperatures under RCPs for Gharakheil agrometeorological station during 2026–2047

	Baseline (1984–2005)	RCP2.6	RCP4.5	RCP8.5
Maximum temperature (°C)	21.18	21.52	21.58	21.61
Change (%)*	-	+0.34 ns	+0.4 ns	+0.43 ns
Minimum temperature (°C)	12.35	12.75	12.76	12.79
Change (%)*	-	+0.4 ns	+0.41 ns	+0.44 ns

*Changes are provided relative to the baseline from 1984 to 2005

nsNon-significant difference

Simulated monthly maximum and minimum temperatures are in excellent agreement with the observed values ($0 < \mathrm{PBIAS} < 10\%$, $0 < \mathrm{NRMSE} < 10\%$). In addition, the model can simulate monthly precipitation in good agreement ($10\% < \mathrm{PBIAS} < 15\%$, $10\% < \mathrm{NRMSE} < 20\%$). In general, the simulation results for precipitation are slightly weaker than for temperature. The obtained results can also be compared to those of Charles et al. (2013) and Shrestha et al. (2014) who stated that the simulated precipitation provides weaker results than temperature due to several driving forces. Nevertheless, it is still reasonably representative and acceptable.2

3.3 Projection of future maximum and minimum temperatures

The simulation results indicate that for the study area, the average annual maximum temperature is expected to increase by 0.34 °C, 0.40 °C, and 0.43 °C under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, during the 2026–2047 period relative to the baseline (Table 9 and Fig. 4a). For the minimum temperature, a larger increase of 0.4 °C, 0.41 °C, and 0.44 °C is projected for the future period for the corresponding scenarios (Table 8 and Fig. 4b). The increment for the RCP8.5 scenario is higher than for the RCP4.5 and RCP2.6 scenarios. The statistical analysis t-test was used to determine whether there is a significant change in maximum and minimum temperature. The results presented in Table 9 show that the increase or decrease for both maximum and minimum temperature are not significant. However, this insignificance can be due to the investigation of the region's climate in the near future, when it is expected that the difference in weather conditions will not be noticeable compared to the baseline period.

Darand and Hamidi (2020) illustrated that the minimum and maximum temperatures over Iran were projected to increase. Minimum air temperature was projected to increase 0.35, 0.6, and 1 °C based on RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. In addition, maximum air temperature was projected to increase by more than 1 °C relative to the baseline period (1979–2005). Boonwichai et al. (2019) in a study carried out in Thailand also concluded that for the early century, the average annual maximum temperature increased by up to 0.9 °C under RCP4.5

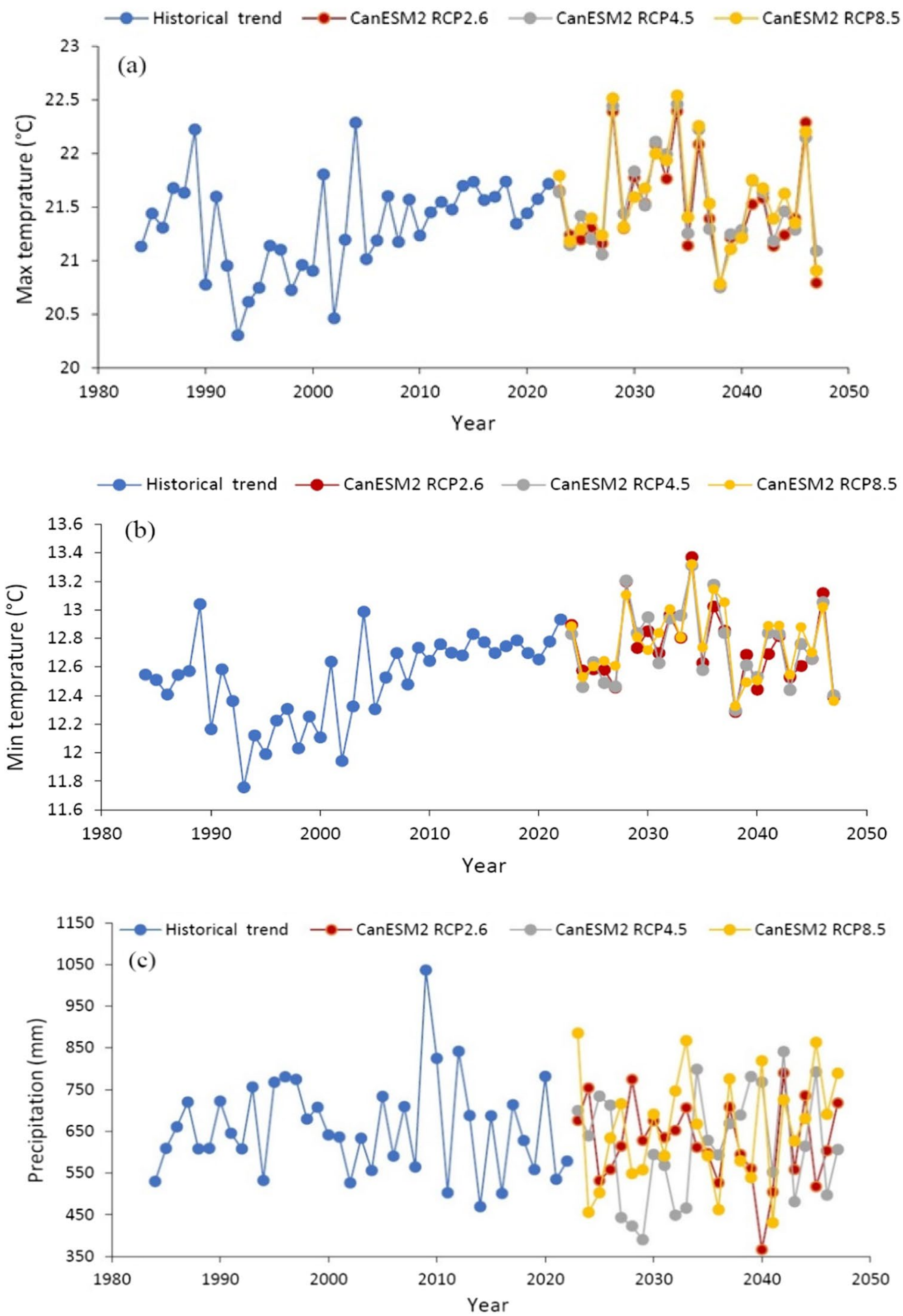


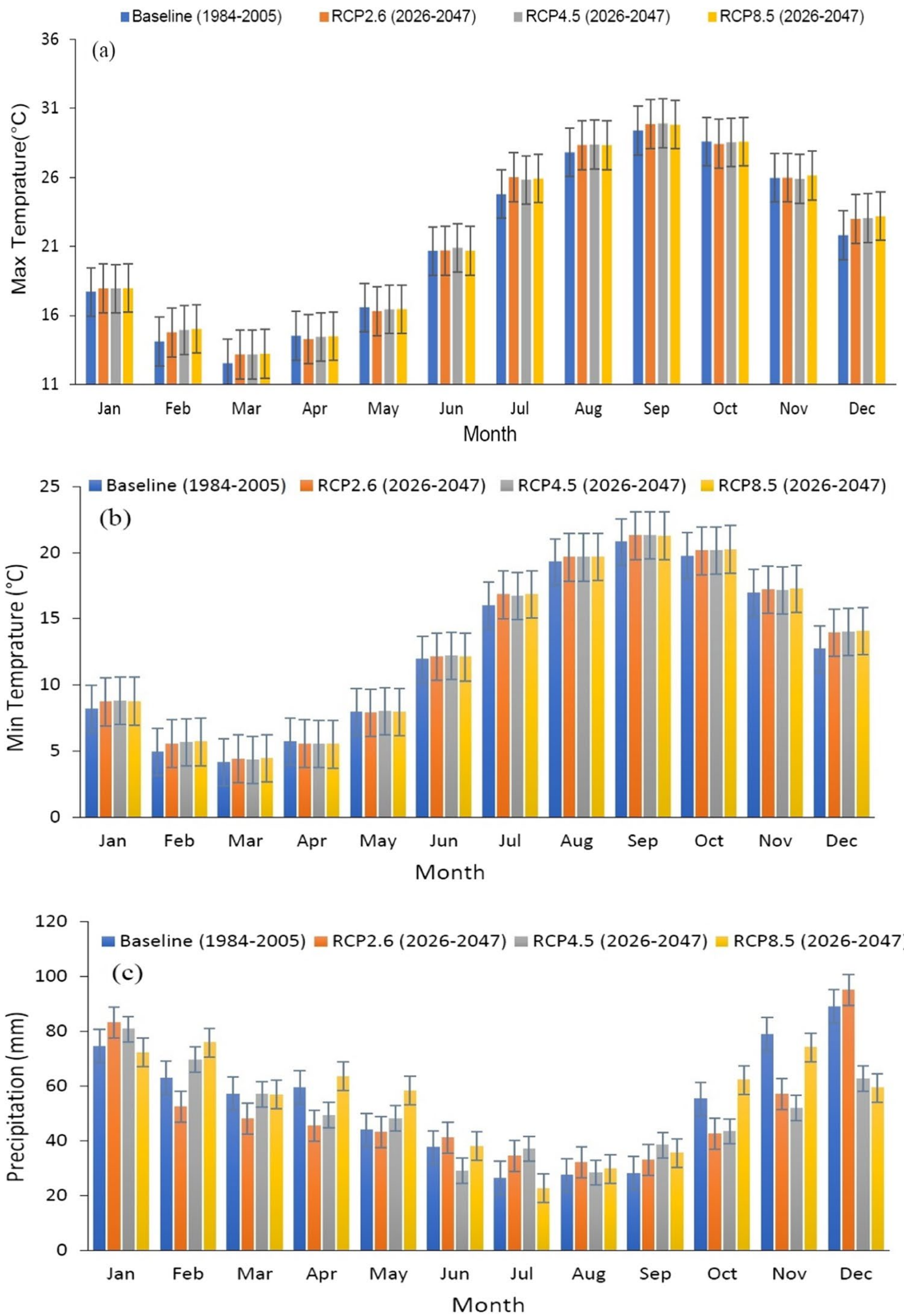
Fig. 4 The time series observed from 1984 to 2005 and projected annual maximum temperature (**a**) minimum temperature (**b**), and precipitation (**c**), under the RCP2.6, RCP4.5, and RCP8.5 scenarios for the period from 2026 to 2047

and 1 °C under RCP8.5, and the average annual minimum temperature increased by up to 0.9 °C under RCP4.5 and 1.1 °C under RCP8.5 scenario. Figure 5 a, b represents the average monthly maximum and minimum temperatures for RCP2.6, RCP4.5, and RCP8.5 scenarios.

A very slight decrease in average monthly maximum temperature is observed for May under RCP2.6 and RCP4.5 scenarios and for May and June under RCP8.5 relative to the baseline. In addition, there is an increase in average monthly maximum temperature for June, July, and August under RCP2.6 and RCP4.5 scenarios and for July and August under RCP8.5 which corresponds to the rice growing season in the study area. According to Boonwichai et al. (2018) the projected trend of temperature rise would increase the crop water requirement and irrigation water requirement (Fig. 5a).

In the case of average monthly minimum temperature, there is an increase for all months from May to August, which corresponds to the rice-growing season for all RCP scenarios except for May under RCP2.6 that shows a slight decrease of 0.06 °C (Fig. 5b). By comparing the average

Fig. 5 Baseline from 1984 to 2005 and projected the average monthly maximum temperature (**a**), minimum temperature (**b**), and precipitation (**c**) under the RCP2.6, RCP4.5, and RCP8.5 scenarios for the period from 2026 to 2047 (error bars indicate standard error of temperature across different years for different months)



monthly maximum and minimum temperatures, there is a smaller increase in minimum temperature for all three RCP scenarios relative to the maximum temperature (Fig. 5 a, b).

3.4 Projection of future precipitation

Based on the results, the decrease of − 5.55% and − 7.47% in precipitation under RCP2.6 and RCP4.5 scenarios and an increase of + 1.07% under RCP8.5 scenario is projected for the period of 2026–2047 relative to the baseline period (Table 10 and Fig. 4c).

Latitude, location, and topography are variables that affect the variability of precipitation (Boonwichai et al. 2018). Recent studies have reported that future precipitation may both increase and decrease in different parts of Iran. Lotfirad et al. (2021) reported that the precipitation may both increase and decrease under RCP4.5 and RCP8.5 scenarios in central Iran for the early century compared to

Table 10 The statistical analysis t-test of the projected change in precipitation for the three RCPs for the Gharakheil agrometeorological station during 2026–2047

	Baseline (1984–2005)	RCP2.6	RCP4.5	RCP8.5
Precipitation (mm)	656.43	619.96	607.35	663.49
Change (%) *	-	−5.55 ns	−7.47 ns	+1.07 ns

*Changes are provided relative to the baseline from 1984 to 2005

nsNon-significant difference

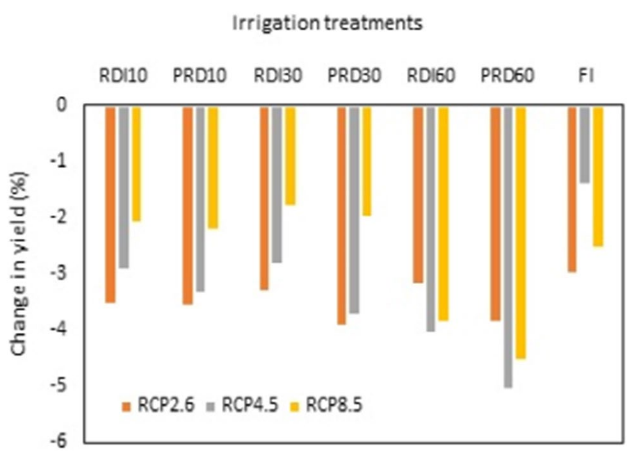


Fig. 6 Change in yield of rice with different irrigation levels under different RCP scenarios in experimental field

the baseline period. Doulabian et al. (2021) also reported that change in precipitation could be either positive or negative for in many different regions of Iran for the midcentury.

Temporal analysis of the projected precipitation indicates a negative change for some months during the rice cultivation in the study area. There are negative changes in precipitation in May, June, and July, which corresponds to the rice-growing season, under RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, relative to the baseline (Fig. 5c). This can affect the crop water availability for the future period.

3.5 Impacts of climate change on rice yield

Based on the simulation results, the average yield of rice cultivar (*Hashami*) is expected to decrease for all irrigation treatments and all RCP scenarios in the study area under future climate (Fig. 6).

It is important to note that, even under irrigated conditions at different levels from deficit irrigation to full irrigation, a reduction in yield will occur under future climate in the study area. However, the yield reductions under all RCPs were not significant. The yield reductions can be attributed to the increase in temperature for all three RCP scenarios, which leads to a higher crop water requirement in the future. Moreover, it is evident that there is a decrease in the amount of precipitation for May, June, and July under RCP2.6, RCP4.5, and RCP8.5 during the rice-growing season. Hence, there will be expected higher irrigation water requirement to occur in the future due to decrease of effective precipitation and increase of crop water requirement which eventually will lead to a reduction in rice yield.

Overall, rising temperature in combination with uncertainty about the start of the rainy season will have impacts even on irrigated rice yield in the future, which makes it necessary to use adaptation strategies against the possible impacts of climate change to enhance rice production.

3.6 Adaptation strategies for irrigated rice yield

Based on the simulation results of CERES-Rice model, the future average yield of irrigated rice is expected to slightly decrease under RCP climate change scenarios as discussed previously. There is, therefore, a need to examine potential adaptation strategies in order to mitigate the impact of climate change on rice yield.

3.6.1 Change in transplanting date

The results of simulations showed that different transplanting dates and irrigation treatments had a significant effect on grain yield for all RCPs. The best approach to increase rice yield was transplanting 2 weeks earlier than the current transplanting date with PRD10 irrigation treatment for all RCP scenarios (Fig. 7 a, b, c).

The increase in yield under 2 weeks earlier could be due to the fact that shifting transplanting date earlier was associated with a decrease in temperature resulting in a lower temperature stress during critical stages of rice growth (flowering and grain filling). Among irrigation treatments; FI, RDI10, PRD10, RDI30, and PRD30 showed the higher average yield compared to the other irrigation treatments, i.e., PRD60 and RDI60 for all RCPs. The RDI60 and PRD60 irrigation treatments could not compensate for decrease in precipitation during rice-growing season. Hence, a late transplanting date with RDI60 and PRD60 irrigation treatments is not advised.

The FI (flooding condition), RDI10 and PRD10 (soil moisture tension at permanent saturation), and RDI30 and PRD30 (soil moisture tension at field capacity) showed a higher average yield ranging from 4.67 to 5.03 ton/ha relative to RDI60 and PRD60 irrigation treatments, with a 4.27 to 4.42 ton/ha for all RCPs. Although RDI10, PRD10, RDI30, and PRD30 irrigation treatments received less water than FI, the drought level was not severe enough to cause a decrease in yield. The simulated soil water content for each irrigation treatment is shown between a depth of 15 to 30 cm (Fig. 8).

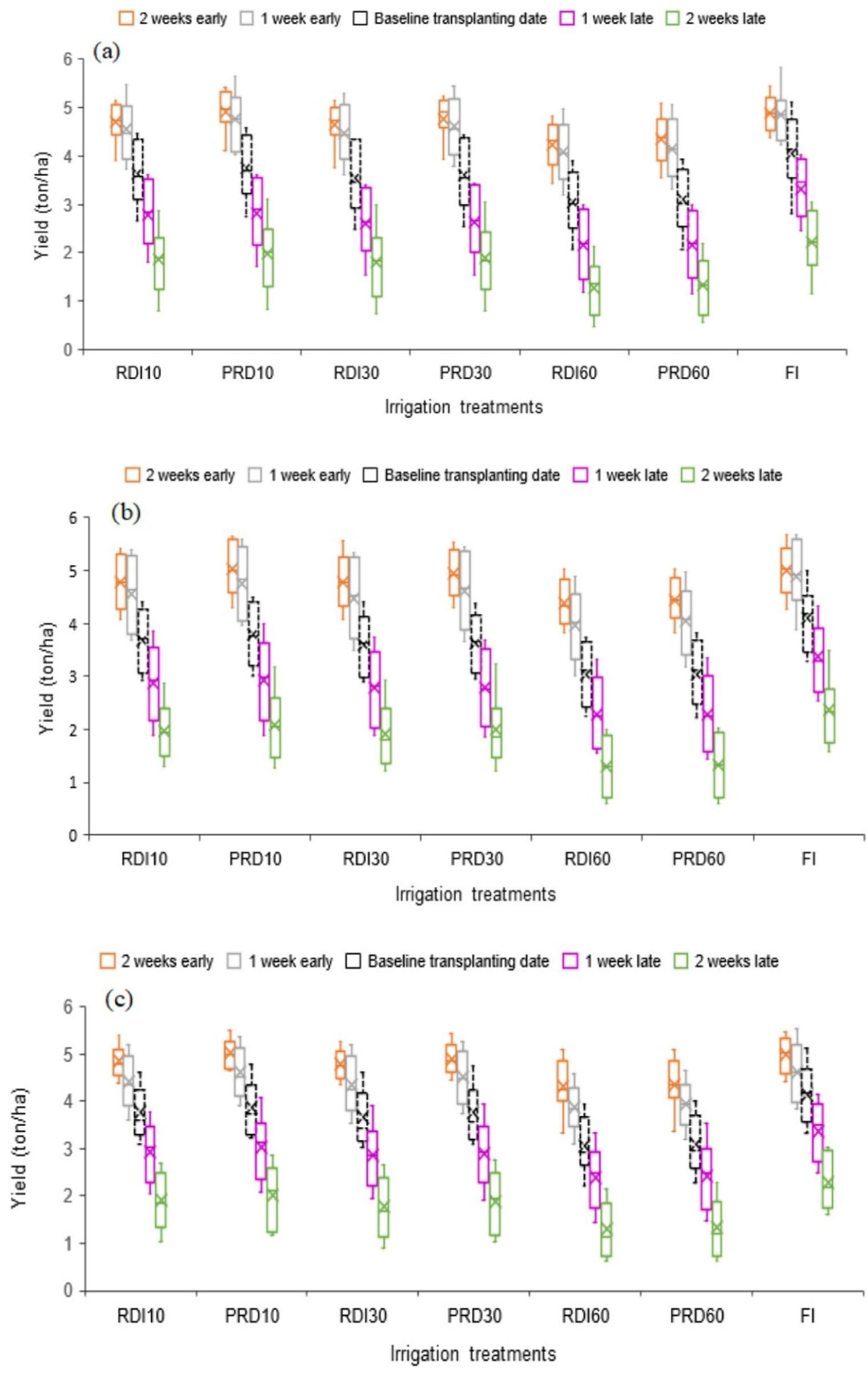


Fig. 7 Irrigated rice yield for adaptation strategy of change in transplanting date under RCP2.6 (**a**), RCP4.5 (**b**), and RCP8.5 (**c**) during the future time period (2026–2047) (the cross-shaped mark inside each box plot indicates the average yield of rice)

Our results also indicated that, among the deficit irrigation treatments, the PRD irrigation treatments (PRD10, PRD30, PRD60) resulted in a slightly higher yield compared to the RDI irrigation treatments (RDI10, RDI30, RDI60) under all RCPs. It was because although the volume of irrigation water in RDI was greater than PRD irrigation treatments (Fig. 8), the simulated potential root water uptake in PRD was higher than RDI treatments.

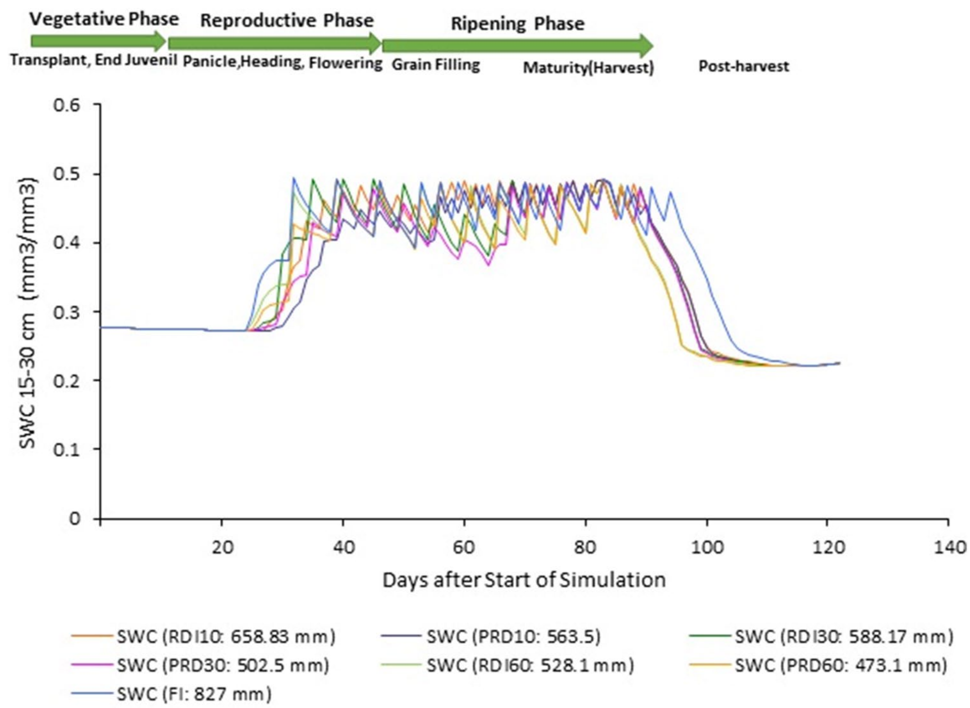


Fig. 8 The time series of soil water content (SWC) at 15–30-cm layer of soil profile based on CSM-CERES-Rice simulation for each irrigation treatment during the rice-growing season

Overall, the simulation results suggest that a change in transplanting date toward earlier dates increases rice yield compared to current transplanting date of the baseline for all seven irrigation treatments and for all three RCP scenarios. Darzi-Naftchali and Karandish (2016) had similar results for a study about rice cultivation management under climate change in northern Iran. They stated that late transplanting dates due to the negative effects of high temperatures and reduced green water will increase the irrigation water requirement of rice in the Mazandaran province. They also concluded that rice crop can be transplanted 2 to 23 days earlier under the climate change, while the number of days required for physiological maturity will be also reduced by 1 to 10 days. However, Shrestha et al. (2014) obtained different results compared to the findings of this investigation. Their results showed that change in transplanting from early to late in central Vietnam will increase irrigated rice yield for the summer cropping season. The difference in results can be related to different climate zones, varying climate models, crop growth models, and analysis methods. The study assumptions and especially the local conditions of a study area can also have significant impacts on the final results (Boonwichai et al. 2019).

3.6.2 Change in nitrogen fertilizer application date

Nitrogen (N) is a fundamental nutrient for optimum grain yield of lowland rice (Fageria et al. 1997). N fertilization may have a diverse effect on grain yield depending on different cultivars (Huo et al. 2012) and climatic conditions (Tayefeh et al. 2018). Although nitrogen fertilizer is essential to rice production in agricultural ecosystems, at the same time, it can also cause environmental pollution at regional and national scales due to leaching to the groundwater.

The results of simulation showed that different nitrogen fertilizer application dates and irrigation treatments had significant effects on grain yield for all RCPs. The highest average yield was in the range from 3.20 to 4.33 ton/ha for shifting the nitrogen fertilizer application date 1 week earlier than the baseline fertilizer (3.03 to 4.1 ton/ha) for RCP2.6 and RCP8.5, while for RCP4.5, the highest average yield was in the range from 3.13 to 4.20 ton/ha for 2 weeks earlier than the baseline fertilizer (3.03 to 4.1 ton/ha) (Fig. 9 a, b, c).

The increase in yield for the early nitrogen fertilizer application date was probably because it enhanced the fertilizer efficiency due to the shift in precipitation and also the notable effects of irrigation treatments. The best approaches were obtained for earlier nitrogen fertilizer application dates with full irrigation treatment (FI). However, the PRD10, RDI10, PRD30, RDI30, PRD60, and RDI60 irrigation treatments also showed a positive response. The simultaneous effect of an earlier nitrogen fertilizer application date and an increase in soil moisture for the FI treatment resulted in a higher yield compared to the other irrigation treatments and other nitrogen fertilizer application dates. Another reason for the increase in yield on early nitrogen fertilizer application date was due to the fact that simulating fertilizer date prior to the critical stages of rice growth including flowering and grain filling could enhance growth of the panicles and an increase in the number of grains per plant, resulting in a higher yield.

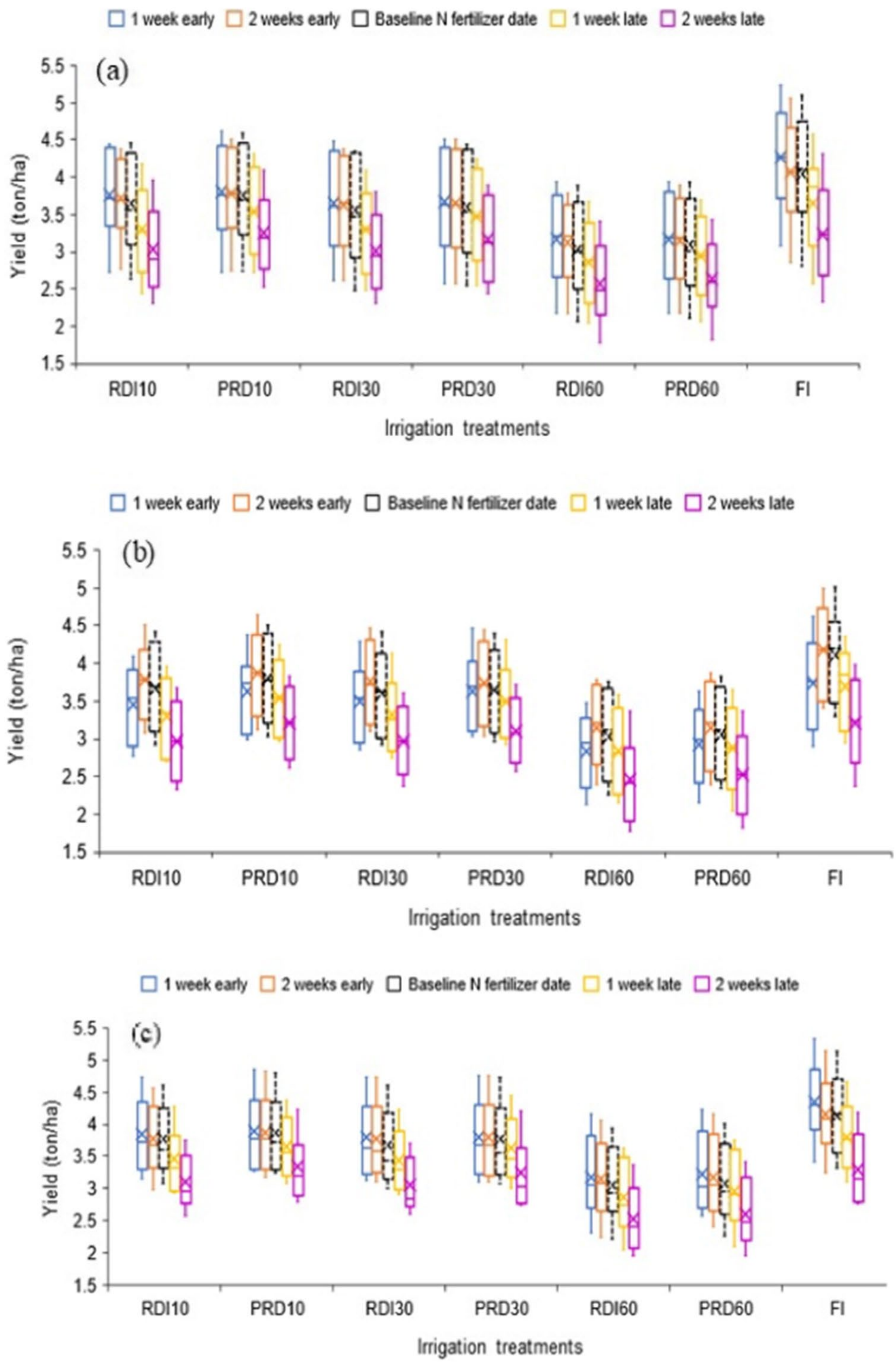


Fig. 9 Irrigated rice yield for adaptation strategy of change in nitrogen fertilizer application date under RCP2.6 (**a**), RCP4.5 (**b**), and RCP8.5 (**c**) for 2026–2047 (the cross-shaped mark inside each box plot indicates the average yield of rice)

Boonwichai et al. (2019) obtained similar results for a study conducted in Thailand. They recommended that applying nitrogen fertilizer earlier could increase rice yield compared to the baseline fertilizer application date under future climate conditions. Applying nitrogen fertilizer application at the appropriate time could increase rice yield (Boonwichai et al. 2019), while at the same time reducing pollution and alleviate GHG emissions (Tayefeh et al. 2018).

3.6.3 Change in nitrogen fertilizer application rate

The results of simulation showed that different irrigation treatments and nitrogen fertilizer application rates had significant effects on grain yield for all RCPs. Reducing the current application rate by 50% (75 kg N/ha) resulted in the lowest average yield for all irrigation treatments and all RCPs (Fig. 10 a, b, c). In contrast, the highest average yield was obtained for 2.5 times the application (375 kg N/ha) of the current application rate for all irrigation treatments and all RCPs, although, application of N fertilizer at the rate of 375 kg N/ha increases production cost, adding N fertilizer application under good management conditions can obtain a satisfactory income for farmers during rice growing season.

Our study showed that the increase in yield with an increase in the amount of fertilizer applied was higher under full irrigation (FI) than deficit irrigation treatments (RDI and PRD). In most cases, the full irrigation (FI) treatment yielded more than the deficit irrigation (PRD

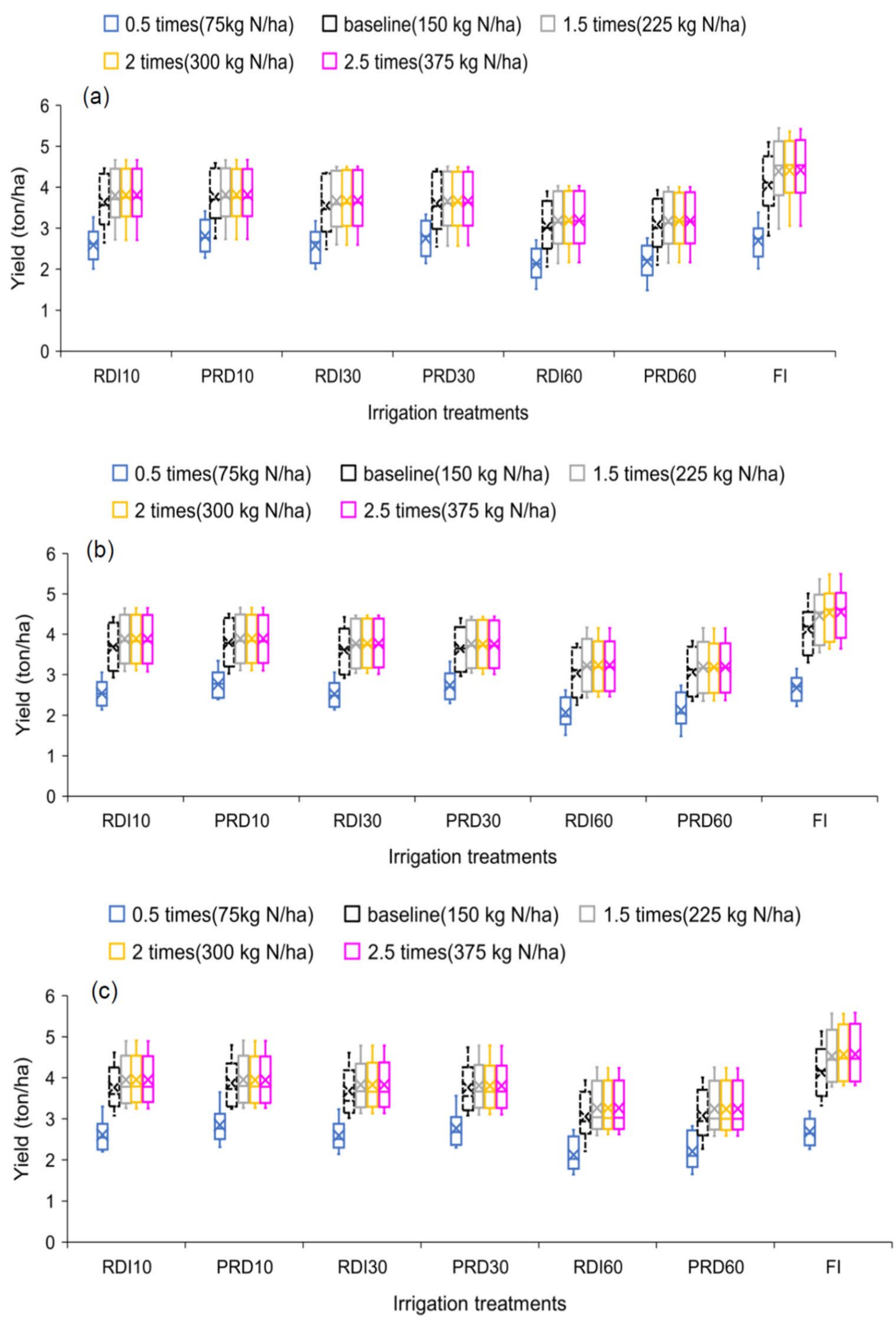


Fig. 10 The effect of the nitrogen fertilizer rate as an adaptation strategy for irrigated rice under RCP2.6 (**a**), RCP4.5 (**b**), and RCP8.5 (**c**) for 2026–2047 (the cross-shaped mark inside each box plot indicates the average yield of rice)

and RDI) treatments. In other words, there was an increase of yield under full irrigation (FI) when compared to deficit irrigation treatments (RDI and PRD) for the same RCP. However, deficit irrigation improved the irrigation water productivity when compared to fully irrigated rice, so that the highest irrigation water productivity was obtained in PRD30. This might be due to reduced losses and improved water use as the soil moisture tension at field capacity mostly targeted the sensitive growth stages of rice crop. Our results also indicated that as the amount of nitrogen fertilizer increased, the yield under RDI was higher than PRD. It was because the simulated nitrogen uptake productivity in RDI was slightly higher than PRD irrigation treatments.

Babel et al. (2011) stated that, although increasing fertilizer application rate will increase rice yield in the future, appropriate timing and amount of the fertilizer applications is vital for crop growth and yield. Excessive fertilizer application rate causes toxicity which consequently leads to reduced yield and even plant death (Kenzie 1998). From the environmental point of view, leaching will bring nitrogen fertilizer through ground water and even surface water which will affect water quality and ultimately can impact human health (Boonwichai et al. 2019). For farmers, nitrogen leaching means yield loss and economic losses. From another environmental point of view, fertilization with higher N rates can contribute to another detrimental effect on rice production as higher N rates promote the emission of NH_3 and N_2O (Tayefeh, et al. 2018). To overcome these potential environmental problems, the use of rice varieties that have high potential of N use efficiency is a favorable approach to limit application of N fertilizers in rice (Wu et al. 2016). Overall, avoiding excessive N application rates along with planning for the appropriate timing of fertilizer application to coincide with the N demand can improve N uptake by rice, which in turn will increase the yield of rice.

It should be noted that the present study is not free from limitations. We only considered one rice cultivar, i.e., *Hashami*, in our study assuming that different rice varieties would give similar response to the impact of climate change on rice production as presented by others (Basak et al. 2010; Dharmarathna et al. 2014), while different rice varieties may give a different response to the impact of climate change as most varieties are locally adapted (Swain and Yadav 2009). However, we realize that breeding for heat tolerant and drought resistant varieties is also a potential adaptation strategy and also part of technological improvements of the current rice breeding programs. In this study, we used the rice cultivar *Hashami* that was first introduced by Iranian farmer named Yousef Hashemi in 1990 and is currently one of the most dominant rice cultivars in northern Iran. This cultivar has the largest cultivated area among the native and high-quality cultivars in the northern Iran, due to its good appearance, high marketability, and good cooking.

4 Conclusion

The main focus of this simulation-based study is to evaluate on-farm water management simultaneously with other adaptation strategies to mitigate the vulnerability of rice production to potential impacts of climate change. The results showed that there was no significant difference between average precipitation and temperature in the baseline and future periods. Therefore, the decrease in yield in the near future in the study area is more caused by deficit irrigation than by the negative effects of climate change. Our findings confirm the hypothesis that simulating adaptation strategies can significantly increase the irrigated rice yield under climate change conditions. The study reveals that shifting transplanting at 2 weeks earlier with FI, RDI10, PRD10, RDI30, and PRD30 showed higher average yields between 4.67 and 5.03 ton/ha relative to RDI60 and PRD60 under all RCPs. Shifting nitrogen fertilizer application date 1 week earlier under RCP2.6 and RCP8.5 and 2 weeks earlier under RCP4.5 with FI gave the highest yields between 4.20 and 4.33 ton/ha. In the case of adjusting nitrogen fertilizer application rate, the highest yield is obtained for 2.5 times the application of the current application with FI treatment for all RCPs. This research enables us to define the best adaptation strategy to enhance rice production and makes a significant contribution to agricultural policies under future climate scenarios. Evaluation of adaptation strategies suggests that shifting transplanting date is the best strategy compared to the other two adaptations, which resulted in higher yield with the same amount of water under all RCPs. The present study showed that CSM-CERES-Rice model could provide valuable information in the design of agricultural management practices that will increase rice production in northern Iran. So, the results can be helpful for policymakers to have perspectives of food security in order to plan in the long term for improving the rice yield. The findings can also be used as a guidance for farmers. However, the implementation adaptation strategies would depend mainly on availability of resources and facilities and also perceptions and beliefs of farmers.

Suggestion for the future of this study is to use models archived in CMIP6 under SSP scenarios due to the complexity of real climate system. It helps to simplify the uncertainties and complexities in future climate projections that arise from differences in model structure and parameterization.

Author contribution Dorsa Darikandeh wrote the manuscript with support from Ali Shahnazari, Mojtaba Khoshravesh and Gerrit Hoogenboom. Ali Shahnazari and Mojtaba Khoshravesh supervised the project and Gerrit Hoogenboom advised the project. Gerrit Hoogenboom aided in interpreting the results from CSM-CERES-Rice model and helped shape the research process, both in terms of content, as well as its impact. All authors provided critical feedback and commented on the final version of the manuscript.

Data availability The authors declare that all data and materials as well as software applications support their claims and comply with field standards. The data sets generated during the current study are available in the main text, tables of the manuscript, and also in the link https://climate-scenarios.canada.ca/?page=pred-canesm2. For more detailed information, please contact the corresponding author.

Code availability (software application or custom code) All software applications used in the submitted work are publicly available. The CSM-CERES-Rice model used in this study is part of the DSSAT crop modeling system and can be requested from the DSSAT portal at www.DSSAT.net.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication The authors approve the manuscript and give their consent for submission and publication.

Competing interests The authors declare no competing interests.

References

Ahiablame L, Sinha T, Paul M, Ji J, Rajib A (2017) Streamflow response to potential land use and climate changes in the James River watershed, Upper Midwest United States. J Hydrol 14:150–166. https://doi.org/10.1016/j.ejrh.2017.11.004

Ahmadi M, Ghermezcheshmeh B (2020) Evaluation of error and uncertainty in downscaling SDSM and ANN. Watershed Eng Manag (IJWMSE) 12(1):340–350. https://doi.org/10.22092/ijwmse.2019.108294.1226

Ahmed Z, Guha G, Shew A, Alam G (2021) Climate change risk perceptions and agricultural adaptation strategies in vulnerable riverine char islands of Bangladesh. Volume 103. Land Use Policy, https://doi.org/10.1016/j.landusepol.2021.105295

Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration: guidelines for computing crop water requirements. FAO irrigation and drainage paper No. 56. FAO, Rome.

Allen MR, Barros VR, Broome J, Cramer W, Christ R, Church JA, Clarke L, Dahe Q Dasgupta,P, Dubash NK (2014) IPCC fifth assessment synthesis report-climate change 2014 synthesis report. Intergovernmental Panel on Climate Change (IPCC), Geneva

Araya A, Kisekka I, Gowda PH, Prasad PVV (2017) Evaluation of water-limited cropping systems in a semi-arid climate using DSSAT-CSM. Agri Syst 150:86–90

Ashraf Vaghefi S, Mousavi SJ, Abbaspour KC, Srinivasan R, Yang H (2014) Analyses of the impact of climate change on water resources components, drought and wheat yield in semiarid regions: Karkheh River Basin in Iran. Hydrol Process 28(4):2018–2032. https://doi.org/10.1002/hyp.9747

Babel MS, Agarwal A, Swain DK, Herath S (2011) Evaluation of climate change impacts and adaptation measures for rice cultivation in Northeast Thailand. Clim Res 46(2):137–146. https://doi.org/10.3354/cr00978

Bajus P, Mraz M, Rigo I, Findura P, Fürstenzeller A, Kielbasa P, Malaga-Tobola U (2019) The influence of drying temperature and moisture of corn seeds planted on their damage. Agric Engin 23(1):5–12. https://doi.org/10.1515/agriceng-2019-0001

Basak JK, Ashraf Ali M, Nazrol Islam Md, Abdur Rashid Md (2010) Assessment of the effect of climate change on boro rice production in Bangladesh using DSSAT model. J Civ Eng 38(2):95–108

Bates B, Kundzewicz ZW (2008) Climate change and water. Technical paper of the intergovernmental panel on climate change. IPCC Secretariat, Geneva, p 210

Belder P, Bouman B, Cabangon R, Guoan L, Quilang E, Yuanhua L, Spiertz J, Tuong T (2004) Effect of water-saving irrigation on rice yield and water use in typical lowland conditions in Asia. Agric Water Manag 65(3):193–210. https://doi.org/10.1016/j.agwat.2003.09.002

Boonwichai S, Shrestha S, Babel MS, Weesakul S, Datta A (2018) Climate change impacts on irrigation water requirements, crop water productivity and rice yield in the Songkhram River Basin. Thailand J Clean Prod 198:1157–1164. https://doi.org/10.1016/j.jclepro.2018.07.146

Boonwichai S, Shrestha S, Babel MS, Weesakul S, Datta A (2019) Evaluation of climate change impacts and adaptation strategies on rainfed rice production in Songkhram River Basin. Thailand Sci Total Environ 652:189–201. https://doi.org/10.1016/j.scitotenv.2018.10.201

Buddhaboon C, Jintrawet A, Hoogenboom G (2018) Methodology to estimate rice genetic coefficients for the CSM-CERES-Rice model using GENCALC and GLUE genetic coefficient estimators. J Agric Sci 156(4):1–11. https://doi.org/10.1017/S0021859618000527

Carpena F (2019) How do droughts impact household food consumption and nutritional intake? A study of rural India. World Dev 122:349–369. https://doi.org/10.1016/j.worlddev.2019.06.005

Charles A, Bertrand T, Elodie F, Harry H (2013) Analog downscaling of seasonal rainfall forecasts in the Murray Darling basin. Mon Weather Rev 141:1099–1117. https://doi.org/10.1175/MWR-D-12-00098.1

Chen Sh, Gong B (2020) Response and adaptation of agriculture to climate change: evidence from China. J Dev Econ 102557. https://doi.org/10.1016/j.jdeveco.2020.102557

Cheng H, Shu K, Zhu T, Wang L, Liu X, Cai W, Qi Z, Feng S (2022) Effects of alternate wetting and drying irrigation on yield, water and nitrogen use, and greenhouse gas emissions in rice paddy fields. J Clean Prod 349. https://doi.org/10.1016/j.jclepro.2022.131487

Chylek P, Li J, Dubey MK, Wang M, Lesins G (2011) Observed and model simulated 20th century Arctic temperature variability: Canadian Earth System Model CanESM2. Atmos Chem Phys 11:22893–22907. https://doi.org/10.5194/acpd-11-22893-2011

Darand M, Hamidi S (2021) Projected changes in Iran temperature based on different scenarios RCP. Nat Hazards 10(28):86–106 (In Persian)

Darzi-Naftchali A, Karandish F (2016) Rice cultivation management in Mazandaran province in the conditions of climate change. Agric Water Manag 30(2):334–346

Darzi-Naftchali A, Karandish F (2017) Adapting rice production to climate change for sustainable blue water consumption: an economic and virtual water analysis. Theor Appl Climatol 135(1):1–12. https://doi.org/10.1007/s00704-017-2355-7

Dharmarathna W, Herath S, Weerakoon SB (2014) Changing the planting date as a climate change adaptation strategy for rice production in Kurunegala district, Sri Lanka. Sustain Sci 9:103–111. https://doi.org/10.1007/s11625-012-0192-2

Dien DC, Mochizuki T, Yamakawa T (2019) Effect of various drought stresses and subsequent recovery on proline, total soluble sugar and starch metabolisms in Rice (Oryza sativa L.) varieties. Plant Prod Sci 22(4):530–545. https://ojs.nassg.org/index.php/rwae

Doulabian Sh, Golian S, Shadmehri Toosi A, Murphy C (2021) Evaluating the effects of climate change on precipitation and temperature for Iran uses RCP scenarios. J Water Clim Change 12(1):166–184. https://doi.org/10.2166/wcc.2020.114

Emediegwu L, Wossink A, Hall A (2022) The impacts of climate change on agriculture in sub-Saharan Africa: a spatial panel data approach. World Dev 158. https://doi.org/10.1016/j.worlddev.2022.105967

English MJ, Musick JT, Murty VVN (1990) Deficit irrigation: management of farm irrigation systems (Hoffman, G.J., Howell, T.A., and Solomon, K.H., Editors). ASAE Monograph no. 9. American Society of Agricultural Engineers publisher, 1020p.

Fageria NK, Baligar VC, Jones CA (1997) Growth and mineral nutrition of field crops, 2nd edn. Marcel Dekker, New York

Feliciano D, Recha J, Ambaw G, MacSween K, Solomon D, Wollenberg E (2022) Assessment of agricultural emissions, climate change mitigation and adaptation practices in Ethiopia. Clim Policy:1–18. https://doi.org/10.1080/14693062.2022.2028597

Gholizade H, Ebadzadeh H, Hatami F, Hosseinpour R (2014) Crop Statistics, Ministry of Agriculture, Deputy of Planning Economical, Information and Communication Technology Center (In Persian).

Giorgi F, Mearns LO (1991) Approaches to the simulation of regional climate change: a review. Rev Geophys 29:191–216. https://doi.org/10.1029/90RG02636

Guo Y, Wu W, Du M, Liu X, Wang J, Bryant CR (2019) Modeling climate change impacts on rice growth and yield under global warming of 1.5°C and 2.0°C in the Pearl River delta. China. Atmosphere 10(10):567. https://doi.org/10.3390/atmos10100567

Hasheminia SM (2004) Water management in agriculture, First Edition, Ferdowsi University of Mashhad Press, 533 p.

Hessami M, Gachon P, Quarda TBMJ, St-Hilaire A (2008) Automated regression based statistical downscaling tool. Environ Model Softw 23(6):813–834

Hoogenboom G, CH Porter, KJ Boote, V Shelia, PW Wilkens, U Singh, JW White, S Asseng, JI Lizaso, LP Moreno, W Pavan, R Ogoshi, LA Hunt, GY Tsuji, JW Jones (2019a) The DSSAT crop modeling ecosystem. In: p.173–216 [K.J. Boote, editor] Advances in crop modeling for a sustainable agriculture. Burleigh Dodds Science Publishing, Cambridge, United Kingdom. https://doi.org/10.19103/AS.2019a.0061.10

Hoogenboom G, CH Porter, V Shelia, KJ Boote, U Singh, JW White, LA Hunt, R Ogoshi, JI Lizaso, J Koo, S Asseng, A Singels, LP Moreno, JW Jones (2019b) Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7.5. DSSAT Foundation, Gainesville, Florida. https://DSSAT.net

Hunt LA, Pararajasingham S, Jones JW, Hoogenboom G, Imamura DT, Ogoshi RM (1993) SOFTWARE GENCALC: software to facilitate the use of crop models for analyzing field experiment. J Agron 85:1090–1094

Huo ZY, Gu HY, Ma Q, Yang X, Li M, Li GY, Dai QG, Xu K, Wei HY, Gao H, Lu Y, Zhang HC (2012) Differences of nitrogen absorption and utilization in rice varieties with different productivity levels. Acta Agron Sinica 38:2061–2068

IPCC (2021) Climate Change 2021: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, In press, https://doi.org/10.1017/9781009157896.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT (2003) The DSSAT cropping system model. Eur J Agron 18(3–4):235–265

Kapela K, Sikorska A, Niewęgłowski M, Krasnodębska E, Zarzecka K, Gugała M (2020) The impact of nitrogen fertilization and the use of bio stimulants on the yield of two maize varieties (Zea mays L.) cultivated for grain. Agronomy 10(9):1408. https://doi.org/10.3390/agronomy10091408

Kenzie RM (1998) Crop nutrition and fertiliser requirements. Food and Rural Development, Lethbridge.

Lotfirad M, Adib A, Salehpoor J, Ashrafzadeh A, Kisi O (2021) Simulation of the impact of climate change on runoff and drought in an arid and semiarid basin (the Hablehroud, Iran). Appl Water Sci 11(168):1–24. https://doi.org/10.1007/s13201-021-01494-2

Maneepitak S, Ullah H, Paothong K, Kachenchart B, Datta A, Shrestha R (2019) Effect of water and rice straw management practices on yield and water productivity of irrigated lowland rice in the Central Plain of Thailand. Agric Water Manag 211:89–97. https://doi.org/10.1016/j.agwat.2018.09.041

Meinshausen M, Smith SJ, Calvin KV, Daniel JS, Kainuma MLT, Lamarque JF, Matsumoto K, Montzka SA, Raper SCB, Riahi K, Thomson AM, Velders GJM, van Vuuren D (2011) The RCP greenhouse gas concentrations and their extension from 1765 to 2300. Clim Change (special Issue). https://doi.org/10.1007/s10584-011-0156-z

Mekonnen MM, Hoekstra AY (2011) The green, blue and grey water footprint of crops and derived crop products. Hydrol Earth Syst Sci 15:1577–1600. https://doi.org/10.5194/hess-15-1577-2011

Mirfenderski R, Darzi-Naftchali A, Karandish F (2022) Climate-resilient agricultural water management to alleviate negative impacts of global warming in rice production systems. Theor Appl Climatol 147:409–422. https://doi.org/10.1007/s00704-021-03813-8

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50(3):885–900

Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, Van vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. Nature 463:747–756. https://doi.org/10.1038/nature08823

Nasir IR, Rasul F, Ahmad A, Asghar HN, Hoogenboom G (2020) Climate change impacts and adaptations for fine, coarse, and hybrid rice using CERES-Rice. Environ Sci Pollut Res 27:9454–9464. https://doi.org/10.1007/s11356-019-07080-z

Nicolas F, Migliaccio KW, Hoogenboom G, Rathinasabapathi BR, Eisenstadt WR (2020) Assessing the potential impact of climate change on rice yield in the Artibonite valley of Haiti using the CSM-CERES-RICE model. Am Soc Agric Biol Eng (ASABE) 63(5):1385–1400. https://doi.org/10.13031/trans.13868

Nikbakht Shahbazi AR (2019) Investigation of crop evapotranspiration and precipitation changes under climate change RCPs scenarios in Khouzestan province. J Water Soil Conserv 25(6):123–139 (In Persian)

Palazzo A, Vervoort JM, Mason-D'Croz D, Rutting L, Havlík P, Islam S, Bayala J, Valin H, Kadi HAK, Thornton P, Zougmore R (2017) Linking regional stakeholder scenarios and shared socioeconomic pathways: quantified west African food and climate futures in a global context. Global Environ Change 45:227e242. https://doi.org/10.1016/j.gloenvcha.2016.12.002

Prasad S, Singh MP, Yadav RK (2012) Physio-chemical changes in rice varieties under drought stress condition. Plant Archives 12:63–66

Prescott J (1940) Evaporation from a water surface in relation to solar radiation. Trans R Soc S Aust 64(1):114–118

Priestley CHB, Taylor RJ (1972) On the assessment of surface heat flux and evaporation using large-scale parameters. Mon Weather Rev 100(2):81–92. https://doi.org/10.1175/1520-0493(1972)100%3c0081:OTAOSH%3e2.3.CO;2

Rezaei M, Asadi R (2013) The effect of using saline water under drought stress on rice yield. Final Project Report. National Rice Research Institute (In Persian).

Rutten M, Dijk M, Rooij W, Hilderink H (2014) Land use dynamics, climate change, and food security in Vietnam: a global-to-local modeling approach. World Dev 59:29e46. https://doi.org/10.1016/j.worlddev.2014.01.020

Sahebi M, Hanafi MM, Rafii MY, Mahmud TMM, Azizi P, Osman M, Miah G (2018) Improvement of drought tolerance in rice (Oryza sativa L.): genetics, genomic tools, and the WRKY gene family. BioMed Res. Int. 2018: 3158474. [CrossRef] [PubMed]. https://doi.org/10.1155/2018/3158474

Shi W, Wang M, Liu Y (2020) Crop yield and production responses to climate disasters in China. Sci Total Environ 750. https://doi.org/10.1016/j.scitotenv.2020.141147

Sakoda K, Taniyoshi K, Wamori W, Tanaka Y (2021) Drought stress reduces crop carbon gain due to delayed photosynthetic induction under fluctuating light conditions. Genet Resour Crop Evol 174(1):1–15. https://doi.org/10.1111/ppl.13603

Sheidaeian M, Ziatabar Ahmadi MKh, Fazloula R (2015) Study on climate change effect on net irrigation requirement and yield for rice crop (case study: Tajan Plain). Journal of Water and Soil 28(6):1284–1297

Shrestha S, Deb P, Bui TTT (2014) Adaptation strategies for rice cultivation under climate change in Central Vietnam. Mitig Adapt Strateg Glob Change 21(1):15–37. https://doi.org/10.1007/s11027-014-9567-2

Soler CMT, Sentelhas PC, Hoogenboom G (2007) Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. Eur J Agron 27(2–4):165–177. https://doi.org/10.1016/j.eja.2007.03.002

Swain DK, Yadav A (2009) Simulating the impact of climate change on rice yield using CERES-Rice model. J Environ Inform 13(2):104–110. https://doi.org/10.3808/jei.200900145

Tayefeh M, Sadeghi SM, Noorhosseini SA, Bacenetti J, Damalas CA (2018) Environmental impact of rice production based on nitrogen fertilizer use. Environ Sci Pollut Res 25:15885–15895. https://doi.org/10.1007/s11356-018-1788-6

Taylor KE, Stouffer RJ, Meehl GA (2009) A summary of the CMIP5 experiment design. CMIP Report, p 30

Thiemig V, Rojas R, Zambrano-Bigiarini M, De Roo A (2013) Hydrological evaluation of satellite-based rainfall estimates over the Volta and Baro-Akobo Basin. J Hydrol 499:324–338. https://doi.org/10.1016/j.jhydrol.2013.07.012

USDA (2021) US Department of Agriculture. https://ipad.fas.usda.gov/countrysummary/Default.aspx?id=IR&crop=Rice

Wilby RL (1999) The weather generation game: a review of stochastic weather models. Prog Phys Geogr 23(3):329–357. https://doi.org/10.1177/030913339902300302

Wilby RL, Dawson CW (2007) SDSM 4.2 a decision support tool for the assessment of regional climate change impacts, user manual.

Wu L, Yuan S, Huang L, Sun F, Zhu G, Li G, Fahad S, Peng S, Wang F (2016) Physiological mechanisms underlying the high-grain yield and high-nitrogen use efficiency of elite rice varieties under a low rate of nitrogen application in China. Front Plant Sci 7:1024. https://doi.org/10.3389/fpls.2016.01024

Yadav MK, Singh R, Singh K, Mall R, Patel C, Yadav S, Singh M (2015) Assessment of climate change impact on productivity of different cereal crops in Varanasi. India J Agrometeorol 17(2):179–184. https://doi.org/10.54386/jam.v17i2.1000

Yan D, Zhu Y, Wang S, Cao W (2006) A quantitative knowledge-based model for designing suitable growth dynamics in rice. Plant Prod Sci 9(2):93–105. https://doi.org/10.1626/pps.9.93

Yarmohammadi S, Zakerinia M, Ghorbani KH, Soltani A (2017) Investigation of the effect of climate change on evapotranspiration and wheat water requirement in Bojnord region. J Water Res Eng 10(35):97–110 (In Persian)

Yousefian M (2018) Investigation of the effects of partial root zoon drying and regulated deficit irrigation on water productivity, methane emission and some physiological traits of rice (Hashemi cultivar). Dissertation, Sari Agricultural Sciences and Natural Resources University (In Persian)

Zhang Z, Zhang S, Yang J, Zhang J (2008) Yield, grain quality and water use efficiency of rice under non-flooded mulching cultivation. Field Crops Res 108(1):71–81. https://doi.org/10.1016/j.fcr.2008.03.004

Zhang L, Zhang Z, Tao F, Luo Y, Zhang J, Cao J (2022) Adapting to climate change precisely through cultivars renewal for rice production across China: when, where, and what cultivars will be required? Agric For Meteorol 316. https://doi.org/10.1016/j.agrformet.2022.108856