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Evaluation of the effect of climate change on maize water footprint under RCPs scenarios in Qazvin plain, Iran

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ABSTRACT

Climate affects agriculture and the main effect of climate change on agriculture largely depends on two variables: temperature (T) and precipitation (P). In this study, the effect of climate change on maize yield and water footprint (WF) in Qazvin plain was investigated. Three scenarios (RCP2.6, RCP4.5, and RCP8.5) for 2021–2040, 2041–2060, 2061–2080, and 2081–2100, respectively, were generated by the LARS-WG model and compared with the baseline period 1986–2015. Yield (Y), water requirement (*WR*), and evapotranspiration (ET) of maize were simulated using the Aqua Crop model for baseline and future periods. In this study, the results of the scenarios were compared with the observed data of Qazvin plain for maize crop by using the statistical error criteria including coefficient of explanation (R^2), normal square root means error (NRMSE), and mean absolute error (MAE). The simulation results of the LARS-WG model in the baseline showed that the model has more accurate in the simulation of minimum temperature (Tmin) and maximum temperature (Tmin) than P. Also, Our findings have investigated that the T will increase in future periods. P changes were seen as both decreasing and increasing. The results showed that the yield decreased in future periods, whereas the *WR* and ET increased in most of the models used. Also, the results showed that the maize WF will increase in future periods. The results obtained and the proposed method will help water managers, users, and agricultural developers for preparing new water-saving strategies and achieving agricultural sustainability.

1. Introduction

Nowadays, climate change and the phenomenon of heating are one of the most important and key issues. Climate change affects various sectors such as agriculture, forestry, water, industry, tourism, energy, etc. (Kemfert, 2009). Crop production is directly dependent on climatic conditions, and climate determines the sources of production and productivity of agricultural activities (Reilly, 1999; Babaee et al., 2021). Therefore, long-term forecasting of climate variables and taking the necessary measures to mitigate the adverse effects of climate change have been considered by many researchers around the world (Elbeltagi et al., 2020b, 2020c). For this purpose, atmospheric public circulation models have been developed. Atmospheric general circulation models can never be used directly and must be micro-scaled before use. Exponential micro-scaling methods are generally divided into two categories: dynamic and statistical. Dynamic micro-scale models include MM5, Regcm 3, and PRECIS. For a variety of statistical micro-scale models, we can name Climate Generator (CLIGEN), Long Ashton Research Station Weather Generator (LARS WG), Automated Statistical Downscaling (ASD), and Statistical Downscaling Model (SDSM). The statistical method has more advantages and capabilities than the dynamic method when lower costs and faster assessment of factors affecting climate change are required (Zarei et al., 2019).

Many researchers have studied the effects of climate changes on several parameters related to crop yield and agricultural water needs (El-mageed et al., 2017; Elbeltagi et al., 2020d, 2020a, 2020e; Bajirao et al., 2021). Mir Saneh et al. (2011) studied the effect of climate change on net irrigation requirement, length of growth period, and date of maize cultivation in Qazvin plain in future periods. In their study, the output of the second version of the Canadian Global Coupled Model (CGCM2) under scenario A2 was used. Their results showed that with increasing temperature in future periods, the length of the maize growth

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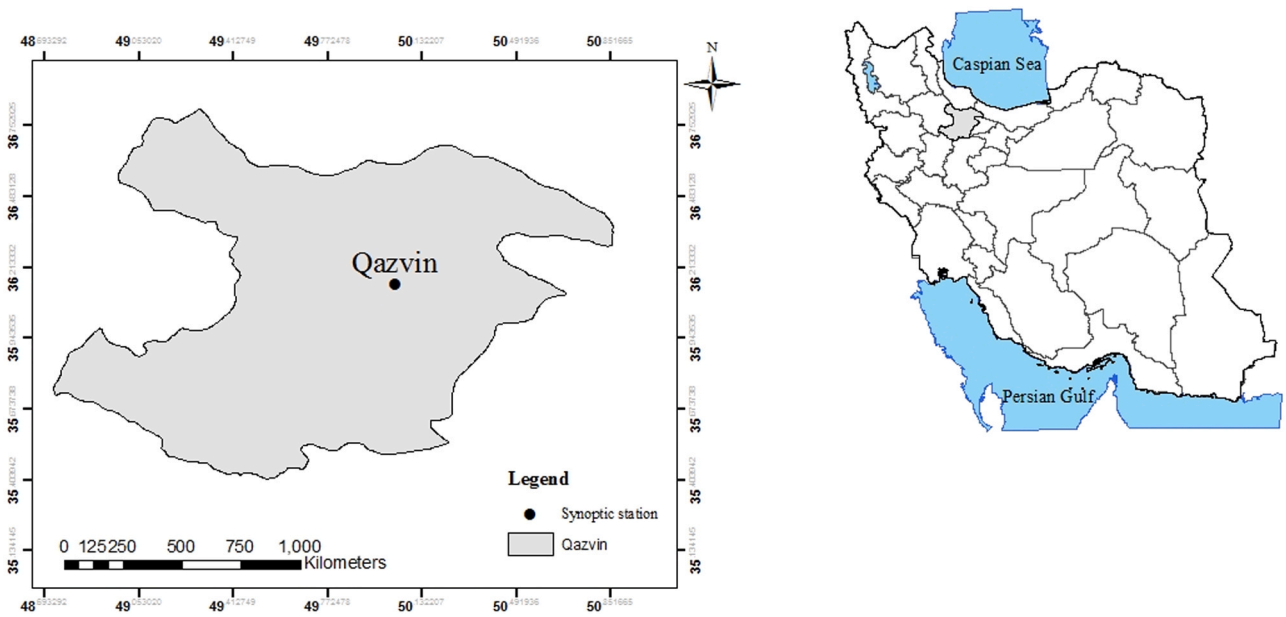

Fig. 1. Qazvin province.

period in the region decreases. In their study, the net irrigation requirement for maize to shift the planting date to warmer months increases significantly. However, this requirement for a specific planting date does not increase significantly in the future compared to the baseline. Parry (1990) examined the impact of climate change in Tanzania. Their results showed a 20% increase in variability in precipitation leading to 4.2, 7.2, and 7.6% and 2 degrees increase in temperature will cause 13, 8.8, and 7.6% decrease in yield on maize, sorghum, and rice plants by 2050, respectively. Moradi et al. (2013) studied climate change on maize production and evaluated the date of cultivation in Mashhad. Their results showed that maize yield will decrease due to climate change in most of the scenarios used. Sun et al. (2018) examined agricultural water demand under the RCP2.6, RCP4.5, and RCP8.5 climate scenarios in the Shanxi Basin in China. Their results showed that in the future period, temperature, effective precipitation, and relative humidity will increase and wind speed will decrease. Burchfield et al. (2020) examined the change in maize yields (winter wheat and maize) in the Central United States under the influence of climate change and technological change. Srivastava et al. (2017) evaluated the effect of climate change on corn production potential in Ghana. Their results showed that the Mean yield of maize in 2030 under the RCP8.5 scenario will increase by 57%.

Water footprint (WF) firstly introduced by Hoekstra (2003), which is one of the newest indicators in the discussion of sustainable water resources management. WF analyzes the relationship between human consumption of fresh water and the use of water in the manufacture of a particular type of product (Hoekstra et al., 2011). WF has three components: The blue water footprint is water that has been sourced from surface or groundwater resources and is either evaporated, incorporated into a product or taken from one body of water and returned to another, or returned at a different time. Irrigated agriculture, industry, and domestic water use can each have a blue water footprint. The green water footprint refers to the volume of rainwater consumed in a production process. This is particularly relevant in agriculture and forestry, where it refers to the total rainwater evapotranspiration (from fields and plantations) plus the water incorporated into the harvested crop or wood. Hoekstra et al. (2009) defined the gray WF in the production of a product as the volume of fresh water required to dilute the pollutants produced in the production process of that product. Many researchers have studied WF for various products such as wheat (Hoekstra and Chapagain, 2007), tea (Jefferies et al., 2012), rice (Chapagain and Hoekstra, 2012; Wu et al., 2021), cotton (Chico et al., 2013), potato (Rodriguez et al., 2015; Herath et al., 2014); maize (Nana et al., 2014; Yao et al., 2021), grape (Ene et al., 2013), wheat and maize (Elbeltagi et al., 2020c), rice and wheat (Kashyap and Agarwal, 2021).

According to research, climate change will affect water requirement (W*R*) and crop yields in the future. So, it is important to study the changes in meteorological parameters and their impact on W*R* and crop yields in each region. And expresses the need for a new approach and the use of comprehensive and efficient criteria or indicators such as water footprint to determine the actual amount of water consumed by agricultural products for planning and optimal and sustainable management of agricultural water consumption. Therefore, this study was conducted to forecast the effect of climate change on the maize yield (Y), evapotranspiration (ET), W*R*, and WF (green and blue) in Qazvin plain. The objective of this study is the investigation of different weather GCMs for Y, ET, and WF, using AR5 scenarios in the Aqua Crop model for maize crop in Qazvin plain.

2. Materials and methods

2.1. Area of study

Qazvin province is located in the north-west of Iran (Fig. 1). Agriculture plays an important role in the economy of Qazvin province. The study area (Qazvin plain) with an area of 450,000 (ha) in terms of agricultural products is important among the plains of Iran. This plain is located in the central plateau of Iran and has a semi-arid climate, hot summers, and relatively cold winters. In this plain, there is a synoptic meteorological station with long-term statistics (Qazvin). Due to the long-term statistics of Qazvin synoptic station, in this study was used the data of this station.The station is located in 50.03° E longitude, and 36.15° N latitude and its height is 1279.2 (m). The annual air temperature varies from maximum 42 °C to a minimum of −24 °C. The average annual relative humidity according to the statistics of the Qazvin synoptic station is 52.9% and the total number of sunny hours is 2896 h per year. The water resources of the plain include water transferred from Taleqan reservoir Dem and groundwater. Qazvin plain is covered by a modern irrigation network which is fed from Talegan Reservoir Dam. The main aquifer of Qazvin plain is naturally fed by the

Table 1
Atmospheric circulation models and climate change scenarios in LARS-WG model.

General circulation model name	Name of provider center	Climate change scenarios		
		RCP2.6	RCP4.5	RCP8.5
EC-Earth	European community Earth-System		✓	✓
GFDL-CM3	Geophysical Fluid Dynamics Laboratory		✓	✓
HadGEM2-ES	Hadley Centre Global Environment	✓	✓	✓
MIROC5	International Center for Earth Simulation		✓	✓
MPI-ESM-MR	Max Planck Institute for Meteorology Earth System		✓	✓

infiltration of surface runoff, especially incoming floods and in the riverbeds, as well as by groundwater flow transferred from sloping aquifers and the infiltration of rainfall. The most important crops in the Qazvin plain are wheat, barley, and maize.

2.2. Estimation of reference evapotranspiration (ET_0)

The Hargreaves-Samani evapotranspiration model does not require extensive data to calculate daily evapotranspiration and was used to study the effects of climate change on agricultural products in the studies of other researchers (Koohi et al., 2020; Elbeltagi et al., 2020d). For this purpose, this model was selected to calculate the daily evapotranspiration of the wheat crop for the baseline (1986–2015) and simulated periods. Samani Hargreaves model for estimating daily transpiration evaporation is defined as Eq. (1):

$$ET_0 = 0.0135 K_T R_a TD^{0.5}(T + 17.8) \tag{1}$$

$$K_T = 0.00185 TD^{0.5} - 0.0433 TD + 0.4023 \tag{2}$$

$$TD = T_{max} - T_{min} \tag{3}$$

T_{min} And $T_{max}$are the minimum and maximum air temperatures in the desired period in terms of degrees Celsius, $R_a$solar radiation above the atmosphere and K_T correction coefficient, respectively.

2.3. Introduction the Aqua Crop model

The basis for estimating yield crop in the Aqua Crop model is the Doorenbos-Kassam relationship, which is presented in issue 33 of the Food and Drainage Journal of the World Food Organization (FAO). Modifications such as the separation of actual evapotranspiration (ET) to evaporation from the soil surface (Es) and transpiration (Ts), as well as yield to biomass (B), and harvest index (HI), have been inferred (Raes et al., 2012):

$$\left(1 - \frac{Y}{Y_x}\right) = K_y\left(1 - \frac{ET}{ET_x}\right) \tag{4}$$

Where Y_x: maximum yield, Y: actual yield, ET_x: maximum evapotranspiration, ET: actual evapotranspiration, and K_y is the ratio between the relative decrease in yield and the relative decrease in evapotranspiration.To calculate the performance of biomass, the Aqua Crop model uses the following equation (Raes et al., 2012):

$$Y = f_{HI} \times HI_0 \times B \tag{5}$$

Where HI_0: reference harvest index (during the physiological maturity stage), Y: grain yield, f_{HI}: is the coefficient that regulates the reference harvest index.

Table 2
Classification of Pearson coefficient and NRMSE.

R^2	< 0.1	0.1–0.2	0.2–0.5	> 0.5
Estimation result	Not correlated	Weak	Moderate	Strong
NRMSE	0–10	10–20	20–30	30 <
Estimation result	Excellent	Good	Moderate	Weak

2.4. Introduction of LARS-WG model

One of the statistical models is the LARS-WG model. This generating model is based on the series method, which can be used to simulate meteorological data at a station under current and future climatic conditions. In the LARS-WG model, precipitation modeling, and its probability of occurrence are performed by quasi-experimental distribution method, and Markov chain, radiation modeling based on quasi-experimental distribution and temperature modeling using Fourier series. The fifth report on climate change presents various public circulation models (Table 1).

2.5. Water footprint

Water footprint (WF) components for maize crop was calculated from the following equations:

$$WF_{Green} = \frac{P \times 10}{Y} \tag{6}$$

$$WF_{Blue} = \frac{(Et - P)}{Y} \tag{7}$$

$$TWF = WF_{Green} + WF_{Blue} \tag{8}$$

In the mentioned relations, the traces of green and blue waters are measured in cubic meters per ton. P is the effective precipitation during the plant growth period in millimeters, ET is the evapotranspiration of each plant during the growth period in millimeters, and Y is the yield of each crop in terms of tons per hectare.

2.6. Statistical evaluation criterions

In this study, the results of the scenarios with the data of Qazvin plain for maize crop, by error statistical criteria including determination coefficient (R^2), normal root mean square error (NRMSE), and mean absolute error (MAE) were compared.

Explanation the coefficient is one of the most important criteria for evaluating the relationship between two variables, x, and y, which is displayed dimensionless. This coefficient is directly related to the correlation coefficient. In this way, by taking the square root of the R^2, the correlation coefficient between the two series can be obtained. As with the correlation coefficient, the closer the value of the R^2 is to one, the stronger the relationship between the two variables. If the Determination Coefficient is multiplied by 100, the value obtained represents the variance of the variable x, described by the variable y. The Pearson coefficient classification is given in the table below (Joinior et al., 2017). Excel software was used to calculate the explanation coefficient.

The NRMSE index indicates the level of estimation. The NRMSE classification by Jamieson et al. (1991) is given in Table 2 (Jamieson et al., 1991).

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{9}$$

Mean absolute error is the difference of the mean absolute value of the estimated amount of the model with to real quantity. The less is its amount, the more is the model's accuracy.

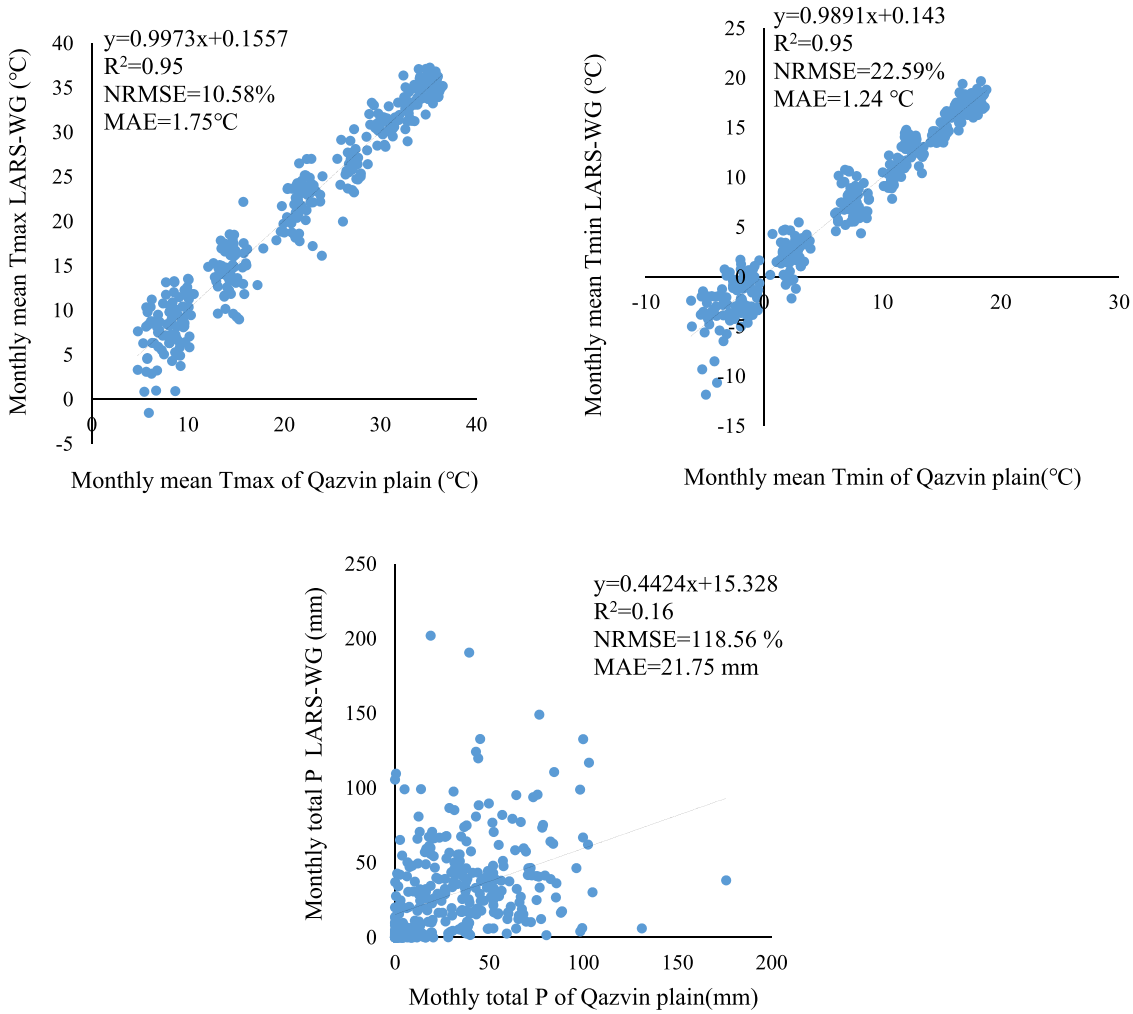

Fig. 2. Total precipitation (P), mean minimum temperature (Tmin) and maximum temperature (Tmax) of Qazvin Plain and simulated with LARS-WG model in the baseline (1986–2015).

$$MAE = \frac{\sum_{i=1}^{n} |P_i - O_i|}{n} \tag{10}$$

O_i and P_i are observational and predicted amount, $\overline{O}$ is the mean of the observational amounts and n is the number of data or time duration series.

3. Result and discussion

3.1. Evaluation of climatic variables

The evaluation results of Precipitation (P) data, minimum temperature (Tmin), and maximum temperature (Tmax) of Qazvin plain and simulated with LARS-WG model in the baseline (1986–2015) are presented in Fig. 2.

The coefficient of explanation for the maximum temperature (Tmin)

Table 3
Percentage of minimum temperature (Tmin), maximum temperature (Tmax) (°C) and precipitation (P) (mm) changes in Qazvin plain under three scenarios and four future periods compared to the baseline (1986–2015).

GCMs	Scenario	2021–2040			2041–2060			2061–2080			2081–2100		
		T min	Tmax	P	Tmin	Tmax	P	Tmin	Tmax	P	Tmin	Tmax	P
EC-EARTH	RCP4.5	13	4.1	9.7	23.2	7.5	7.5	29.2	9.5	13.9	28.3	9.4	0.3
	RCP8.5	12.9	4	11.3	27.9	9.1	9.1	45.5	14.9	12	44.6	14.9	-1.3
GFDL-CM3	RCP4.5	19.5	8.2	4	30.8	13.7	13.7	39	17.2	-3.7	38.1	17.2	-16.1
	RCP8.5	24.6	10.3	0.5	37.2	16.6	16.6	55.8	24.6	-2	54.9	24.5	-13.4
HadGEM2-ES	RCP2.6	19.2	7.1	17.7	26	10.7	10.7	24.1	9.1	22.9	23.2	9	9.2
	RCP4.5	16.4	6. 9	9.2	27	10.4	10.4	37.8	16	18.9	37	15.9	5.1
	RCP8.5	21.5	8.5	7.4	36.3	14.7	14.7	57.9	23.2	18	57.1	23.1	4.1
MIROC5	RCP4.5	12.1	4.9	4.7	21.1	8.3	8.3	26.2	11.4	0.7	25.3	11.3	-10.6
	RCP8.5	12.3	4	15.9	27.5	10.7	10.7	42	16	11.9	41.1	15.9	-1.13
MPI-ESM-MR	RCP4.5	13.2	5.8	-4	21.5	8.1	8.1	29	11.8	-1.8	28.1	11.7	-13.5
	RCP8.5	15.6	6.1	7.6	31	11.8	11.8	47.9	18.9	-7.1	47. 0	18.9	-17.5

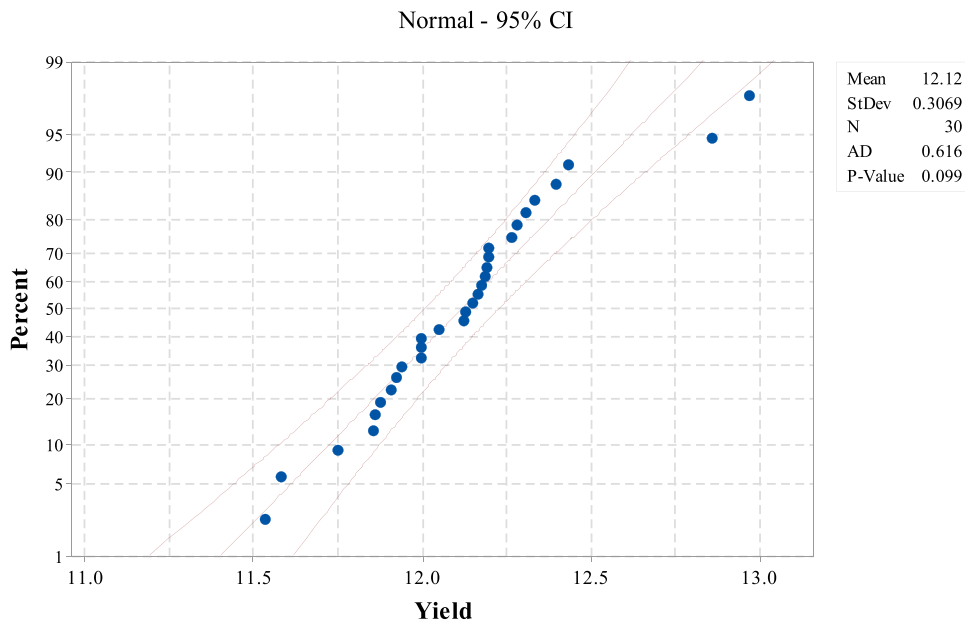

Fig. 3. Probability plot of yield.

and minimum temperature (Tmax) simulated with the LARS-WG model showed that the simulated data and the Qazvin plain data have a high correlation (Fig. 2). An explanation coefficient greater than 90% indicates that more than 90% of the variance in the Tmin and Tmax data of the Qazvin plain is described by the LARS-WG model data. The NRMSE value is in the good category at the Tmax and in the medium category at the Tmin. The value of the MAE index was obtained for a Tmin of 1.26 °C and for a Tmax of 1.75 °C.

The coefficient of explanation for the precipitation (P) simulated with the LARS-WG model showed that the simulated data and the data of the Qazvin plain are not highly correlated and the coefficient of explanation decreases to less than 0.5 (Fig. 2). The NRMSE value for P was in the weak category and the MAE index value was 21.75 mm. The results showed that the model is more accurate in simulating minimum and maximum temperatures than precipitation. Goudarzi et al. (2015) investigated the performance of LARS-WG and SDSM microscopic exponential models in simulating climate change in the catchment area of Lake Urmia. Their results showed that both models are more accurate in simulating temperature than precipitation, which is consistent with the results of the present study.

The percentage of changes of minimum temperature (Tmin), maximum temperature (Tmax), and precipitation (P) in future periods compared to the baseline (Table 3).

The results showed that the minimum temperature (Tmin) in all models (EC-Earth, HadGEM2-ES, MIROC5, GFDL-CM3, MPI-ESM-MR) under all three scenarios (RCP2.6, RCP4.5 and RCP8.5) In future periods (2021–2040, 2041–2060, 2061–2080, 2081–2100) compared to the baseline (1986–2015) will increase and the highest percentage of changes in the HadGEM2-ES model under the RCP8.5 scenario in the period 2061–2080 has been calculated (Table 3). The results showed that the maximum temperature (Tmax) will increase in the future periods compared to the baseline and the highest percentage of changes in the GFDL-CM3 model under the RCP8.5 scenario was achieved in the period 2061–2080 (Table 3). The results showed that the percentage of simulated precipitation (P) changes in the violating models under RCP2.6, RCP4.5, and RCP8.5 scenarios in future periods compared to the baseline varies between 25.72 and −17.49 (Table 3).

Ghorbani et al. (2017) investigated the effects of climate change on the climatic zoning of Golestan province during the baseline of 1982–2010. In their study, they used the LARS-WG model based on the output of the HADCM3 model, under different scenarios. Their results showed that under the influence of climate change, rainfall and temperature increase in Golestan province but its amount varies in different years. Their results showed that in the near future (2011–2040), increasing rainfall is superior to temperature and causes humidity of climates, but in the future periods (2071–2100) increasing temperature has a greater effect and causes warmer climates, which with the results The present study is consistent. Asadi et al. (2020) used the LARS-WG model and scenarios A2, A1B and B1 to study the changes in minimum temperature (Tmin), maximum temperature (Tmax), precipitation (P), and sundial of Hamedan in the period 2046–2065. Their results showed that the minimum and maximum temperatures increased and the precipitation changes were estimated to be both incremental and decreasing, which is consistent with the results of the present study.

Table 4
Regression coefficients and equation between climate variables and maize yield (1986–2015).

Variable	Coefficient	R^2	P-value
P	0.002	0.44	0.00
ET	-0.003	0.16	0.027
Tmax	-0.157	0.24	0.007
Tmin	-0.207	0.19	0.016
Regression equation	Yield= 10.97 − 0.113 Tmin + 0.092 Tmax + 0.001573 P-0.00077 ET	0.45	0.004

3.2. Evaluation of maize yield

In order to investigate the relationship between climatic variables and crop yield, the crop yield distribution at 5% level was investigated Fig. 3. The probability distribution of maize yield was normal.

Regression analysis was performed to investigate the effect of climatic variables on maize yield (Table 4). The relationship between yield and each of the climatic variables was investigated. The relationship between precipitation and yield was positive, while the relationship between Evapotranspiration, minimum and maximum temperature was negative.

Results of maize yield estimated by Aqua Crop model in Qazvin plain for RCP2.6, RCP4.5, and RCP8.5 scenarios and general circulation

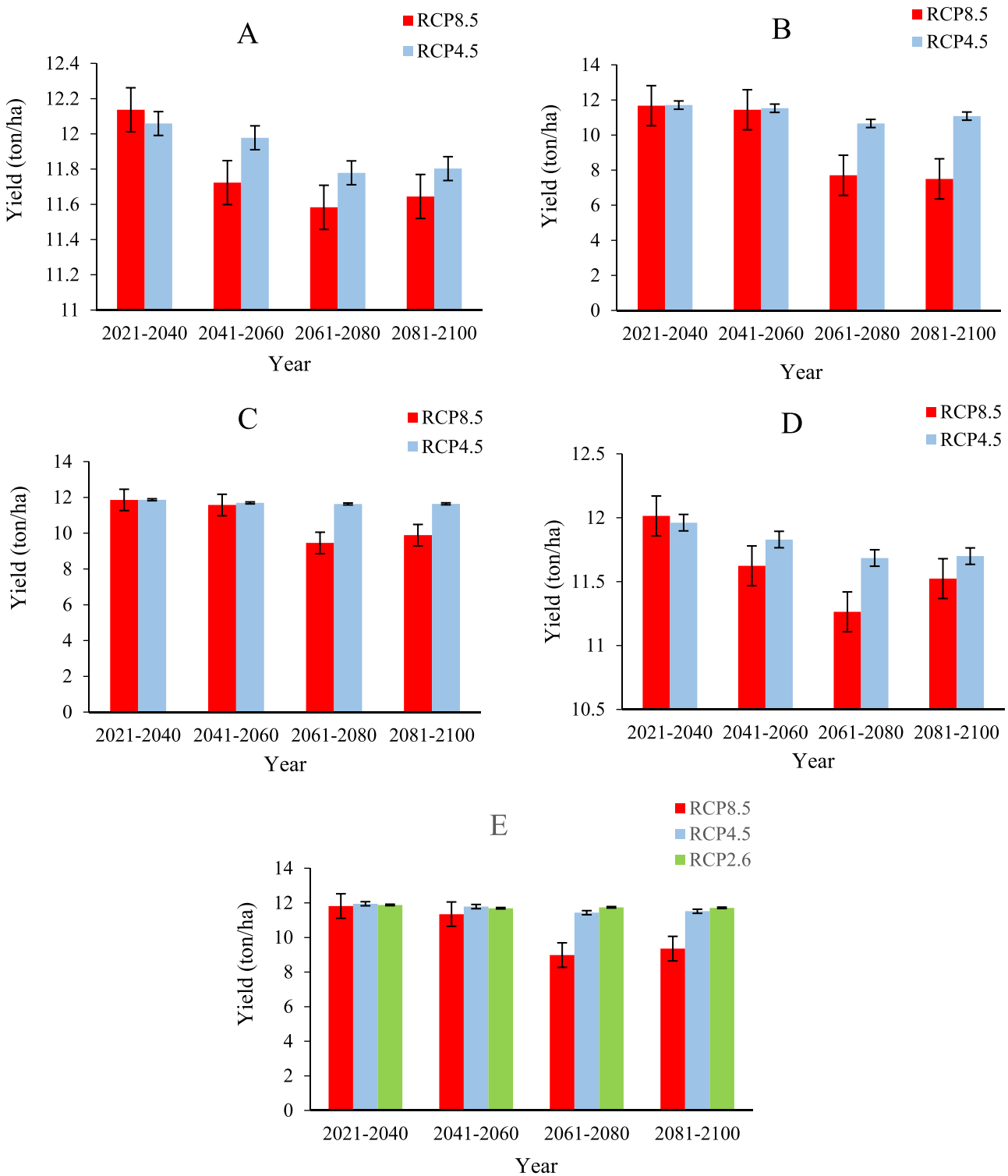

Fig. 4. A- Average annual yield EC-EARTCH model, B- Average annual yield GFDL-CM3 model, C- Average annual yield MPI-ESM-MR model, D- Average annual yield MIROC5 model, E- Average annual yield HadGEM2-ES model for the periods (2021–2040), (2041–2060), (2060–2081) and (281–2100).

Table 5
Percentage of changes maize yield (Y) (ton/ha), water requirement (W*R*) (mm) and evapotranspiration (ET) (mm) in Qazvin plain under three scenarios and four future periods compared to the baseline (1986–2015).

GCMs	Scenario	2021–2040			2041–2060			2061–2080			2081–2100		
		Y	W*R*	ET	Y	W*R*	ET	Y	W*R*	ET	Y	W*R*	ET
EC-EARTH	RCP4.5	-0.5	15.6	3.7	-1.1	4.1	2.6	-2.8	5.1	1.3	-2.6	6.7	-1.2
	RCP8.5	0.2	20.7	3.5	-3.2	6.1	0.7	-4.4	5.3	-2.8	-3. 9	-16.8	-9.8
GFDL-CM3	RCP4.5	-3.4	45.2	14.1	-4.8	53.9	19.9	-12.0	57.9	22.9	-8.5	59.9	18.6
	RCP8.5	-3.6	44.7	15.6	-5.6	57.1	20.8	-36.4	84.7	28.9	-38.1	56.3	19.6
HadGEM2-ES	RCP2.6	-1.9	53.4	9.9	-3.5	45.1	13.8	-3.1	51.34	10.8	-3.3	60.9	8.9
	RCP4.5	-1.4	59.2	13.3	-2.7	50.2	15.9	-5.6	55.1	20.8	-4.9	61.4	17.5
	RCP8.5	-2.5	49.8	11.4	-6.3	64.6	19.5	-25.9	68.1	19.0	-22.8	63.8	10.6
MIROC5	RCP4.5	-1.3	36.3	8.0	-2.4	44.9	9.3	-3.6	47.5	12.6	-3.4	61.2	9.5
	RCP8.5	-0.8	19.8	5.2	-4.1	42.7	10.2	-7.0	45.9	6.5	-4. 9	19.5	-0.9
MPI-ESM-MR	RCP4.5	-2.1	49.9	11.5	-3.5	46.1	11.9	-4.0	51.0	13.8	-3.9	65.7	10.8
	RCP8.5	-2.1	48.6	11.4	-4.5	49.7	12.9	-22.0	63.8	16.6	-18.4	58.8	8.8

models in LARS-WG model (EC-Earth, GFDL-CM3, HadGEM2-ES, MIROC5 MPI-ESM-MR) in the future periods: 2021–2040, 2041–2060, 2061–2080, and 2081–2100 are presented (Fig. 4) and Table 5.

The average maize yield for the baseline was 12.12 (ton/ha). The average maize yield will decrease in future periods.

The maximum maize yield in the baseline was 12.96 (ton/ha) and the maximum maize yield predicted in the period 2021–2040 and the EC-Earth model with RCP8.5 scenario equal to 12.43, in the period 2041–2060, 2061–2080, and 2081–2100 and EC-Earth model with RCP4.5 scenario were estimated to be 12.24, 12.04, and 11.97 (ton/ha), respectively. The results showed that in 2021–2040 in the EC-Earth model with RCP8.5 scenario, in 2041–2060 in MIROC5 model with RCP4.5 scenario, in 2061–2080 and 2081–2100 in the EC-Earth model. With RCP4.5 scenario, it had the lowest percentage of changes in maize yield compared to the baseline (Table 5).

Maize is one of the C4 plants that is sensitive to climate change (Meza et al., 2008). Many studies show that maize is sensitive to very high temperatures and rising temperatures can greatly reduce the yield of this plant (Dupuis and Dumas, 1990; Moradi et al., 2013), which is consistent with the results of the present study. Xiao et al. (2020) conducted the effect of climate change on wheat and maize yield in northern China, their results showed that climate change will have a positive effect on wheat yield but a negative effect on maize yield. Yano et al. (2007) examined the effect of climate change on water requirement and maize growth in Mediterranean areas in Turkey. Their results show an increase in temperature and a decrease in rainfall by the end of 2100 and a decrease in maize yield, which is consistent with the results of the present study. Meza et al. (2008) investigated the effect of climate scenarios on maize production in Chile, and the results indicate that maize can be affected by climate change and be associated with crop decline depending on the climate change scenarios used.

The prediction uncertainties, as measured by the standard deviation (SD) in predicted yield, water requirement, and evapotranspiration (Figs. 4–6). The results showed that RCP 8.5 has a higher SD. He et al. (2011) used standard deviation for the evaluation of sweet corn yield.

3.3. Evaluation of maize water requirement

Results of maize water requirement estimated by Aqua Crop model in Qazvin plain for RCP2.6, RCP4.5, and RCP8.5 scenarios and general circulation models in the LARS-WG model (EC-Earth, GFDL-CM3, HadGEM2-ES, MIROC5 MPI-ESM-MR) in the following periods: 2021–2040, 2041–2060, 2061–2080 and 2081–2100 are presented (Fig. 5) and Table 5.

The average water requirement (W*R*) of maize in the baseline was 56.27 mm, which will increase in future periods. The highest W*R* in 2021–2040 is 269.8 (mm) in the HadGEM2-ES model under RCP4.5 scenario, in 2041–2060 is 278.85 (mm) in HadGEM2-ES model under RCP8.5 scenario, In the period 2061–2080 equal to 312.85 (mm) in the GFDL-CM3 model under the RCP8.5 scenario and in the period 2081–2100 equal to 280.7 (mm) in the MPI-ESM-MR model under the RCP4.5 scenario. The results showed that the lowest percentage of changes in W*R* in future periods compared to the baseline in the HadGEM2-ES model is estimated under the RCP4.5 scenario (Table 5).

3.4. Evaluation of maize evapotranspiration

Results of maize evapotranspiration estimated by Aqua Crop model in Qazvin plain for RCP2.6, RCP4.5, and RCP8.5 scenarios and general circulation models in the LARS-WG model (EC-Earth, GFDL-CM3, HadGEM2-ES, MIROC5 MPI-ESM-MR) in the following periods: 2021–2040, 2041–2060, 2061–2080 and 2081–2100 are presented (Fig. 6) and Table 5.

The average evapotranspiration (ET) of maize for the baseline was 316.27 (mm). The results show that the ET increases in all models and scenarios in 2040–2021 and 2060–2041, and in 2080–2061 in EC-EARTH model under RCP8.5 scenario and in 2100–2081 in EC-EARTH model under RCP4.5 and RCP8.5 scenarios and MIROC5 model decreases under RCP8.5 scenario (Fig. 6). The results show that the GFDL-CM3 model under RCP8.5 scenario in the period 2061–2080 had the highest increase in ET compared to the baseline (Table 5). The maximum ET of maize at the baseline was 379 (mm) and the maximum ET predicted in the period 2021–2040, 2041–2060, 2061–2080 and 2081–2100 of the GFDL-CM3 model under the RCP8.5 scenario were 396, 416, 444 and 415 (mm), respectively. The minimum ET of maize was obtained in the baseline of 277 (mm) and the minimum ET of maize in the periods of 2021–2040, 2041–2060, 2061–2080, and 2081–2100 and the EC-EARTH model under the RCP8.5 scenario were equal to 299, 348, 283 and 255 (mm) are calculated.

Nikbakht Shahbazi (2018) examined the rate of changes in precipitation and evapotranspiration of agricultural products including wheat, barley, rice, maize, and sugarcane in Khuzestan province under the influence of climate change. To analyze and simulate the data, SDSM statistical micro-scale model and CanESM2 general circulation model under RCP scenarios were used. Their results showed that the rate of evapotranspiration obtained for all studied agricultural products showed an increasing trend that is consistent with the results of the present study.

3.5. Water footprint

The maize water footprint (WF) simulated with the Aqua crop model in Qazvin plain in the baseline are presented (Fig. 7).

The average total water footprint (WF) of maize in Qazvin plain was estimated at about 260 (m^3/ton) in which the share of the green water footprint is 6.78% and the share of blue water footprint is 93.23%. The high share of traces of irrigated water compared to green water indicates a low rainfall rate and indicates the stability of arid and semi-arid

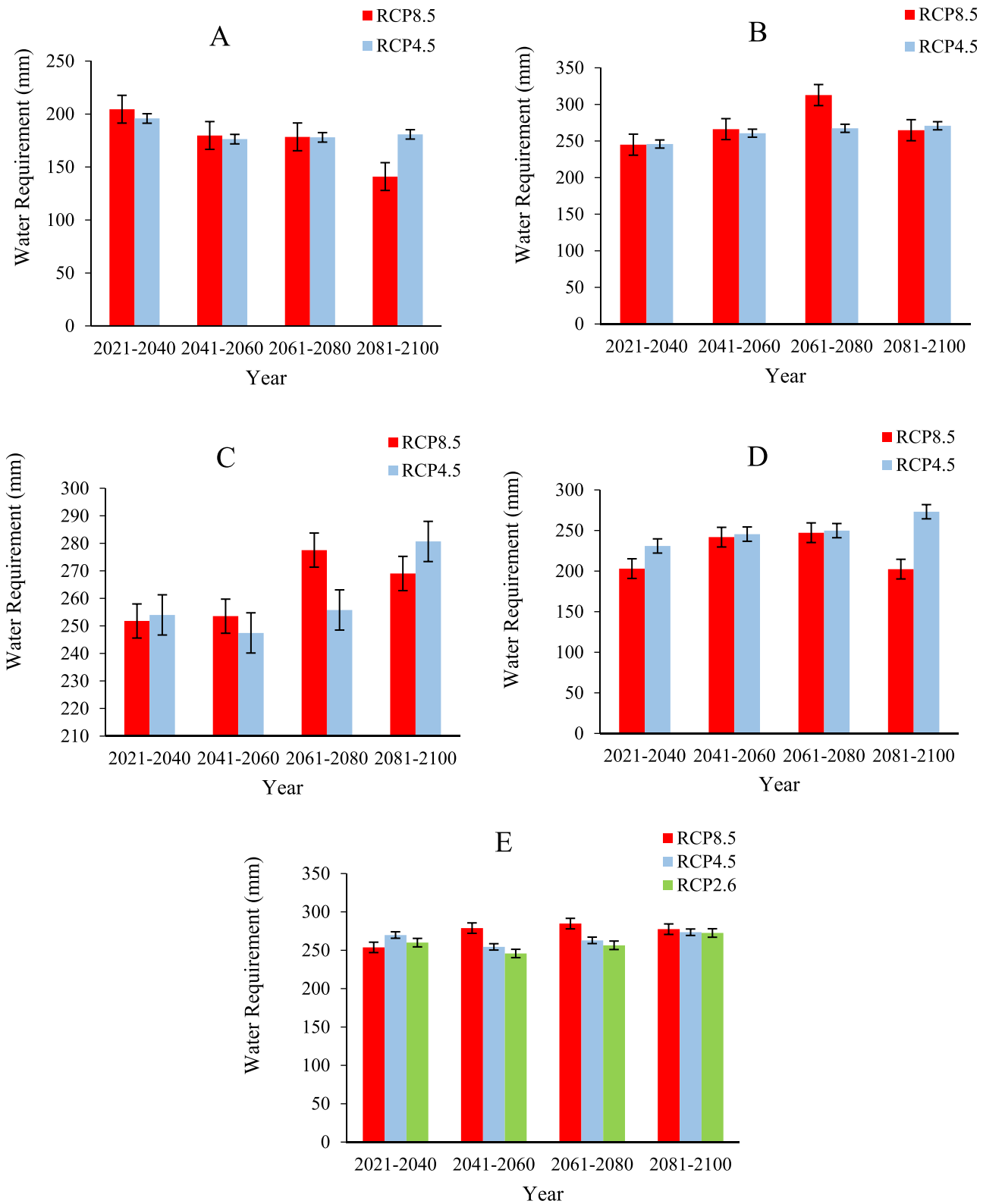

Fig. 5. A- Average annual water requirement EC-EARTCH model, B- Average annual water requirement GFDL-CM3 model, C- Average annual water requirement MPI-ESM-MR model, D- Average annual water requirement MIROC5H model, E- Average annual water requirement HadGEM2-ES model for the periods (2021–2040), (2041–2060), (2061–2080) and (2081–2100).

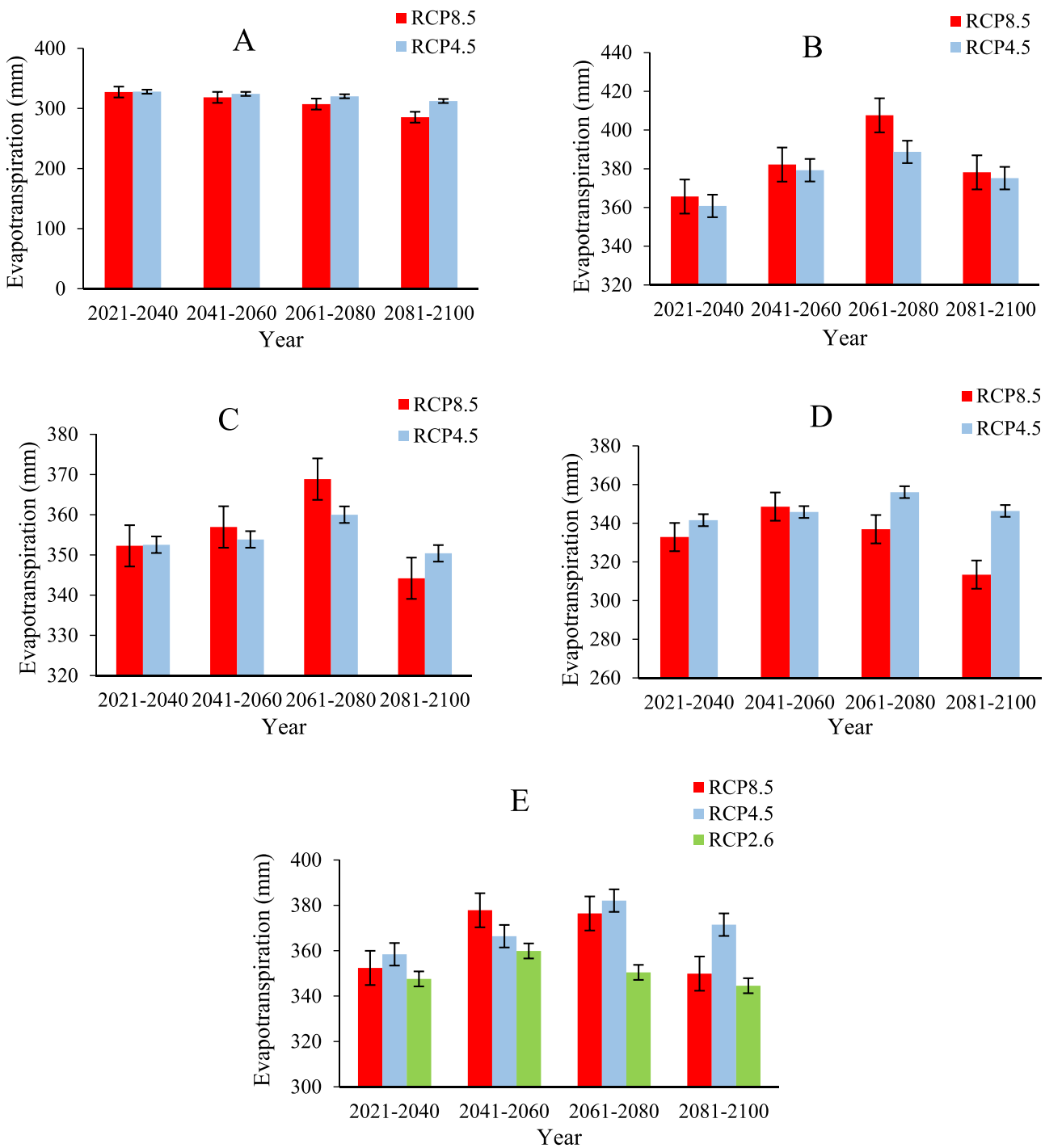

Fig. 6. A- Average annual evapotranspiration EC-EARTCH model, B- Average annual evapotranspiration GFDL-CM3 model, C- Average annual evapotranspiration MPI-ESM-MR model, D- Average annual evapotranspiration MIROC5H model, E- Average annual evapotranspiration HadGEM2-ES model for the periods (2021–2040), (2041–2060), (2061–2080) and (2081–2100).

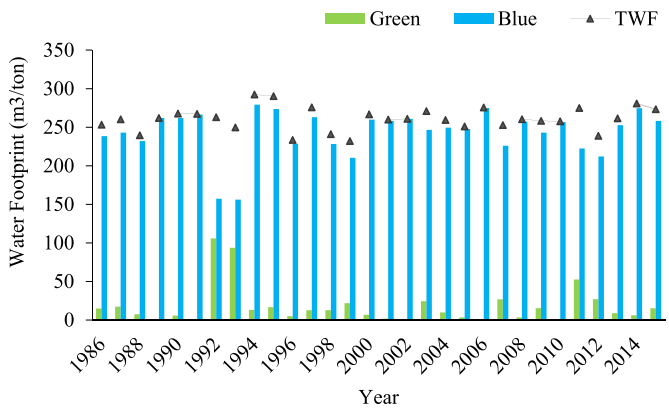

Fig. 7. Maize water footprint of Qazvin plain in the baseline (1986–2015).

positive effect of evapotranspiration (ET), precipitation (P) and maximum temperature (Tmax) and the negative effect of minimum temperature (Tmin) had the highest coefficient of explanation (0.32).

Results of maize water footprint (green and blue) estimated by Aqua Crop model in Qazvin plain for RCP2.6, RCP4.5 and RCP8.5 scenarios and general circulation models in LARS-WG model (EC-Earth, GFDL-CM3, HadGEM2-ES, MIROC5 MPI-ESM-MR) in the following periods: 2021–204, 2041–2060, 2061–2080 and 2081–2100 are presented Fig. 10 and Table 7.

The maximum water footprint (WT) in the baseline was 292.35 (m^3/ton). The maximum WT in the period 2021–2040 in the model GFDL-CM3 under the scenario RCP8.5 is equal to 337.19 (m^3/ton), in the period 2041–2060 in the model HadGEM2-ES under the scenario RCP8.5 equal to 397.28, in the period 2061–2080 and 2081–2100 in GFDL-CM3 model under RCP8.5 were estimated to be 1917.01 and 1048.24 (m^3/ton), respectively. The results show that the WF will increase in future periods. Bocchiola et al. (2013) examined the effect of climate change scenarios on crop yield and WF of maize in the Po valley of Italy. Their results showed under the worst, more likely future scenarios of increasing temperature and decreasing precipitation, crop yield decreased and water footprint, especially blue, increased, due to increased evapotranspiration, higher irrigation demand, and lower final yield, which is consistent with the results of the present study.

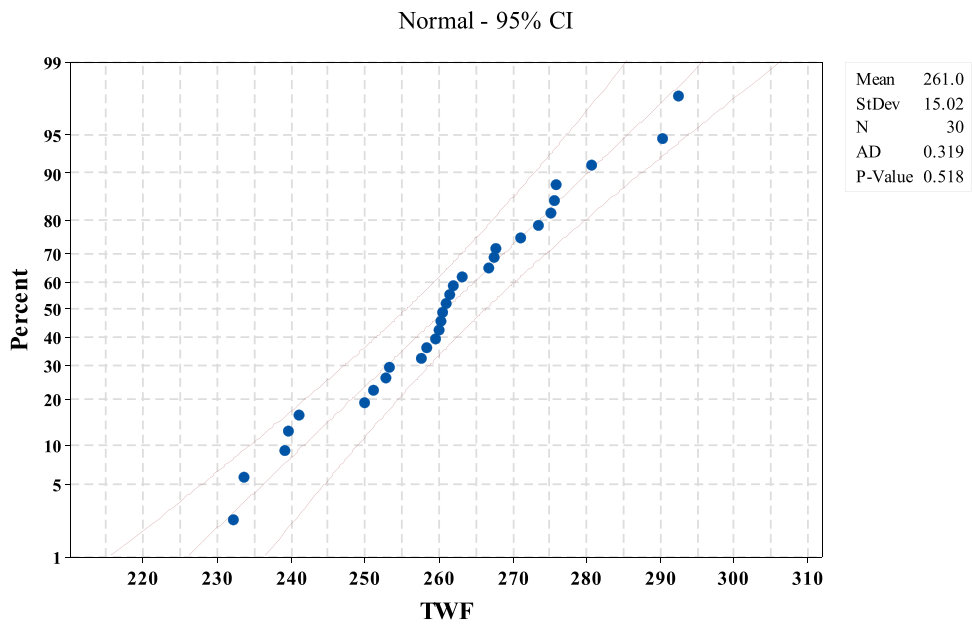

Fig. 8. Probability plot of Total water footprint in baseline (1986–2015).

climate in terms of agriculture (Aligholinia et al., 2019). Aligholinia et al. (2016) estimated and evaluated water and green water footprints in the Urmia watershed. In their study, the water footprint of 5 major crops including wheat, sugar beet, tomato, alfalfa, and maize were examined and the results showed that the share of green water footprint and blue water are 25% and 75%, respectively and the share of water is higher. Which is consistent with the results of the present study.

In order to investigate the relationship between climatic variables and maize water footprint, the distribution of maize water footprint in the baseline and future doubles at 5% level were investigated (Figs. 8 and 9). The probability distribution of maize water footprint was normal.

The prediction uncertainties, as measured by the standard deviation (SD) in predicted total water footprint (WF) (Figs. 8 and 9). The results showed that RCP 8.5 has a higher SD.also, result showed (WF) EC-EARTCH model with RCP4.5 has a lower SD.

Regression analysis was performed to investigate the effect of climatic variables on maize water footprint (WF) (Table 6). The relationship between WF and each of the climatic variables was investigated. The correlation coefficient between WF and climatic variables is low and among the variables, evapotranspiration has the highest correlation coefficient (0.18) at the level of 5%. The regression equation with the

4. Conclusion

Agriculture is one of the most important economic sectors in which climate change can have a major impact and affect crop yields. Because agricultural activities ensure food supply, it is important to study the effects of climate change, as it can provide the right planning and strategies for adapting to future climate change (Georgopoulou et al., 2017). So in this study, precipitation (P), and minimum temperature (Tmin), and maximum temperature (Tmax) of Qazvin plain and simulated and evaluated with LARS-WG model in the baseline (1986–2015). The results showed that the coefficients of explanation for the Tmin and Tmax simulated with the LARS-WG model and the Qazvin pain data were highly correlated. The NRMSE value is in the good category at the Tmax and in the medium category at the Tmin. The results showed that the

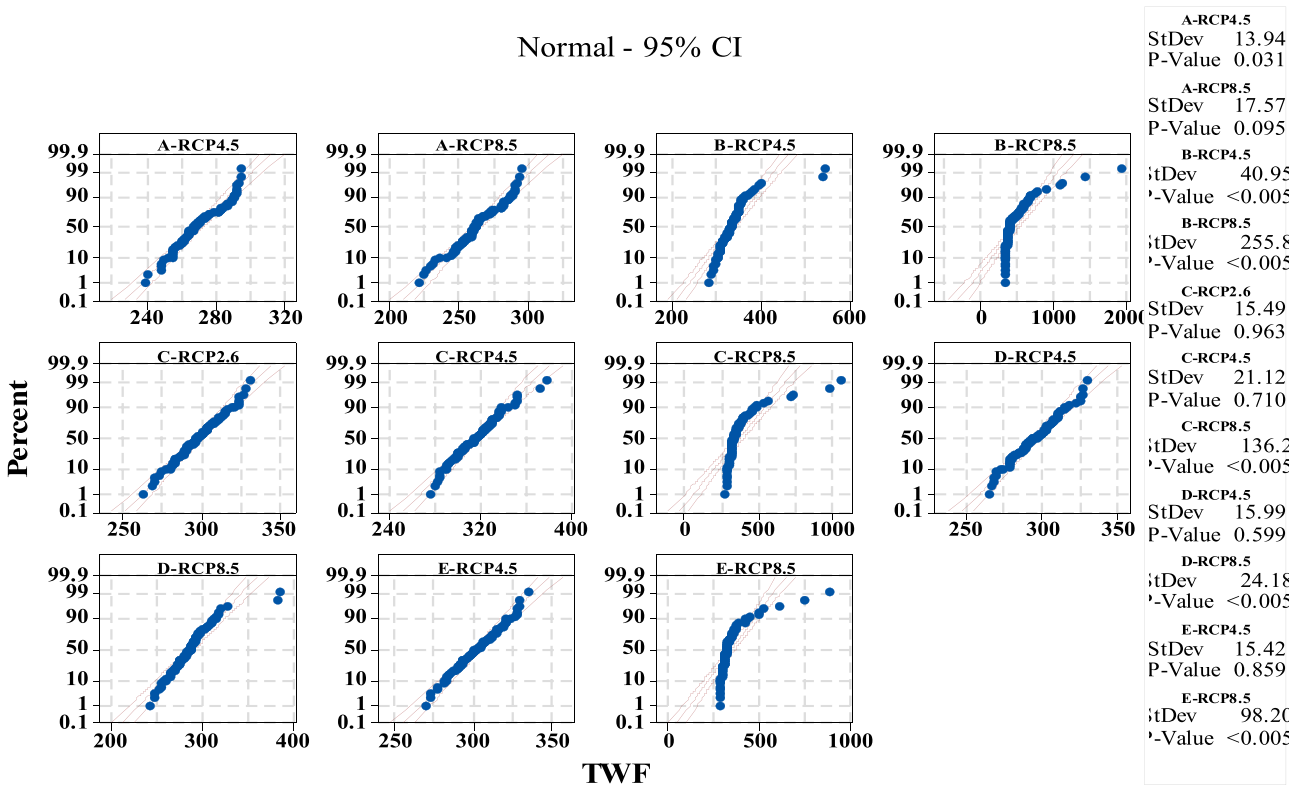

Fig. 9. A- Probability plot of maize total water footprint EC-EARTCH model, B- Probability plot of maize total water footprint GFDL-CM3 model, C- Probability plot of maize total water footprint HadGEM2-ES model, D- Probability plot of maize total water footprint MIROC5H model, E- Probability plot of maize total water footprint MPI-ESM-MR model for the period 2021–2100.

Table 6
Regression coefficients and equation between climate variables and maize total water footprint (1986–2015).

Variable	Coefficient	R^2	P-value
Precipitation (P)	-0.004	0.013	0.849
Actual evapotranspiration (ET)	0.149	0.182	0.019
Max Temperature (Tmax)	2.01	0.016	0.503
Min Temperature (Tmin)	-0.99	0.002	0.824
Regression Equation	TWF= 110–10.6 Tmin + 2.5 Tmax + 0.0216 P + 0.234 ET	0.319	0.041

explanation coefficient for the simulated P with LARS-WG model and Qazvin plain data are not highly correlated and the explanation coefficient decreases to less than 0.5. In general, the model results in simulating Tmin and Tmax are more accurate than P. To predict Tmin, Tmax, and P in future periods (2021–2040,2041–2060,2061–2080, 2081–2100) from LARS-WG models (EC-Earth, HadGEM2-ES, MIROC5, GFDL-CM3, MPI- ESM-MR) was used under the scenarios (RCP2.6, RCP4.5, and RCP8.5). The results showed that the Tmin and Tmax in all models under all three scenarios will increase in future periods compared to the baseline and the highest percentage of Tmin changes in the HadGEM2-ES model under RCP8.5 scenario in 2061–2080 and the highest The Tmax in the GFDL-CM3 model was calculated under the RCP8.5 scenario in the period 2061–2080. The percentage of simulated P changes in the offending models under RCP2.6, RCP4.5 and RCP8.5 scenarios in future periods compared to the baseline varies between 25.72 to − 17.49. Also in this study, the effect of climate change on yield (Y), water requirement (W*R*) and evapotranspiration (ET) of maize was evaluated. The results showed that the amount of Y decreases in future periods and the W*R* increases. ET increases in all models and scenarios in 2021–2040 and 2041–2060, and in 2061–2080 in EC-EARTH model under RCP8.5 scenario and in 2081–2100 period in EC-EARTH model under RCP4.5 and RCP8.5 and the MIROC5 model decreases under the RCP8.5 scenario. Also in this study, the WF (green and blue) of maize under climate change in future periods was evaluated. The results showed that WF will increase in future periods. In general, it can be said that due to climate change and increase in temperature and decrease in precipitation in future periods, we will have a decrease in maize yield and increased evapotranspiration in Qazvin plain. The results of the present study on the effect of future climate change on Y and ET of maize in the Qazvin plain can be a useful tool for managers, experts, planners, and policy makers in the water sector to properly and sustainable management of water resources and agricultural development. Due to the effects of climate change, in order to increase agricultural production, the use of new varieties of agricultural products to improve yields, expand the area under crops with less water requirements and change the planting time to more suitable times in the coming years is recommended.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

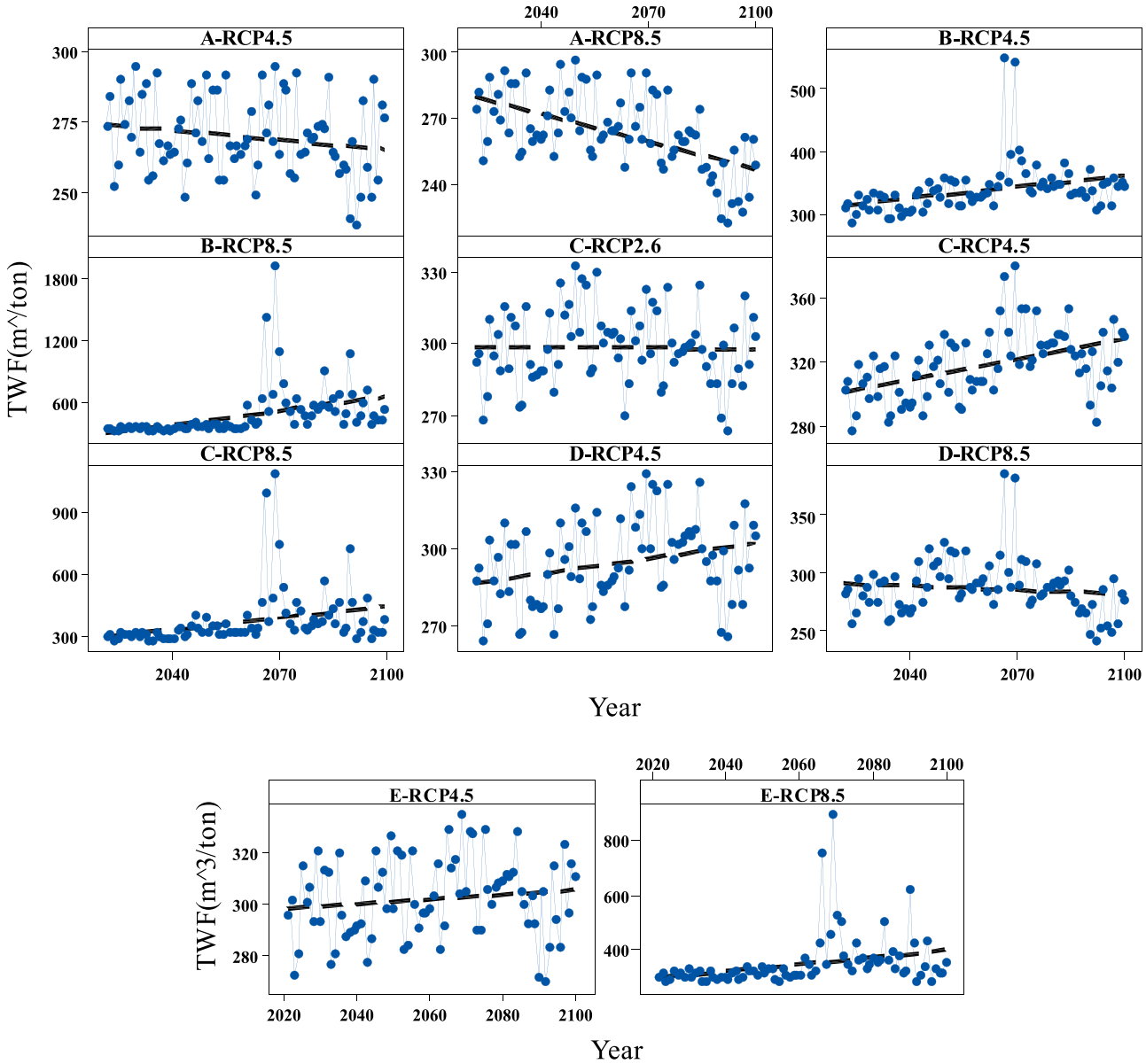

Fig. 10. A- Total water footprint (m^3/ton) EC-EARTCH model, B- Total water footprint (m^3/ton) GFDL-CM3 model, C- Total water footprint (m^3/ton) HadGEM2-ES model, D- Total water footprint (m^3/ton) MIROC5H model, E- Total water footprint (m^3/ton) MPI-ESM-MR model for the period 2021–2100.

Table 7
Percentage of changes maize water footprint in Qazvin plain under three scenarios and four future periods compared to the baseline (1986–2015).

GCM	Scenario	2021–2040	2041–2060	2061–2080	2081–2100
EC-EARTH	RCP4.5	4.30	3.86	4.32	1.55
	RCP8.5	3.44	4.14	1.82	-5.96
GFDL-CM3	RCP4.5	18.14	26.08	42.47	30.11
	RCP8.5	20.08	28.13	147.00	109.42
HadGEM2-ES	RCP2.6	12.15	17.85	14.52	12.87
	RCP4.5	15.01	19.21	28.35	23.75
	RCP8.5	14.36	27.88	80.96	51.21
MIROC5	RCP4.5	9.52	12.04	16.92	13.60
	RCP8.5	6.29	14.84	15.39	4.35
MPI-ESM-MR	RCP4.5	13.86	15.83	18.77	15.53
	RCP8.5	13.73	18.21	61.17	38.43

the work reported in this paper.

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