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EVALUATION OF CLIMATE CHANGE IMPACTS ON RICE PRODUCTION UNDER WATER MANAGEMENT IN NORTHERN IRAN

Shabnam Roshani[1], Mohammad Hasan Rashed Mohassel[2], Reza Sadrabadi Haghighi[1*], Ebrahim Amiri[3]

[1]Agricultural Science Department, Mashhad Branch, Islamic Azad University, Mashhad, Iran
[2]Department of Agronomy, Faculty of Agriculture, Ferdowsi University of Mashhad, Iran
[3]Department of Water Engineering, Lahijan Branch, Islamic Azad University, Lahijan, Iran
[*]Corresponding author. E-mail: rsadrabadi@mshdiau.ac.ir

ABSTRACT

This research studied the effects of climate change on rice yield under irrigation by using the AquaCrop model and the various climate change scenarios for the crop years 2017 and 2018 at the research farm of the Rice Research Institute of Iran, Rasht. The LARS-WG6 model was employed to simulate the meteorological data obtained from Rasht Meteorological Station under the RCP8.5 and RCP4.5 scenarios for the 2020-2050 and 2060-2090 periods. The simulated values were assessed based on the measured values of total biomass and grain yields using the coefficient of determination (R^2), the relative error parameters, and the normalized root mean square error ($RMSE_n$). The calculated values of $RMSE_n$ varied from 7 to 4% for grain yield and from 3 to 7% for biomass yield at the calibration and validation stages, respectively. The results suggested that the AquaCrop model had suitable accuracy in predicting biomass and grain yields. The findings indicate that climate change decreased mean rice grain yield by 17 to 23% under the RCP4.5 scenario and by 18 to 23% under the RCP8.5 scenario for 2050 and 2090, respectively, in non-flooded irrigation management. The lowest simulated mean biomass and grain yields were obtained under irrigation at 11-day intervals in scenario RCP8.5 for the second future period (2060-2090). In general, non-flooded irrigation management had negative effects on rice grain yield under climate change. Moreover, the mean rice growing period under both RCP8.5 and RCP4.5 scenarios declined by 2090. These findings can be used for a broad spectrum of users such as farmers, agricultural engineers, and project managers in practical policymaking and making correct decisions compatible with the region in order to increase rice grain yield productivity under future climate conditions in northern Iran.

Keywords: climate change, irrigation, AquaCrop, rice, yield.

INTRODUCTION

In the last FAO report on cereal supply and demand, 2.72 billion tons of cereals including wheat, coarse cereals and rice were produced throughout the world in 2019, which was 1.2 million tons larger than the preliminary estimates of this organization and showed a 2.4% increase in grain yield over the total 2018 production (FAO, 2020). Based on FAO 2018 statistics, Iran had 580,000 hectares under rice cultivation in this year and produced 2.9 to 3 million tons paddy and 1.99 million tons white rice. The mean rice yield in Iran is 4.3 t ha^{-1} (FAO, 2018). Rice (*Oryza sativa* L.) is a staple food consumed every year (FAO, 2020), and its growth is considerably affected by weather changes followed by water scarcity (Pan et al., 2017). Gilan Province in northern Iran ranks second in rice production with 32.4% of the total area under rice cultivation and 28.4% of the total produced crop (Amiri et al., 2011). Consequently, it is especially important to pay attention to rice production in this province. The Sefidrud Dam, constructed at the intersection of the Ghezel Ozan River and Shahroud River (with an annual inflow of more than 1 billion m^3), is the main source of irrigation water for Gilan Province. Construction of storage dams upstream of the Ghezel Ozan River will reduce the inflow to the Sefidrud Dam considerably and the quality of the water will also decline (Japan International Cooperation Agency., 2012). The unprecedented growth

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in demand for water in the industrial sector and for drinking purposes, and the reduced volume of water that can be used in the agriculture sector (water from this dam supplies 73% of the water needs of the rice paddies in Gilan Province), have decreased the sources of water supply for rice production and threatened rice production (Amiri et al., 2011).

The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change points to the unprecedented increase in the greenhouse gases carbon dioxide (CO_2), methane (CH_4) and nitrogen dioxide (NO_2) (IPCC, 2007). Study of the effects that climate change has on agriculture and production of field crops requires a prediction of the future of Earth's climate. The agriculture sector both influences and is influenced by climate change. The developed countries have designed and applied climate models to simulate the effects of climate variables. The RCP scenarios are models used to study the effects of increases in CO_2 concentration and climate change (Wang et al., 2021). Most climate models under RCP scenarios agree that the global mean surface temperature will increase by >1.5°C, and in the worst-case scenario by >2°C, by the end of the 21st century compared to the period 1850-1900 (IPCC, 2014). Considering the different effects of climate change on the average values of the meteorological parameters in different studied regions and on various species of crop plant, different reports have been published some of which have reported a decrease and some an increase in crop yields. Since temperature and CO_2 can have antagonistic effects on crop yield, the general impact of climate change on future crop production remains uncertain (Wang et al., 2021). Higher temperatures can increase evapotranspiration and rainfall variability and flood and drought frequency and intensity thereby affecting growth and yield of crops (Arunrat et al., 2018; Boonwichai et al., 2018). High CO_2 concentrations also have significant positive effects on production of C3 crops and on increases in grain yield (Li et al., 2017). In assessing effects of climate change on rice yields in 4 regions in Thailand, Arunrat et al. (2020) reported that rice yield increased by 1.3 to 29% under the RCP4.5 scenario and by 8.3 to 29% under the RCP8.5 scenario. Boonwichai et al. (2019) predicted that changing fertilizer application and planting dates under the RCP4.5 scenario would increase rice yield by 12 and 8%, respectively, in the 2080s because the high CO_2 concentrations and higher rainfall would offset the effects of the predicted minimum and maximum temperatures. Conversely, the effects of increased temperature on crop growth and yield can be negative depending largely to the effect of the increase in the threshold of effective temperature on crop yield (Shi et al., 2017). The findings by Wang et al. (2021) demonstrated that the mean rice yield under the RCP4.5 and RCP8.5 scenarios will decrease by 3.5 to 4.9% and 10.5 to 47.9%, respectively, for the 2050-2080 period because the increase in CO_2 concentration will not offset the decline in yield resulting from the increase in temperature.

Iran is one the water-scarce regions of the world and highly vulnerable to climate change since its agriculture is greatly dependent on weather conditions. It is expected that climate change will influence the amounts of precipitation and the degrees of temperature and their patterns in the various regions of this country causing different effects on spatial and temporal water distribution of water resources. If CO_2 concentration doubles before the year 2100, the average temperature in Iran will increase by 1.5 to 4.5°, which will have tangible impacts on water resources, agriculture, food production, energy and forestry (Amiri and Eslamian, 2010). Consequently, study of the effects of climate change on agriculture throughout the country seems to be necessary. Investigation on the effects of climate change on agriculture and crop production requires an assessment of future of Earth's climate.

Models have been used in recent years to study various factors such as water management, nitrogen management, plant density, and climate change that influence crop yield (Xu et al., 2018). Simulation models can be used to evaluate the complex interactions between various climate factors related to crop production such as temperature, rainfall, CO_2 concentration and crop management measures (Amiri et al., 2011). Simulation models for crop plants are useful tools for understanding the biophysical processes governing the soil-plant-atmosphere system (Timsina and Humphreys, 2006). The AquaCrop model is based on water consumption, simulates plant canopy and biomass above ground surface in response to transpiration and finally simulates yield based on daily plant respiration rates **(**Ojeda et al., 2018; Jin et al., 2018). Compared to the other simulation models, AquaCrop has fewer parameters and data inputs for simulating plant response to water and researchers can use it worldwide for most plant products and main crop plants. These parameters are often directly selected and the model has great simplicity, accuracy and ability (Steduto et al., 2009), and can investigate the effects of water stress that happens at a specific time during the growing season (Raes et al., 2009). Therefore, AquaCrop concentrates on crop yield response to water (Steduto et al., 2009). Xu et al. (2019) used AquaCrop on rice under different irrigation management practices in eastern China. They reported RMSE value of lower than 0.61 t ha^{-1} for biomass and relative error of 3.6% for yield and emphasized that the model had considerable ability in simulating biomass and yield. Maniruzzaman et al. (2015) employed AquaCrop on rice under various irrigation management practices in Bangladesh and reported that the values of the R^2 for biomass and grain yields were in the 0.94 to 0.99 range and the RMSEn value for grain yield in the 8 to 21% range. Pointing to the good ability of the model, they also reported the percentage prediction error of the model was 5 to 11% for grain yield and 2 to 11% for biomass. Saadati et al. (2011) calibrated AquaCrop to simulate rice yield under different irrigation practices in a semi-arid region. The relative error percentages were 0.1 to 7.8% in 2000 and from -19 to 0.2% in 2001. The results indicated that, given the ability of AquaCrop in simulating plant cover development and yield of rice crop under different irrigation management practices, it can be used to determine the optimal management strategies for improving water productivity in growing rice in the study region.

This research calibrated AquaCrop and assessed its performance in studying the effects of climate change on rice growing season and grain yield under various irrigation management practices in future climate periods for the Rasht region in Gilan Province in northern Iran by using a general circulation model (GCM) under the RCP4.5 and RCP8.5 scenarios.

MATERIAL AND METHODS

The present study was conducted during growing season of 2017 and 2018 on Rice Research Institute of Iran with latitude of 37°12’19” N, longitude 49°38’28” E and altitude of 7 meter below the sea level in Rasht. The experimental design based on randomized complete block arrangement and three replications per treatment. The irrigation was at four levels (flood irrigation and irrigation with intervals of 5, 8, and 11 days). Cultivar Ali Kazemi was used in the experiment. After translating to the mainland, the plots were kept in flood irrigation for 10 days for complete of rice establishment. The water management was performed on the plots using the volume counters to assess the amount of water volume. The plots were hydrologically separated by plastic sheets installed to 40 cm below the soil surface to restrict water flow between plots. Some physical properties of experimental field are shows in the (Table 1).

Table 1. Soil physical properties of experiment field

Depth (cm)	Sand (%)	Loam (%)	Clay (%)	Bulk density (g cm^{-1})	Moisture content (vol %)			K_S (cm day^{-1})
					θ_{SAT} (-)	θ_{FC} (-)	θ_{PWP} (-)	
0-10	14	39	47	1.10	0.65	0.40	0.27	575
10-20	17	39	44	1.20	0.62	0.40	0.30	308
20-30	9	44	47	1.32	0.62	0.41	0.30	4
30-40	11	42	47	1.31	0.60	0.42	0.30	114

Abbreviations are: θ_{SAT} = saturated volumetric water content, θ_{FC} = field capacity volumetric water content, θ_{PWP} = permanent wilting point, Ks = saturated hydraulic conductivity.

The grain yield and biomass yield were measured by removing 5 square meters in the middle of each plot. The required climate information was gathered by using Rasht synoptic weather station. Transpiration and evapotranspiration were assessed also by Mantis penman FAO method and by the use of ET_o calculator (Allen et al., 1998).

The AquaCrop model describes soil-plant-atmosphere parameters. This model results from Doorenbos and Kassame equation (1979), in which relative evapotranspiration is the basis of yield assessing (Raes et al., 2009).

Equation 1:

$$\frac{Y_x - Y_a}{Y_x} = k_y \frac{ET_x - ET_a}{ET_x} \qquad (1)$$

where:

Y_x = the maximum yield;

Y_a = the actual yield;

ET_x = the maximum transpiration;

ET_a = the actual evapotranspiration;

Ky = the coefficient of proportion between relative yield decrease and evapotranspiration decrease.

In fact, the AquaCrop, a simple vegetation growth and aging model has been developed by separating evaporation from transpiration as the basis to estimate transpiration separate from evaporation, final yield simulation (Y) as a function of the final biomass yield (B) and harvest index (HI) and the separation of effects of water stress on four components of canopy, aging, stomata closure, transpiration decrease and harvest index.

Dividing ET into Tr and E prevents non-productive use of water through E, especially when vegetation conditions are not complete. Daily transpiration (Tr_i) that has been normalized using daily ET_o and water productivity (WP) using the need for evapotranspiration and carbon dioxide concentration became biological weight of the plant shoot (Raes et al., 2012).

Equation (2) represents the followings:

$$B_i = WP^* \times \left[\frac{Tr_i}{ET_{o_i}}\right] \qquad (2)$$

In which, B_i is the plant shoot weight in day i (gr m^{-2}), Tr_i is the daily transpiration (mm), ET_{oi} refer to plant transpiration evapotranspiration in day i (mm), WP* is normal water productivity (gr m^{-2}) and its value under the same climatic conditions is constant and equal for C_3 and C_4 plants. Normal water productivity for C_4 plants like corn is changing between 28 to 33 (gr m^{-2}).

Climate change modelling

After calibrating and evaluating the model, the long-term grain yield and biomass were simulated from 1970 to 2010 based on the daily meteorological data obtained from the synoptic meteorological station in Rasht to present the trends in biomass and grain yields. Daily values of the climate data (precipitation, minimum temperature, maximum temperature, and sunshine hours) were simulated for the 40-year period. The LARS-WG6 model was thus run using these two scenarios (RCP4.5 and RCP8.5) of climate change that have been approved by the IPCC. The RCP4.5 and RCP8.5 were used as the optimistic and the worst-case scenarios. The time series simulated by the LARS-WG6 model were reentered into the AquaCrop model, run for all the various years as the meteorological data, and used to reach a better conclusion concerning the effects the studied treatments had on rice grain and biomass yields under different climate change scenarios.

The input files including the characteristics of the studied station and the files of precipitation, minimum temperature, maximum temperature and radiation during the monitoring period were prepared to run the LARS-WG6 model. The 1970-2010 period was considered the monitoring period for the LARS-WG6 model, and the meteorological data from the stations of interest were entered into the model. The model was then run for statistical downscaling of the 5 different GCMs. These models differ in spatial resolution power, designer institute, atmospheric predictor variables, and ocean predictor variables (IPCC, 2014). After running the software for the GCMs that included HadGEM2-ES, EC-EARTH, MPI-ESM-MR, MIROC5, GFDL-CM3, the mean monthly output data of the model were compared with the observational data for the 2011-2016 period to determine which model was better able to simulate each meteorological parameter. For statistical assessing of simulating results, besides the t-test, the RMSE (root mean square error), $RMSE_n$ (normalized root mean square error) (Bouman and Laar, 2006) and MAE (mean absolute error) were calculated (Willmott and Matsuura, 2005).

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

$$RMSE_n = 100\sqrt{\frac{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}{O_{mean}}} \quad (4)$$

$$MAE = \frac{\sum_{i=1}^{n}|P_i - O_i|}{n} \quad (5)$$

where:
P_i = Simulated amount of value;
O_i = Actual assessed amount of value;
n = Actual assessed number of values;
O mean = Mean assessed amount of value;
RMSE = Root Mean Square Error;
$RMSE_n$ = Normalized Root Mean Square Error;
MAE = Mean Absolute Error.

In this method the simulation considers excellent with a $RMSE_n$ of less than 10%, good if the RMSEn is greater than 10 and less than 20%, fair if the $RMSE_n$ is greater than 20% and less than 30%, and poor if the normalized RMSE is greater than 30% (Jamieson et al., 1991). Paired t-tests and linear regression analysis were also used to assess the goodness-of-fit between the observed and simulated results. If the P-value [P (t)] from the paired t-test was greater than 0.05, it was concluded that no significant differences existed between the measured and simulated values.

In this way, the model with the least difference between the simulated and observational data and the largest number of normal data items among the GCMs was selected as the best model for the climatic region of interest. Based on the comparison of the mentioned models, the MIROC5 model made the best predictions of the climate variables. After selecting the best GCM for each climate, the meteorological parameters were predicted for the future 60-year period under the RCP4.5 and RCP8.5 scenarios. For this purpose, the meteorological components for the period 2018-2100 were predicted for the synoptic stations by selecting the model of interest. The mean long-term annual values for the future 83-year period were then compared with those of the baseline period (1970-2010). This will determine to what extent the values of each component will change in the future decades compared to the baseline period. The 2020-2050 and 2060-2090 periods were considered the first and second future climate periods.

RESULTS AND DISCUSSION

Calibration and Validation of AquaCrop model

The statistical variables to assess the ability of AquaCrop in simulating grain and biomass yields during the two crop years were then determined (Tables 2 and 3). The 2017 and 2018 data were used to calibrate and validate the data, respectively. The model was then run and the values for grain and biomass yields that were obtained from the simulation were compared with the measured ones based on the statistical indices. The values of RMSE and $RMSE_n$ for grain yield simulation were (267 kg ha^{-1} and 7%) in 2017 and (297 kg ha^{-1} and 4%) in 2018, and the corresponding values for biomass simulation (294 kg ha^{-1} and 3%) in 2017 and (625 kg ha^{-1} and 7%) in 2018. The results indicated that there was a strong correlation between the measured and simulated values. These findings agree with the R^2 values of (0.84 to 0.93) for grain yield and (0.67 to 0.98) for biomass (Tables 2 and 3). The R^2 values indicated that there was a good correlation between the simulated and the observed values for biomass and grain yields.

Table 2. Evaluating the AquaCrop model simulation results under calibration conditions, 2017

	N	X_{obs}	X_{sim}	RMSE	$RMSE_n$ (%)	P(t)	R^2
Grain yield	4	3961	4214	267	7	0.17	0.93
Biomass yield	4	9748	9757	294	3	0.49	0.98

N: number of measured/simulated data, X_{obs}: mean measured values, X_{sim}: mean simulated values, RMSE: Root Mean Squared Error, RMSEn: Normalized Root Mean Squares Error, R^2: adjusted linear correlation coefficient between simulated and measured values.

Table 3. Evaluating the AquaCrop model simulation results under calibration conditions, 2018

	N	X_{obs}	X_{sim}	RMSE	$RMSE_n$ (%)	P(t)	R^2
Grain yield	4	3806	3940	297	4	0.31	0.84
Biomass yield	4	9470	9076	625	7	0.29	0.67

N: number of measured/simulated data, X_{obs}: mean measured values, X_{sim}: mean simulated values, RMSE: Root Mean Squared Error, RMSEn: Normalized Root Mean Squares Error, R^2: adjusted linear correlation coefficient between simulated and measured values.

The values of $RMSE_n$ ($3 \leq NRMSE \leq 7$) for model evaluation demonstrated that AquaCrop performed suitably in simulating rice grain and biomass yields under conditions of climate change. Vahdati et al. (2020) reported $RMSE_n$ values of 6% to 12% for grain yield and 6% to 8% and biomass yield in Iran. Moreover, Pirmoradian et al. (2020) found $RMSE_n$ values of 2.28% to 15.09% for grain yield and 5.48% to 18.34% for biomass yield in semi-arid and wet regions in Iran. Based on the results, the model was able to simulate grain yield more accurately compared to biomass. The AquaCrop model overestimated grain yield in calibration and evaluation processes, Xu et al. (2019) also slightly overestimated biomass and grain yields in simulating them during the growing season and emphasized that the AquaCrop model exhibited acceptable performance in simulating biomass and grain yields. The relative error percentages of the model in simulating biomass and grain yields were in the (-4% to 0.25% and 4% to 6% ranges, respectively) (Tables 4 and 5). Similar results have been reported in Iran. Vahdati et al. (2020) reported in their simulation of rice biomass and grain yields that the relative error percentages of the model for them were in the -38% to 20% and -22% to -11% ranges, respectively. In another study in Iran, Amiri (2016) noticed that the relative error percentages of the model in simulating rice were in the -16% to 39% range. Saadati et al. (2011) evaluated the AquaCrop model in simulating rice yield in the semi-arid region of Iran and reported that the relative error percentages of the model were in the 0.1% to 7.8% range for the calibration and in the -19% to 0.2% range for validation.

Table 4. Simulated and observed grain yield values of rice and relative error percentage of the model simulation

2018			2017			Irrigation management
Relative error (%)	Simulated (kg ha^{-1})	Observed (kg ha^{-1})	Relative error (%)	Simulated (kg ha^{-1})	Observed (kg ha^{-1})	
4	4422	4267	5	4492	4289	flood
12	3968	3550	7	4426	4123	5-day interval
7	3863	3607	9	4240	3878	8-day interval
-8	3505	3801	4	3699	3555	11-day interval
4	3940	3806	6	4214	3961	average

Table 5. Simulated and observed biomass yield values of rice and relative error percentage of the model simulation

2018			2017			Irrigation management
Relative error (%)	Simulated (kg ha^{-1})	Observed (kg ha^{-1})	Relative error (%)	Simulated (kg ha^{-1})	Observed (kg ha^{-1})	
-7	10212	10941	-4	10341	10722	flood
3	9136	8875	-1	10182	10308	5-day interval
-1	8891	9017	1	9830	9694	8-day interval
-11	8065	9049	5	8674	8267	11-day interval
-4	9076	9471	0.25	9757	9748	average

The field results showed that the highest grain yield was achieved under the flood irrigation management practice. Flooded conditions prepare a suitable situation for the various growth stages of rice whereas rice yield suffers a relative decline under dry conditions. Tarahomi et al. (2010) stated that drought stress resulting from non-flooded irrigation prevented transfer of salts and nutrients to plants and reduced photosynthesis thereby decreasing biomass accumulation and eventually yield. Changing flood irrigation to non-flooded irrigation reduced actual yield. The AquaCrop model also simulated lower yields at various irrigation intervals compared to flood-irrigation conditions. In general, the actual yield declined by (10, 12 and 14%) under conditions of 5, 8 and 11-day irrigation intervals, respectively. The model also clearly confirmed this by reporting a declining trend in simulated yields with decreases of (6, 9 and 19%) at these irrigation intervals (Tables 4 and 5).

Climate change

Under the RCP4.5 and RCP8.5 scenarios, there were changes in all the measured parameters compared to the baseline period for both future periods. The results of assessing the data produced by using the LARS-WG6 model and the observed data in the baseline period indicated that the R^2 values were considerable in all cases (Table 6).

Moreover, the mean absolute error (MAE) in simulating the minimum temperature, the maximum temperature, precipitation and radiation confirmed that simulation error was larger for precipitation than the other parameters. Considering the obtained results, the smallest and largest observed difference between the observational and simulated values, during the baseline period in data production by the model, were those of rainfall and maximum temperature, respectively (Table 6). In addition, the results of the t-test on the LARS-WG6 model in simulating the radiation and minimum temperature variables for April and May in all years, for precipitation except for September, and for maximum temperature in November suggested lack of significant difference.

Table 6. Evaluating the LARS-WG6 model simulation results

MAE	RMSE	R^2	parameter
0.90	1.02	0.98^*	minimum temperature
1.31	1.54	0.98^*	maximum temperature
0.98	1.09	0.82^*	precipitation
0.65	0.79	0.97^*	radiation

*: No significant difference in 5% probability level.

The results revealed that the simulated values for minimum temperature in June, July, August, September, October and November under the RCP4.5 scenario and for May, June, July, August, September, October, November and December under the RCP8.5 scenario increased compared to the baseline period (Figures 1 and 2). Under the RCP8.5 scenario, increases in minimum temperature in May, June and December occurred only in the second future climate period, with the largest increase in minimum temperature (8.6°C) observed in the future climate happening in September and under the RCP8.5 scenario in the second future climate period (Figure 2). The simulated maximum temperatures for all months under both the RCP4.5 and RCP8.5 scenarios increased compared to the baseline period. Increases in maximum temperature in September, October, November and December under the RCP4.5 scenario took place only in the second future climate period (Figure 1). The largest increase in maximum temperature (5.01°C) was that of July under the RCP8.5 scenario in the second future climate period (Figure 2). Under the predicted conditions of climate change, the mean monthly precipitation in most months of the year in both future climate periods underwent changes under the RCP4.5 and RCP8.5 scenarios compared to the baseline period. Of courses these changes were not regular so that precipitation was lower than the baseline period in March, April, May, June, July, August, September, October, and November, but it was higher than the baseline period under the RCP4.5 and RCP8.5 scenarios in January, February and December. The increase in rainfall in December was only observed in the future climate periods under the RCP4.5 and RCP8.5 scenarios, respectively. The largest reduction in mean monthly precipitation (18.7 mm) was that of June under the RCP8.5 scenario in the second future climate period (Figure 2). Considering the results of this research, we can conclude that solar radiation declined in the first future climate period in all months except for January and February under the RCP4.5 scenario and in January, February and December under the RCP8.5 scenario. Moreover, reduction in solar radiation was also observed in the second future climate period in all months except for January, February and December under the RCP4.5 scenario and in January, February, March, November and December under the RCP8.5 scenario. July in both the first and second future climate periods under the RCP4.5 scenario and August and July in the first and second future climate period, respectively, under the RCP8.5 scenario had the largest decrease in radiation. The largest difference in radiation compared to the baseline period (8.8) happened under the RCP8.5 scenario in August in the first future climate period (Figures 1 and 2).

In general, the results indicated that the LARS-WG6 model was able to simulate minimum temperature, maximum temperature, and radiation with high accuracy. However, in precipitation simulation compared to other parameters, it provided more but acceptable errors. These results conform to those found by Hosseini et al. (2016) and Darzi-Naftchali and Karandish (2016). Study of the seasonal and monthly precipitation indicated that average precipitation in both future climate periods declined from March to November compared to the baseline period, with the largest reduction observed for December. Precipitation in December, January and February increased compared to the baseline period. This can be explained considering the increase in minimum and maximum temperatures in fall and summer resulting in higher temperatures of the Caspian Sea water that may cause injection of more water into the atmosphere and increases in autumn rainfall in the region. Since at present northern Iran has most of its annual precipitation in autumn, especially in October, the predictions suggested that a major part of annual rainfall happened with a two-month delay in December. To find out the reason for this delay in maximum annual rainfall compared to the present time, spatial and temporal changes of the atmospheric systems influencing precipitation in the northern coastal region in Iran in the future periods should be studied. The mean monthly rainfall in spring and summer under both the RCP4.5 and RCP8.5 scenarios declined until 2090.

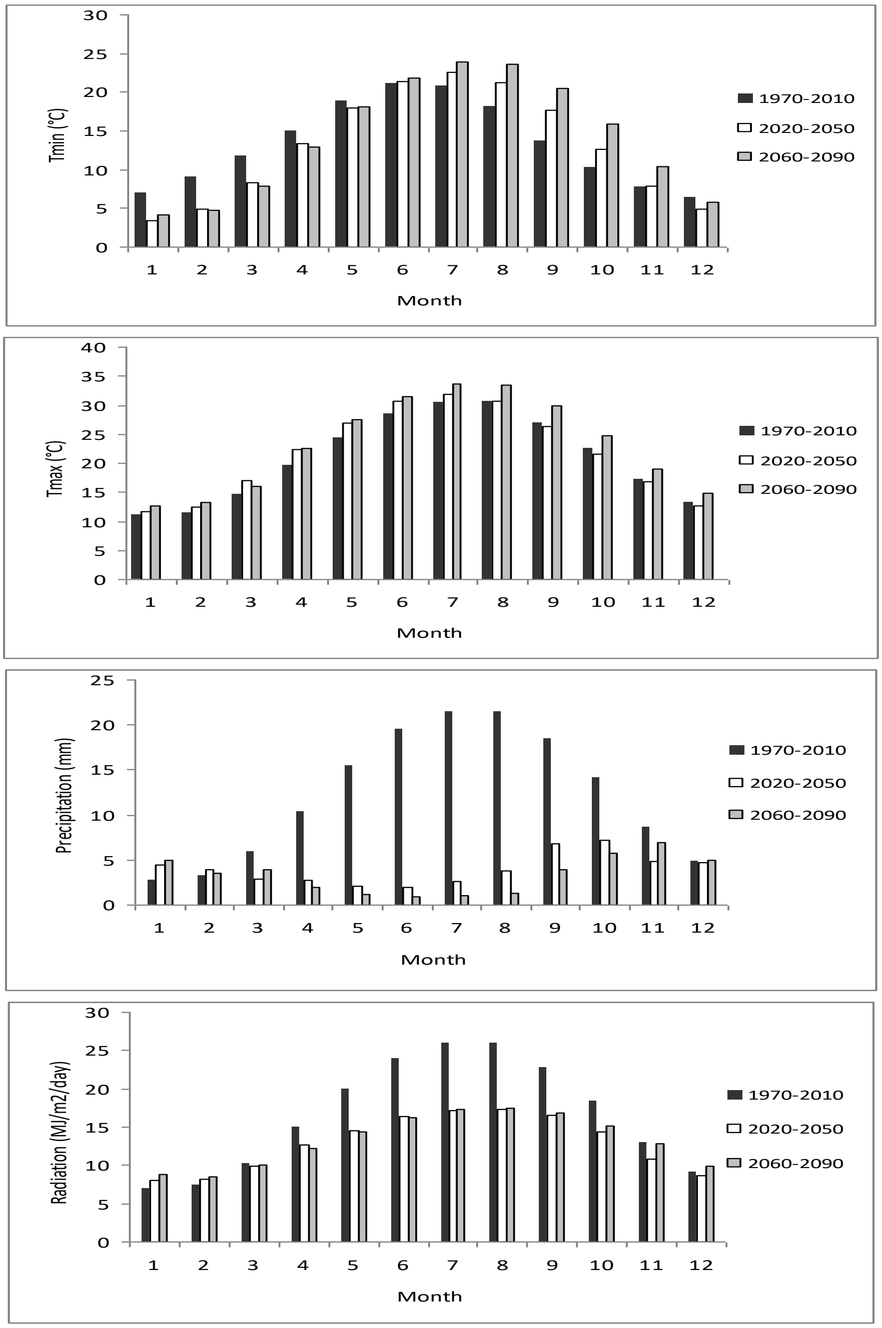

Figure 1. Frequency and normal distributions of TKW for Hap II and Non-Hap II haplotypes

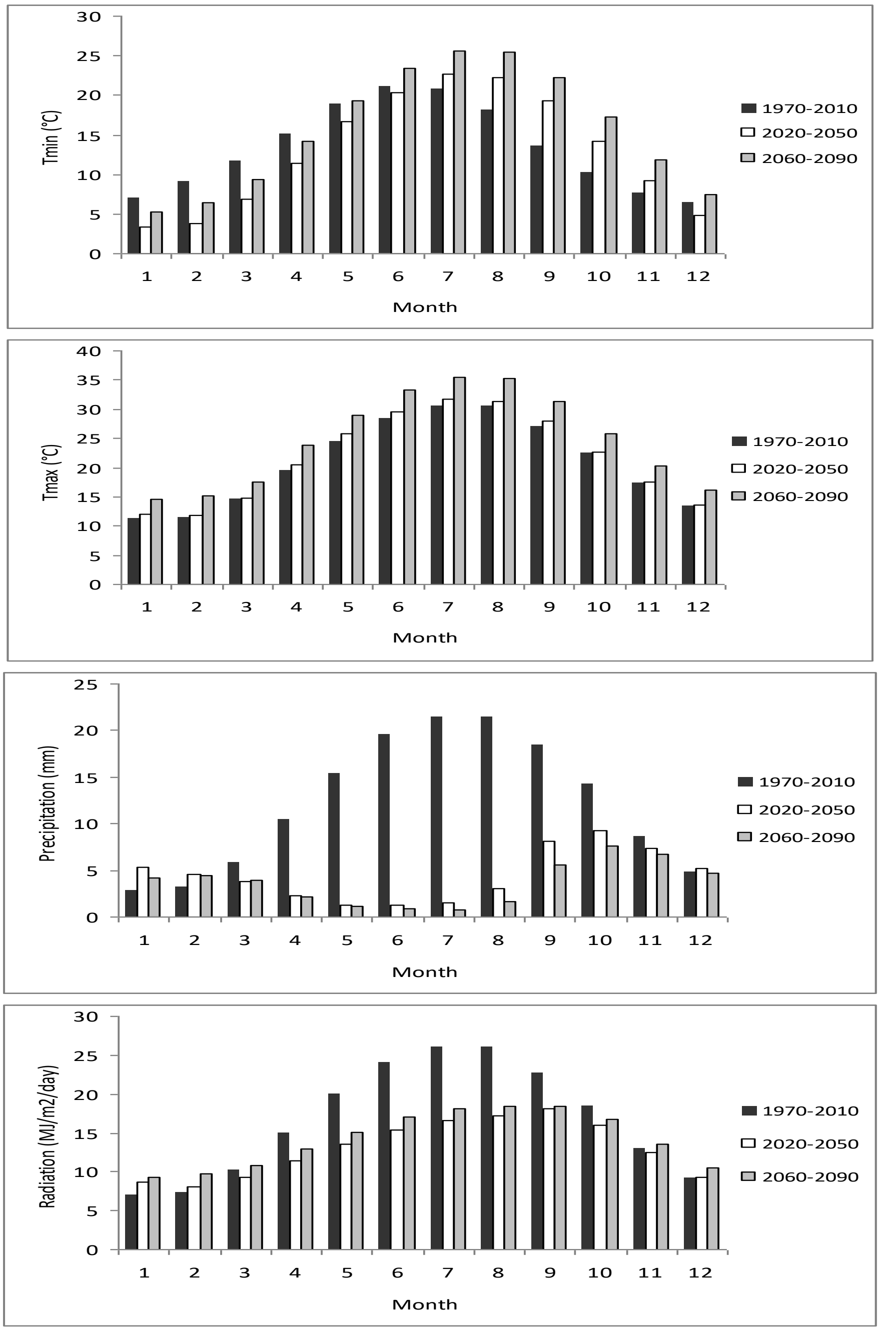

Figure 2. Monthly average of different variables in different periods under RCP 8.5 climate change scenario

Effects of climate change on rice grain yield and biomass

This research also showed that the introduced model could be useful in simulating and evaluating the effects of climate change variables on rice biomass and grain yields (Tables 8 and 9).

Table 8. Simulated grain yield of rice in irrigation management under all scenarios and with respect to the baseline period

Average yield (kg ha^{-1}) 2060-2090		Average yield (kg ha^{-1}) 2020-2050		Average yield (kg ha^{-1}) 1970-2010	Irrigation management
RCP4.5	RCP8.5	RCP4.5	RCP8.5		
4761	5239	4553	4465	4191	flood
2769	2814	3036	2997	3597	5-day interval
2760	2853	2869	2875	3408	8-day interval
1787	1782	2019	1982	2550	11-day interval
3019	3172	3119	3080	3437	average

Table 9. Simulated biomass of rice in irrigation management under all scenarios and with respect to the baseline period

Average biomass (kg ha^{-1}) 2060-2090		Average biomass (kg ha^{-1}) 2020-2050		Average yield (kg ha^{-1}) 1970-2010	Irrigation management
RCP4.5	RCP8.5	RCP4.5	RCP8.5		
11036	12141	10557	10377	9732	flood
6987	7263	7222	7157	8395	5-day interval
6607	6760	6914	6802	8031	8-day interval
4160	4115	4726	4667	6107	11-day interval
7198	7570	7355	7251	8066	average

Based on the simulations, rice biomass and grain yields increased in flood-irrigation management practice in the future climate periods under the RCP4.5 and RCP8.5 scenarios until the end of 2090 whereas mean biomass and grain yields declined in all non-flooded irrigation practices under the RCP4.5 and RCP8.5 scenarios until the end of 2090. Under flood irrigation management, rice yield in the RCP4.5 and RCP8.5 scenarios increased by (8 to 13 and 6 to 25%, respectively), until the end of 2090 whereas rice yield in all non-flooded irrigation practices under the RCP4.5 and RCP8.5 scenarios decreased by (17 to 23 and 18 to 23%, respectively). Moreover, biomass in flood-irrigation management under the RCP4.5 and RCP8.5 scenarios increased in the future climate periods by (8 to 13 and 6 to 24%) whereas biomass in all non-flooded irrigation practices under the RCP4.5 and RCP8.5 scenarios declined by (16 to 21% and 18 to 21%) until the end of 2090. The increases and decreases in biomass and grain yields were larger in the 2060-2090 periods under both scenarios. However, Arunrat et al. (2020) reported increased rice yield by 1.3 to 29% under the RCP4.5 scenario and by 8.3 to 29% under the RCP8.5 scenario in 4 regions in Thailand.

Boonwichai et al. (2019) also predicted that changing rice fertilizer application and planting dates under the RCP4.5 scenario would increase yield by 12 and 8%, respectively, during the 2080s. Other studies suggested that rice yield would decrease under the conditions of climate change in future. For example, Wang et al. (2021) reported that by 2080 climate change would decrease mean rice yield by 3.5 to 4.9% under the RCP4.5 scenario and by 10.5 to 47.9% under the RCP8.5 scenario, but will have positive effects on rice yield in eastern China by the middle of the 20th century. The higher yields under water stress-free conditions in future under both RCP4.5 and RCP8.5 scenarios result from the possible increases in photosynthetic rates due to higher CO_2 concentrations (Ventrella et al., 2015) that may increase rice production. Research has indicated that increased atmospheric CO_2 concentrations improve yields of C3 crops (rice, soybean, etc.) and slightly raise yields in C4 crops (corn, sugar cane, sorghum) (Fischer et al., 2007). In the present research, sensitivity of the rice cultivars to changes in temperature and precipitation demonstrated that rice biomass and grain yields will decrease with increases in temperature and, since flood irrigation is used in growing rice in the Caspian region, this crop has low sensitivity to reduced precipitation and its yield will suffer only when there is a sharp decrease in precipitation. Consequently, the study of the effects of changes in temperature and precipitation in future climate periods showed that increased temperature and decreased precipitation in the region with the flood irrigation regime will not have adverse effects on rice biomass and grain yields but will reduce them under non-flooded irrigation practices. Rice biomass and grain yields in the region decreased with increases in temperature and decreases in precipitation, and this reduction had a rising trend in the second future climate period. The effect of temperature on yield depends largely on the related region. In other words, the undesirable effects of climate change in warm and dry regions of Iran will be very severe (Parry et al., 2004). High temperatures reduce the rice growing season resulting in reduced access to radiation, which is required to carry out photosynthesis. At low temperatures, plants spend more days to reach maturity and hence more biomass is accumulated whereas higher temperatures reduce grain weight.

CONCLUSIONS

This research studied the effects of climate change on rice in northern Iran. The results of evaluating the ability of the AquaCrop model in simulating rice biomass and grain yields indicated that it had good accuracy in predicting biomass and grain yield. The results obtained from the AquaCrop model revealed that water stress decreased biomass and grain yields and prediction error of the model had a direct relationship with increased levels of water stress. The findings also confirmed that AquaCrop estimated the normalized error in biomass and grain yields of the rice crop to be less than 5 percent under irrigation managements. This showed the high accuracy and ability of the model in predicting biomass and grain yields. Consequently, the AquaCrop model can be recommended for planning rice irrigation in the study region and also as a support tool in decision making for planning irrigation in growing rice under the conditions of future climate change in Gilan Province. The required climate data were obtained from the synoptic meteorological station in Rasht to predict the effects of future climate change under the RCP4.5 and RCP8.5 scenarios. The results revealed that the effects of the predicted climate change in future on rice biomass and grain yields under flood irrigation management in the RCP4.5 and RCP8.5 scenarios will be positive until late 21st century. However, these effects will be negative under non-flooded irrigation managements and will decrease biomass and grain yields until late 21st century under the mentioned scenarios, with larger reductions in the second future climate. The average growing period of this crop will also decline in the future climate periods. Contrary to our expectations, the simulation results related to the length of the growing season did not differ for the RCP4.5 and RCP8.5 scenarios under different irrigation management. Therefore, it is recommended to investigate the method used for calculating the length of the growing season. It must be noted that the simultaneous effects of increased CO_2 concentrations and higher temperatures on production of crops are complicated and will be influenced by the climate change scenarios, the simulation model and the geographical location of the study region. Consequently, accurate understanding of the crop production situation under conditions of future climate requires carrying out studies on regional and national scales.

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