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Assessment of the Impacts of Climate Change on Soybean Yield and Water Requirement Using Crop Models

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ABSTRACT

Climate change can have significant impacts on crop growth, yield, water requirement and, consequently, crop water productivity. In this study, the effect of climate change under RCP2.6, RCP4.5, and RCP8.5 projection scenarios of the CanESM2 model on soybean yield and water requirement was investigated in Kermanshah, west of Iran. Crop growth was simulated using crop growth simulation models (DSSAT and AquaCrop) based on historical (1985-2015) and projected (2025-2064) weather data. Using the AquaCrop model in RCP2.6, RCP4.5, and RCP8.5 scenarios, the average increase in seasonal crop evapotranspiration (ETc) was estimated to be 9.4, 11, and 14.9%, respectively. The results of the DSSAT model showed 4.1, 8.5, and 12.1% increase in seasonal ETc under the RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. Based on the AquaCrop and DSSAT models, soybean yield decreases by 5.3, 3.7, and 2% and by 5.7, 4.8, and 1.6% for the RCP8.5, RCP4.5, and RCP2.6 scenarios, respectively. The results also show a decrease in crop water productivity under climate change scenarios as a result of increased ETc and reduced grain yield. According to AquaCrop and DSSAT models, the maximum daily ETc that should be used for the design of irrigation systems will increase by 11.5 and 10.2%, respectively.

Keywords: AquaCrop, CanEsm2, Crop yield, DSSAT.

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INTRODUCTION

Climate plays a crucial role in crop water productivity in rainfed and irrigated areas. Climate change is expected to affect agriculture worldwide (Figueiredo Moura da Silva *et al*., 2021) and especially in Iran, where water is the major constraint of crop production (Sharafati *et al*., 2022). Increasing rainfall intensity, rising temperatures, drought, and other types of climatic hazards can affect the quantity and quality of agricultural products. So far, several models have been presented to project weather data under climate change scenarios. Most climate projections are based on general climate change and simulations of General Circulation Models (GCM).

The output of GCM models should be spatially downscaled for the study area. Statistical downscaling has been more widely applied in impact studies (Trzaska and Schnarr, 2014) due to its simplicity in design and implementation and computational efficiency (Muluye, 2012). In statistical downscaling models, based on historical data, a relationship is established between large-scale model output (predictor) and local-scale variables (predictant), then, this relationship will be implemented for downscaling of large-scale data (Laflamme *et al*., 2016; Muluye, 2012). Although there are several statistical downscaling models in

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the literature (Tabari *et al*., 2021), SDSM (Statistical DownScaling Model) (Wilby *et al*., 2002) is one of the commonly used models for this purpose (Baghanam *et al*., 2020). SDSM has been used to downscale various climate parameters (such as maximum temperature, minimum temperature, precipitation) in different parts of the world (Muluye, 2012; Phuong *et al*., 2020; Saymohammadi *et al*., 2017; Shahriar *et al*., 2021; Souvignet *et al*., 2010; Stennett-Brown *et al*., 2017).

There are different varieties of crop modeling software such as the Decision Support System for Agrotechnology Transfer (DSSAT) that has specific models to simulate the growth of various plants (Jones *et al*., 2003). CROPGRO-Soybean model (Boote *et al*., 2018) has been developed by the DSSAT software makers to simulate the growth of soybean. This model uses experimental equations to describe the developmental phenological processes, canopy development, organ formation, photosynthesis, allocation of photosynthetic materials, and soil water content (Jones *et al*., 2003). This model can simulate the effects of climate on crop growth and yield using daily weather data.

AquaCrop is a water-driven crop growth simulation proposed by FAO (Food and Agriculture Organization of the United Nations) (Raes *et al*., 2009). The AquaCrop simulates the effect of the environment and management on crop production. The model has two types of crop parameters: (i) Conservative parameters, which do not need to calibrate because these are valid for all cultivars in all environments, and (ii) Cultivar specific parameters, which are affected by field management, planting mode, soil profile conditions, and climate-related parameters. The basic principles of the model for simulating the crop growth process are presented by Steduto *et al*. (2009). This model is inferred from the equation by Doorenbos and Kassam (1979). The use of AquaCrop model due to the need for low input parameters and adequate simulation accuracy has made this model a valuable tool for crop growth simulation under irrigation scenarios (Heng *et al*., 2009).

A study of the effects of climate change on water requirement in Judalkavir River Basin, Spain, showed that crop water requirement in 2050 would increase by 15-20% (Rodríguez Díaz *et al*., 2007). Woznicki *et al.* (2015) projected soybean irrigation demand under climate change scenarios in the Kalamazoo River watershed, Michigan, USA. Their results showed an 11% increase in irrigation demand in 2020-2039 and a 9% decrease in 2060-2079 compared to the base period (1980-1999). Voloudakis *et al*. (2015) provided climate change data using 8 climate simulation models, predicted cotton yield using AquaCrop model and stated that, considering the increasing temperature in the future, the results of climate change models and crop models would be useful for irrigation management.

Soddu *et al*. (2013) studied the adaptation of durum wheat to climate change using AquaCrop model in southern Sardinia, Greece. They stated that in the coming years there would be an increase in precipitation, temperature, and CO_2 concentration in their study area. The projected weather data were used as the input of AquaCrop model and they found that potential crop yield and productivity would be increased in their study area. Yang *et al*. (2017) investigated the response of maize yield to climate change scenarios in Portugal. They used ESM-RCA4 climate change model under RCP4.5 and RCP8.5 scenarios – (Representative Concentration Pathway) during 2021-2080. They used AquaCrop and STICS models to project crop yield. Their results showed a 17% reduction in crop yield. Abd-Elmabod *et al*. (2020) studied the effect of climate change on crop yield reduction of sunflower and wheat in a Mediterranean region using two agricultural-environmental sub-models. The results showed that the yield of sunflower decreased more compared to wheat. Kothari *et al*. (2022), while stating that the accurate estimation of crop yield under climate change scenarios is necessary, found considerable variability among models in simulated soybean yield responses to climate change (increasing temperature and CO_2). Figueiredo Moura da Silva (2021) using the CROPGRO-Soybean model found an increase in soybean yield and water productivity in Brazil, under climate change scenarios of RCP4.5 and RCP8.5 (2040–2069) compared to the base period (1987-2017). They stated that the positive effect of increasing CO_2 on crop water productivity overcomes the negative effects of temperature and water stress increases on rainfed Brazilian soybeans.

The results of climate change studies using the UKMO model in Iran showed that the average temperature increase in all studied stations in the spring season would be 3.1 and 3.9°C; 3.8 and 4.7°C in summer; 2.3 and 3°C in autumn, and 2 and 2.4°C in winter, respectively, in 2025 and 2050 (Koocheki *et al*., 2007). Saymohammadi *et al*. (2017) used the A2 scenario of the HadCM3 model and predicted an increase of 1.99 and 2.58°C in Kermanshah in the minimum and maximum temperature in the period of 2040-2059 compared to the base period (1990-1961).

The aim of this study was to predict the impact of climate change on soybean yield using a specific model of CROPGRO-Soybean and a generic model of AquaCrop under RCP2.6, RCP4.5, and RCP8.5 scenarios of CanESM2 model (Canadian Earth System Model) in Kermanshah, Iran.

MATERIALS AND METHODS

Two years (2013 and 2015) of field experiment data were used to calibrate and validate the crop growth simulation models. The results of the study in 2013 (Esmaeili, 2014) were used for models calibration. The results of the second study in 2015 (performed in this study) have been used to validate the models. For validation, a field experiment was conducted in the Research Farm of Razi University, Kermanshah, Iran, with an altitude of 1,320 m above sea level, the longitude of 47° 6' 12" E, and latitude of 34° 19' 33" N (Figure 1). The average annual rainfall and temperature in the study area are 456 mm and 14°C, respectively. Monthly values of weather parameters during the field experiment are presented in Table 1.

Hobbit cultivar of soybean, which is a limited-growth type, was studied. Rows were made by furrower at a distance of 50 cm. Soil's physical properties are shown in Table 2. During the growing period, weeds and pests were controlled. The amount of fertilizer was determined based on the soil test results and in consultation with agricultural experts (150 kg ha^{-1} of triple superphosphate and 200 kg ha^{-1} of urea fertilizer). This experiment was performed in a Randomized Complete Block Design (RCBD) with eight irrigation treatments and three replications. The characteristics of irrigation treatments are presented in Table 3.

The design consisted of 24 plots with dimensions of 4×4 m, in which seven rows were planted in each plot. The final harvest was done on September 6, 2015, and the yield and yield components were determined. The water requirement of the control treatment with full irrigation (T1) was calculated using the daily weather data recorded at an automatic weather station, near the research field. The daily potential evapotranspiration of the reference crop (ETo) was calculated based on the FAO Penman-Monteith equation (Allen *et al*., 1998). Crop water requirement (ETc) was calculated by multiplying ETo by crop coefficient (Kc). Crop coefficient was obtained from Iran's national document for Kermanshah Plain. The water requirement of other treatments was determined based on the stated percentage of T1 treatment. Irrigation interval was determined to be seven days according to the soil physical properties (Table 2). The amount of irrigation in each treatment is reported in Table 3. The reason for selecting over-irrigation treatment (T2: 120%) was inadequate uncertainty in the method of crop water requirement of the control treatment, which was also reported by Ahmadpour *et al*. (2017) and Esmaeili *et al*. (2015). Irrigation was performed by surface irrigation (furrow irrigation). The amount of water entering each furrow was measured with an accuracy of 0.1 liters using a volumetric flow meter connected to the hose outlet. Green canopy cover, leaf area index, dry weight of above ground biomass and grain were measured every ten days.

CanESM2 large-scale model was used to project weather parameters under climate change scenarios and downscaled using the SDSM model. Daily meteorological data (maximum and minimum temperature, precipitation, wind speed, sunny hours and relative humidity) of Kermanshah weather station in the periods of 1961-1985 and 1986-2004 obtained from the Iranian Meteorological Organization were used for calibration and validation. The relationship between observed (predicted) and large-scale (predictor) weather data has varying strengths and weaknesses. Therefore, the best predictors should be selected with the highest correlation with the projected data. At the screening stage, the best predictor was determined based on the statistical indicators specified for each meteorological parameter. The output of the CanESM2 model was used under three projection scenarios (RCP2.6, RCP4.5, and RCP8.5). After calibration and validation of the model, meteorological data were generated under three scenarios.

For each crop growth simulation model, a crop file was prepared. The crop growth was simulated using AquaCrop and DSSAT models based on weather data in the base period as well as climate change scenarios. Finally, crop yield, water requirement, and water productivity were calculated based on

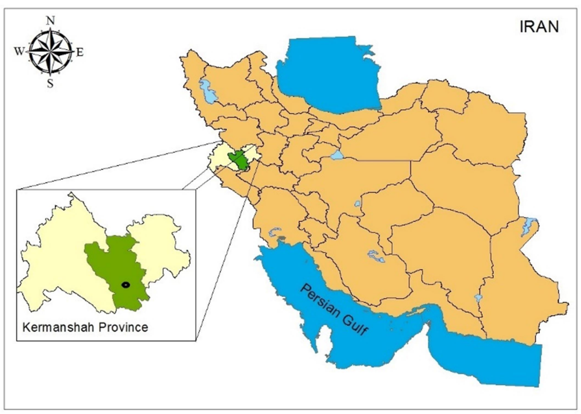

Figure 1. Location of study area in Kermanshah Province, Iran.

Table 1. Monthly values of weather parameters during the field experiment.

Weather Parameter	Unit	May	June	July	August	September
Maximum temperature	℃	32	35	38	39.1	35
Minimum temperature	℃	6.7	13	17	17.1	14.1
Sunshine hours	h	8.3	9.7	10	9.9	10.3
Wind speed at 2 m	m s^{-1}	0.9	1.4	1.2	1.1	1.1
Relative humidity	%	22.9	19.6	19	17.2	22.1

Table 2. Soil physical characteristics of the research farm

Soil depth (cm)	Available water (mm per meter)	Soil texture	Volumetric soil moisture (%)			Bulk density (g cm^{-3})
			Saturation	Field capacity	Permanent wilting point	
0-30	160	Clay loam	48.4	34	20	1.3
30-60	140	Clay loam	48.7	37	23	1.31
60-90	130	Clay	47.9	39	25	1.25

Table 3. Specifications of the irrigation treatments

Treatment	Period of deficit irrigation	% Irrigation in the reproductive stage	% Irrigation in the vegetative stage	Total water application (mm)
T1	---	100	100	842
T2	---	120	120	960
T3	Whole period	80	80	724
T4	Whole period	60	60	605
T5	Vegetative phase	100	80	827
T6	Vegetative phase	100	60	797
T7	Reproductive phase	80	100	746
T8	Reproductive phase	60	100	650

historical and projected weather data. Crop water productivity was calculated as the ratio of grain yield (kg ha^{-1}) to seasonal evapotranspiration (m^3 ha^{-1}).

The statistical indicators of Standard Error (SE) and the coefficient of determination (R^2) were used to assess the goodness-of-fit measures of the statistical downscaling model (Emami and Koch, 2018). The normalized Root Mean Square Error (nRMSE), and Efficiency Factor (EF) were used for the evaluation of the performance of crop models in the calibration and validation stages (Equations 1 and 2).

$$\mathrm{nRMSE} = \frac{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2\right)}}{O_{ave}} \quad (1)$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{ave})^2} \quad (2)$$

Where, O_i is the Observed data, P_i is the simulated data, O_{ave} is the average of the Observed data, and n is the number of observed data.

RESULTS AND DISCUSSION

The SDSM model evaluation indicators in the calibration and validation stages are presented in Tables 4 and 5. The low standard error and relatively high correlation between simulated and observed data in calibration and validation indicate the model's effectiveness in downscaling weather data. The correlations were higher than the values of 0.29 for rainfall and 0.6 and 0.57 for maximum and minimum temperature reported by Fiseha *et al*. (2012).

Crop models were calibrated based on the results of previous studies in the study area (Esmaeili *et al*., 2015). The performance of calibrated models was evaluated based on the field experiments conducted in the current study. Based on statistical indices of nRMSE and EF, it can be said that DSSAT

Table 4. Performance evaluation indicators of SDSM model in calibration and validation stages (Predictants: Maximum temperature, minimum temperature, amd wind speed).

Month	Maximum temperature				Minimum temperature				Wind speed			
	Calibration		Validation		Calibration		Validation		Calibration		Validation	
	SE	R^2	SE	R^2	SE	R^2	SE	R^2	SE	R^2	SE	R^2
Jan	1.90	0.75	2.01	0.71	2.88	0.68	2.78	0.67	2.17	0.68	2.24	0.70
Feb	2.10	0.71	2.30	0.69	2.26	0.81	2.66	0.68	2.28	0.60	1.97	0.64
Mar	2.20	0.68	2.40	0.63	2.45	0.78	2.50	0.61	2.16	0.65	2.10	0.55
Apr	2.01	0.61	2.51	0.65	2.21	0.72	2.61	0.71	2.57	0.55	2.03	0.51
May	2.30	0.63	2.45	0.65	2.36	0.76	2.56	0.65	2.20	0.58	2.07	0.55
Jun	2.15	0.70	2.31	0.70	2.84	0.79	2.74	0.60	2.24	0.74	1.96	0.57
Jul	2.12	0.62	2.20	0.72	2.26	0.60	2.66	0.60	2.54	0.51	2.87	0.53
Aug	2.14	0.64	2.25	0.68	1.98	0.64	2.10	0.64	2.85	0.66	2.72	0.57
Sep	2.11	0.70	2.30	0.71	1.83	0.73	2.02	0.68	2.29	0.57	2.56	0.53
Oct	2.10	0.71	2.26	0.73	2.10	0.84	2.32	0.63	2.54	0.70	2.34	0.57
Nov	2.15	0.68	2.30	0.69	1.89	0.83	2.15	0.72	2.46	0.60	2.00	0.54
Dec	1.89	0.72	2.12	0.67	1.76	0.77	2.01	0.76	1.89	0.78	2.29	0.67

Table 5. Performance evaluation indicators of SDSM model in calibration and validation stages (Predictants: Sunshine hours, relative humidity, amd precipitation)

Month	Sunshine				Relative humidity				Precipitation			
	Calibration		Validation		Calibration		Validation		Calibration		Validation	
	SE	R^2	SE	R^2	SE	R^2	SE	R^2	SE	R^2	SE	R^2
Jan	2.89	0.61	2.45	0.77	2.05	0.79	2.49	0.70	2.19	0.79	2.90	0.45
Feb	2.94	0.62	2.02	0.80	2.95	0.74	2.70	0.58	2.71	0.76	2.37	0.57
Mar	2.53	0.64	2.08	0.66	2.40	0.73	2.15	0.65	1.46	0.47	1.26	0.45
Apr	2.59	0.75	2.85	0.65	2.06	0.78	2.74	0.51	1.48	0.42	2.05	0.49
May	2.72	0.78	2.53	0.60	2.02	0.69	2.58	0.55	1.69	0.63	2.42	0.60
Jun	2.80	0.65	2.53	0.79	2.72	0.69	2.30	0.76	1.63	0.80	1.88	0.67
Jul	2.92	0.64	1.97	0.71	2.82	0.70	2.30	0.64	1.64	0.55	1.12	0.43
Aug	2.21	0.77	2.33	0.65	2.46	0.72	2.47	0.60	1.56	0.72	1.19	0.56
Sep	2.15	0.79	2.86	0.62	2.72	0.67	2.93	0.74	1.45	0.68	1.10	0.61
Oct	2.65	0.76	1.86	0.63	2.88	0.65	2.28	0.67	2.13	0.78	1.12	0.62
Nov	2.11	0.72	2.77	0.67	2.24	0.71	1.91	0.55	1.66	0.76	2.36	0.68
Dec	1.86	0.78	2.86	0.62	2.12	0.76	2.40	0.50	1.45	0.42	0.94	0.58

simulated soybean better than AquaCrop in the studied area (Table 6).

CanEsm2 was downscaled using the SDSM model and based on the weather parameters of the Kermanshah station under RCP2.6, RCP4.5, and RCP8.5 emission scenarios. The results indicate that the air temperature during the future (2025-2064) is increasing. The maximum temperature under RCP2.6, RCP4.5, and RCP8.5 emission scenarios will increase, on average, by 0.3, 0.6, and 1.1°C compared to the current climate weather data in Kermanshah station. This increase will be 0.3, 0.6, and 0.8°C for the minimum temperature, respectively. The increase in minimum and maximum temperature is less than 1.99 and 2.58°C reported by Saymohammadi *et al*. (2017) in 2050 based on the HadCM3 model.

Relative humidity is one of the parameters that affect crop Evapotranspiration (ETc). Relative humidity will increase in winter

Table 6. Performance evaluation of AquaCrop and DSSAT models in the validation stage.

Statistical index	Treatment	Biomass		Grain		Leaf area index	Crop canopy
		DSSAT	AquaCrop	DSSAT	AquaCrop	DSSAT	AquaCrop
nRMSE (%)	T1	17.18	10.67	15.02	34.36	14.88	17.1
	T2	21.05	24.79	8.52	26.23	11.87	17.45
	T3	21.71	13.83	24.66	27.89	15.98	23
	T4	25.26	62.27	28.28	45.86	14.44	18.36
	T5	22.16	35.58	11.72	41.9	13.56	32.65
	T6	17.37	24.25	8.43	31.52	7.72	29.59
	T7	23.41	26.44	7.47	28.14	17.35	15.66
	T8	19.71	38.56	23.82	35.59	17.22	22.46
	Average	20.98	29.55	15.99	33.94	14.13	22.03
EF	T1	0.95	0.97	0.97	0.48	0.94	0.75
	T2	0.92	0.86	0.98	0.72	0.96	0.76
	T3	0.92	0.94	0.96	0.54	0.94	0.59
	T4	0.88	0.39	0.96	0.45	0.94	0.69
	T5	0.92	0.73	0.98	0.68	0.95	0.55
	T6	0.95	0.88	0.98	0.6	0.99	0.41
	T7	0.91	0.79	0.98	0.44	0.92	0.79
	T8	0.93	0.4	0.97	0.41	0.92	0.46
	Average	0.92	0.75	0.97	0.54	0.95	0.63

(December, January, and February) and decrease in other seasons. The highest increase in relative humidity will be 2.8% in February under the RCP8.5 scenario. This increase will be 0.2 and 1.4% for RCP4.5 and RCP2.6 scenarios, respectively. The highest reduction in relative humidity under the RCP8.5 scenario would be 3.9% in May, which would be 3.2 and 2.8% for the same month under RCP4.5 and RCP2.6 scenarios, respectively (Figure 2).

Precipitation is another weather parameter that was projected under climate change scenarios. Although the mean precipitation decreases under climate change, in some months (October and November) precipitation is predicted to increase (Figure 2). The greatest reduction of rainfall in March for RCP8.5, RCP4.5, and RCP2.6 scenarios will be 44, 44, and 40 mm, respectively. Solar radiation under all emission scenarios shows an increasing trend in the future. The highest increase will be under the RCP8.5 scenario, followed by RCP4.5 and RCP2.6. The highest increase in solar radiation under all scenarios would occur in April. The mean increase under RCP8.5, RCP4.5, and RCP2.6 scenarios would be 0.9, 0.7, and 0.6 MJ m^{-2} per day (Figure 2).

The results also indicate an increase in wind speed in the future. The highest wind speed increase will occur in July under RCP8.5 scenarios at 0.6 m s^{-1}. In the same month, under RCP4.5 and RCP2.6 scenarios, this increase will be 0.4 and 0.3 m s^{-1}, respectively (Figure 2).

ETo increases with increasing air temperature, wind speed, radiation, and decreasing relative humidity. Due to the increase in air temperature, wind speed, solar radiation and decrease in relative humidity (except in winter) in the climate change conditions, ETo will increase. The

Table 7. Calculated ETo in the base and future periods (mm).

Month	Base	RCP2.6	RCP4.5	RCP8.5
Jan	39.1	42.2	45.6	46.8
Feb	48.2	50.7	52.9	54
Mar	87.7	88.7	89.6	91.8
Apr	119.7	125.4	128.1	129.6
May	167.1	176.1	179.2	185.7
Jun	229.5	241.2	243.6	251.4
Jul	259.8	275	279.6	290.5
Aug	249.2	261	267.2	279
Sep	192.6	201	204.3	212.7
Oct	130.5	126.8	130.8	135.2
Nov	68.4	71.4	71.7	73.8
Dec	44.3	46.8	47.7	49
Sum	1636.1	1706.2	1740.4	1799.4

highest increase in ETo will occur in July under RCP8.5 scenario. The mean annual increase in the ETo under RCP2.6, RCP4.5, and RCP8.5 scenarios was estimated to be 70, 104, and 163 mm, respectively, which indicates an increase of 4.3, 6.2, and 10%, respectively, compared to the base period (Table 7). Almost the same results (68 and 111 mm ETo increase under RCP4.5 and RCP8.5 scenarios) were calculated for ETo increase in Ilam province, which is close to the study area (Ahmadi and Azizzadeh, 2020).

The crop models were run based on the climate files of the base and future periods. The average monthly soybean evapotranspiration estimated based on the models is shown in Figure 3. The results indicated that, under all three emission scenarios, the ETc will increase compared to the base period. The maximum and minimum increase will occur in the RCP8.5 (18 and 19% for AquaCrop and DSSAT, respectively) and RCP2.6 (6 and 10% for AquaCrop and DSSAT, respectively) scenarios.

Given that in these models the crop growth period is defined in terms of degree-days/ photothermal days, the reduction of the crop growth period due to the increase in temperature was also considered. The results showed an increase in seasonal ETc and a reduction in crop yield (biomass and grain) in the future. The RCP8.5 scenario had the largest increase in ETc. The results show that, under all the three emission scenarios, the seasonal ETc estimated by AquaCrop and DSSAT models increases compared to the base period (Table 8). The average seasonal ETc increase under RCP8.5, RCP4.5, and RCP2.5 scenarios was estimated as 14.9, 11, and 9.4% for AquaCrop and 12.1, 8.5, and 4.1% for DSSAT, respectively. An increase in crop water requirements under climate change scenarios has been reported in several studies (Farhadi Bansouleh *et al*., 2017; Rodríguez Díaz *et al*., 2007; Woznicki *et al*., 2015), while there are reports of a decrease in crop water requirements due to a shortened growing season (Karimi *et al*., 2018).

According to the analysis, the grain and biomass yield in soybean will reduce under climate change scenarios. In the AquaCrop model, this reduction will be 3.2-6.9% for biomass and 2-5.3% for grain. The estimated reduction in grain and biological yield by the DSSAT model will be 1.6- 5.7 and 2.2-5.2%, respectively. Crop yield under climate change conditions is influenced by two main parameters, i.e. the amount of CO_2 and the

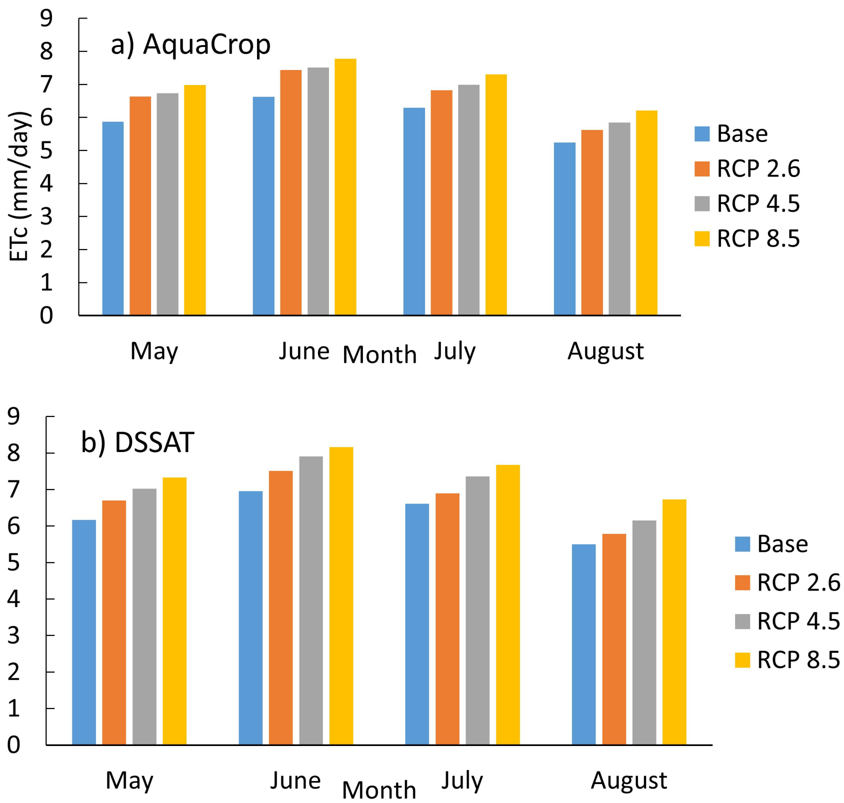

Figure 3. Average of monthly evapotranspiration (mm d^{-1}).

Table 8. The seasonal Evapotranspiration (ETc), biological yield, and grain yield estimated by AquaCrop and DSSAT.

Parameter	Unit	Model	Base period (1985-2015)	Future period (2025-2064)		
				RCP2.6	RCP4.5	RCP8.5
Seasonal evapotranspiration	mm	AquaCrop	672	735	746	772
		DSSAT	705	734	765	790
Biological yield	Kg ha^{-1}	AquaCrop	9180	8890	8750	8540
		DSSAT	11130	10890	10780	10560
Grain yield	Kg ha^{-1}	AquaCrop	2460	2410	2370	2330
		DSSAT	3160	3110	3010	2980
Crop water productivity	g m^{-3}	AquaCrop	366	328	318	302
		DSSAT	448	424	393	377

length of the growth period, which has the opposite effect. According to which of these parameters has the most influence in the studied areas, the increase or decrease in crop yield has been reported. Ghorbani and Soltani (2014) concluded that the yield of soybean for irrigated cultivation will decrease slightly under climate change scenarios in Gorgan, Iran, while Rostami Ajirloo *et al*. (2021) reported an increase in the yield of this crop in the Parsabad Plain of Moghan, Iran. As a result of increasing the seasonal crop water requirement and decreasing crop yield, crop water productivity decreases (Table 8).

CONCLUSIONS

According to the results, based on downscaling of the CanEsm2 climate change model, the air temperature in the study area will increase under climate change scenarios. This increase in RCP2.6, RCP4.5, and RCP8.5 was estimated to be 0.3, 0.6, and 0.95°C, respectively. This increase will reduce the crop growth period in this area. The length of soybean growth period in the future will decrease between 3 and 5 days in different emission scenarios. An increase in air temperature, wind speed, and solar radiation and a decrease in relative humidity in climate change conditions cause evapotranspiration and crop yield to change as well. RCP8.5 and RCP2.6 scenarios had higher and lower changes in weather parameters, ETo, seasonal crop water requirement, and crop yield, respectively. The RCP4.5 scenario was intermediate between the two mentioned scenarios. ETo will increase between 5.8 and 11.8 % under the studied climate change scenarios. Seasonal crop evapotranspiration increases by 9.4-15% in the AquaCrop model and 4.1-12% in the DSSAT model. The estimated reduction in soybean yield based on the AquaCrop and DSSAT models will be 2-5.3 and 1.6-5.7%, respectively. In the future, the maximum evapotranspiration, which is the basis of the design of irrigation systems, will increase by an average of 11.8 and 8.2% based on AquaCrop and DSSAT models. If this issue is not included in the designs of irrigation networks, in the future, we will have to apply less irrigation or reduce the area under cultivation. The results of this type of studies can be used in water resource development programs by agricultural water planners.

REFERENCES

1. Abd-Elmabod, S.K., Muñoz-Rojas, M., Jordán, A., Anaya-Romero, M., Phillips, J.D., Jones, L., Zhang, Z., Pereira, P., Fleskens, L. and van Der Ploeg, M. 2020. Climate Change Impacts on Agricultural Suitability and Yield Reduction in a Mediterranean Region. *Geoderma,* **374**: 114453.
2. Ahmadi, H. and Azizzadeh, J. 2020. The Impacts of Climate Change Based on Regional and Global Climate Models (RCMs and GCMs) Projections (Case Study: Ilam Province). *Model. Earth Syst. Environ.,* **6(2):** 685-696.
3. Ahmadpour, A., Farhadi Bansouleh, B. ans Ghobadi, M. 2017. Effects of Deficit Irrigation on Growth Trend, Quantity and Quality Characteristics of Maize in Kermanshah. *J. Water Soil Resour. Conserv.,* **6(3):** 99-112. (in Persian).
4. Allen, R., Pereira, L., Raes, D. and Smith, M. 1998. *Crop Evapotranspiration - Guidelines for Computing Crop Water Requirements.* FAO Irrigation and Drainage Paper No. 56, Rome, Italy.
5. Baghanam, A.H., Eslahi, M., Sheikhbabaei, A. and Seifi, A.J. 2020. Assessing the Impact of Climate Change over the Northwest of Iran: An Overview of Statistical Downscaling Methods. *Theor. Appl. Climatol.,* **141**: 1135-1150.
6. Boote, K.J., Jones, J. W. and Hoogenboom, G. 2018. Simulation of Crop Growth: CROPGRO Model. In: "*Agricultural Systems Modeling and Simulation*", (Eds.): Peart, R. M. and Curry, R. B. CRC Press, PP. 651-692.
7. Doorenbos, J. and Kassam, A. 1979. *Yield Response to Water.* FAO Irrigation and Drainage Paper No. 33, Rome, Italy, 257 PP.
8. Emami, F. and Koch, M. 2018. Evaluation of Statistical-Downscaling/Bias-Correction Methods to Predict Hydrologic Responses

to Climate Change in the Zarrine River Basin, Iran. *Climate*, **6(2):** 30.
9. Esmaeili, M. 2014. Estimation the Effects of Water Deficit Irrigation on Soybean Crop Yield in Kermanshah under Climate Change Scenarios Using AquaCrop Model. MSc. Thesis, Razi University, Kermanhah, Iran. (in Persian).
10. Esmaeili, M., Farhadi Bansouleh, B. and Ghobadi, M. 2015. Effects of Deficit Irrigation on Quantity and Quality of Soybean Crop Yield in Kermanshah Region. *J. Water Soil*, **29(3):** 551-559. (in Persian).
11. Farhadi Bansouleh, B., Asadi, A., Hafezparast Mavadat, M., 2017. Changes in potential evapotranspiration of maize and barley under climate change situation in Kermanshah Province. *J. Water Soil Conserv*., **24(3)**: 185-202. (in Persian).
12. Figueiredo Moura da Silva, E. H., Silva Antolin, L. A., Zanon, A.J., Soares Andrade, A., Antunes de Souza, H., dos Santos Carvalho, K., Aparecido Vieira, N. and Marin, F. R. 2021. Impact Assessment of Soybean Yield and Water Productivity in Brazil Due to Climate Change. *Eur. J. Agron*., **129**: 126329.
13. Fiseha, B., Melesse, A., Romano, E., Volpi, E. and Fiori, A. 2012. Statistical Downscaling of Precipitation and Temperature for the Upper Tiber Basin in Central Italy. *Int. J. Water Sci.*, **1(3)**: 1-14..
14. Ghorbani, K. and Soltani, A. 2014. The Effect of Climate Change on Soybean Yield in Gorgan. *J. Plant Prod. Res.,* **21(2):** 67-85. (in Persian)
15. Heng, L.K., Hsiao, T., Evett, S., Howell, T. and Steduto, P. 2009. Validating the FAO AquaCrop Model for Irrigated and Water Deficient Field Maize. *Agron. J.,* **101(3):** 488-498.
16. Jones, J. W., Hoogenboom, G., Porter, C. H., Boote, K. J., Batchelor, W. D., Hunt, L. A., Wilkens, P. W., Singh, U., Gijsman, A. J. and Ritchie, J. T. 2003. The DSSAT Cropping System Model. *Eur. J. Agron.,* **18(3):** 235-265.
17. Karimi, V., Karami, E. and Keshavarz, M. 2018. Climate Change and Agriculture: Impacts and Adaptive Responses in Iran. *J. Integr. Agric.,* **17(1):** 1-15.
18. Koocheki, A., Nasiri mahalati, M. and Kamali, G. 2007. Climate Indices of Iran under Climate Change. *Iran. J. Field Crops Res.,* **5(1)**: 133-142. (in Persian)
19. Kothari, K., Battisti, R., Boote, K. J., Archontoulis, S. V., Confalone, A., Constantin, J., Cuadra, S. V., Debaeke, P., Faye, B., Grant, B., Hoogenboom, G., Jing, Q., van der Laan, M., Macena da Silva, F. A., Marin, F. R., Nehbandani, A., Nendel, C., Purcell, L. C., Qian, B., Ruane, A. C., Schoving, C., Silva, E. H. F. M., Smith, W., Soltani, A., Srivastava, A., Vieira, N. A., Slone, S. and Salmerón, M. 2022. Are Soybean Models Ready for Climate Change Food Impact Assessments? *Eur. J. Agron.,* **135:** 126482.
20. Laflamme, E. M., Linder, E. and Pan, Y. 2016. Statistical Downscaling of Regional Climate Model Output to Achieve Projections of Precipitation Extremes. *Weather Clim Extrem.* **12:** 15-23.
21. Muluye, G. Y. 2012. Comparison of Statistical Methods for Downscaling Daily Precipitation. *J. Hydroinforma.*, **14(4):** 1006-1023.
22. Phuong, D. N. D., Duong, T. Q., Liem, N. D., Tram, V. N. Q., Cuong, D. K. and Loi, N. K. 2020. Projections of Future Climate Change in the Vu Gia Thu Bon River Basin, Vietnam by Using Statistical Downscaling Model (SDSM). *Water*, **12(3):** 755.
23. Raes, D., Steduto, P., Hsiao, T. C. and Fereres, E. 2009. AquaCrop—The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agron. J.,* **101(3):** 438-447.
24. Rodríguez Díaz, J. A., Weatherhead, E. K., Knox, J. W. and Camacho, E. 2007. Climate Change Impacts on Irrigation Water Requirements in the Guadalquivir River Basin in Spain. *Reg. Environ. Change,* **7(3):** 149-159.
25. Rostami Ajirloo, A. A., Asgharipour, M. R., Ganbari, A., Joudi, M. and Khoramivafa, M. 2021. Soybean Yield in Future Climate Scenarios under Low Irrigation Conditions. Case Study: Pars

Aabad of Moghan Plain, Iran. *Agrotech. Ind. Crops,* **1(1)**: 36-51.

26. Saymohammadi, S., Zarafshani, K., Tavakoli, M., Mahdizadeh, H. and Amiri, F. 2017. Prediction of Climate Change Induced Temperature and Precipitation: The Case of Iran. *Sustainability*, **9(1):** 146.
27. Shahriar, S. A., Siddique, M. A. M. and Rahman, S. M. A. 2021. Climate Change Projection Using Statistical Downscaling Model over Chittagong Division, Bangladesh. *Meteorol. Atmos. Phys.,* **133(4):** 1409-1427.
28. Sharafati, A., Moradi Tayyebi, M., Pezeshki, E. and Shahid, S., 2022. Uncertainty of Climate Change Impact on Crop Characteristics: A Case Study of Moghan Plain in Iran. *Theor. Appl. Climatol.,* **149(1):** 603-620.
29. Soddu, A., Deidda, R., Marrocu, M., Meloni, R., Paniconi, C., Ludwig, R., Sodde, M., Mascaro, G. and Perra, E. 2013. Climate Variability and Durum Wheat Adaptation Using the AquaCrop Model in Southern Sardinia. *Procedia Environ. Sci.*, **19:** 830-835.
30. Souvignet, M., Gaese, H., Ribbe, L., Kretschmer, N. and Oyarzún, R. 2010. Statistical Downscaling of Precipitation and Temperature in North-Central Chile: An Assessment of Possible Climate Change Impacts in an Arid Andean Watershed. *Hydrol. Sci. J.,* **55(1):** 41-57.
31. Steduto, P., Hsiao, T.C., Raes, D. and Fereres, E. 2009. AquaCrop—The FAO Crop Model to Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agron. J.*, **101(3):** 426-437.
32. Stennett-Brown, R. K., Jones, J. J., Stephenson, T. S. and Taylor, M. A. 2017. Future Caribbean Temperature and Rainfall Extremes from Statistical Downscaling. *Int. J. Climatol.*, **37(14):** 4828-4845.
33. Tabari, H., Paz, S.M., Buekenhout, D. and Willems, P. 2021. Comparison of Statistical Downscaling Methods for Climate Change Impact Analysis on Precipitation-Driven Drought. *Hydrol. Earth Syst. Sci.,* **25(6):** 3493-3517.
34. Trzaska, S. and Schnarr, E. 2014. *A Review of Downscaling Methods for Climate Change Projections.* United States Agency for International Development by Tetra Tech ARD, 42 PP.
35. Voloudakis, D., Karamanos, A., Economou, G., Kalivas, D., Vahamidis, P., Kotoulas, V., Kapsomenakis, J. and Zerefos, C. 2015. Prediction of Climate Change Impacts on Cotton Yields in Greece under Eight Climatic Models Using the AquaCrop Crop Simulation Model and Discriminant Function Analysis. *Agric. Water Manag.,* **147**: 116-128.
36. Wilby, R. L., Dawson, C. W. and Barrow, E. M. 2002. SDSM — A Decision Support Tool for the Assessment of Regional Climate Change Impacts. *Environ. Model. Softw.,* **17(2)**: 145-157.
37. Woznicki, S. A., Nejadhashemi, A. P. and Parsinejad, M. 2015. Climate Change and Irrigation Demand: Uncertainty and Adaptation. *J. Hydrol.: Reg. Stud.,* **3:** 247-264.
38. Yang, C., Fraga, H., Ieperen, W. V. and Santos, J. A. 2017. Assessment of Irrigated Maize Yield Response to Climate Change Scenarios in Portugal. *Agric. Water Manag.,* **184:** 178-190.

ارزیابی اثرات تغییر اقلیم بر عملکرد و نیاز آبی سویا با استفاده از مدل‌های گیاهی

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چکیده

تغییر اقلیم می تواند تأثیرات قابل توجهی بر رشد ، عملکرد، نیاز آبی و در نتیجه بهره وری مصرف آب گیاهان داشته باشد. در این مطالعه، تأثیر تغییر اقلیم تحت سناریوهای انتشار RCP2.6، RCP4.5 و RCP8.5 مدل CanESM2 بر عملکرد و نیاز آبی سویا در کرمانشاه، واقع در غرب ایران بررسی شد. رشد گیاه با استفاده از مدل‌های شبیه‌سازی رشد گیاهی (DSSAT و AquaCrop) بر اساس داده‌های آب‌وهوایی دوره گذشته (۲۰۱۵ - ۱۹۸۵) و پیش‌بینی‌شده (۲۰۶۴ - ۲۰۲۵) شبیه‌سازی شد. میانگین افزایش تبخیر و تعرق فصلی (ETc) با استفاده از مدل AquaCrop در سناریوهای RCP2.6، RCP4.5 و RCP8.5 به ترتیب ۹.۴، ۱۱ و ۱۴.۹ درصد برآورد شد. نتایج مدل DSSAT به ترتیب ۴.۱، ۸.۵ و ۱۲.۱ درصد افزایش در ETc فصلی تحت سناریوهای RCP2.6، RCP4.5 و RCP8.5 را نشان داد. بر اساس مدل های AquaCrop و DSSAT، عملکرد سویا به ترتیب ۵.۳، ۳.۷، و ۲٪ و ۵.۷، ۴.۸، و ۱.۶٪ در سناریوهای RCP8.5، RCP4.5 و RCP2.6 کاهش می یابد. نتایج همچنین کاهش بهره‌وری مصرف آب را تحت سناریوهای تغییر اقلیم در نتیجه افزایش ETc و کاهش عملکرد دانه نشان می‌دهد. طبق مدل‌های AquaCrop و DSSAT حداکثر ETc روزانه که برای طراحی سیستم‌های آبیاری استفاده می‌شود به ترتیب ۱۱.۵% و ۱۰.۲% افزایش می‌یابد.