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Predicting Maize Productivity Under Climate Change in the Semiarid Region of Northwest China Through the AquaCrop Model

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Abstrac. An increasingly warm, dry climate and the rise in atmospheric carbon dioxide concentration are having profound impacts on agricultural production. Maize (Zea mays L.) is the second most important cereal crop in Gasu province of China, playing a key role in national food security. The objective of this study was to predict the consequence of climate change on spring maize yield using the AquaCrop model. The AquaCrop model was firstly calibrated using the climate data collected from a baseline period of 1981-2020 to simulate past trends in spring maize yields. The model was further used to predict maize yield under different climate scenarios with changes in temperature (-2℃-2℃), precipitation (-20%-20%), and evapotranspiration (ET0) (-25%-25%). Results showed that maize yield continued to grow under the influence of climate change. The grain yield was far more sensitive to climate change than the above-ground biomass. Grain yield was highly associated with the meteorological factors, with temperature resulting in a greater impact compared to ET0, and precipitation. Increasing temperature and precipitation, and decreasing ET0 resulted in higher spring maize productivity. These results highlight the importance of climate change on spring maize production in the semi-acid region, and suggest that soil temperature and moisture are the key limiting factors for agricultural production.

Keywords: Climate change; AquaCrop model; Spring maize; All-film double-furrow sowing.

1. Introduction

Agricultural production is intricately influenced by meteorological factors such as temperature, rainfall and solar radiation, and are thus sensitive and vulnerable to climate change. This susceptibility may directly lead to a series of disruptions in the agricultural ecosystems, such as altering planting structures, or crop distribution. For instance, manipulating temperature by methods like plastic mulching could promote thermophilic crops and multiple cropping practices to migrate northward within China. This, in turn, could led to expanded crop boundaries at higher latitudes and elevations, with corresponding increases of land restoration index[1]. Studies have found that changes in temperature and rainfall can directly affect crop growth period, with reduced rainfall causing delays in planting, and higher temperature shoring growth cycles[2-3]. Moreover, the observed trend of drying and warming in China has greatly increased the use of agricultural irrigation facilities, chemical fertilizers, and pesticides[4-5].

Early studies explored the effects of meteorological factors on crop physiology, quality, and yield through controlled field experiments. However, due to the complexity of multi-factor interactions and the artificial nature of controlled experiments, these studies diverge from actual agricultural ecosystem conditions under climate change. To address these limitations, models have emerged as valuable tools. Synthesizing knowledge from crop physiology, ecology, and agricultural meteorology, crop growth models provide dynamic and quantitative descriptions of crop development. Various models have been widely used to predict crop production potential, develop strategies of farmland irrigation and fertilization, and assess meteorological disasters[6-7]. AquaCrop, a water-driven model, has been extensively tested for various soils, crops, and climates to identify crop growth and production, demonstrating a balance between simulation accuracy and numerical stability[8-9].

Changes in greenhouse gas concentrations, radiation, and temperature patterns may have substantial consequences for crop yields. Various studies showed that improving crop adaptation to climate change has the potential to significantly reduce negative impacts on crop productivity[10-11]. Maize, being less resilient compared to other C4 crops, is projected to suffer from decreased yields due to rising temperatures and shifting rainfall pattern. Several studies have revealed that high temperature could accelerate maize phenology, with a doubling temperature variability leading to yield reduction by 50%[12]. However, certain high-altitude or cold regions might experience positive effects on crop growth from climate change[13]. In northeast China, a 1.2 °C temperature increase over two decades positively impacted food production, primarily due to reduced chilling effects during the maize seedling period, resulting in an overall increased yield curve[14]. Therefore, the vulnerability of maize production to climate change lies in the variability of precipitation and occurrences of extreme hot and cold weather.

Given the current knowledge gap on climate change's effect on maize production in China, a simulation analysis was carried out using the AquaCrop model. The objectives of this study were (1) to assess the trends and variations in spring maize yield in response to historical climate changes; and 2) to further predict maize yield under several future climate scenarios with shifting changes in atmospheric temperature, precipitation, and ET0.

2. Materials and Methods

2.1 Study site and materials

The study was conducted in the city of Lanzhou (36°12′N, 103°53′E; 1680 m elevation), located in the center of Gansu Province. The study site has an annual mean rainfall of 265.8 mm, mainly concentrated from June to September, an annual mean temperature of 7.2 °C, an annual average evaporation of 1660 mm, an annual average sunshine duration of 2,591 h, and a frost-free period of approximately 180 d. The soil of the study area is silt loam. The top (0-20 cm) soil has an organic matter content of 9.0 g kg-1, a total nitrogen content of 0.64 g kg-1, total phosphorus of 0.74 g kg-1, total potassium of 10.2 g kg-1, ammonium nitrogen of 12.4 mg kg-1, instant phosphorus of 26.8 mg kg-1, instant potassium of 93.3 mg kg-1, and a pH of 8.2.

In this study, we chose the hybrid maize namely Xianyu335 which was widely sown in there regions, with an all-film double-furrow planting system employed, which is representative of the primary agricultural techniques in dryland areas (Figure 1). This planting approach is characterized by a large ridge width of 70 cm and a small ridge width of 40 cm, along with respective heights of 20 cm and 10 cm.

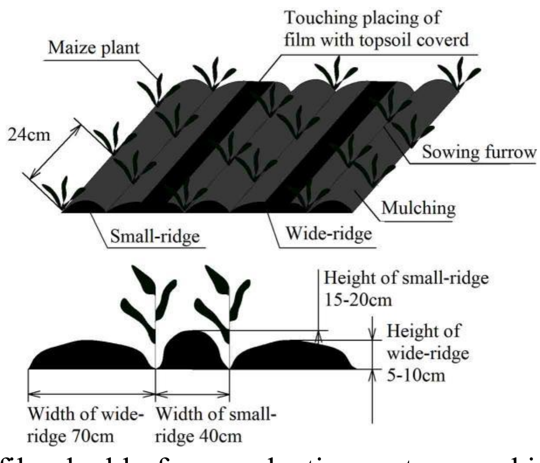

Figure 1. All-film double-furrow planting system used in this study

2.2 Method

2.2.1 AquaCrop model

A dynamic crop growth model, AquaCrop, which was developed for calculating agricultural yield potential on the basis of physiological, atmospheric and agronomic information, was used because it has been calibrated and validated in regions with climates similar to the current study.

2.2.2 Yield simulation of baseline climate

Crop yield can be categorized into potential yield, availability yield, and the average farmer yield. Potential yield is calculated through crop model simulation, not accounting for nutrients and water stressduring growth (Lv et al., 2013). Using the validated AquaCrop model, potential yield simulations was conducted using baseline climate data for the past 40 years (1981—2020) under constant treatments. Then, annual variation in grain yield and above-ground biomass were calculated and analyzed (Fig. 2). The influence of climate change on potential maize yield was expressed by cumulative probability of distinct productivity levels, variability, and coefficient of variation, given by Equation 1).

$$CP_r = \frac{f_r}{n} \times 100 \tag{1}$$

where CP_r represents the cumulative probability of a certain horizontal region, f_r represents the number of an r yield region, and n is the total sample size.

The dispersion can reflect the individual difference, and was calculated as:

$$D = \frac{Y_{\max} - Y_{\min}}{\overline{Y}} \tag{2}$$

where D represents the dispersion, $Y_{\max}$ represents cluster maximum value, $Y_{\min}$ represents cluster minimum value, and $\overline{Y}$ represents cluster average value.

2.2.3 Yield simulation of climate change scenarios

The climate in northwest China shows a pattern of dry warming, with a projected average temperature increase of 1.5-2℃, and precipitation changes ranging from -15% to 15% by the end of the century[1]. To streamline the simulation process and reduce the number of required experiments, we conducted the Box-Behnken test to establish a regression model linking meteorological factors with yield. In this model, temperature, precipitation, and evapotranspiration (ET0) were the independent variables, yield was the response value. ET0 was used as a comprehensive index to measure crop water demand and soil evaporation, and was influenced by temperature, sunshine duration and precipitation. Gradients for each meteorological factor were calculated based on the historical climate date (Table I). Subsequently, potential yield was simulated for various climate scenarios, keeping crop variety, management and soil parameters constant (Fig. 2).

The regression model between the gradient of each meteorological factor and the potential productivity was constructed using the Statistical Analysis Software (SAS). We tested the quadratic regression model and regression coefficient using variance analysis. Differences were considered statistically significant at $P \leq 0.05$. The magnitude of the coefficient of the first term of the regression model determined the sequence of influence of a single impact factor on the index; higher values indicated greater influence.

Table I. Gradient Setting Of Meteorological Factors.

Coding	Factors		
	Relative change in temperature X_1	Relative change in precipitation X_2	Relative change in ET_0 X_3
-1	-2℃	-20%	-25%
0	Historical climate	Historical climate	Historical climate
1	+2℃	+20%	+25%

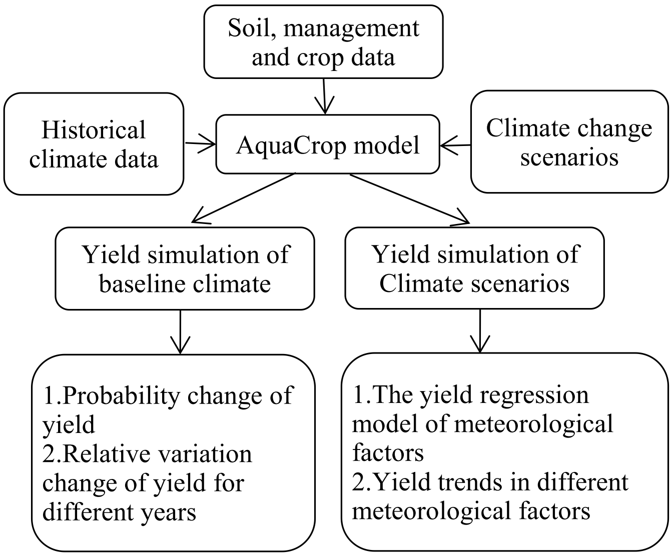

Figure 2. Yield simulation under different climate change scenarios

2.3 Model set-up

This model is easily applicable to a wide range of weather data combinations, local crop species parameters, soil characteristics and management strategies at the experimental site. In this study, we employed the model to simulate maize above-ground biomass accumulation and grain yield, changing only the weather data while keeping all other parameters constant.

2.3.1 Soil data

The model inputs for soil parameters included soil layer numbers and thickness, permanent wilting point, field water capacity, bulk density, saturated conductivity, and saturated water content. The thickness of each soil layer were 0-20 cm, 20-40cm, 40-60cm, 60-80cm, 80-100cm, respectively. Soil physical and chemical properties of the study site were incorporated into the model and saved as an .SOL file (Table II).

Table Ii. Main Soil Parameters Of Experimental Site Used As Model Inputs.

Soil thickness (cm)	Bulk density ($g \cdot cm^{-3}$)	Field capacity (%)	Saturated hydraulic conductivity ($mm \cdot d^{-1}$)	Saturation moisture content (%)	Permanent wilting point (%)
0-20	1.32	28.5	295	46.8	12.6
20-40	1.34	29.2	280	47.5	14.0
40-60	1.46	25.5	360	40.6	13.5
60-80	1.51	24.6	425	35.2	11.5
80-100	1.36	22.0	530	30.3	10.0

2.3.2 Meteorological data

The meteorological data included minimum temperature (T_{min}), maximum temperature (T_{max}), precipitation, and ET_0. ET_0 was calculated using a FAO calculator software, by considering daily maximum temperatures, minimum temperatures, and sunshine duration. Additional parameters were provided by the Lanzhou Benchmark Meteorological Station (36°21′N, 103°57′E; 1668.5 m elevation), located 38 kilometers away from the experimental field site. The changes in meteorological factors for the research area from 1981 to 2020 were calculated. Average temperature exhibited a rising trend of 0.28 ℃ per decade (Fig. 3a), while average annual precipitation demonstrated a trend of 15.56 mm per decade (Fig. 3b). Meanwhile, average annual ET_0 was 912.5 mm with a rising trend (Fig. 3c) of 5.134 mm per decade. Sunshine duration was

6.95 h and showed a rising trend (Fig. 3d) of 0.1 h per decade, and the change trend of meteorological factors did not reach significant difference. Analysis of the variability and variation coefficient indicate that the order of dispersion degrees, from largest to smallest, was precipitation, ET_0, average temperature and sunshine duration (Table III). The area's precipitation was notably low and highly variable, emphasizing the need for enhanced cultivation and management measures to improve water utilization efficiency.

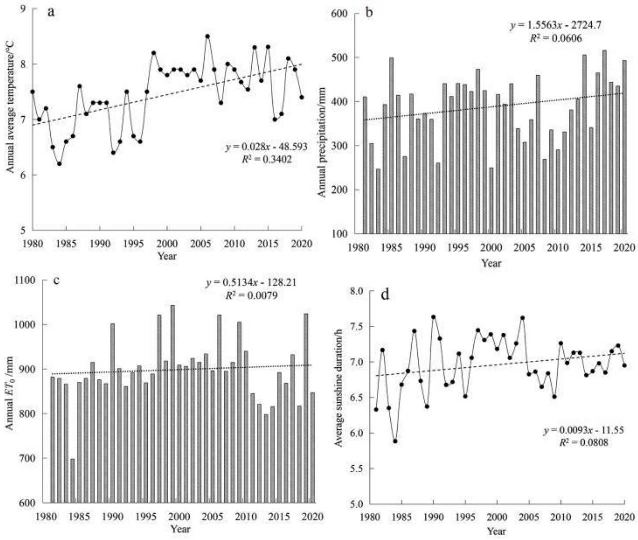

Figure 3. The annual temperature, precipitation, ET0, and sunshine duration in central Gansu province from 1981 to 2020.

Table Iii. Pattern Of Meteorological Factors In Central Gansu Province From 1981 To 2020.

Factors	Indexes			
	Average	Climate tendency rate	Variability	Variable coefficient
Precipitation	388.6 mm	15.56 mm·(10yr^{-1})	61.1 mm	13.81%
Average temperature	7.4℃	0.28℃·(10yr^{-1})	0.51℃	8.17%
Sunshine hours	6.95h	0.093h·(10yr^{-1})	0.33h	5.76%
ET_0	912.5 mm	5.134 mm·(10yr^{-1})	48.7mm	10.75%

2.3.3 Management data

In the AquaCrop model, management parameters were defined across the crop, irrigation and field modules. The crop module requires inputs including sowing data, seeding density, and planting method. For this study, the values used were April 20, 60600 plants ha-1, and direct sowing, respectively. Optimal nitrogen fertilization was assumed for spring maize, and soil fertility stress was set as non-limiting. The planting pattern was all-film double-furrow sowing, with soil surface coverage reaching 80%. Additionally, furrow rainwater catchment greatly reduced the runoff. Therefore, in the field module, soil cover by mulches reached 80%, with no impact on surface runoff. Because the area is mainly rain-fed agriculture, the irrigation module was not implemented in the model.

2.3.4 Variety and environment stress parameters for the AquaCrop-Maize model

The variety and environmental stress parameters in the model were calibrated using a trial-and-error approach. Default values and ranges of the maize parameters were provided by FAO. Local parameters were adjusted based on previous model adaptive evaluation research, utilizing data from the literature (Table IV)[15]. Reference parameters including harvest index (HI0), standard water productivity (WP ＊), and the largest canopy coverage (CCx) showed high sensitivity for productivity simulation and were crucial for simulation accuracy. Our simulation found that the root mean square error (RMSE) was 612.07 kg ha-1 and the normalized root mean square error (NRMSE) was 8.84% between measured and simulated yields, reflecting high simulation accuracy in the region.

Therefore, parameter calibration and verification were excluded when simulating the productivity of different climate scenarios.

Table Iv. Variety And Stress Parameters Of Dryland Maize Under All-Film Double-Furrow Sowing.

Model parameters	Definition	Value	Unit
CC_x	Maximum green canopy cover	92	%
CGC	Canopy growth coefficient	8.3	%/day
CDC	Canopy decline coefficient	9.7	%/day
HI_o	Reference harvest index	47	%
WP*	Crop water productivity normalized for ET_0 and air CO_2	36.4	g/m^2
REW	Readily evaporable water	3	mm/day
S_{avg}	Average root extraction water	2.1	cm/day
$P_{exp,lower}$	Fraction of TAW at which CGC becomes 0	0.13	-
$P_{exp,upper}$	Fraction of TAW at which CGC starts to be reduced	0.68	-
$P_{sto,upper}$	Water stress coefficient for stomatal closure	0.72	-
$P_{sen,upper}$	Fraction of TAW at which early canopy senescence is triggered	0.67	-

3. Results

3.1 Changes in the climate productivity of spring maize in the research area

With consistent variety, cultivation, and farming management, the maize potential grain yield ranged 1968-9286kg ha-1 with an average of 7437 kg ha-1(Table V). The dispersion was 98.4%, indicating that the grain yield level was low and susceptible to climate changes. Analysis of historical climate change revealed that the grain yield and above-ground biomass of spring maize increased by 46.90 kg ha-1 yr from 1981 and 1999, and by 60.48 kg ha-1 yr from 2000 to 2020 (Fig. 4), and the change trend did not reach significant difference.

Table V. Maize Grain Yield And Above-Ground Biomass Under Climate Change From 1981 To 2020.

Grain yield and above-ground biomass levels	Grain yield
Maximum value (kg ha^{-1})	9286.3
Cumulative probability of 80% (kg ha^{-1})	8725.9
Cumulative probability of 20% (kg ha^{-1})	6308.4
Minimum value (kg ha^{-1})	1968.5
Average (kg ha^{-1})	7437.4
Variable coefficient (%)	25.72%
Dispersion (%)	98.39%

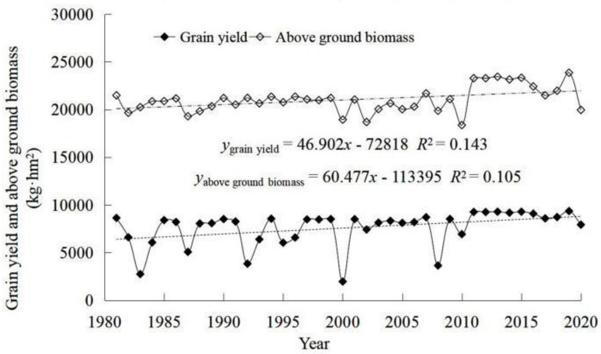

Figure 4. Changes in maize potential yield and above-ground biomass in the central Gansu province from 1981 to 2020.

Among these ranges, the middle level represents the general productivity range, accounting for 60% of cases. An examination of the grain yield column and cumulative probability reveals distinct intervals: the low-level grain yield range falls between 1968.5 and 6308.4 kg ha^{-1}, the general range spans from 6308.4 to 8725.9 kg ha^{-1}, showing relatively concentrated values, while the high-level grain yield range stretches from 8725.9 to 9286.3 kg ha^{-1}, with collective occurrences observed mainly between 2010 and 2020. By categorizing the potential climate yield into ascending ranges with intervals of 900 kg ha^{-1}, it becomes apparent that the range centered around 8100 to 9000 kg ha^{-1} boasts the highest probability, occurring 16 times (Fig. 5).

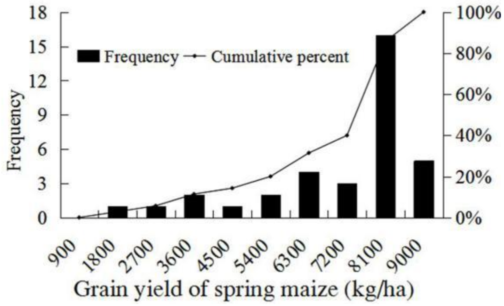

Figure 5. The frequency and cumulative percentage of different productivity range of grain yield from 1981 to 2020.

3.2 Regression model between maize production and meteorological factors

The AquaCrop model generated the following mathematical model of grain yield, where Y is the grain yield, and X_1, X_2, X_3 represents temperature, precipitation and ET_0, respectively. The calculated maize grain yield and above-ground biomass were presented in Table VI.

Table Vi. Grain Yield And Above-Ground Biomass Under Different Climate Change Scenarios

Testing No.	Temperature X_1	Precipitation X_2	ET_0 X_3	Grain yield Y_1(kg/ha)	Above-ground biomass Y_2(kg/ha)
1	-1	-1	0	7541.4	22042.7
2	1	-1	0	9267.9	24723.9
3	-1	1	0	8050.7	22115.1
4	1	1	0	9577.2	24803.4
5	-1	0	-1	8485.3	22297.3
6	1	0	-1	9517.6	25010.6
7	-1	0	1	8166.3	21165.2
8	1	0	1	9054.1	23728.4
9	0	-1	-1	8337.7	24261.3
10	0	1	-1	9235.6	24280.1

11	0	-1	1	8743.3	22626.7
12	0	1	1	8987.1	23331.1
13	0	0	0	9193.4	24034.2
14	0	0	0	9194.3	24035.3
15	0	0	0	9291.4	24032.4
16	0	0	0	9174.2	24035.0
17	0	0	0	9294.0	24034.9

$$\begin{aligned}Y_1 &= 9193.43 + 509.15X_1 + 32.54X_2 - 178.20X_3 + \\ &0.0075X_1X_2 - 11.11X_1X_3 + 61.46X_2X_3 - \\ &227.12X_1^2 - 7.04X_2^2 - 135.48X_3^2\end{aligned} \quad (3)$$

The above quadratic regression model and regression coefficient were further tested using variance analysis (Table VII). The model had an overall *P* value lower than 0.001 and a mean square of pure error of 1.48, indicating a significant relationship between the meteorological factors and spring maize yield or aboveground biomass. there was no interactive effect between any climatic factors, as suggested by that the *P* values were all greater than 0.05. Based on the regression coefficient and the *P* value of each factor. Through the analysis of the model for given meteorological range conditions, the primary order of influence on spring maize yield was X_1 (temperature) > X_3 (*ET*0) > X_2 (precipitation), with each factor significantly affecting accuracy of fitting model (P<0.001 or P<0.05).

Table Vii. Variance Analysis Of Regression Equations Between Meteorological Factors And Maize Grain Yield.

Variance source	Sum of squares	Degree of freedom	Mean square	*F*	*P*
Model	2.664E+006	9	2.960E+005	303.64	< 0.0001
X_1	2.074E+006	1	2.074E+006	2127.33	<0.0001
X_2	8471.46	1	8471.46	8.69	0.0215
X_3	2.540E+005	1	2.540E+005	260.59	<0.0001
X_1X_2	2.250E-004	1	2.250E-004	2.308E-007	0.9996
$X_1 X_3$	493.95	1	493.95	0.51	0.4996
$X_2 X_3$	15109.33	1	15109.33	15.50	0.056
X_{12}	2.172E+005	1	2.172E+005	222.79	<0.0001
X_{22}	208.62	1	208.62	0.21	0.6577
X_{32}	77288.06	1	77288.06	79.28	<0.0001
Residual	6824.08	7	974.87		
Lack of fit	818.17	3	272.72	0.46	0.4365
Pure error	5.91	4	1.48		

3.3 Effects of different climate scenarios on the climate productivity of spring maize

It was observed that alterations in temperature within the range of -2 to 2 ℃ corresponded to changes in yield ranging from 8000 to 9500 kg ha^{-1}. Notably, when temperatures elevated from -2 ℃ below the baseline to 1 ℃ above the baseline, the yield experienced a sharp increase. However, the rate of increase diminished as the temperature further rose from 1℃ to 2 ℃ above the baseline. In contrast, shifts in precipitation within the range of -20% below the baseline to 20% above the baseline resulted in relatively minor changes in grain yield. Overall, the influence of temperature on spring maize yield was significantly more pronounced than that of precipitation (Fig. 6a). When considering the combined effects of temperature (-2 ℃- to 2 ℃) and ET_0 (-25% to 25%), gain yield fluctuated between 8000 and 9500 kg ha^{-1}. Under the concurrent influence of precipitation (-20% and 20%) and ET_0 (-25% and 25%), grain yield fluctuated between 8700 and 9200 kg ha^{-1}. In these scenarios, temperature and precipitation exerted a positive impact on yield, whereas ET_0 demonstrated a negative impact (Fig. 6b). Under the combination of precipitation (-20%~20%) and ET_0 (-25%~25%), the range of grain yield changes was 8700~9200 kg ha^{-1}, and the precipitation had a positive effect on grain yield, while ET_0 had a negative effect. However, the effect of ET_0 on yield was slightly greater than precipitation (Fig. 6c).

The response surface figure between the meteorological factors and above-ground biomass can also be drawn. It was found that while the temperature changed by -2 ℃~2 ℃ and the precipitation changed by -20%~20%, the change range of above-ground biomass was 22000~25000 kg ha^{-1}, the biomass increased dramatically with the rising temperature, but increased slowly with the rising precipitation. As a whole, the effect of temperature on the above-ground biomass of spring maize was significantly greater than that of precipitation, and all had a positive effect on biomass (Fig. 6d). Under the combination of temperature (-2 ℃~2 ℃) and ET_0 (-25%~25%), the range of biomass changes was 21000~25000 kg ha^{-1}, and the temperature had a positive effect on the above-ground biomass, while ET_0 has a negative effect; meanwhile the effect of temperature on above-ground biomass of spring maize was significantly greater than that of precipitation (Fig. 6e). Under the combination of precipitation (-20%~20%) and ET_0 (-25%~25%), the range of above-ground biomass changes was 22800~24500 kg ha^{-1}, the precipitation had a positive effect on biomass, while ET_0 has a negative effect, but the effect of ET_0 on biomass was slightly greater than that of precipitation (Fig. 6f).

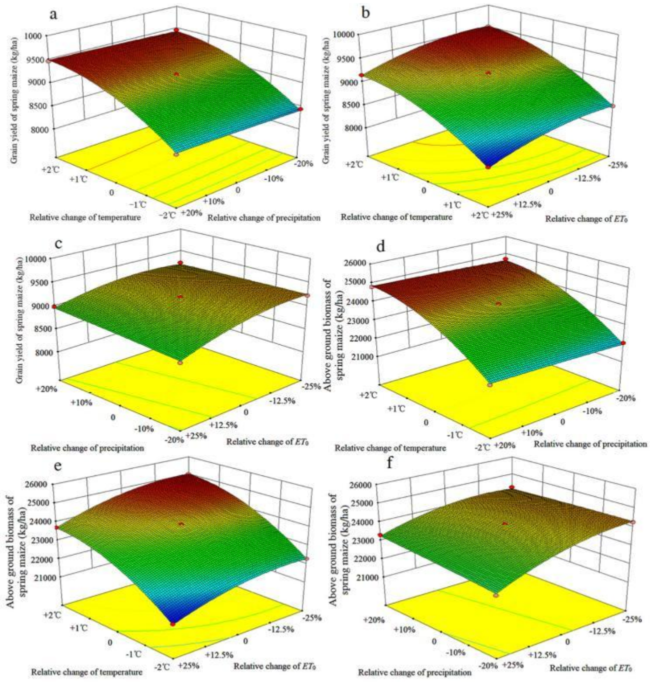

Figure 6. Relationships between meteorological factors combinations and maize yield.

4. Discussion

Crop production resources such as light, temperature, and water re all greatly influenced by climate changes, which ultimately poses a threat to national food production security[16]. In this study, we found that the region experienced an increase in temperature and a decrease in rainfall from 1981 to 2020. Overall, the climate exhibited a trend of drying and warming, aligning with conclusions drawn by Zhang et al[1] and Shang et al[17]. Although there were relatively stable variations in sunshine duration, its increase positively impacted production by extending crop photosynthesis periods and promoting organic material accumulation. In the face of climate change, prudent utilization of meteorological resources and the implementation of effective cultivation and management strategies are essential to ensure stable and progressively increasing production.

The AquaCrop model was developed to better simulate the effects of factors such as moisture and temperature on crop yields in arid and semi-arid areas. The parameter settings of this model have mulching options, which are suitable for crop cultivation in a loess plateau region. With fewer parameters and data to simulate the potential of crop production using the AquaCrop model, it can be widely deployed by crop scientists, economists and administrators to resolve serious food security issues and other problems[18].

By simulating climate impact on maize yield across four decades in the region using the AquaCrop model, we observed a rise in productivity amidst global climate changes. These results are consistent with those of Yin et al[19]. But different from typical findings that climate change usually exerted negative impact on crop yields. The discrepancy can be attributed to the region's lower average temperature compared to global averages, accompanied by larger day-night temperature variations, leading to diminished climate potential productivity. Enhanced temperature and sunshine duration effectively mitigated the impact of chilling injuries on crop yield, bolstering photosynthetic efficiency and organic material accumulation during crop growth[20]. It should be noted that this study did not account for the temporal changes for relationships between meteorological factors and spring maize productivity during different crop growth stages.

Precipitation is considered an important factor influencing crop yield variability, particularly in countries with a monsoon climate[21]. Similary, our study showed that any reduction in precipitation from the baseline had a severe impact on maize productivity. However, precipitation-induced potential productivity changes in maize were less pronounced compared to temperature in the research area. This can be attributed to the absence of distinct precipitation trends during maize growth periods and limited variation in precipitation when changing by around 20% from lower baseline levels. Moreover, the all-film double-furrow sowing cultivation method, designed to mitigate soil evaporation and enhance water use efficiency, partially offsets the effects of reduced precipitation in arid regions.

Overall, the AquaCrop model used in our study provides a practical tool to assess future pattern of crop productivity under climate change scenarios. However, Wu[22] pointed out that crop models tend to become more accurate when applied to broader scales of interest. As such, exploring the application of crop models on larger scales warrants further investigation.

Acknowledgment

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