Prediction of Potential Sorghum Suitability Distribution in China Based on Maxent Model*

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Abstract

It is increasingly relevant to study the effects of climate change on species habitats. Using a maximum entropy model, 22 environmental factors with significant effects on sorghum habitat distribution in China were selected to predict the potential habitat distribution of sorghum in China. The potential distribution of sorghum under baseline climate conditions and future climate conditions (2050s and 2070s) under two climate change scenarios, RCP4.5 and RCP8.5, were simulated, and the receiver operating curve under. The accuracy of the model was evaluated using the area under the receiver operating curve (AUC). The results showed that the maximum entropy model predicted the potential sorghum habitat distribution with high accuracy, with Bio2 (monthly mean diurnal temperature difference), Bio6 (minimum temperature in the coldest month), and Bio13 (rainfall in the wettest month) as the main climatic factors affecting sorghum distribution among the 22 environmental factors. Under the baseline climate conditions, potential sorghum habitats are mainly distributed in the southwest, central, and east China. Over time, the potential sorghum habitat expanded into northern and southern China, with significant additions and negligible decreases in potential sorghum habitat in the study area, and a significant increase in total area, with the RCP8.5 scenario adding much more area than the RCP4.5 scenario.

Keywords

Sorghum, Potential Fitness Zone, Prediction, MaxEnt Model

1. Introduction

Sorghum liquor has a long history and reputation as a unique liquor in China.

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Sorghum is rich in starch and a small amount of protein, and is used as the raw material for many of China's most famous liquors. Some of the more famous Chinese liquors that use red sorghum as the main raw material are the following: Moutai, Wuliangye, Luzhou Laojiao, and Fenjiu.

Climatic conditions are one of the most important conditions affecting the geographical distribution of plants [1]. Since the 21st century, with the continuous progress and development of human civilization, greenhouse gas emissions have been increasing year by year, and the global climate has become warmer and warmer, which has led to corresponding changes in the survival conditions of species [2] [3]. In recent years, the Species Distribution Model (SDM) has emerged [4], and many scholars have predicted and studied the trends of potential distribution areas of species based on climate change. By combining climate change and ecological niche models, SDM predicts areas with high ecological stability, thus demonstrating the objective law of species' suitable developmental changes, which has certain conservation significance for the suitable distribution of species and has important theoretical and practical significance for strengthening the management of plant diversity in hotspots. In recent years, as the research on species fitness under climate development changes has become more and more extensive, the development of species distribution models based on statistical algorithms and ecological niches has been rapid, and there are dozens of models available. The model is widely used for species distribution prediction, and it can predict the prediction results with high accuracy with fewer sample points.

There are many specific studies based on the MaxEnt model. Wang Rulin [5] used the MaxEnt ecological niche model to predict the distribution area of the Tibetan locust, which mainly combined 23 climatic index data and topographic factors, and the results showed that the Tibetan locust has a high degree of habitability in China, and analyzed and studied the main environmental variables affecting the Tibetan locust. Li Lihe [6] used the MaxEnt model to establish the key monitoring area of Canada's Lepidoptera by integrating various influencing factors; Xiong Qiaoli [7] used the maximum entropy model to simulate the distribution pattern under different climate scenarios and analyze the suitable areas for the geographical distribution of alpine vegetation in southwest China by combining the vegetation type map and climate variables data in China; Zhu Mengjie [8] used the maximum entropy model to combine the current climate scenario model and the geographic distribution records of civet-tailed bean (Uraria The maximum entropy model combined with the current climate scenario model and the geographic distribution records of Uraria plants to analyze the climatic factors of the current fitness distribution of plants and infer their potential ranges of fitness distribution under past (LGM), current and future climate scenarios; Xueping Cao [9] *et al.* Geographic Information System (GIS) to assess the geographic distribution of Acanthopanax, and to study and analyze the main environmental factors affecting the geographic distribution of Acanthopanax [10].

In this paper, MaxEnt ecological niche modeling was selected to predict the nationwide distribution of sorghum fitness based on certain species distribution records and relevant environmental variables.

2. Overview of the Study Area

Sorghum, as one of the five wine grains of Wuliangye, is a traditional cereal crop, an annual herb of the grass family Sorghum, with multiple edible and medicinal effects. The main production areas are concentrated in the northeastern region, eastern Inner Mongolia, and the hilly mountains of the southwestern region. The historical survey of sorghum distribution in China shows that sorghum is grown in China across five climatic zones: cold temperate, temperate, warm temperate, subtropical, and tropical. China is a vast country with complex topography that spans the subtropical and northern temperate zones with varying climates.

3. Data Sources and Research Methods

3.1. Spatial Distribution of Sorghum Research Data

In this paper, literature and specimen data were reviewed to obtain the distribution loci of sorghum. For this study, sorghum sample point data were selected from data recorded in the Chinese Herbarium (CVH, http://www.cvh.ac.cn) as well as the National Specimen Platform (NSII, http://www.nsii.org.cn/). The data were selected by removing specimens that were too old and trying to select sample points with clear records. As some of the data were recorded as approximate locations without specific latitude and longitude information, they belonged to the surface data, which were obtained through ArcGis combined with Baidu maps to get the central latitude and longitude information of these surface data, and 128 sample points were obtained.

As shown in Figure 1, the sorghum suitability distribution map generated in the current climate was compared with 128 sample point distribution data, and the suitability distribution map of sorghum in Arcgis 10.8 was overlaid with a 1:1 million digital plant layer to remove distribution record points that were not within the sorghum suitability distribution area. In addition, the distribution points were subjected to buffer analysis and 128 data sample points were proofread and screened to finally identify 108 sorghum distribution points [11].

3.2. Predictive Environmental Factors

Climate factors are widely used as important environmental variables and modeling references in biodistribution prediction [12]. In this study, a total of 22 predictive environmental factors related to sorghum distribution were selected, of which 19 climatic factors represent mainly temperature and precipitation and seasonal variation characteristics [13], and the other three are topographic factors mainly containing elevation slope slope direction. The WorldClim climate dataset (version 1.4) is the highest resolution climate data publicly available, and
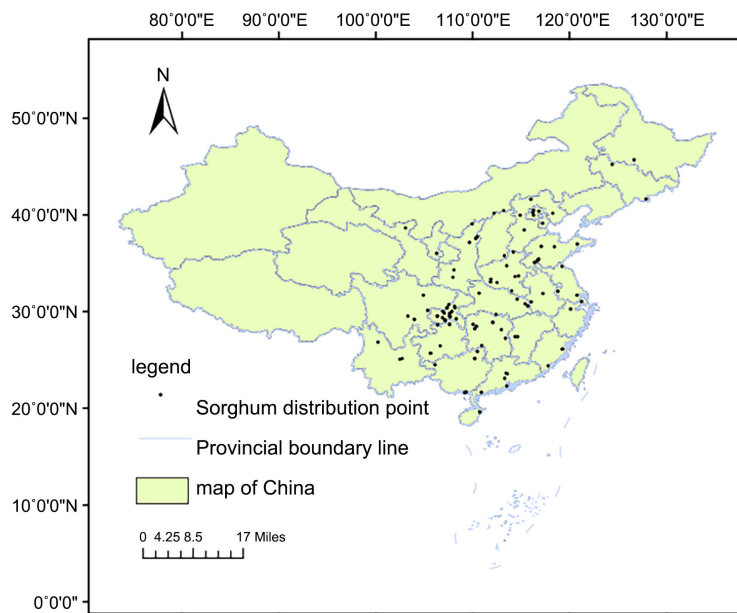
Figure 1. Distribution of sample points.

the current (year 2000) 19 climate factors and future climate factors (2050s and 2070s) for different emission scenarios with a resolution of about 1 km were obtained from the WorldClim website. Topographic data were obtained from the National Geographic. The topographic data were downloaded from the National Geographic Data Cloud SRTM dataset (version 4.1) with a resolution of 30 m. The topographic factors of elevation, slope, and slope direction were extracted using the 3D Analyst tool in ArcGIS 10.8.1 software.

Using ArcGIS 10.8.1, the 22 environmental factor raster data were processed separately into a transformed format and unified to the same coordinate system, same range, and 1kmx1km resolution.

There are certain correlations among environmental factors [14]. In correlation analysis, the correlation coefficient is a quantity that describes the degree and direction of the prevailing relationship. Correlation analysis refers to the analysis of two or more variable elements with correlation, so as to measure the correlation degree of two variable factors. Correlation analysis can be carried out only when there is a certain connection or probability between the elements of correlation. It is generally expressed as r. Generally, an absolute value of r is greater than 0.95 represents the presence of a significant correlation, and an absolute value of r is greater than 0.80 is highly correlated. Highly correlated environmental factors are highly likely to be over-fitted, which will increase the AUC value in prediction, so correlation analysis and screening of environmental variables should be performed.

As shown in Table 1, according to the study in this paper, Pearson correlation analysis was performed on 22 environmental variables by SPSS software to calculate the correlation coefficient matrix between variables, remove variables with little biological significance in the group of significantly correlated variables, and

establish independent and biologically significant environmental variables [15]. The final 12 climate factors were identified as Bio2 monthly mean diurnal temperature difference, Bio3 ratio of diurnal temperature difference to annual temperature difference, Bio4 standard deviation of temperature seasonal variation, Bio5 maximum temperature in the hottest month, Bio6 minimum temperature in the coldest month, Bio9 mean temperature in the driest quarter, Bio13 rainfall in the wettest month, Bio14 rainfall in the driest month, Bio15 variance of rainfall Bio16 wettest quarter rainfall, Bio18 warmest quarter average rainfall, Bio19 coldest quarter average rainfall for modeling.

Table 1. Correlation matrix of bioclimatic variables.

	bio_1_ Band_1	bio_2_ Band_1	bio_3_ Band_1	bio_4_ Band_1	bio_5_ Band_1	bio_6_ Band_1	bio_7_ Band_1	bio_8_ Band_1	bio_9_ Band_1	bio_10_ Band_1	bio_11_ Band_1	bio_12_ Band_1	bio_13_ Band_1	bio_14_ Band_1	bio_15_ Band_1	bio_16_ Band_1	bio_17_ Band_1	bio_18_ Band_1	bio_19_ Band_1
bio_1_ Band_1 Pearson	1																		
bio_2_ Band_1 Pearson	−0.867**	1																	
bio_3_ Band_1 Pearson	0.758**	−0.729**	1																
bio_4_ Band_1 Pearson	−0.295**	0.135	0.317**	1															
bio_5_ Band_1 Pearson	0.948**	−0.794**	0.715**	−0.406**	1														
bio_6_ Band_1 Pearson	−0.308**	0.695**	−0.354**	−0.291**	−0.142	1													
bio_7_ Band_1 Pearson	−0.938**	0.962**	−0.839**	0.129	−0.906**	0.520**	1												
bio_8_ Band_1 Pearson	0.955**	−0.837**	0.825**	−0.258**	0.982**	−0.215*	−0.946**	1											
bio_9_ Band_1 Pearson	−0.293**	0.676**	−0.302**	−0.008	−0.245*	0.757**	0.523**	−0.311**	1										
bio_10_ Band_1 Pearson	−0.933**	0.963**	−0.770**	0.195*	−0.881**	0.536**	0.976**	−0.912**	0.552**	1									
bio_11_ Band_1 Pearson	−0.496**	0.839**	−0.521**	−0.197*	−0.341**	0.957**	0.692**	−0.428**	0.820**	0.707**	1								
bio_12_ Band_1 Pearson	−0.943**	0.972**	−0.771**	0.233*	−0.915**	0.518**	0.992**	−0.938**	0.542**	0.983**	0.692**	1							
bio_13_ Band_1 Pearson	−0.884**	0.777**	−0.790**	0.038	−0.771**	0.349**	0.833**	−0.821**	0.244*	0.830**	0.513**	0.816**	1						
bio_14_ Band_1 Pearson	−0.677**	0.658**	−0.459**	0.305**	−0.609**	0.257*	0.640**	−0.634**	0.380**	0.664**	0.439**	0.665**	0.799**	1					
bio_15_ Band_1 Pearson	−0.679**	0.605**	−0.664**	−0.218*	−0.464**	0.440**	0.622**	−0.544**	0.161	0.666**	0.536**	0.591**	0.822**	0.521**	1				
bio_16_ Band_1 Pearson	0.675**	−0.544**	0.751**	0.287**	0.538**	−0.327**	−0.637**	0.604**	−0.063	−0.618**	−0.407**	−0.583**	−0.700**	−0.191*	−0.802**	1			
bio_17_ Band_1 Pearson	−0.804**	0.716**	−0.607**	0.259**	−0.732**	0.240*	0.742**	−0.758**	0.283**	0.747**	0.427**	0.753**	0.908**	0.959**	0.621**	−0.373**	1		
bio_18_ Band_1 Pearson	−0.668**	0.599**	−0.634**	−0.199*	−0.445**	0.447**	0.605**	−0.522**	0.150	0.654**	0.541**	0.579**	0.817**	0.527**	0.992**	−0.789**	0.622**	1	
bio_19_ Band_1 Pearson	−0.752**	0.682**	−0.573**	0.315**	−0.730**	0.171	0.714**	−0.752**	0.360**	0.713**	0.376**	0.728**	0.830**	0.943**	0.474**	−0.270**	0.962**	0.471**	1

** was significant correlation at the 01 level (bilateral). * was significantly correlated at the 0.05 level (bilateral).

3.3. Future Climate Scenario Data

In this paper, the distribution of sorghum under future climate scenarios is modeled using two GHG emission scenarios, the medium GHG emission scenario (RCP4.5) and the highest GHG emission scenario (RCP8.5). The RCPs (Representative Concentration Pathways), as new climate change scenarios, contain four scenarios (SRES (Special Report on Emissions Scenarios, SRES), a climate scenario used in past studies, focuses more on future changes in greenhouse gas emissions than the RCPs scenario. It also combines greenhouse gas emissions with climate change, and has a stronger scientific and accurate prediction of future climate change.

Future climate scenarios for the years 2050s and 2070s were chosen for this study. The corresponding 19 climate factors for 2050s and 2070s are the average of the climate factor data for the decade 2041-2060 and 2061-2080, respectively. Under the RCP4.5 scenario, the annual mean temperature in the 2050s study area increases by 2.71°C and the annual precipitation increases by 61.82 mm, respectively, compared with the base year. In the RCP8.5 scenario, the mean annual temperature in the 2050s study area increases by 3.55°C and the annual precipitation increases by 70.41 mm. The mean annual temperature in the 2070s study area increases by 5.52°C and the annual precipitation increases by 84.58 mm compared to the base year.

3.4. Model Simulation and Evaluation

In this paper, the Maxent model was selected to predict the sorghum fitness distribution under different climate patterns. The model has the advantages of simple modeling, accurate prediction, and high stability, and is widely used in several research areas.

Research related to species distribution models has developed rapidly in recent years, and several distribution prediction models that are currently widely used are mainly as follows. First is the bioclimatic (Bioclim) model [16], the Bioclim model as the earliest species distribution model, the early application of the MaxEnt model has a great relevance [17], the disadvantage of this model is that it is only suitable for some species and has limitations for some species biological categories, the advantage is that the simulation results are more accurate in the case of specific ecological amplitude and environmental characteristics [17] [18]; followed by the regional environmental (Domain) model [19], which has the disadvantage of requiring a high level of specialized knowledge, requiring subjective judgment thresholds, and low requirements for objectivity, leading to unstable accuracy of simulation results; followed by the genetic rule set (GARP) model: the disadvantage of the GARP model is its high sample size requirements and poor simulation results [20]; CLIMEX is a climate specific tool that assesses region-specific adaptation of target species in terms of climate change and predicts potential distribution, climate similarity and seasonal phenology [21].

The MaxEnt model helps one to adapt environmental variables such as land cover, distance and geographical factors and to evaluate the contribution of each variable [22]. The MaxEnt model has more advantages than several traditional species distribution models, which are based on certain algorithms to project the ecological requirements of species and combine different climate scenario models to make scientific predictions of suitable species distribution areas, with high objective accuracy of the prediction results and without restricting species categories, which can be predicted with less data on sample points [13].

In this study, MaxEnt 3.4.1 maximum entropy model prediction software was used to model the data and ArcGis software was used to analyze the data. Max-Ent software was used to load the sorghum sample point distribution data in CSV format and the processed environmental factor data, and the proportion of distribution points in the test set was set to 25% (testing data) and the proportion of distribution points in the training set was set to 75% (training data), and the contribution of each climate factor to the model in the prediction was analyzed using the Jackknife method (Jackknife). The contribution of each climate factor to the model was analyzed using the Jackknife method. The accuracy was evaluated using the receiver operating characteristic curve (ROC), and the area under the ROC curve is the AUC value. The AUC value is independent of the diagnostic threshold and has a low sensitivity to species occurrence, and is currently recognized as the best model predictor. The correlation between the environmental variables and the distribution model is positively correlated, and when the AUC value is greater than 0.8 it indicates that the prediction results are quite accurate [14] [23]. The AUC value evaluation the model was evaluated with reference to the following criteria: 0.90 - 1.00, excellent; 0.80 - 0.90, good; 0.70 - 0.80, fair; 0.60 - 0.70, poor; 0.50 - 0.60, failure [12].

Model simulations generated species presence probability raster plots as simulation results, with values within 0 - 1. Values closer to 0 indicate a lower probability of presence at the point, while the opposite indicates a high probability of species presence at the point [11]. In this study, the probability value P (P = 0.32) was used as a threshold [24] to classify sorghum habitats as highly suitable (P ≥ 0.5), suitable (0.32 < P < 0.5), and non-suitable (P < 0.32) [11].

4. Research Results

4.1. Current Potential Habitat Distribution of Sorghum

As shown in Figure 2, Contemporary climatic conditions of sorghum are mainly distributed at 22° - 44°N and 103° - 125°E, and the above suitable distribution areas coincide with the distribution of actual sorghum specimen sites. The species presence probability raster map showed a suitable habitat distribution area of 229.677413 (in Decimal Degrees), and the results of sorghum suitability distribution under the current climate scenario model showed that about 40% of the areas in China are suitable for sorghum growth with a large suitability area, with the Golden Triangle of Baijiu (Yibin, Guizhou, and Luzhou) being located
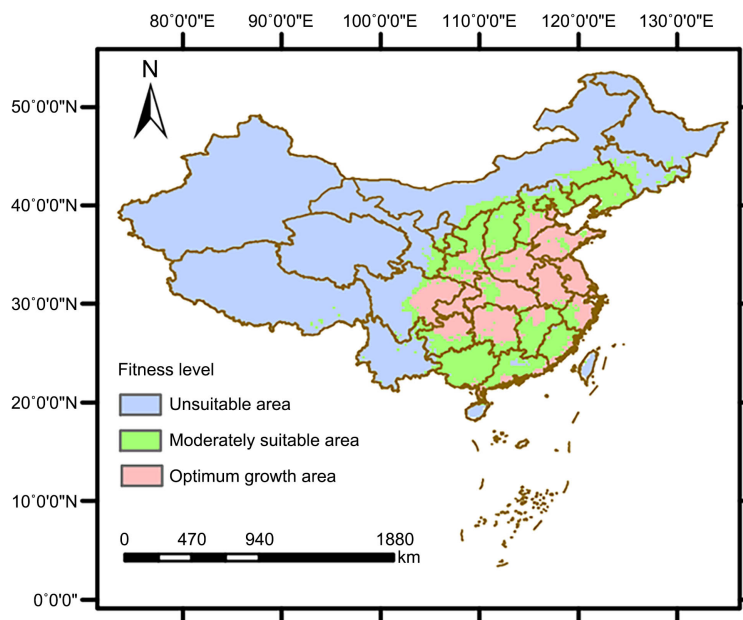
**Figure 2.** Suitable distribution areas for sorghum.

in areas with high suitability. To further analyze the suitability of potential habitats, the suitable habitats for sorghum were classified into the most suitable habitats (P > 0.5) and medium suitable habitats [25] (0.32 < P < 0.5). The high suitable areas are mainly distributed in southwest, central and east China. It starts from the central part of Sichuan Province in the west and covers Chongqing City in the east, Hunan, Anhui, Jiangsu and Shandong Provinces, and is also present in large areas in Guizhou, Hebei, Zhejiang, Henan and Hubei Provinces. The distribution of the general fitness zone is more continuous compared with that of the high fitness zone, and since the distribution of the high fitness zone spreads like north and south, covering the eastern part of southwest China, south, central and east China, and a small part of north China. Shaanxi Province, Shanxi Province, Hebei Province, Liaoning Province, Guangxi Zhuang Autonomous Region, Guangdong Province, Jiangxi Province and Fujian Province are all located within the distribution of the general fitness zone.

4.2. Analysis of Important Factors Affecting Potential Sorghum Habitat Distribution

As shown in **Figure 3**, the results of the knife-cut test showed that Bio2 (monthly mean diurnal temperature difference), Bio6 (minimum temperature in the coldest month), Bio13 (rainfall in the wettest month) and Bio14 (rainfall in the driest month) were prominent in the gain of the tested variables.

As shown in **Figure 4**, the monthly mean diurnal temperature difference is the sum of the diurnal difference in daily temperature for a given month divided by the number of days. The response curves of the monthly mean diurnal temperature difference and the probability of existence are as follows: The results show that the probability of existence remains at a certain level when the monthly
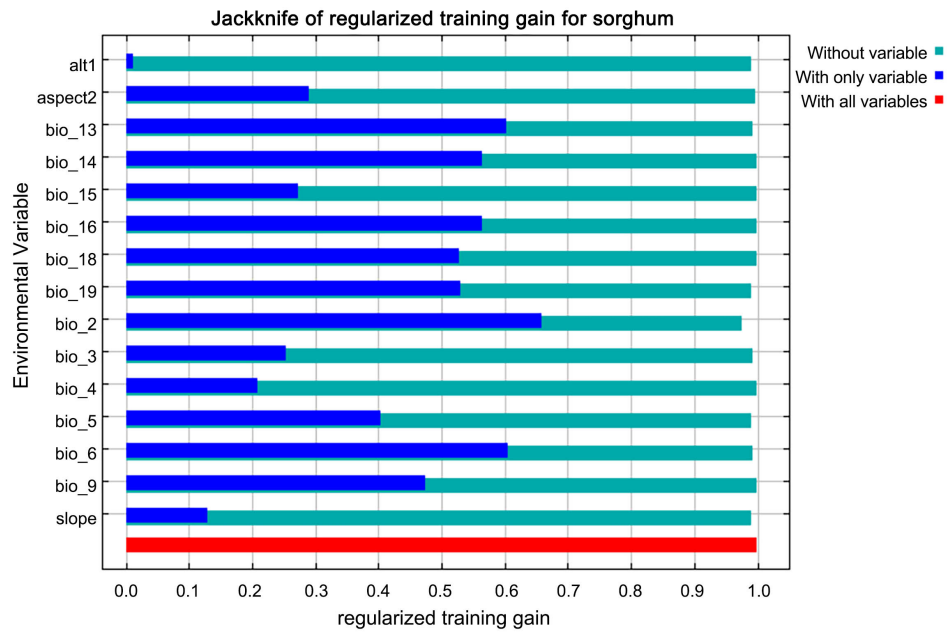
Figure 3. Knife cut method to test the importance of environmental variables on the distribution of sorghum.

Monthly average diurnal temperature difference Minimum temperature in the coldest month (unit: ˚C*10)

Rainfall in the wettest month (mm)   Rainfall in the driest month (mm)
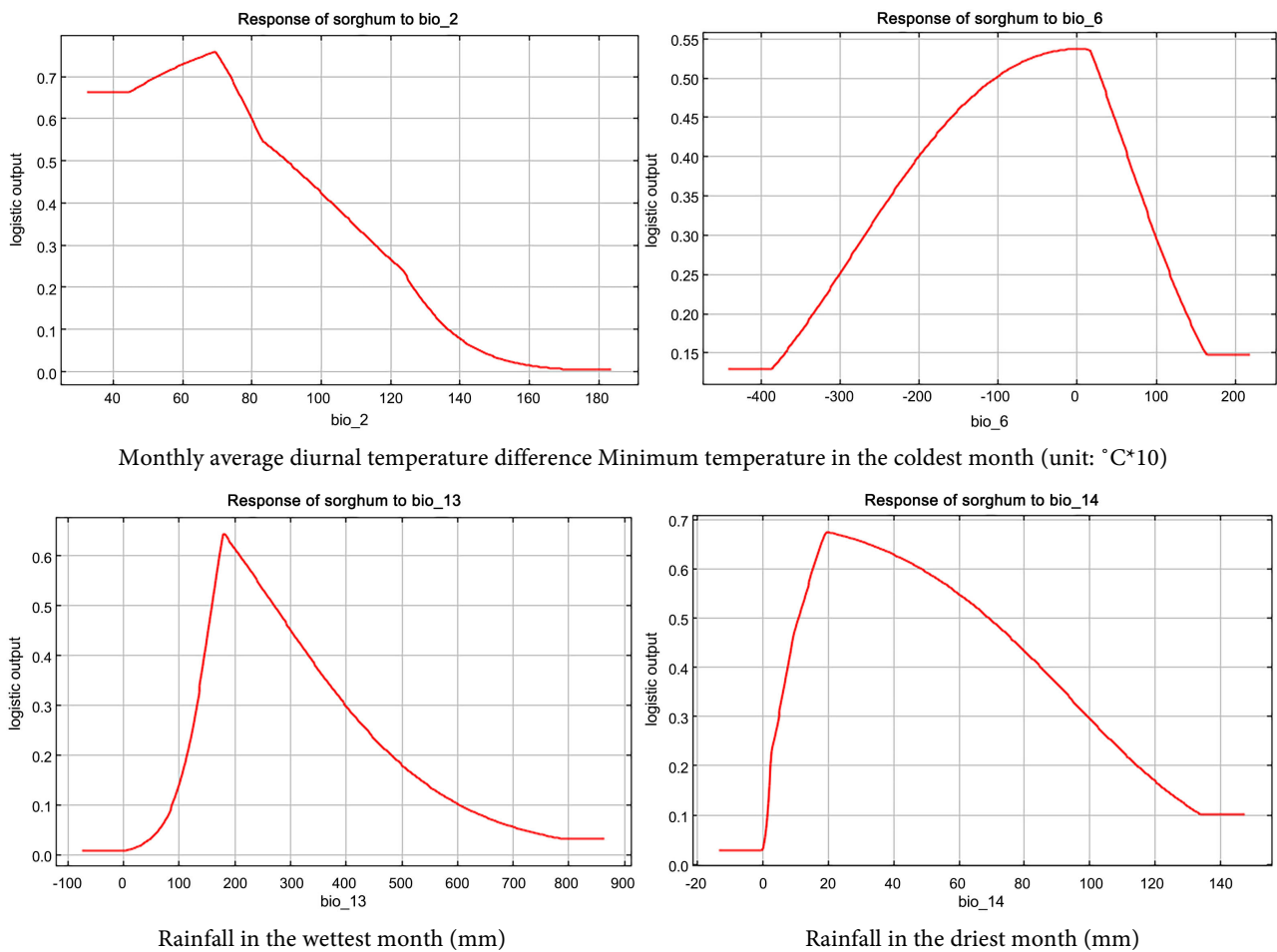
**Figure 4.** Response curves of important environmental variables.

mean diurnal temperature difference is less than 69, and after the mean value exceeds 69, the probability of existence drops sharply and the diurnal temperature difference is too large for the growth of sorghum. The minimum temperature in the coldest month remained positively correlated with the probability of existence, and as the temperature increased, the probability of existence increased to 17˚C when the probability of existence was maximum and the probability of existence then remained constant. The response curves for rainfall and probability of presence in the wettest month indicate that sorghum growth is appropriate when precipitation in the wettest month ranges from 130 mm to 410 mm, with a positive correlation from 130 mm to 180 mm and a negative correlation when precipitation is greater than 180 mm. Combined with the relationship between precipitation and temperature, when precipitation is not higher than 180 mm and the minimum temperature is greater than minus ten degrees, the probability of existence of the genus is greater than 0.32, meeting the minimum fitness conditions. When the rainfall in the driest month was between 10 mm and 52 mm, the probability of existence was greater than 0.5, and the fitness probability was high.

As shown in Table 2, the 13 environmental variables were ranked in descending order according to the contribution and importance of the variables in the output results. The top four were rainfall in the wettest month, rainfall in the driest month, the ratio of diurnal temperature difference to annual temperature difference, and minimum temperature in the coldest month, and these four environmental variables contributed 86.2% to the model, accounting for 29.5%, 27.5%, 27.5%, and 14.2%, respectively. The contribution of precipitation to the model was higher than the temperature-related variables, and the environmental factors that contributed less than 1% were altitude 0.8%, Bio5 maximum temperature in the hottest month 0.8%, Slope slope 0.8%, Bio15 rainfall variance 0.5%, and slope direction 0.3%, which shows that the importance of temperature and humidity on the distribution of suitable areas for sorghum is much greater than the influence of topographic factors on suitable areas This shows that temperature and moisture have a much greater impact on the distribution of suitable areas for sorghum than topographic factors on the suitable areas.

4.3. Changes in Spatial Distribution Patterns of Sorghum under Climate Change

The fitness results under the four climate models were reclassified using ArcGIS 10.8.1 software [26], and the results under each of the four climate models were overlaid with the current fitness results for mapping, resulting in a map of fitness changes under the four climate scenarios, as shown in Figure 5. As can be seen from the figure, compared to the suitability distribution area under the current climate model, the divisional change map under the future climate scenario model more clearly shows that the suitability area of sorghum increases more significantly and shows a northward expansion. Most of the suitable areas

remain unchanged, a small number of suitable areas are lost, and the lost areas are scattered in southern China, with an overall trend of expansion of suitable areas.
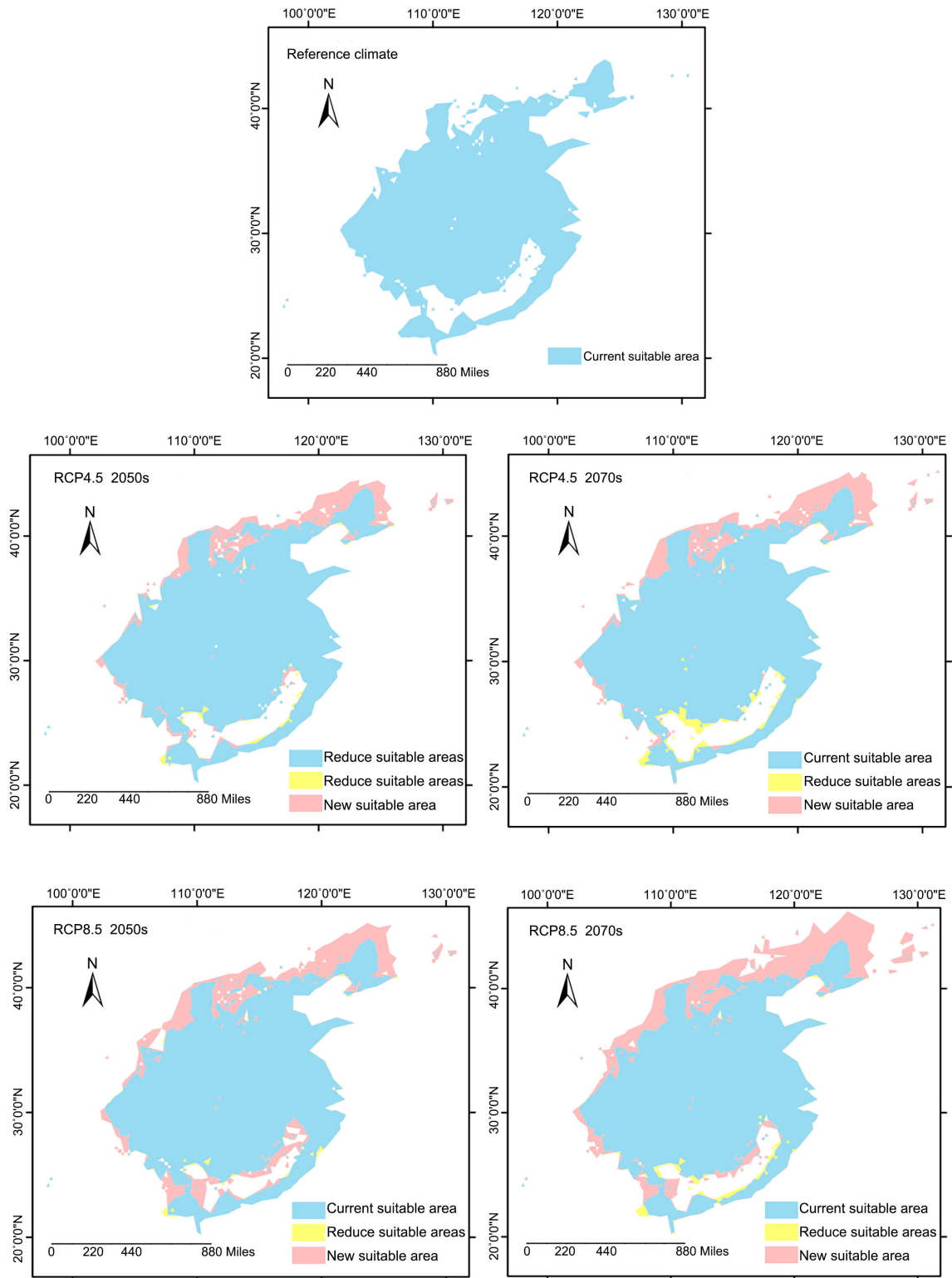
Figure 5. Distribution of suitable sorghum habitats under different climatic conditions.

Table 2. Contribution and importance ranking of variables in MaxEnt output results.

Climate variables	describe	Contribution rate
Bio13	Rainfall in the wettest month	29.5%
Bio14	Rainfall in the driest month	27.5%
Bio3	Ratio of diurnal temperature difference to annual temperature difference	15%
Bio6	Lowest temperature in the coldest month	14.2%
Bio2	Monthly mean temperature difference between day and night	4.9%
Bio9	Average temperature in the driest quarter	2.4%
Bio19	Coldest season precipitation	1.9%
Bio4	Standard deviation of seasonal variation of temperature	1.2%
Alt	altitude	0.8%
Bio5	Highest temperature in hottest month	0.8%
Slope	slope	0.8%
Bio15	Variance of rainfall variation	0.5%
Aspect	Slope direction	0.3%

4.4. Changes in Sorghum Range Area under Climate Change

Using ArcGIS10.8 to rank future sorghum suitable habitats according to the (P > 0.32) criteria, the changes in the area of suitable areas and the percentage of them were counted, and Table 3 shows that climate change has a great impact on the distribution of sorghum habitats. By comparing the change in area of suitable sorghum habitat at different stages and under different emission scenarios, it was concluded that the overall area of sorghum habitat showed an increasing trend.

A comparison of the suitable area under the future climate model with the current suitable area shows that the suitable area for sorghum under both future climate scenarios increases significantly, and the area increases more significantly under the high concentration emission scenario, while the reduction in suitable area is few, and the total area shows a significant increase. The additional area showed less variation in extent between projection time periods for the same future emission scenarios. Compared to contemporary times, the most significant rate of additions was found in the 2070s under the RCP8.5 emission scenario, reaching 26.56%, with most of the new areas spreading to the north and a small portion of new areas in southern China. The total suitable habitat area for sorghum increased by 12.82% and 15% in the 2050s and 2070s phases, respectively, in the RCP4.5 scenario, and by 20.8% and 26.56% in the 2050s and 2070s phases, respectively, in the RCP8.5 scenario, with a significantly higher increase in the total suitable habitat area for sorghum than in the RCP4.5 scenario.

Table 3. Variation in sorghum area under different climate scenarios (in Decimal Degrees).

Climate scenario	Comparison period	Increase in habitat	Decrease in habitat	Total habitat growth
RCP4.5	now-2050s	29.436698	2.469239	26.967459
RCP4.5	now-2070s	34.50024	6.390336	28.109904
RCP8.5	now-2050s	47.807343	1.705689	46.101654
RCP8.5	now-2070s	61.012129	4.018414	58.993715

5. Discussion

5.1. Sorghum Distribution in Relation to Environmental Factors

In the future, with global warming, the sorghum suitability pattern changes significantly and the area of suitability increases significantly. In this study environmental data as an important factor influencing sorghum fitness distribution, temperature, humidity, and topographic data all have an impact on the geographic distribution of sorghum. The ranking of contribution and importance showed that rainfall was more important in the wet and dry months, while the results of the knife cut test showed that the temperature factor was more important. In this case, the wettest month has precipitation between 130 mm and 410 mm for sorghum growth. When the precipitation is not higher than 180 mm and the minimum temperature is greater than minus ten degrees, the genus has a probability of existence greater than 0.32 and meets the minimum fitness conditions. When the rainfall in the driest month was between 10 mm - 52 mm the probability of existence P value was greater than 0.5 and the probability of fitness was high. The presence probability is high when the monthly average value of diurnal temperature difference is less than 69, and the presence probability is highest when the minimum temperature is up to 17˚C in the coldest month.

Drought and flood tolerance as characteristics of sorghum are sensitive to both temperature and moisture. The results of this study showed that temperature and precipitation environmental variables contributed 86.2% to the model, with rainfall in wet and dry months affecting sorghum habitat distribution by as much as 57%, fully demonstrating that sorghum is heat tolerant but not cold tolerant, and in the selection of habitat, try to avoid places with high low temperatures and humidity.

5.2. Accuracy Evaluation of Simulation Results

This study used sample data from the Chinese Natural Herbarium and Botanical Library combined with the MaxEnt model ecological niche modeling to establish a predictive map of the distribution of sorghum suitability zones across the country. A comprehensive analysis of the ecological characteristics affecting sorghum was conducted and the distribution of sorghum suitability areas was obtained visually. The maximum entropy model was validated by ROC curve analysis, and the ROC curve was relatively close to 1. The AUC value for the training model dataset was 0.881, and the AUC value for the test dataset was

0.841, indicating good prediction results.

In this study, nineteen climatic factors and three topographic factors were used to model the main effects of climate change on the distribution of sorghum in China. However, the conditions of species present are quite complex and there are likely to be some environmental factors of species presence that we do not know at present. This study has not yet considered the effects of soil, water quality, and community environment elements on sorghum growth and some stochastic factors. From the analysis of the modeling results, it was determined that the habitat of sorghum suitable for growth is similar to that of known sorghum, but this determination is not absolute and does not necessarily mean that sorghum exists in this area. Environmental factors and climatic conditions are not static, and the survival dynamics of any one species can change. In addition, the prediction results may vary depending on the climate scenario model selected [27]. In summary, multiple realistic factors need to be fully considered in future studies to make the prediction results more accurate.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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