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Future Water Requirements and Crop Productivity at Al-Najaf Governorate Under Different Climate Change Scenarios (2020–2080)

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HIGHLIGHTS

- The effect of climate change on net irrigation water requirements and crop productivity was investigated.
- Barley has the most influence on climate change.
- An increase in the quantity of water required for irrigation for the common crops under climate change.
- Climate change has negative effects on all crops' yield under different climate change scenarios.

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ABSTRACT

This study aims to predict the effect of climate change on net irrigation water requirements (NIWR) and agricultural productivity from five common crops (wheat, barley, summer maize, and sorghum) in the Al-Najaf Governorate in Iraq. GFDL-ESM2M mode was used to predict the lower and upper temp and precipitation for two time periods (2020-2080) with 30 years for two periods (P1 and P2) under representative concentrations paths (RCP 2.5, RCP6, and RCP8.5). The CROPWAT model is used to determine NIWR, and the extreme learning model was used to estimate agricultural yields using previous crop yield production and weather data, supported vectors machine (SVM) is executed as a Machines Learns algorithm. Results showed NIWR increment to consider cropping owing to climate change. Barley is the crop most affected by climate change under the (RCP2.5, RCP6, and RCP8.5) scenarios, with increasing crop water requirements (NIWR) of (22%, 23%, and 24%) for P1 and (23%, 24%, and 29%) for P2, respectively. Summer maize is the crop least affected by climate change under all climate change scenarios, with increasing crop water requirements of (1%, 2%, and 4%) for P1 and (1%, 2%, and 5% for P2. Climate change negatively affects the crop yield of all crops under the different climate change scenarios. The findings of this study could be used as a guide to developing adaptation strategies for dealing with potential changes in water availability and agricultural water productivity due to climate change.

1. Introduction

Iraq has adequate water resources when compared with the many countries in Middle Eastern neighbors. Despite this, water reaches farmers' crops late or in inadequate quantities [1]. One of the most important reasons is the old and inefficient irrigation system (i.e flood irrigation system) [2]. In the past, the management of water resources has needed to be more effective, notably in irrigation due to the high amount of water in the two rivers (Euphrates and Tigris). Nowadays, because of climate change and a reduction in the major river's discharge and rainfall, it is becoming increasingly vital to address water scarcity as a genuine problem in the future. As a result, water resources need to be managed with extreme efficiency by giving a particular and optimal amount of water, depending on an accurate understanding of crops' basic water requirements[3]. This knowledge is essential for the agricultural sector's performance because any drop in water during the growing season could reduce crop production. In addition, any increase in irrigation water, to a certain extent, leads to wasting water and affecting soil properties[4]. In arid areas, evapotranspiration (Et), or water lost in the atmosphere from soil and plants, is a major constraint to better agricultural productivity. To meet crop water requirements, rainfall or irrigation should balance the amount of water loss. As a result, to address the issue of excessive water use, the amounts of evapotranspiration should be precisely determined [2].

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Climate change will occur gradually. The average temperature in the middle east could increase to 2.5°C in 2050 [5]. Climate change may have an impact on the future water availability globally because rising temperatures, increase in evaporation, and variable rainfall have a considerable impact on agricultural water requirement[6].

There are many estimation models for water requirement for agriculture, for example, FAO CROPWAT, Geo WRSI, and GCW[7,8]. The CROPWAT model used an equation of the penman-Monteith to change the weather factors such as the air pressure average by control on the longitude and latitude [9,10]

Many successful applications of using CROPWAT to determine the crop's water needs under climate change in different countries of the world [11–14]. In Iraq, a few studies evaluated the effect of climate change on the irrigation water requirements of crops. Saeed et al. [15] evaluate the spatiotemporal sensitivity of the net irrigation water requirement (NIWR) under climate changes for four irrigation projects located in arid and semi-arid regions of Iraq for North Jazeera Irrigation Project (NJIP), Kirkuk Irrigation Project (KRIP), Upper Khalis Irrigation Project (UKIP), and Dalmaj Irrigation (DLIP), respectively, So This study is considered the first study that determines the climate changes effects on net irrigation water requirements and crop productivity by CROPWAT and machine learning in Iraq (AL-Najaf governorate) under future climate change scenarios. Three climate change scenarios were utilized to estimate future climate data (RCP2.5, RCP 6, and RCP8.5). The RCP2.5 scenario is the lowest to stability, the RCP6 scenario represents a moderate approach, and the RCP8.5 scenario represents the most extreme case for greenhouse gas emissions.

Stakeholders and policymakers can use this study to offer solutions for crop problems under climate change conditions.

2. Research data and Modelling Methods

2.1 Study Area

The selected study area in this study is located in Al-Najaf provenance, Iraq,161 kilometers from south Baghdad on the bank of the Euphrates River [16], as shown in Figure 1. The geographic area is located between (42°–44°) in longitudes and (29°–32°) in latitudes [17] as shown in Figure 1.With an area of (29,000 km^2) and forms 7% of the total area of Iraq. The study area is situated in the Plateau area at an altitude of about (60 m). It was sloping were flats and graduated to the north, northwestern, east, southeast, and south, when, it much steeps and form natural edges towards the west and southwest. It consists of successive rock formations from the sedimentary origin [18]. Al-Najaf-city has an arid and semi-arid climate, with the longest, hot, dry, summers there average-approximately 45 °C, and short, cold- winters with average temperatures of 24 °C. It rains from October to April. In a rainy year, the grosses annual-rainfall average are around 100 mm, while in a- dry year, it is around 30- mm [19].

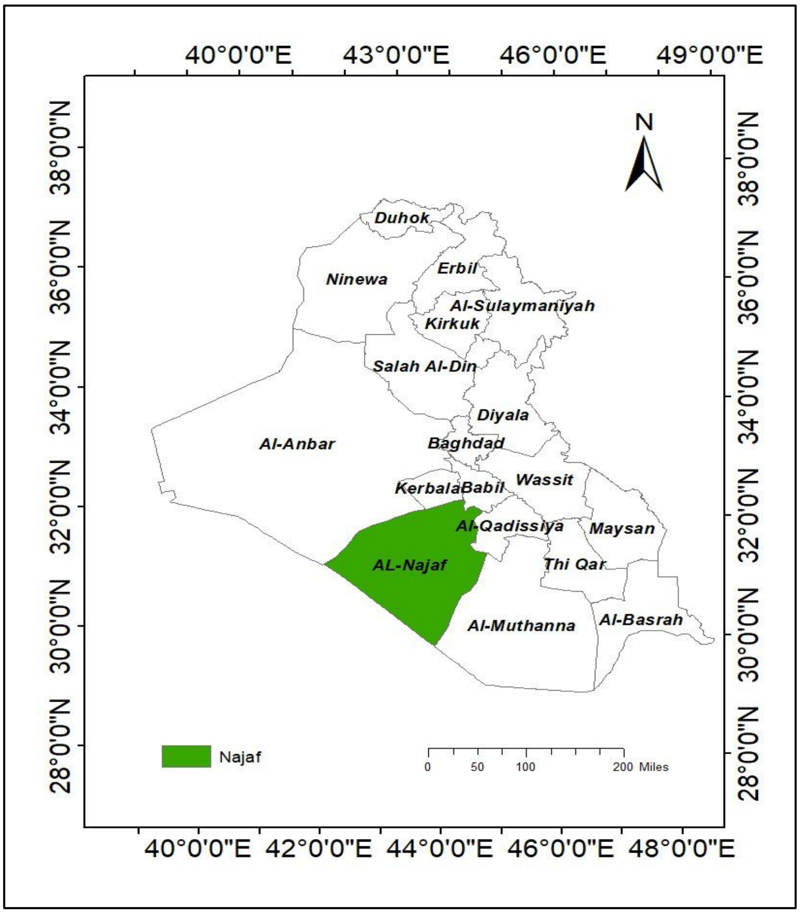

Figure 1: The location of the study area

2.2 Modelling methods

2.2.1 The CROPWAT model

The CROPWAT model predicts how much water will be needed for irrigation. The- (Land- and Water-Developments Division) at FAO created the CROPWAT to organize and control water use during irrigation. CROPWAT is supposed to be used in the planning, design, and management of irrigation systems, and in the general computation of reference evapotranspiration and crop irrigation requirements[20]. CROPWAT uses the Penman-Monteith equation to assess reference evapotranspiration as expressed (Equation 1) [21]:

$$ETo = \frac{0.408\Delta\ (Rn-G)+\Upsilon(\frac{900}{T_a+273})U_2(e_s-e_a)}{\Delta+\Upsilon(1+0.34U_2)} \tag{1}$$

Where ET_o (mm/day) is the reference evapotranspiration, Rn- ($MJ.m^2$/ day) is the net radiations for the crop surface, G ($MJ.m^2$ /day) is the density of the heat-flux density of the soil, T_a is the average daily air temperature (°C), $U_2(m/sec)$ is the average daily speed of wind at a two-meter height, e_s (kPa) is the saturation vapor pressure, e_a is the mean actual vapor pressure, Δ is the slope of the relation curve between saturation vapor pressure, and temperature (kPa /°C), and γ (kPa /°C) is psychometric constant.

Crop evapotranspiration (Etc) in mm/day is calculated by multiplying the C evapotranspiration ($ET_\circ$) by the crop coefficient (KC) (Equation 2) [22]:

$$ETc = ETo \times KC \tag{2}$$

The Soil-Conservation Service (S.C.S) method of the US Department-of-Agriculture (USDA) and rainfall data was used to compute the effective rainfall Equation (3,4) [23]:

$$P_{eff} = Ptot\ \frac{125\_0.2\times Ptot}{125}\quad , \qquad for\ Ptot < 250\ mm \tag{3}$$

$$P\ e_{ff} = 125{+}0.1{\times}\ Ptot\quad , \qquad for\quad P > 250\ mm \tag{4}$$

Whereas P_{eff}: effective rainfall, and P: total rainfall

The net irrigation water requirements (NIWR) represent the amounts of water that should be delivered to the crop through the irrigation system to guarantee that the crop fulfills its full water requirement. The-water demand for crop irrigation that obtains water from one source (surface water) is more than for crops that obtain water from another source (such as deep seepages and rain). Hence, NIWR was computed by using (Equation 5) [18]:

$$NIWR\ = \ ETc - P_{eff} \tag{5}$$

The total gross irrigation water requirements (GIWR) are calculated by using equation (6) as follows:

$$GIWR = (NIWR + Lr)/Ea \times 100 \tag{6}$$

Ea is the efficiency of irrigation, and Lr is a requirement of leaching (mm), which is calculated by Lr = f × NIWR, where f ranges from (five to twelve) percent upon available soil salinity [15]

2.2.2 Extreme Learning Machine Technique

Conventional single hidden layering feed-forwards neural network, often known as SLFN, has seen widespread use in the approximation of functions across various study domains[24]. On the other hand, the models almost have a slow learning speed, which hinders their use. The ELM was proposed to improve the functionality of the conventional SLFN. When compared to traditional learning algorithms like the backpropagation method, the ELM model is characterized by its lightning-fast learning speed and reliable generalization [25].

In addition, the ELM model does not suffer from the problems of overfitting or local minima problems, which results in the model's performance being superior to that of classic ANN models. The ELM model, in its most basic form, of three layers: the input layer, the hidden layer, and, the output layer Equations (7) [25].

The standard expression of an SLFN having L hidden -nodes and g(x) activation- function:

$$f_L(x_j) = \sum_{i=1}^{L} \beta_i g((w_i x_i + b_i), \quad j = 1,\ \ 2, \ldots N \tag{7}$$

*where wi = [wi1, wi2, ··, win] are the weights vector connecting the ith hidden-neuron and the input-neurons, βi = [β_{i1}, β_{i2}, ···, β_{im}] are the weights vector connecting the ith hidden-neuron and the output-neurons, and bi is the- threshold of the ith hidden-neuron. wi · xj denote the inner- products of wi and xj . N is the number of the sample. *

(Equations7) could be written compactly as Equation (8) [25]:

$$H\beta = T \quad (8)$$

While H named the hidden-layer output matrix of the neural network.

The ELM can be built by the following three stages for a given activation function g(x) as well as the number of hidden nodes L for such a training dataset:

1. Using a randomization process to assign input weights (ω) and biases (b_i);
2. Determining the hidden layer output matrix H.
3. Computing the output weight matrix.

The ELM diagram is shown in detail in Figure 2.

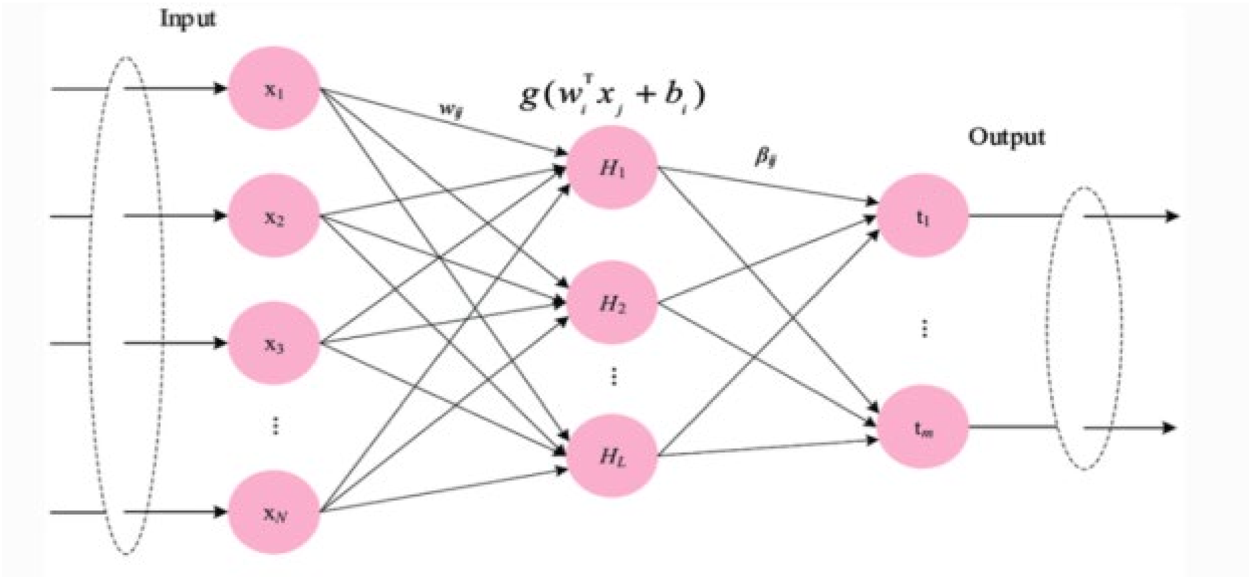

Figure 2: The ELM network schematic diagram [26]

2.3 Research Datasets

2.3.1 Meteorological data

Daily precipitation, humidity, maximum and minimum temperatures, sunlight hours, and wind speed data from the beginning of January 1988 to the end of December 2019 for AL-Najaf Governorate, these data were gotten from the Iraqi "Metrological Organization and Seismology". Table 1 shows the statistical analysis of rainfall and climatological data. The ET_o ranged from 1.53 to 9.73 mm, whereas the effective rainfall ranged (from 0 -16) mm. The minimum and maximum temperatures ranged from 6 to 17 and 30 to 45 degrees Celsius, respectively.

2.3.2 Generated Future data

The future climate dataset was forecasted for two time periods: P1(2020-2050) and P2(2051-2080), using the GFDL-ESM2M model under the RCP2.5, RCP6, and RCP8.5 scenarios. CROPWAT 8 and learning machine algorithms were used to calculate Future ET0, NIWR, and crop yield. The data on the potential future climate was taken from the "ISIMIP" [27] site, which was started via the "Potsdam Instituting to the Climates Impacts Research (PIK) and the International Institute for, Applied-Systems Analysis (IIASA), and have since- grown for included over-100 modeling group from the-around the-world".

2.3.3 Crop Data

CRORWAT requires crop-related data. FAO organization and the Iraqi-ministry of Water Resources provided this data. which data includes the type of crops, the dates planted and harvested, critical depletion, and the growing season of the crop. Table 2 shows the crop data. Crop yield data for the period (1988-2019) was downloaded from the website (Our World in Data) [28], which is used to forecast future crop yield using extreme machine learning.

2.4 Methodology

The methodology followed in this study is illustrated in Figure 3. Climate data for the period of 1988-2019, crop data which includes some information about crops. In addition, future climate data were forecasted using (GFDL- ESM2M model) for three scenarios of RCP 2.5, RCP6, and RCP8.5, It was categorized into P1 (2020-2050) and P2 (2051-2080). Then used CROPWAT model for calculated references evapotranspiration and net irrigation-water requirement under present and future climate data within five-common crops, "sorghum, wheat, barley summer maize, and, autumn maize," in Al-Najaf, southwest

Iraq. Furthermore, the future crop yield was computed using the ELM method, and the support vector(SVM) executed as a machine algorithm is utilized in this study.

Table 1: Historical climatic parameters

Month	Min Temp °C	Max Temp °C	Humidity %	Wind Km/day	Sun Hours	Rad MJ/m²/day	ETo Mm/day	Rain Mm	Eff rain Mm
January,	6	17	67	102	5	10	1.53	16	16
February,	8	20	58	138	7	14	2.44	12	12
March,	12	25	47	173	8	18	3.96	10	10
April	18	31	41	173	7	20	5.17	14	13
May	24	38	31	173	9	23	7	3	3
June,	28	43	25	225	10	25	9.15	0	0
July	30	45	23	225	11	26	9.73	0	0
August,	29	45	24	173	10	23	8.24	0	0
September	26	41	29	138	9	20	6.36	0	0
October,	20	35	40	112	8	16	4.39	6	6
,November	13	25	56	95	7	12	2.52	17	16
December,	8	19	65	86	6	10	1.6	13	12
TOTAL	22	384	506	1813	95	216	62	91	89
Average	18	32	42	151	9	19	5	7	7
MIN	6	17	23	86	5	10	1.53	0	0
MAX	30	45	67	225	11	26	9.73	17	16
Median	19	33	41	156	8	19	5	8	8
ST DEV	9	11	16	47	2	6	3	7	7
Mode	_	_	_	173	_	_	_	0	0
Skewness	-0.1	-0.1	0.3	0.2	0.1	-0.2	0.2	0	0
Coefficient of Variation (CV)	48	33	39	31	21	29	56	89	89

Table 2: Crops data of the study area. (Ministry of water resources)

Crops	Planting and harvesting date	Critical depletion	Crop Growth Periods (Days) Initial season	Developed season	Mild season	Late season
Wheat	1/11-9/5	0.55	22	64	73	31
Barley	16/11-9/5	0.55	21	48	63	43
Autumn maize	8/7-30/10	0.55	20	32	38	25
Sorghum	15/3-29/7	0.55	20	37	47	33
Summer maize	15/3-29/7	0.55	24	39	43	31

2.5 Model Training and Testing

Typically, five climatic variables are responsible for driving the ET_0 process. These variables are maximum and minimum temperature, rainfall, relative humidity, and wind speed; the data is divided into two sets, 70% and 30% of which were used for training and testing, respectively. Model training is also based on this portion as more training of data is more accurate.

Then training the model utilizing the preferred algorithm. trial and error method was used to select the best algorithm which gives us better accuracy, Non-Linear SVM was selected which got a precision of 62% accuracy, which was low and unsuitable for data. Then Linear-SVM was chosen which got us the precision value of 93% accuracy.

3. Result and Discussion

3.1 Performance Evaluation

The Machine Learning model trained via a Support Vector Machine has obtained an accuracy percentage of 93%. Furthermore, a root means square error (RMSE) was 0.18, which is a suitable data value.

3.2 Reference Evapotranspiration (ET_0)

The CROPWAT 8.0 model requires future series data such as sunshine hours, minimum temperature, wind speed, and maximum temperature, to calculate the future ET_o under different periods (2020-2050) and (2051-2080) as shown in Table 3. The maximum value of ET_0 was estimated to be 10.02 mm in July under the RCP 8.5- scenario. The minimum value of ET_0 was 1.59 mm in January under RCP 2.5 scenario. Whereas, the minimum and the maximum value of the reference ET_0 were

9.73 in June and 1.53 in January, respectively. The monthly average of the highest ET_0 value was 5.42 mm under the RCP8.5 scenarios due to the high temperatures in this scenario. Under the reference and RCP 2.5 scenarios, the lowest average monthly value of ET_0 is 5.18 mm. ET_0 rises with time due to climate change, as shown in Figure 4; hence, it is simple to conclude that the ET_0 is directly proportional to temperature as well as high temperatures and high evapotranspiration is caused by conditions including low humidity and strong winds [29].

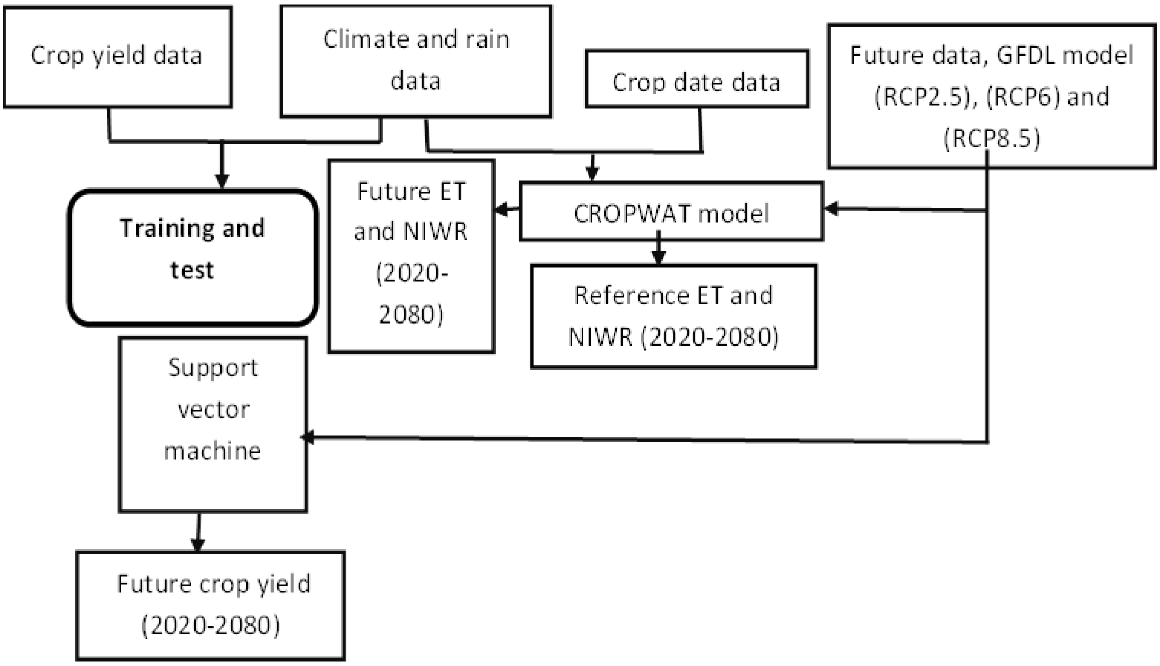

Figure 3: Framework for analyzing the effects of climate change on crop productivity, and net irrigation water requirement (NIWR)

3.3 Rainfall and effective rainfall

The Climatological Station and the GFDL-ESM2M model were used to collect total monthly present and future rainfall and effective rainfall data; however, CROPWAT-8 was utilized for obtaining the effective rainfall of the study area. As shown in Table 4, the maximum effective rainfall was expected to be 1.1 mm in December under the RCP 8.5 scenario for the period (2020-2050), while the minimum value was estimated to be 0 during the dry season from June to September under all scenarios. Under the RCP 8.5 scenarios in P1 and P2, the average monthly effective rainfall's minimum and maximum values were expected to be 0.17 mm and 0.31 mm, respectively.

3.4 Net Irrigation Water Requirements (NIWR)

The net irrigation water requirement is the quantity of water that should be applied to supply the crop with the water it needs to produce its full yield. There is not a consistent distribution of the amount of water that is required for plant growth across the entirety of its life cycle [30].

NIWR for the five crops (Summer Maize, Sorghum, Autumn Maize, Wheat, and Barley). The summer maize required the most irrigation of another four crops, and barley required less irrigation. The findings indicate that the average NIWR will rise in the future under climate change; temperature change might increase the rate of evaporation and transpiration, which would also affect the NIWR. Precipitation may not be sufficient to irrigate crops. Due to the increase in evapotranspiration, the NIWR for crops in the three future scenarios is more than in the reference scenario, as shown in Table 5.

Barley was the crop most affected by climate change under the (RCP2.5, RCP6, and RCP8.5) scenarios, with an increase in net irrigation water requirement (NIWR) by (22%, 23%, and 24%), for P1 and (23%, 24%, and 29%) for P2, respectively. Summer maize is the crop least affected by climate change under all climate change scenarios, with increases in crop water requirement of (1%, 2%, and 4%) for P1 and (2%, 4%, and 5%) for P2 as shown in Figure 5.

Table 3: Monthly evapotranspiration under reference and climate change scenarios.

Month	Reference ET_0(mm)	ET_0 RCP2.5 (mm)		ET_0 RCP6 (mm)		ET_0 RCP8.5 (mm)	
	Reference	P1	P2	P1	P2	P1	P2
January	1.53	1.59	1.58	1.61	1.6	1.6	1.68
February	2.44	2.53	2.51	2.52	2.51	2.56	2.61
March	3.96	4.01	4.1	4.07	4.11	4.1	4.23
April	5.17	5.19	5.2	5.22	5.35	5.25	5.48
May	7	6.9	6.96	6.96	7.03	6.99	7.2
June	9.15	9.05	9.09	9.04	9.27	9.11	9.29
July	9.73	9.65	9.66	9.7	9.84	9.71	10.02
August	8.24	8.19	8.21	8.23	8.31	8.22	8.54
September	6.36	6.45	6.48	6.47	6.59	6.53	6.79
October	4.39	4.43	4.48	4.51	4.53	4.48	4.72
November	2.52	2.57	2.55	2.6	2.64	2.67	2.75
December	1.6	1.64	1.67	1.66	1.66	1.7	1.78
Maximum	9.73	9.65	9.66	9.7	9.84	9.71	10.02
Minimum	1.53	1.59	1.58	1.61	1.6	1.6	1.68
Average	5.18	5.18	5.21	5.22	5.29	5.24	5.42

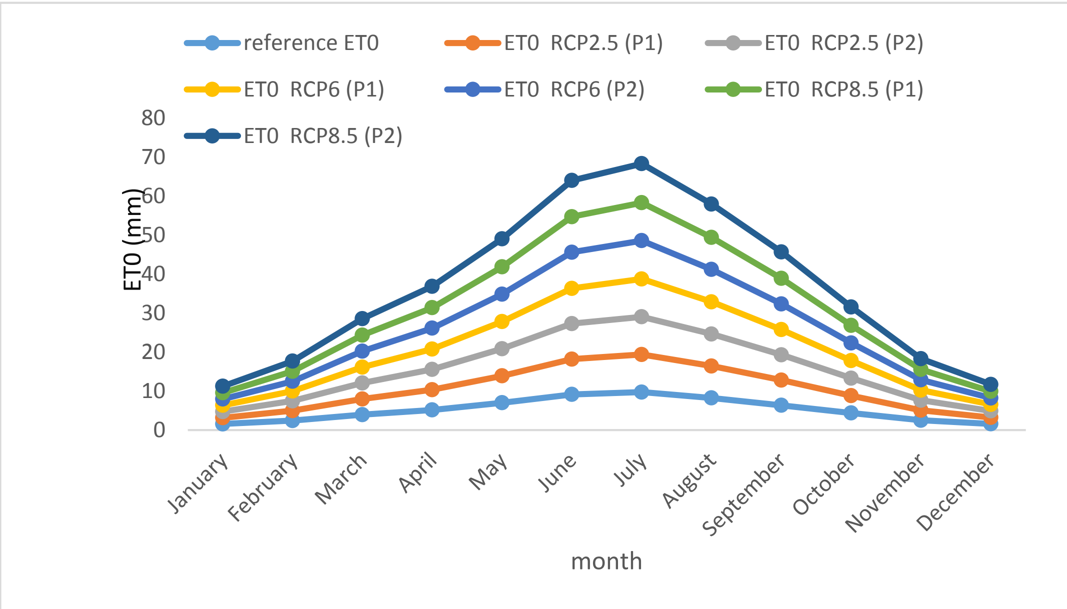

Figure 4: Reference ETo under different climate change scenarios

3.5 Crop yield production

The ELM model (Support Vector algorithm) was used to simulate the yield for five common crops in Iraq under RCP2.5, RCP6, and RCP8.5. According to Table 6, the future yield of wheat and barley would be expected to remain constant under (RCP2.5, RCP6, and RCP8.5) because the growing season of these crops doesn't affect by temperature, and evaporation was low in this season. The production of other crops decreases due to rising temperatures and evaporation. Due to an increment in temperature and a decrease in precipitation, crop water usage will rise in all three scenarios. Under scenario RCP 6 for P1, crop production remains constant due to climate parameters in this scenario having a close value to the second period of RCP.

Findings shown in Table 3 indicated that values of ET_o for RCP 2.5, 6, and 8.5 for period two (P2) are more than ET_o for the period (P1); this increase is owing to an increase in the temperature in period two (P2).

Despite the decrease in effective rainfall with time, it is an increase in the second period of RCP6 and one period of RCP8.5, An increase in precipitation in these periods may be associated with more intense and extreme precipitation events. as shown in Table 4. The precipitations of Iraq during the 21st century tended for decreasing in the a-northern region, while a small increase was expected in the southern region due to climate changes [31]. A northward shifting of the intertropical convergence zone under climate change conditions which carried much more moisture for the southern part of the Arabian Peninsula should generate more fluctuation in the precipitation pattern in these regions [32].

Table 4: Monthly effective rainfall under reference and climate change scenarios.

MONTH	Reference Eff (mm)	Eff RCP2.5 (mm)	Eff RCP2.5 (mm)	Eff RCP6 (mm)	Eff RCP6 (mm)	Eff RCP8.5 (mm)	Eff RCP8.5 (mm)
	Reference	**P1**	**P2**	**P1**	**P2**	**P1**	**P2**
January.	16	0.3	0.4	0.3	0.7	0.5	0.4
February.	12	0.6	0.3	0.2	0.3	0.3	0.1
March	10	0.3	0.4	0.3	0.4	0.3	0.4
April	13	0.2	0.2	0.2	0.3	0.2	0.2
May	3	0.1	0.1	0.1	0.2	0.2	0.1
June	0	0	0	0	0	0	0
July	0	0	0	0	0	0	0
August	0	0	0	0	0	0	0
September	0	0	0	0	0	0	0.1
October	6	0.5	0.5	0.6	0.6	0.7	0.3
November	16	0.6	0.8	0.2	0.7	0.4	0.3
December	12	0.2	0.5	0.2	0.4	1.1	0.1
Average	7.3	0.23	0.27	0.18	0.3	0.31	0.17
Maximum	16	0.6	0.8	0.6	0.7	1.1	0.4
Minimum	0	0	0	0	0	0	0

Table 5: NIWR for crops under present and future climate change scenarios

Crops	**Reference scenario (1988-2019)**	**Climate change scenario**					
		RCP2.5		**RCP6**		**RCP8.5**	
	NIWR (mm)	**NIWR (mm)**		**NIWR (mm)**		**NIWR (mm)**	
	(1988-2019)	(2020-2050)	(2051-2080))	(2020-2050)	(2051-2080	(2020-2050)	(2051-2080)
Wheat	451.8	538	540	545.5	547.2	548.9	571.6
Barley	362.3	442.2	444.5	445.6	447.5	449	466.7
Autumn Maize	618.2	637.8	640.5	642.4	664.8	665.2	668.7
Sorghum	802.2	817	821.5	821.2	845.8	846	846
Summer maize	881.3	892.5	897	897	913.3	914	923.8

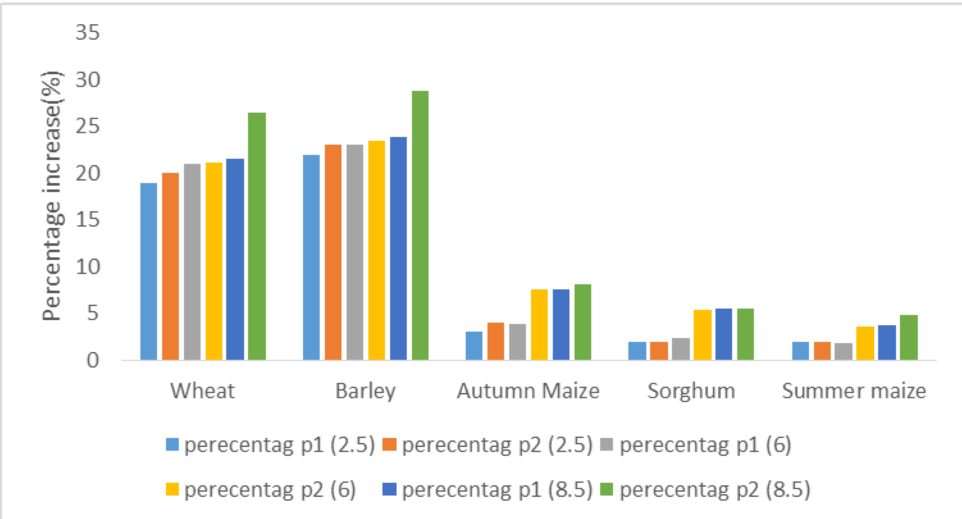

Figure 5: Percentage increase of crop water requirement under different climate change scenarios

Table 6: Crop yield under different scenarios

crops	Climate change scenario					
	P1(2020-2050)	P2(2051-2080)	P1(2020-1050)	P2(2051-2080	P1(2020-1050)	P2(2051-2080)
Wheat	88404	88404	88404	88404	88404	88404
barley	1966	1966	1966	1966	1966	1966
autumn maize	3254	3254	3092	3092	3092	3090
Sorghum	3.3	3.3	3.1	3.1	3.1	3
spring maize	13.1	13.1	12.4	12.4	12.4	12.3

The high difference in the effective rainfall values between the reference and all scenarios. due to there more than one flood year through the years of the reference scenario (1988-2019)

Table 5 showed an increment in the net irrigation water requirements for two periods under all scenarios for all crops, although increasing effective rainfall in the RCP6 with P2 and RCP8.5 with P1 because the high rate of ET_o in the study area was a pivotal factor controlling within NIWR-Equation (5) rather than Peff. which study showed that NIWR is affected by ET_o caused by the high rate of ET_o drains soil moisture faster in the study area.

According to Table 6, the future yield of wheat and barley would remain constant under different scenarios. In contrast, the yield of other crops decreases due to rising temperatures and evaporation.

Similar results were obtained by [33] found a decrease in water for irrigation by 2.9 MCM/under climate change. [34] also concluded that climates changes negatively affect the irrigation water requirements of all crops in this study. [35] shows the large negative effect of climate change on corn yield. The NIWR of barley was sensitive to climate change with an increase in NIWR by 38–79% compare to the increase for-maize by 0.2–1.4% under RCP-2.6 and, RCP-8.5 [36].

4. Conclusions

Based on obtained results from this study, The RCP8.5 and RCP2.5 scenarios had the highest and lowest average temperatures, respectively, which caused the maximum and minimum real control evapotranspiration (ET) to be found in those two scenarios. The Rainfall and effective rainfall results show that the maximum effective rainfall was expected to be 1.1 mm in December under the RCP 8.5 scenario for the period (2020-2050), while the minimum value was estimated to be 0 during the dry season from June to September under all scenarios. The NIWR Result shows that Barley is the crop most affected by climate change under the RCP2.5, RCP6, and RCP8.5 scenarios, with increases in crop water requirement (NIWR) of 22%, 23%, and 24% for P1 and 23%, 24%, and 29% for P2, respectively. Summer maize is the crop least affected by climate change under all climate change scenarios, with an increment in NIWR of 1%, 2%, and 4% for P1 and 2%, 4%, and 5% for P2. In summary, for all possible futures, the quantity of water needed for common crop irrigation will increase due to climate change.

The production of wheat and barley remains the same under the RCP2.5, RCP6, and RCP8 scenarios. Climate change adversely affects the crop productivity of other crops (maize, sorghum, and summer maize) under the different climate change scenarios. The findings of this research may be utilized to develop adaptation strategies for dealing with potential changes in water availability and crop productivity due to climate change.

Author contributions

All authors contributed equally to this work.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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