

Article

Application of DSSAT CERES-Maize to Identify the Optimum Irrigation Management and Sowing Dates on Improving Maize Yield in Northern China

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Abstract: The increase in irrigated maize plantings in Northern China has increased the demand for irrigation water in the region, resulting in chronic water shortages in drier years. Efficient irrigation and water use are essential for the sustainable development and management of water resources in the area. This research applied DSSAT-maize in the Loess Plateau (Fenhe basin) to determine the suitable irrigation management and optimum sowing dates to ensure the stability of spring maize production. The model was calibrated using the full irrigation treatment of 2017–2019 growing seasons. Crop data, such as plant phenological phases, aboveground biomass, crop yield, and leaf area index, were used for model calibration. The calibration showed great consistency between the measured and simulated data, with nRMSE (normalized root mean square error) ranging from 0.77% to 21.6%. The field values of crop yield, aboveground biomass, LAI, soil water content, and water use efficiency were used to evaluate the calibrated model's performance, the model evaluation was found to be satisfactory with acceptable nRMSE ranging from 1.9% to 25.3%. Optimum simulated sowing dates for increased productivity and water efficiency were between 15 and 25 May. The optimum irrigation timing and volume of irrigation water application were 85 mm at the tasseling phase and 85 mm at the grouting phase respectively. Therefore, the yield of maize can be increased by applying irrigation and altering the sowing date in case rainfall is insufficient to satisfy the water demand of the crops in the Fenhe basin.

Keywords: DSSAT model; optimum irrigation management; maize; sowing dates; Northern China; loess plateau



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1. Introduction

The Loess Plateau (Shanxi Fenhe basin) of the northern part of China is a semi-arid region. Spring maize is among the region's most important crops accounting for more than 25% of the total arable land [1]. The spring maize participates in promoting economic growth and ensuring food security in this area [2]. Additionally, for worldwide maize production, China is the second producer following the United States. Therefore, the production of maize in China has a significant impact on the world's economy. In previous years, maize and other cereals' improvement in China have been recognized as one of the most outstanding achievement stories in agricultural science and technology policy reform [3,4].

However, water resources in semi-arid areas are limited, and the need for water for domestic use, irrigation, and nature's services (agroecosystems, forest ecosystems, grassland ecosystems, and aquatic ecosystems) is rising [5]. This suggests that, for the sustainable management of agriculture and related resources, it is essential to increase the amount of

beneficial water in agriculture and reduce the amount of non-beneficial water [6,7]. Farmers in China, just like elsewhere in the world, face some technical challenges, such as a lack of information on the exact amount of water required for the crop to grow up, the appropriate time to irrigate a crop, the optimum amount of water a particular crop needs for optimum yield, and how much water can be saved through proper irrigation management [8]. In this region, farmers can carry out additional irrigation at many development phases of crops to avoid the impact of water stress [5]. Relevant literature shows that during water shortage conditions, the use of irrigation schemes depend on additional irrigation can potentially increase grain production [9]. Supplementary irrigation can provide the needed quantity of water at different phases of crops in order to minimize the negative effect of water scarcity on plants [10]. Nowadays, this practice is dependent on agriculture models to ameliorate irrigation management.

In previous years, several crop system models have been developed, like the Decision Support System for agrotechnology Transfer (DSSAT) [11], Food Agriculture Organization (FAO) Aqua crop model [12], the Agricultural Production Systems Simulator (APSIM) [13], etc. Crop system models have been used to simulate agricultural practices and help calibrate and evaluate many aspects of the relationship between the factors affecting plant development and production [11]. Those factors include soil type, cultivar selection, sowing date, seeding rates, fertilizer, irrigation management, and weather patterns [14]. DSSAT is the most commonly used model for simulating biomass and yield production. The DSSAT model is a multipurpose model that has been applied for the evaluation of crop development, such as crop phenology, biomass, and yield production [15]. The CERES-maize model within DSSAT can accurately predict soil moisture at various levels under fully irrigated conditions [16,17]. Using long-term weather information to identify the best sowing dates DSSAT CERES-maize model was used for yield prediction under various irrigation scenarios [12,18] and production forecast response to climate change [19].

In addition to agronomic practices and irrigation systems, the sowing date is critical for maximizing maize production (grain yield and biomass). As a result, farmers must be aware of the yield response of maize to the sowing date. Inaccurate sowing time can lead to critical damage or limit the plants' growth and development [20]. Furthermore, the optimum sowing time may change from region to region, depending on climate differences. The DSSAT model has been used in several parts of China in recent years, such as Northwest China [21]. Herein, our work found that it is also important to conduct research using the DSSAT model in the Loess Plateau to predict maize production using sowing dates and irrigation strategies under various climatic conditions. Therefore, it is crucial to determine the optimum irrigation management and sowing dates under different weather conditions [5]. For this context, the major objective is to minimize crop water stress and enhance productivity through irrigation in the current study area. Additional objectives include (1) calibrating and evaluating the DSSAT CERES in the Fenhe basin, and (2) using the DSSAT model to determine the best maize sowing day and irrigation quantity to enhance maize production via rainfall and irrigation scenarios.

2. Research Area and Data

2.1. Research Area

Experiments were carried out at the Fenhe River Basin Experiment Station (37°17' N, 112°12' E, altitude 750 m) in Wenshui County, Shanxi Province, Northern China, in 2017–2019 Figure 1. The climate in the research area is temperate continental semi-arid with 450 mm of average rainfall, average annual evaporation of 1563.3 mm (20 cm evaporating pan), and average annual minimum and maximum air temperatures of 3.1 °C and 16 °C, respectively. Daily minimum and maximum air temperature (°C) and precipitation (mm) during the growing season (2014–2019) were obtained at the Wenshui meteorological station Figure 2. Soil samples were taken at various intervals down to 1.5 m soil depth and used to determine the fundamental soil properties of the research area Table 1.

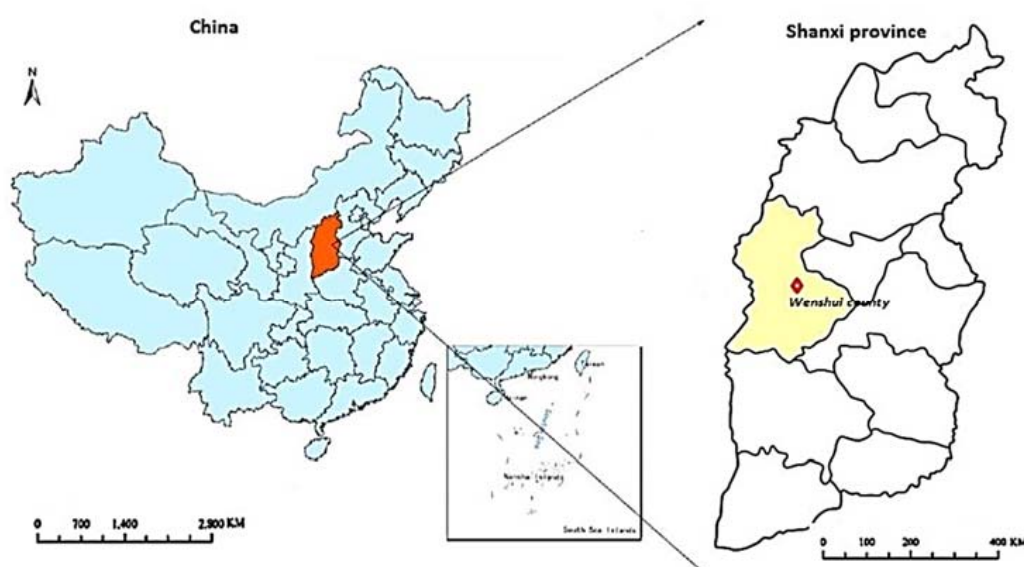


Figure 1. Study area map.

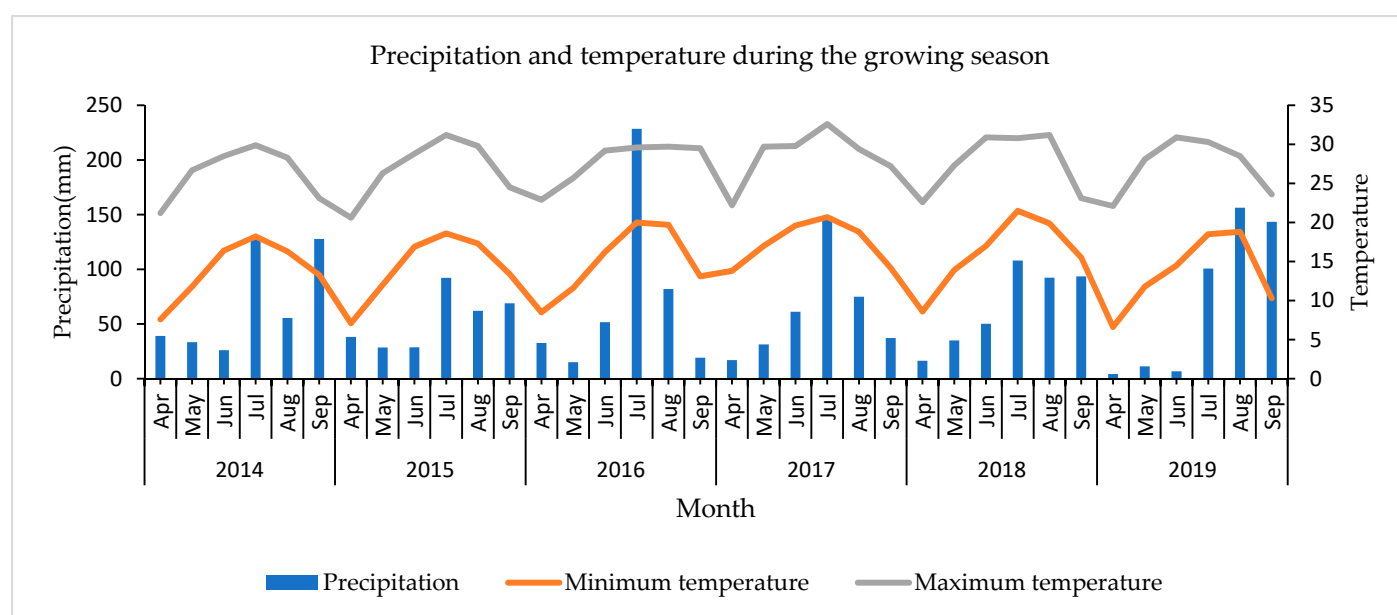


Figure 2. Average monthly precipitation and temperature during the growing season (2014–2019) at the Wenshui Experiment Station, Shanxi, China.

Table 1. Soil properties in Wenshui Shanxi province.

Soil Properties	0–15 cm	15–30 cm	30–60 cm	60–100 cm	100–150 cm
Sand %	26	25	23.9	25.3	30.2
Silt %	51.9	52	53.1	52	48.5
Clay %	22.1	23	23	22.7	21.3
PH	7.4	7.4	7.4	7.4	7.4
Bulk density g/cm ³	1.48	1.47	1.48	1.48	1.49
Organic matter %	1.16	1.1	0.97	0.43	0.2
Lower limit cm ³ /cm ³	0.11	0.103	0.09	0.079	0.086
Upper limit m ³ /cm ³	0.227	0.201	0.193	0.165	0.178

2.2. Datasets

2.2.1. Information on Crop Management and Irrigation

The Denghai 679 maize variety which is widely promoted and planted in this study area, was used in the experiment. Maize seeding took place on the 20 April, 30 April, and 8 May in the 2017–2019 growing seasons, respectively. The maize planting density was 6 plants/m², the row spacing was 65 cm, and the plant spacing was 32 cm. The plot size was 8.9 m long, 7.5 m wide, and 66.75 square meters of area. In this study, the sprinkler irrigation method was used, the irrigation was applied in the case soil water content dropped to 50% of field capacity. The irrigation treatments received 100% (full irrigation), 75%, and 50% of applied irrigation volume. However, water was delivered through hoses, while irrigation water was measured by water meters. By using the partial orthogonal experimental design process, nine deficit irrigation treatments were planned, with triplicate for experiments in 2017–2019. Table 2 describes the design method and amount of irrigation water applied in the Fenhe basin.

Table 2. Irrigation design method and amount of irrigation applied in 2017, 2018, and 2019.

Treatment	May	June	July	August	Total Amount of Irrigation Applied (mm)		
					2017	2018	2019
T1	1.0	1.0	1.0	1.0	340	320	350
T2	1.0	0.75	0.75	0.75	276	260	284
T3	1.0	0.5	0.5	0.5	212	200	219
T4	0.75	1.0	0.75	0.5	255	240	262
T5	0.75	0.75	0.5	1.0	254	240	260
T6	0.75	0.5	1.0	0.75	255	240	264
T7	0.5	1.0	0.5	0.75	212	220	240
T8	0.5	0.75	1.0	0.5	221	220	242
T9	0.5	0.5	0.75	1.0	212	220	256

2.2.2. Sampling and Laboratory Procedures

- Yield and aboveground biomass

Plant size (height and stem thickness) was measured every week, with ten plants randomly selected at each plot. For each plot, crop phenology was measured three times per week. All crop phenology phases (emergence, anthesis, and maturity phases) were recorded in form of the year's day. All plants were harvested near the ground for aboveground biomass, and fresh weight was weighed. Sub-samples were heated for 0.5 h at 110 °C and dried to a constant weight at 80 °C. The middle two rows of each plot were hand-harvested for grain yield measurement at harvest time. Grain yield from shelled ears was determined and adjusted to 14% moisture content.

- Leaf area index (LAI)

The measurements for leaf area were taken seven times during the planting period at various growth phases, the leaf area index (LAI) was calculated, from the sampled plants, the length and the width of each leaf was measured, and the leaf area was calculated using Equation (1):

$$\text{Leaf area} = \text{length} \times \text{width} \times 0.75 \quad (1)$$

The leaf area index (LAI) obtained by using Equation (2):

$$\text{LAI} = \text{leaf area}(\text{m}^2\text{plant}^{-1}) \times \text{plant density}(\text{plant ha}^{-1})/10,000 \text{ m}^2\text{ha}^{-1} \quad (2)$$

- Soil water content

The soil moisture content, was measured during the growing season, before the sowing time, a day before and after every irrigation, and at harvest time. Samples were

collected at different intervals down to a 1.5 m soil depth using a 5-cm diameter corer. Soil cores were weighted while they were still wet, then oven-dried to 105 °C until constant weight and then were measured on a dry weight basis. Gravimetric water content obtained by the Equation (3):

$$\text{Water content} = (\text{Wet weight} - \text{Dry weight}) / \text{Dry weight} \quad (3)$$

- Water Use Efficiency

Water use efficiency calculated by Equation (3):

$$\text{WUE} = Y / \text{ETc} \quad (4)$$

where Y is the grain yield (kg/ha), and ETc is the seasonal crop evapotranspiration (mm). For each irrigation treatment, the seasonal crop evapotranspiration was calculated. Using Equation (5):

$$\text{ET} = P + I - D - R \pm \Delta s. \quad (5)$$

$$\Delta s = I + P - \text{ES} - \text{EP} - D - R \quad (6)$$

where P is the total precipitation (mm), I is the irrigation volume (mm), and D (mm) is the downward drainage out of the root zone, during the growing season, soil water consumption was less than the field water holding capacity of the root zone, thus it was ignored. R (mm) is the runoff, since the rainfall was not intense and the area was flat, and was assumed to be zero. DS is the variation in soil water content, ES is the soil evaporation, and EP is the transpiration.

3. Methodology

3.1. Description, Calibration, and Evaluation of the DSSAT Model

In terms of the human-computer interface, the DSSAT model is one of the more intuitive crop models. The first version of DSSAT, Version 2.1, was released in 1989. The most recent version of DSSAT, 4.7, can simulate more than 42 different types of crops [11]. Initial soil conditions, daily weather data, detailed crop management, and various crop cultivar coefficients are all necessary inputs for the DSSAT version 4.7 module [22].

In this research, the CERES-maize model within DSSAT 4.7 was used. The CERES-maize model inputs include cultivar coefficients, daily weather data, soil information, crop management practices, planting density, and sowing dates [23]. For calibration of the model and maize cultivar coefficient estimation, the essential crop data (aboveground biomass, crop physiological phases, final grain yield, and leaf area index) during the three growing seasons (2017–2019) were chosen, from the full irrigation treatment (T1). The genetic coefficient for the spring Denghai 679 cultivar was calculated using the DSSAT-GLUE package within the DSSAT model.

The DSSAT model performance was evaluated using the field values, aboveground biomass, crop yield, LAI, and soil water content selected from the remaining irrigation scenarios (T2–T9) of the 2017–2019 growing seasons. This study used three common statistical indicators for model evaluation; RMSE (root mean square errors), nRMSE, and d-index value:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (S_i - M_i)^2}{n}} \quad (7)$$

$$\text{nRMSE} = \frac{\text{RMSE} \times 100}{M} \quad (8)$$

$$d = 1 - \left[\frac{\sum_{i=1}^n (S_i - M_i)^2}{\sum_{i=1}^n (|S_i| + |M_i|)^2} \right], 0 \leq d \leq 1 \quad (9)$$

Here, n is the number of observations, S_i is the i -th measurement of simulated values, M_i is the i -th measurement of measured values, M is the average of observed values, $S_i' = S_i - M$ and $M_i' = M_i - M$.

The lower value for nRMSE and the higher value for d-index indicate that the measured and simulated data are well fitted.

In general, when $nRMSE < 10\%$ model performance is great, when $20\% > nRMSE > 10\%$ it is considered good, when $20\% < nRMSE < 30\%$ the model performance is fair, and when $30\% < nRMSE$ it is considered to be poor [24].

3.2. Crop Cultivar Coefficient

To simulate crop growth rates, biomass yield, and other factors, crop cultivar coefficients are required [25]. There are six genetic coefficients in CERES-maize; degree days (base 8 °C) from emergence to the end of the juvenile phase (P1), coefficient of photoperiod sensitivity (P2), from silking to physiological maturity in degree days (base 8 °C) (P5), the number of potential kernels (G2), the rate of potential kernel growth mg/(kernel d) (G3), and PHINT, degree days it takes for a leaf tip to emerge (phyllochron interval) (°C d) [26].

Table 3 describes the calibration of the genetic coefficients of the Denghai 679 obtained from the GLUE program.

Table 3. Genetic parameters of Denghai 679.

	P1	P2	P5	G2	G3	PHINT
Calibrated value	302.40	0.6292	990.00	800.0	11.00	50.286

3.3. Simulation Controls

3.3.1. Sowing Date Treatments

The DSSAT model's seasonal software was used in the simulation of yield for various planting dates. To decide the optimum sowing date based on various irrigation scenarios in the Fenhe basin, the seasonal analysis was conducted, using six years of historical weather information from the Wenshui weather Station. Different crop parameters like crop cultivar, crop management data and others. Sowing dates were chosen, at five-day intervals, between 20 April and 20 June for the study of optimum sowing date. The simulation results are represented in a table and by Box [27].

3.3.2. Irrigation Strategies

The irrigation treatments were adjusted based on the various stages of crop development—emergence, jointing, tassel, grouting, and maturity phases—with various irrigation scenarios. Thirty-two irrigation schedules through different combinations of phenological periods used in simulation: no irrigation, single irrigation, double irrigation, triple irrigation, quadruple irrigation, and quintuple irrigation (85 mm of water per each irrigation) Table 4. Each simulation is carried out with the hypothesis of no nutrition stress.

Table 4. Irrigation treatments simulated with the CERES-maize model.

Irrigation Combination	Phases of Crop Development and Irrigation Volume (mm)				
	Emergence	Jointing	Tassel	Grouting	Maturity
I1	rain	rain	rain	rain	rain
I2	85				
I3		85			
I4			85		
I5				85	

Table 4. Cont.

Irrigation Combination	Phases of Crop Development and Irrigation Volume (mm)				
	Emergence	Jointing	Tassel	Grouting	Maturity
I6					85
I7	85	85			
I8	85		85		
I9	85			85	
I10	85				85
I11		85	85		
I12		85		85	
I13		85			85
I14			85	85	
I15			85		85
I16				85	85
I17			85	85	85
I18		85		85	85
I19	85			85	85
I20		85	85	85	
I21	85	85		85	
I22	85	85	85		
I23		85	85		85
I24	85		85		85
I25	85		85	85	
I26	85	85			85
I27	85	85	85		85
I28	85	85	85	85	
I29	85	85		85	85
I30	85		85	85	85
I31		85	85	85	85
I32	85	85	85	85	85

4. Results and Discussion

4.1. Model Calibration

During the model's calibration, the different parameters of treatment one (T1) were simulated during the growing season of 2017–2019. Table 5 shows the differences in emergence, anthesis, aboveground biomass, maturity grain yield, and maximum leaf area index between measured and simulated results. The simulated emergence date differed by 1–2 days from the observed emergence date with nRMSE% range between 0.83 and 1.45, simulated and measured of anthesis date varying between 2–5 days with nRMSE% ranging between 0.99 and 2.42, and a predicted maturity date ranging from two to three days and nRMSE% from 0.81 to 1.16. The results indicate that the simulated aboveground biomass, grain yield, and leaf area values were in excellent accordance with measured values, the nRMSE (%) range between 4.1% and 21.6% [17]. Thus, the CERES-maize model can simulate yield potential in the research area.

4.2. Model Evaluation

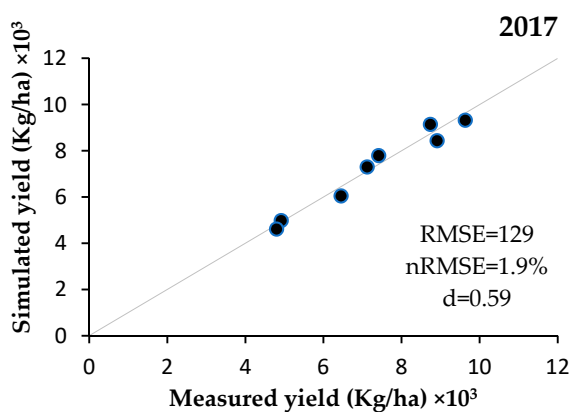
4.2.1. Aboveground Biomass and Grain Yield

The DSSAT CERES-maize model evaluated by comparing simulated and measured aboveground biomass and grain yield under various irrigation treatments (T2–T9). Analytical statistics shows that the RMSE of the measured and the predicted grain yields ranged between 129 kg to 1084.7 kg/ha, d-index ranged from 0.59–0.98, and nRMSE of 1.9%, 4.04%, and 13%, during the 2017–2019 growing period, respectively Figure 3. Aboveground biomass showed concordance between measured and predicted data, with the RMSE ranging between 624 and 1927.91 kg/ha, the nRMSE ranging from 4.02% to 12.7%, and the d-index ranging from 0.86 to 0.89. Predicted aboveground biomass and crop yield results are related to the results presented by [28]. The objective of this analysis was to study

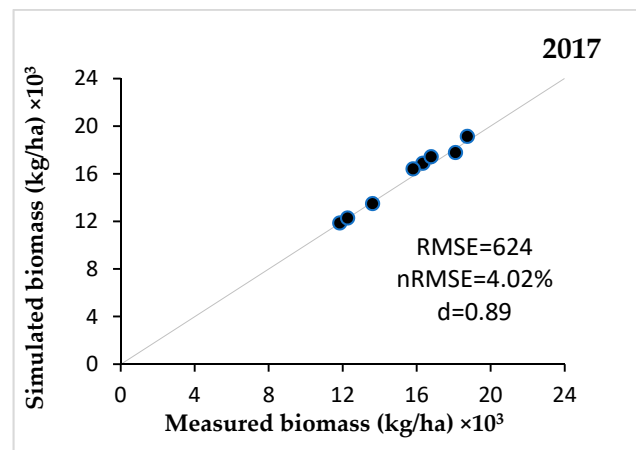
how well the model predicts the impact of various irrigation methods on aboveground biomass and grain yield. The predicted and the measured outcomes show that the DSSAT model can effectively calibrate and predict the biomass and yield under various irrigation managements.

Table 5. The simulated and observed results of the CERES-maize of (T1) during 2017, 2018, and 2019 growing seasons.

Parameters	Year	Measured	Simulated	nRMSE (%)
Emergence (DOY)	2017	120	119	0.83
	2018	129	128	0.77
	2019	138	136	1.45
Anthesis (DOY)	2017	189	186	1.58
	2018	201	199	0.99
	2019	206	201	2.42
Maturity (DOY)	2017	246	244	0.81
	2018	258	255	1.16
	2019	265	268	1.13
Grain yield (kg/ha)	2017	8495	7692.6	9.06
	2018	9175	8642.8	5.8
	2019	9913	9506	4.1
Aboveground biomass (kg/ha)	2017	16,890	17,013	7.2
	2018	17,460	15,280	12.4
	2019	19,385	17,332	10.6
Maximum leaf area index (LAI)	2017	4.1	3.5	14.63
	2018	3.7	2.9	21.6
	2019	3.58	3.0	16.2



(a)



(b)

Figure 3. Cont.

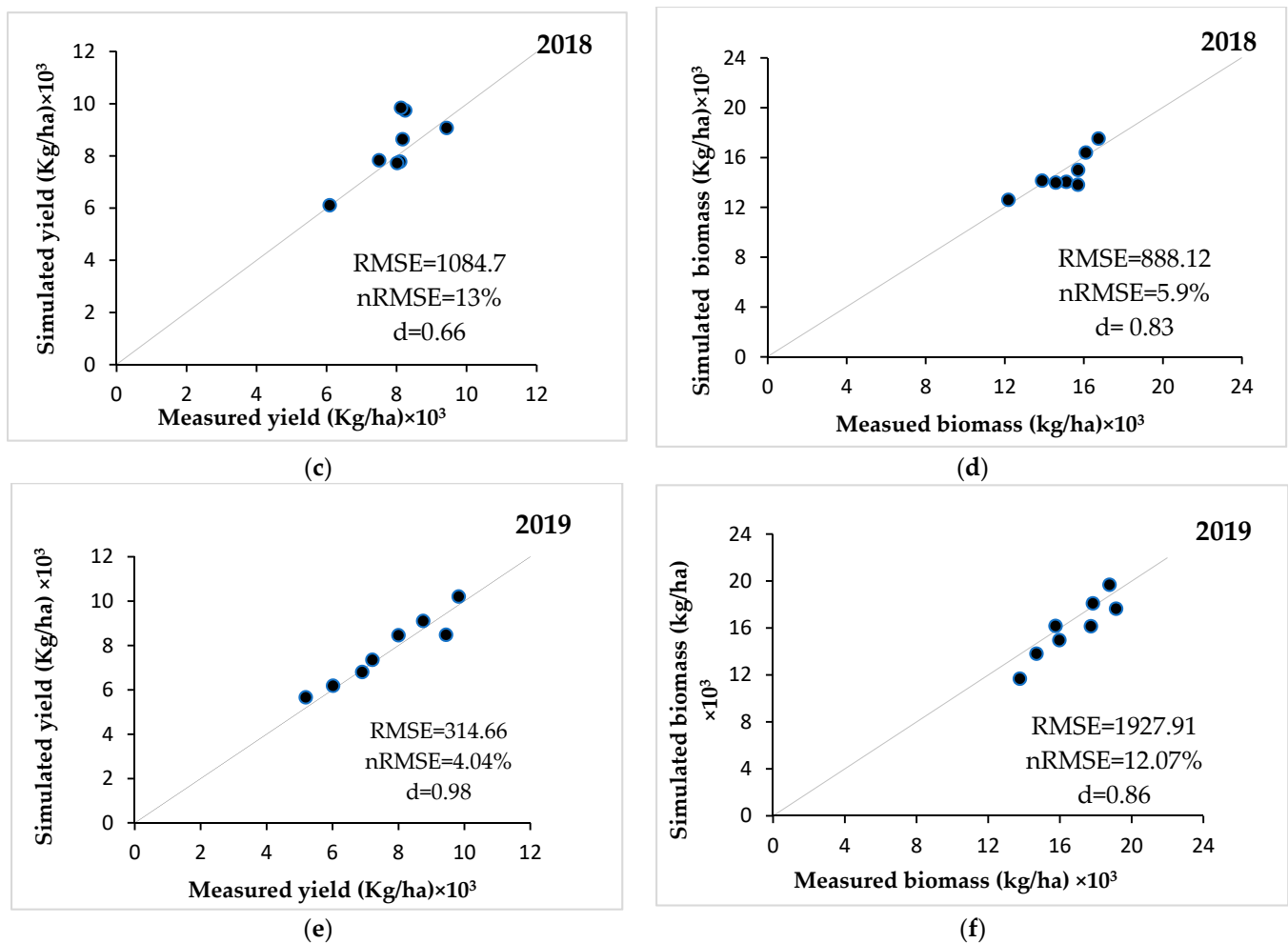


Figure 3. Comparison between measured and simulated grain yield (a,c,e) and aboveground biomass (b,d,f) under various irrigation treatment for 2017–2019 growing seasons.

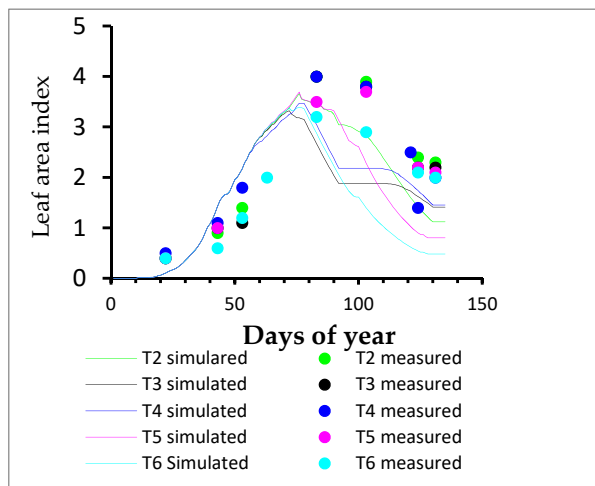
4.2.2. Leaf Area Index

To evaluate the model using the Leaf Area Index, we used 2017 growing season irrigation treatments (T2–T9). Measured and predicted leaf area index were in accordance, with nRMSE of 16.9% and d index of 0.79 Figure 4. During the first days of the growing season, the simulation of LAI was almost identical to the observed LAI. After 75 days, the difference between measured and simulated data for every treatment seems to increase slightly, as discussed earlier by [27]. The model outcomes indicate that after 75 days during the growth period, LAI decreases to these outcomes are consistent with past studies that used the DSSAT model [29].

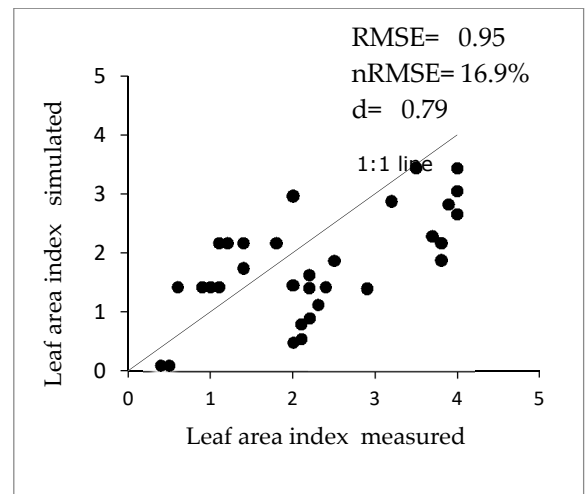
4.2.3. Soil Water Content

Since one of our objectives was to analyze the best use of irrigated water when water availability is scarce, it was necessary to check whether the model can also correctly simulate soil water content. To simulate soil moisture at various soil depths (0–15 cm, 15–60 cm, 60–100 cm, and 100–150 cm), the model used the full irrigation treatment of the 2017 growing season. The results in Figure 5 show the nRMSE values ranged between 2.3% and 25.3%, the RMSE of the entire soil profile between the predicted and observed soil moisture content range was from 0.01 to 0.54, and the d-index values for all soil levels ranged between 0.12 and 0.62. The measured and simulated soil water content of soil levels under 60 cm (60–150 cm) showed a good agreement, compared to soil levels above

60 cm, this reported in previous studies [8]. Moreover, many related studies have shown the model can correctly simulate the soil water content of various soil levels.

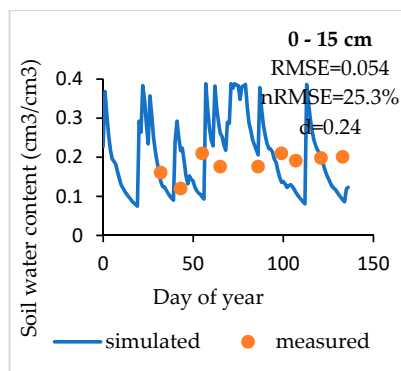


(a) Variation of simulated and measured leaf area index with the days after starting of simulation

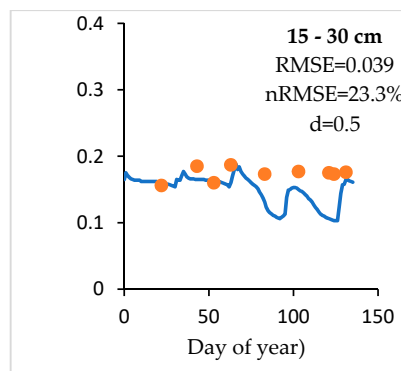


(b) Simulated and measure leaf area index

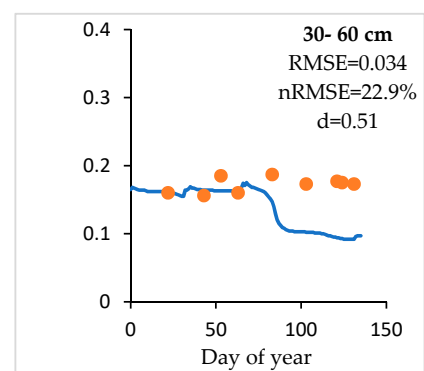
Figure 4. The 2017 growing season simulated and measured leaf area indices.



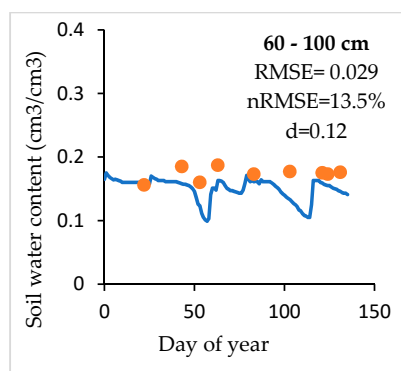
(a)



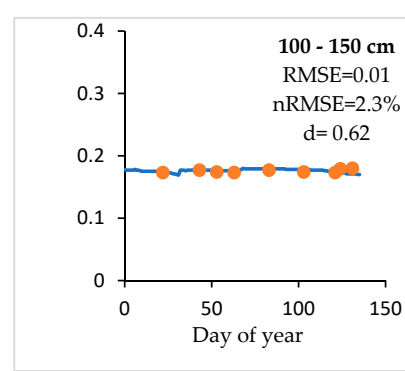
(b)



(c)



(d)



(e)

Figure 5. Measured and simulated soil water content at various soil levels of the 2017 growing season. (a–e) Simulated and measured soil water content at a depth of 0–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, and 100–150 cm, respectively.

4.2.4. Water Use Efficiency

Water usage efficiency was measured and simulated for the 2017 and 2019 growing seasons, and the results showed a good agreement with nRMSE ranging from 2.6% to 9.6% and 3.5% to 8.5%, respectively. The rain-fed measured and simulated water use efficiency during the 2017 growing season was 15.6 and 14.1 kg ha⁻¹ mm⁻¹, respectively. During the 2019 growing season, the measured and simulated rain-fed water use efficiency was 15.2 and 13.9 kg ha⁻¹ mm⁻¹, respectively Table 6. The measured and simulated WUE values for full irrigation in both growing seasons are very close. In comparison to limited irrigation, water use efficiency for full irrigation was accurately simulated. Simulated water use efficiency for T1 in both the 2017 and 2019 growing seasons was comparable to irrigation treatments T4, T7, and T9 WUE, showing that deficit irrigation could improve the water use efficiency.

Table 6. Measured and simulated water use efficiency for maize during the 2017 and 2019 growing periods.

Treatments	2017 WUE [kg(yield) ha ⁻¹ mm ⁻¹]			2019 WUE [kg(yield) ha ⁻¹ mm ⁻¹]		
	Measured	Simulated	nRMSE (%)	Measured	Simulated	nRMSE (%)
T1	26.4	25.7	2.6	25.3	26.2	3.5
T2	24.1	25.0	3.7	21.5	20.6	4.2
T3	25.2	23.5	6.7	20	18.7	6.5
T4	25.4	26.9	5.9	23.5	24.6	4.7
T5	22.1	23.6	6.8	19.8	21.2	7.4
T6	25.1	26.4	5.2	18.9	17.4	7.9
T7	25.3	23.8	5.9	24.1	25.6	6.2
T8	25.0	26.5	6.0	20.4	18.9	7.3
T9	25.3	26.4	4.3	26.2	24.6	6.1

4.3. Model Application

4.3.1. Optimum Sowing Date

The DSSAT CERES-maize model's seasonal analysis revealed that different irrigation scenarios and planting dates influenced grain yield at different crop development stages. Table 7 shows the simulated seasonal grain yield results under 32 scenarios of irrigation, the simulated grain yield under rainfed conditions and full irrigation treatment (I32) are box plotted in Figure 6. The simulated results showed that under all irrigation scenarios the maximum yields were obtained from 15 to 25 May (20 May with the highest average maximum yield). Moreover, results show that changing the sowing date from 20 April to 20 May results in a continuous increase in yield from 8264 kg/ha to 10,047 kg/ha under all irrigation strategy scenarios, and that delayed sowing dates to 25 May showed a significant decrease in yields Figure 6. For several years in this area, sowing dates were suggested based on local farmer's experience rather than local climate conditions. This study revealed that grain yield depends on sowing dates with respect to irrigation and climate conditions.

Table 7. Simulated yield under different irrigation scenarios using six years (2014–2019) of weather data with various sowing dates.

Irrigation	20 April	25 April	30 April	5 May	10 May	15 May	20 May	25 May	30 May	5 June	10 June	15 June	20 June
I1	7162	8199	8378	8556	8699	8810	9106	8709	8411	7913	7410	7045	6022
I2	7296	8177	8424	8599	8670	8910	9204	8822	8504	8313	7953	7754	7645
I3	7671	7930	8431	8426	8862	9121	9392	8967	8770	8618	6581	8300	8480
I4	8078	8648	8794	8998	9287	9733	9998	9702	8997	8562	8550	8567	7864
I5	7772	7899	7993	8505	8872	9101	9558	9019	8775	8341	8299	7789	6842
I6	7182	8209	8372	8576	8459	8818	9196	8819	8418	7998	7475	7545	6672
I7	7616	7999	9311	9453	8771	9103	9590	9238	9120	8771	8789	8455	8379
I8	7847	8551	8465	8534	8968	9173	9619	9303	9033	8874	8671	8165	8163

Table 7. Cont.

Irrigation	20 April	25 April	30 April	5 May	10 May	15 May	20 May	25 May	30 May	5 June	10 June	15 June	20 June
I9	7991	8337	8455	8533	9228	9230	9129	8772	8428	8431	8276	8093	7809
I10	7728	7687	8158	8345	8245	8522	8863	8674	8404	8211	8181	7675	7544
I11	8262	8887	8975	9211	9302	9929	10,989	10,076	9422	9316	9225	9220	8998
I12	8092	8453	8683	8972	9124	9459	9803	9502	9099	8990	8878	8800	8833
I13	8104	8493	8458	8558	8771	8975	9466	9107	9064	8887	8807	8439	7918
I14	9601	9681	9775	9876	10,068	10,172	10,636	10,248	9643	9456	9121	9000	8924
I15	8432	8697	8879	8937	9011	9276	9773	9416	9071	8892	8818	8567	8464
I16	7874	8431	8762	8897	9156	9453	10,036	9377	9031	8812	8769	7798	6842
I17	9490	9581	9703	9753	10,003	10,093	10,741	10,209	9333	9240	9036	8812	8424
I18	8073	8654	8761	8900	9113	9778	10,068	9821	9400	9017	9008	8975	8883
I19	8266	8564	8586	8765	8877	9243	9566	9141	8937	8799	8567	8453	8009
I20	9536	9811	9941	10,071	10,317	10,596	11,232	10,689	10,232	10,096	9612	9534	8674
I21	8398	8232	8673	8996	9095	9675	10,074	9776	9567	9443	9124	8876	8578
I22	8679	8492	8879	9123	9234	9745	10,336	10,131	9767	9345	9004	8751	8544
I23	8719	8990	9123	9320	9326	10,077	10,777	10,176	9878	9435	9234	8001	8998
I24	8552	8657	8896	9073	9234	9441	9885	9410	9234	9148	8976	8730	8664
I25	9388	9408	9456	9551	9732	10,064	10,288	10,011	9774	9567	9456	9444	9348
I26	7953	8098	8356	8670	8890	9030	9556	9203	8857	8680	8456	8390	8379
I27	8707	8715	8884	8974	9007	9886	10,443	10,087	9678	9231	8897	8853	8844
I28	8993	8990	9078	9245	9436	10,126	10,761	10,744	9875	9465	8998	8907	8875
I29	8388	8707	8817	8898	9234	9917	10,094	9622	8976	8670	8684	8570	8178
I30	8705	9404	9576	9665	9674	9988	10,293	9999	9459	9087	8677	8614	8217
I31	9408	9655	9846	9972	10,249	10,554	11,754	10,765	10,204	9973	9815	9528	9074
I32	9158	9532	9420	9955	10,057	10,355	11,236	10,654	9836	9679	9533	9077	8375

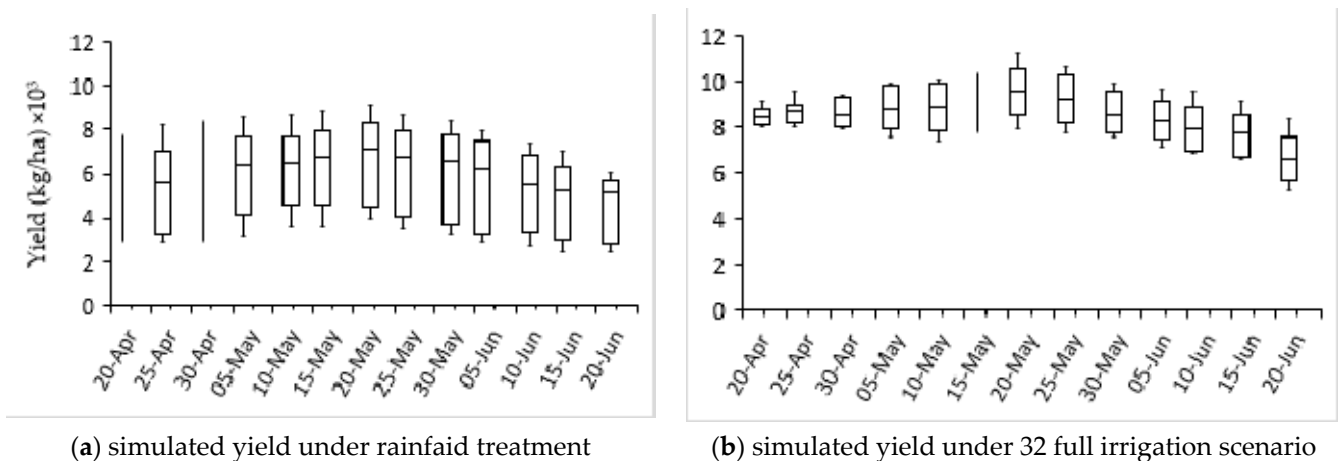


Figure 6. Simulated yield under rainfed conditions and the full irrigation scenario (I32) using six years (2014–2019) weather data with various sowing dates.

4.3.2. Impact of Irrigation on Maize Yield

After determining the best sowing date 20 May, the next step was to determine the best irrigation phases with the required amount of irrigation to apply during the crop growth period. In the DSSAT model, 32 different irrigation scenarios were set Table 4, simulated using six years of weather data (2014–2019) from the Wenshui meteorology station, received precipitation during a growing period range between 318 mm and 420 mm Figure 2.

Figure 7 shows the variability of the simulated yield of spring maize based on climatic data between 2014 and 2019. The maximum yield, was obtained in 2018 and the low yield was obtained in 2019 and 2016 as a result of heavy rainfall during the spring maize growth period in both years. The maize yield was lower in 2019 because most precipitation was in August and September with less precipitation in June.

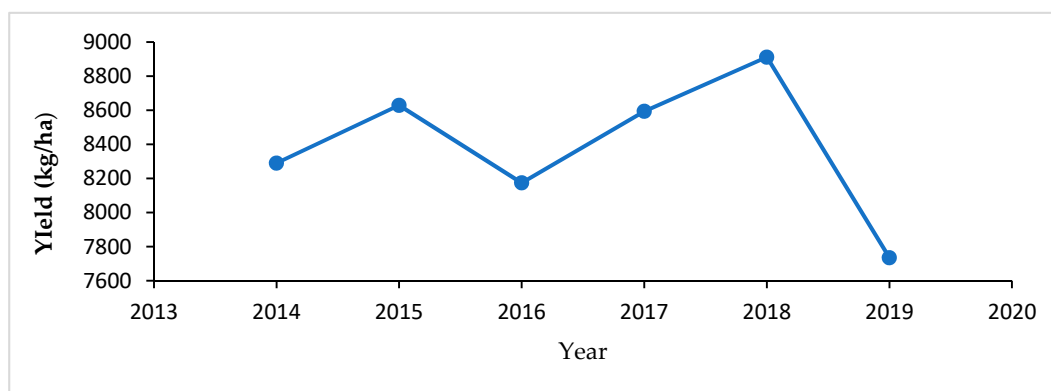


Figure 7. Simulated maize yields under different seasonal climatic conditions (2014–2019).

The yield of maize grain increases as the volume of supplementary irrigation increases. Single irrigation (85 mm) at the tassel and grouting phases increased maize production from 7250 to 8882 kg/ha, and 6803 to 8820 kg/ha, respectively Figure 8. However, the maize yield did not increase at the emergency, jointing, and maturity phases compared to irrigation applied at the tassel and grouting phases. These two phases are the critical phases determining the final yield of maize. At these phases, maize needs more water, nutrients, temperature, and light [8,30]. In the double irrigation (I14) scenario, 85 mm of water was applied at the tasseling phase, and 85 mm at the grouting phase yield range was between 8605.5 and 10,069 kg/ha. In triple irrigation, higher grain yields were obtained in I17, I20, and I25 irrigation scenarios. In the I17 irrigation scenario 85 mm was applied at the tasseling, grouting, and maturity stage grain yield was between 8693.3 and 9926 kg/ha. In the I20 irrigation scenario 85 mm was applied at jointing, tasseling, and grouting phase grain yield was between 8946.7 and 9927 kg/ha. In the I25 irrigation scenario 85 mm was applied at emergence, tasseling, and grouting phases grain yield was between 8413.7 and 9843 kg/ha. The yield was between 9002.2 and 9981 kg/ha for the quadruple irrigation scenario (I31), where 85 mm of water was applied at the jointing, tasseling, grouting, and maturity phases.

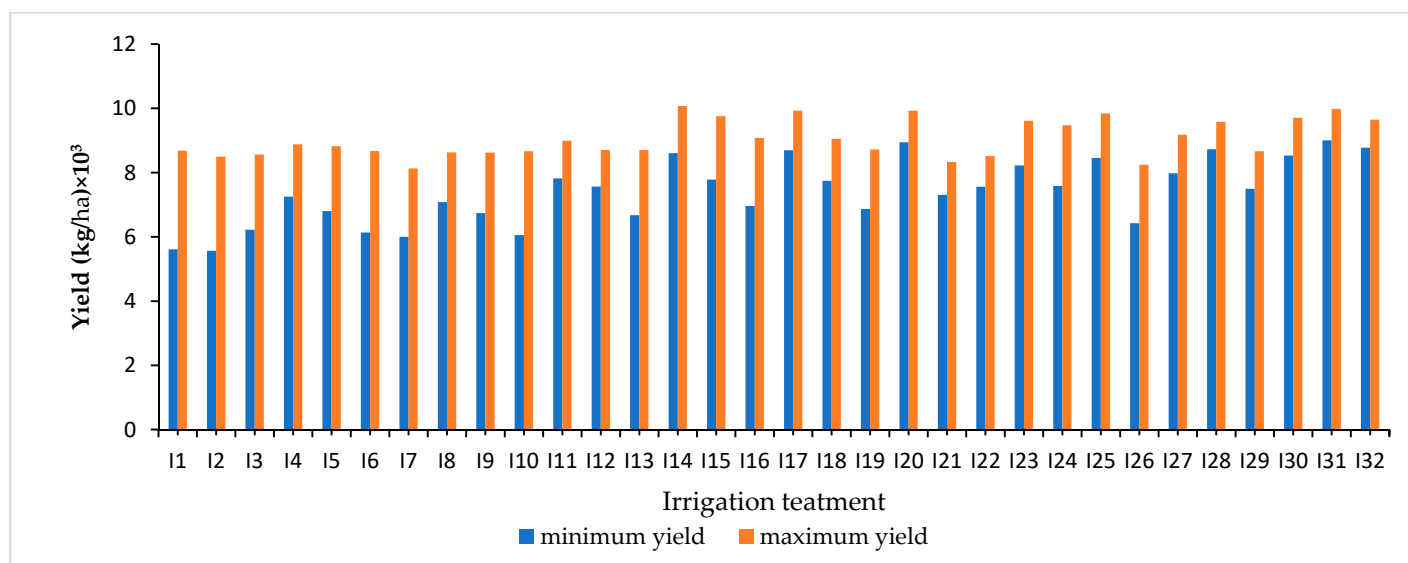


Figure 8. Simulation results of maize yield under different irrigation combinations based on six years of historical weather data from 2014 to 2019.

Furthermore, the irrigation scenario (I14) yielded results that were slightly similar to those of the three irrigation (255 mm) and four irrigation application scenarios (350 mm). In contrast, to irrigation scenarios with high irrigation volumes (I17, I20, I23, and I31), a double irrigation treatment I14 (170 mm) is more effective for achieving a higher yield Figure 8. These findings indicate that irrigation application has a significant effect, on spring maize production, under the restricted supply of irrigation water in the Fenhe basin. If irrigation water supplies are insufficient, it is critical to consider the irrigation at the tasseling and grouting phases during the crop growth period. When there is no irrigation applied during these two phases, this may cause plant stress and low yield, These results are confirmed by the findings of our study [30].

4.3.3. The CERES-Maize Model Benefits

After model calibration and evaluation, the seasonal analysis tool within the DSSAT model was used to analyze the best use of irrigation water management and optimum sowing date in order to maximize maize crop yield in the Fenhe irrigation district. This study proves that in this location changing, the sowing date from 20 April to 20 May results in increasing the yield from 8264 kg/ha to 10,047 kg/ha, around 20% of the yield productivity, and the study proves that sowing after 25 May will decrease the yield production Figure 6. Furthermore, this study discovered that, in the case of a water shortage, well-organized irrigation timing and irrigation volume application could help save irrigation water. Regarding [26], after reaching the tasseling and grouting phases, the maize plants grow vigorously. At this phase, a shortage of water causes poor crop growth. Therefore, it is important to irrigate maize during the tasseling and grouting phases, to compensate for the lack of precipitation in this area.

According to the local farmers, the current irrigation quantity in the area is 425 mm per single irrigation [31]. Whereas the model simulation shows that the minimum amount of water required to ensure that the irrigation needs are met is 170 mm, with 85 mm during the tasseling process, and 85 mm during the grouting phase. As a result, 225 mm of water would be saved. Therefore, in consideration of the actual irrigation situation in the region, the irrigation of maize at the tasseling and grouting phases, with an irrigation volume of 170 mm, is highly recommended.

The crop model can effectively simulate and predict the optimum irrigation management and best planting time. The DSSAT crop growth model is widely recommended and is extremely effective in assessing the result of the amount of irrigation applied and the date of sowing on crop yields. However, this study only conducted simulation studies in a small region (the Fenhe basin). Further simulation studies should be carried out within a larger regional area. Additionally, we have only used six years of weather data; in future studies a longer range of years should be considered to provide a more accurate simulation.

5. Conclusions

The CERES-maize model was applied to the Fenhe basin, the measured and simulated values of maize yield, aboveground biomass, phenology, leaf area index, and soil moisture are in good agreement. The model proposed that, for the dates from 15 to 25 May, 20 May is optimal for maximum crop yield. Simulation of the model for choosing the optimum irrigation amount and time was performed with various irrigation scenarios at different maize growth phases. As a result, the best irrigation timing is during the tasseling and grouting phase, with an optimum amount of irrigation of 170 mm during the spring maize-growing period. At these two phases, crops must be irrigated because less precipitation or less irrigation causes crop stress. Irrigation application at tasseling and grouting phases could produce a similar grain yield as obtained from irrigation applications with a higher amount of water (255 mm, 350 mm, and 422 mm) of water with no crop stress. In general, the CERES-maize model revealed that the consequences of low rainfall or low availability of water on agricultural output could be adjusted by taking into account the amount of irrigation water and sowing date in a systematic manner.

All these estimates will assist farmers with productive crop production and provide a partial basis for policymakers in preparing irrigation systems when water is scarce.

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