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The Effect of Climate Change on Spring Maize (*Zea mays* L.) Suitability across China

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Abstract: Spring maize (*Zea mays* L.) is a thermophilic C_4 crop which is sensitive to climate change. This paper provides a detailed assessment of the effect of climate change on the crop from a new perspective, by predicting the probability of the potential distribution of spring maize across China. The affected area of spring maize suitability was identified, and then the affected area was subdivided into the improved area and the deteriorated area. Our results confirmed that there was a detrimental consequence for spring maize suitability under observed climate change from 1961–1990 to 1981–2010. However, our results revealed that warming scenarios of 1.5 °C and 2 °C were helpful for the suitable area expansion of spring maize. The affected area was smaller under warming scenarios than under historical climate change, revealing that temperature rise alone was not enough to trigger a "tipping point" (a threshold value after which abrupt shifts occur) for spring maize, even if warming is 2 °C above the level of 1961–1990. Our results not only benefit China in the design of mitigation and adaptation strategies, but also provide a theoretical judgement that the impact of global warming on the crop ecosystem is not serious if other climate factors remain unchanged.

Keywords: spring maize; potential distribution; climate change; tipping point; warming scenarios; suitability

1. Introduction

Maize (*Zea mays* L.) is grown over a wider range of altitudes and latitudes than any other food crop [1]. Maize can be categorized into spring maize (spring-sown) and summer maize (summer-sown) according to the difference in sowing time. In China, spring maize is cultivated widely. Spring maize is usually sown in spring and harvested in autumn across China. The impact of climate change on the crop is very significant, since spring maize as a thermophilic C_4 crop is especially sensitive to global warming and extreme changes in precipitation and radiation [2–4]. Previous studies have reported that historical climate change benefited spring maize growth in high latitudes where thermal resource is limited and resulted in the northward expansion of spring maize [5–7]. Some opposite views argue that climate change resulted in a negative impact on spring maize by analyzing extreme disasters from climate factors [8–10]. It is probable that the impact of climate change is not consistent in all regions. However, it is not well known where climate change is favorable and where climate change is harmful for spring maize growth.

Climate change might affect maize yield worldwide. It was estimated by the use of a regression line that global warming decreased maize yields by 4% worldwide for the 1980 to 2008 period [11].

Compared with estimates of under 2 °C global warming, it was estimated that keeping global warming within 1.5 °C has great benefits for reducing future maize yield loss risk, which is projected to decrease from 81 to 75% for the United States based on the ensemble mean of 97 climate model simulations [12]. Using two representative concentration pathway (RCP2.6 and RCP8.5) scenarios, a spatial grid-based analysis showed that the suitable areas for maize change little under RCP2.6 scenarios, but shift northward under RCP8.5 scenarios in China [13]. However, it is unclear where this is beneficial and where it is harmful for maize suitability under climate change.

A range of crop models, focusing on different crops and regions, have become available. Early crop models were developed for application at the plot or field scale with a single crop. Later crop models supported the simulation of different crops, cropping systems and production situations for larger areas such as regions, nations, large watersheds, and so forth. Recently, process-based crop models have become the primary scientific tools available to quantitatively evaluate the potential impacts of climate change on cropping systems [14,15]. There are two main classes of process based crop models currently used to study crop responses to climate: (1) agronomy crop models, including APSIM (Agricultural Production Systems sIMulator), DSSAT (Decision Support System for Agrotechnology Transfer), EPIC (Erosion Productivity Impact Calculator or Environmental Policy Integrated Climate), Hybrid-Maize, and CropSyst (cropping systems simulator), and (2) crop models in the framework of earth system models (ESMs). Agronomy crop models are suitable to simulate field-level crop growth and yield. The crop models in the framework of earth system models are suitable to simulate the two-way feedback between climate and agricultural systems [16]. However, most process-based crop models simulate on a daily time step, so it is difficult to simulate multi-year dynamics. The maximum entropy model (MaxEnt) provides a more suitable tool than crop models in exploring the potential impact of long-term climate change on maize, because this model can identify the geographic shifts in the potential distribution of crop species [17].

Scientists have predicted that some ecosystems would be at greater risk of warming by 2 °C than by 1.5 °C relative to preindustrial levels (1850–1920) [18,19]. The 2015 Paris Agreement of IPCC (Intergovernmental Panel on Climate Change) was asked to provide a scientific assessment on the adverse consequences for important ecosystems under global warming scenarios of 1.5 °C and 2 °C [20,21]. For spring maize, catastrophic impacts of global warming might occur suddenly when it exceeds a specific threshold. There are disagreements about whether global warming has resulted in degeneration or improvement after temperature warming of up to 2 °C in China, because the increasing temperature tends to cause drought in spite of reducing cold damage in northern China [8,10].

For the observed climate change and warming scenarios of 1.5 °C and 2 °C above the level of 1961–1990, this paper provides a detailed assessment of the impact of climate change on spring maize across China using the MaxEnt model, which is more successful in predicting habitat suitability than other ecological niche models [22,23]. Our objectives are to (1) reveal the beneficial or harmful effects on spring maize under historical climate change; (2) confirm whether there exists a "tipping point" (a threshold value after which abrupt shifts occur) for spring maize suitability under warming scenarios of 1.5 °C and 2 °C; and (3) identify the roles of environmental factors in restricting spring maize suitability.

2. Methods

2.1. MaxEnt Model

The maximum entropy model (MaxEnt) has often been used to forecast the habitat suitability of a species [24]. This model provides the potential probability of species distribution under given conditions by seeking statistical relationships between species distribution and environmental variables [25]. Therefore, the model was selected to quantify habitat suitability by the probability value of spring maize occurrence.

The idea of MaxEnt is to estimate a target probability distribution by finding the probability distribution of maximum entropy subject to the constraint that the expected value of each feature under this estimated distribution matches its empirical average. The building blocks of the MaxEnt model are a set of statistics of the training sample.

Starting from a set of data (target species presence, environmental variables), the unknown target probability distribution (π) is over a finite set X. The distribution π assigns a non-negative probability $\pi(x)$ to each site x, and these probabilities sum to 1.

An observer picks a random site x from the set X of sites in the study area, and records 1 if the species is present at x, and 0 if it is absent. If we denote the response variable (presence or absence) as y, then $\pi(x)$ is the conditional probability $\mathrm{P}(x|y)$. According to Bayes' rule:

$$\mathrm{P}(y=1|x) = \frac{\mathrm{P}(x|y=1)\mathrm{P}(y=1)}{\mathrm{P}(x)} = \pi(x)\mathrm{P}(y=1)|\mathrm{X}|$$

Approximation of π is also a probability distribution ($\hat{\pi}$). The entropy of $\hat{\pi}$ is defined as:

$$\mathrm{H}(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$$

where ln is the natural logarithm [25,26].

2.2. Input Data

The input data in the MaxEnt model includes species (spring maize) distribution, annual climate variables, elevation, and the hypothetical warming scenarios. The species (spring maize) distribution was the geographical locations of a series of agrometeorological monitoring stations planting spring maize for at least five consecutive years. The annual climate variables were the recorded data at 741 meteorological observation stations for the period 1961–2010. All the annual climate variables were obtained from National Meteorological Information Center (http://cdc.cma.gov.cn), China Meteorological Administration. The multi-annual climate variables were counted out (including mean annual temperature, extreme low temperature, the coldest month (January) temperature, the warmest month (July) temperature, annual precipitation, and annual radiation) for the periods of 1961–1990 and 1981–2010, respectively. Then, the climate variables were interpolated to layers with a spatial resolution of 10 km $\times$ 10 km grid cells. The elevation variable, deriving from a digital elevation model, was resampled to match the spatial resolution of the climate variables.

Warming scenarios were obtained from the data of 1961–1990, assuming that four temperature variables (mean annual temperature, extreme low temperature, the coldest month temperature, and the warmest month temperature) increased by 1.5 °C and 2 °C above the observed temperature in 1961–1990. The corresponding variables in 1961–1990 were used as a benchmark to reveal whether temperature rise alone can lead to a "tipping point" for spring maize suitability.

2.3. Model Calibration and Validation

The MaxEnt model was calibrated using 75% of the randomly selected records of spring maize distribution and environmental variables as training data, and the remaining 25% were used for model validation as testing data to test model performance. The receiver operating characteristic (ROC) curve and AUC (area under the ROC curve) were used as an index to provide overall validation.

AUC provides a single measure of model performance. The ROC curve is obtained by plotting sensitivity on the y axis and 1–specificity on the x axis for all possible thresholds. For a continuous prediction, the ROC curve typically contains one point for each test instance, while for a discrete prediction, there will typically be one point for each of the different predicted values, in addition to the origin. The area under the curve (AUC) is usually determined by connecting the points with straight lines [25].

The value of the AUC ranges from 0 to 1. An AUC value of 0.5 shows that model predictions are not better than random, 0.5–0.7 indicates poor performance, 0.7–0.9 indicates reasonable/moderate performance and >0.9 indicates high performance [27,28]. In this study, the average AUC for ten replicate runs was 0.869, so the accuracy estimate of the model is acceptable (Figure 1).

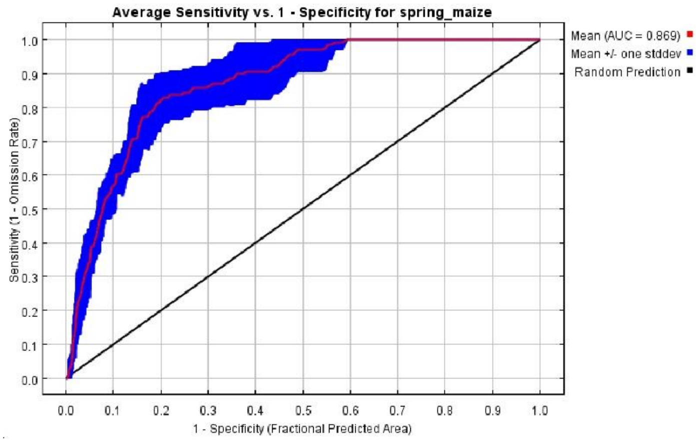

Figure 1. The receiver operating characteristic (ROC) curve for the averaged ten replicate runs. The average area under ROC curve (AUC) is 0.869, indicating acceptable model prediction with a reasonable performance.

2.4. Overlay Analysis

The MaxEnt model outputs the probability value of spring maize occurrence for each grid of cells of 10 km × 10 km. Firstly, the spring maize suitability was classified into four types (unsuitable, slightly suitable, moderately suitable, and optimum) by the three probability values (0.3, 0.4, and 0.5). Secondly, the overlay analysis was conducted to identify the spatial shift among these suitable areas for different periods. Thirdly, the spatial shift areas were identified as showing improvement or deterioration in suitability. Improvement in suitability is beneficial to spring maize, while deterioration is harmful.

3. Results

3.1. The Beneficial and Harmful Effects on Spring Maize under Observed Climate Change

A suitable area for spring maize was defined as a region with a probability value larger than 0.3, because a probability value of 0.3 ensured that more than 95% of spring maize was located in the suitable area (Figure 2). The overlay analysis method allows us to identify changes in the suitable area under historical climate change. During the baseline period of 1961–1990, the suitable area for spring maize was 1,747,600 km^2. The suitable area was reduced by approximately 2.76% (48,200 km^2) from 1961–1990 to 1981–2010. The reduction of suitable area revealed a harmful consequence for spring maize suitability under historical climate change.

The historical climate change affected spring maize suitability with an area of 54.8 × 10^4 km^2. In the affected area, the improved area and the deteriorated area were further distinguished (Figure 3A). The improved area in suitability accounted for 43% (23.7 × 10^4 km^2), and the deteriorated area accounted for 57% (31.1 × 10^4 km^2) (Table 1). Significantly, the deteriorated area was larger than the improved area. The proportion of the improved area and the deteriorated area also indicated the harmful consequences for spring maize suitability under historical climate change.

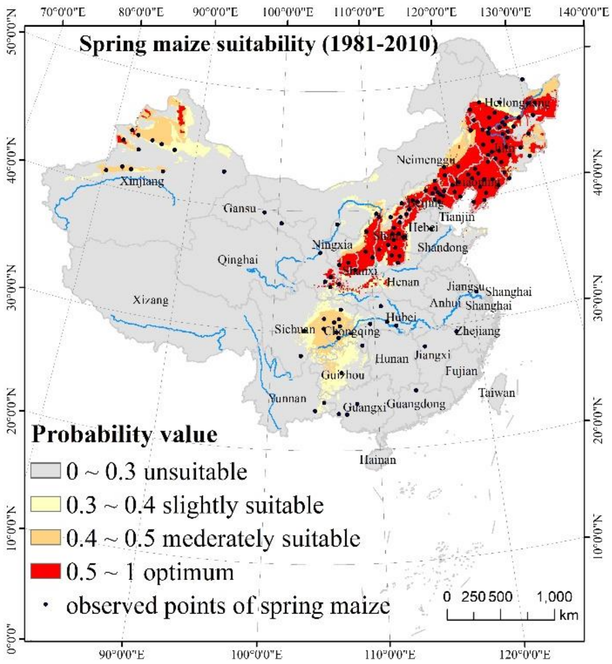

Figure 2. The probability value 0.3 ensured more than 95% of the observed points for planting spring maize were located in the simulated suitable area, so the value of 0.3 was used to distinguish the suitable and unsuitable areas.

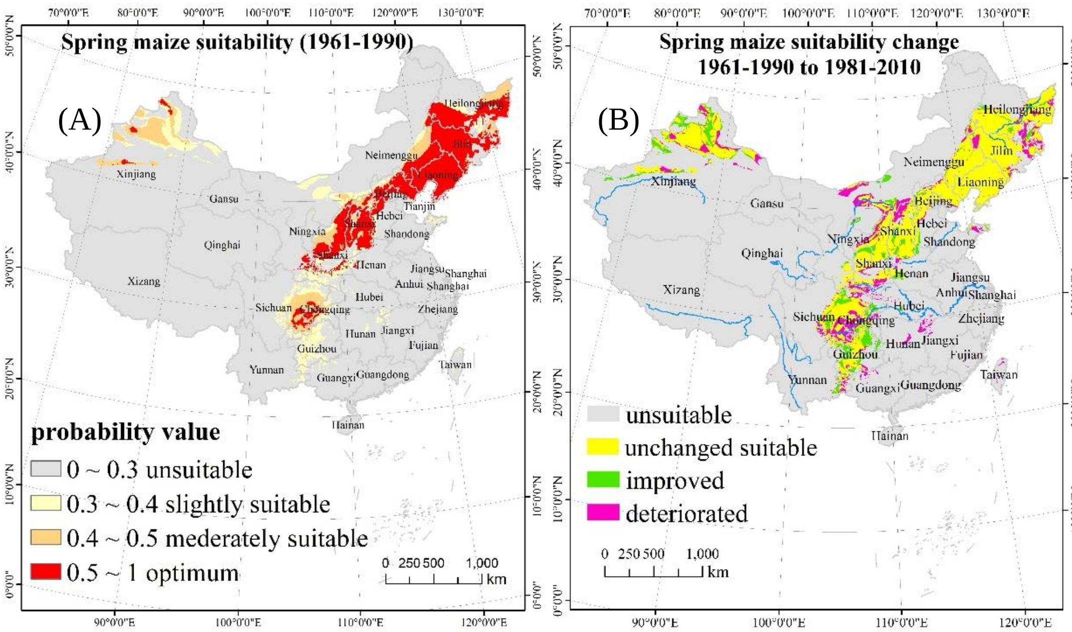

Figure 3. The distribution of spring maize suitability (slightly suitable, moderately suitable, and optimum) across China in the period of 1961–1990 (**A**), and the change in suitable area from the period of 1961–1990 to 1981–2010 (**B**).

Table 1. The improved area and the deteriorated area from the period of 1961–1990 to 1981–2010, and warming of 1.5 °C and 2 °C relative to the baseline period of 1961–1990.

		1961–1990 to 1981–2010	**1961–1990 to Warming 1.5 °C**	**1961–1990 to Warming 2 °C**
Improved area (10^4 km^2)	unsuitable to slightly suitable	11.1	1.8	2.4
	unsuitable to moderately suitable	0.7	0.2	0.2
	unsuitable to optimum	0.4	0.0	0.1
	slightly suitable to moderately suitable	5.7	1.0	1.4
	slightly suitable to optimum	0.6	0.0	0.1
	moderately suitable to optimum	5.2	0.3	0.2
	Total	23.7	3.4	4.4
Deteriorated area (10^4 km^2)	slightly suitable to unsuitable	15.2	1.3	1.8
	moderately suitable to unsuitable	0.7	0.1	0.1
	moderately suitable to slightly suitable	4.8	0.7	0.8
	optimum to unsuitable	1.0	0.0	0.1
	optimum to slightly suitable	1.3	0.0	0.1
	optimum to moderately suitable	8.1	1.1	2.1
	Total	31.1	3.4	5.0

3.2. The "Tipping Point" for Spring Maize Suitability under Hypothetical Warming Scenarios

Compared with the suitable area of 1,747,600 km^2 during the period of 1961–1990 (Figure 3A), the suitable area for spring maize increased by 0.23% (4000 km^2) and 0.36% (6300 km^2) under warming scenarios of 1.5 °C and 2 °C. These warming scenarios, therefore, were helpful for the spatial expansion of the suitable area for spring maize.

The affected area of spring maize suitability was smaller under warming scenarios of 1.5 °C and 2 °C compared with the affected area under historical climate change. The affected area under warming scenarios of 1.5 °C and 2 °C accounted for 3.9% (6.8×10^4 km^2) and 5.4% (9.4×10^4 km^2) of the suitable area in 1961–1990 (Figure 4). The results revealed a slight effect of the warming scenarios on spring maize.

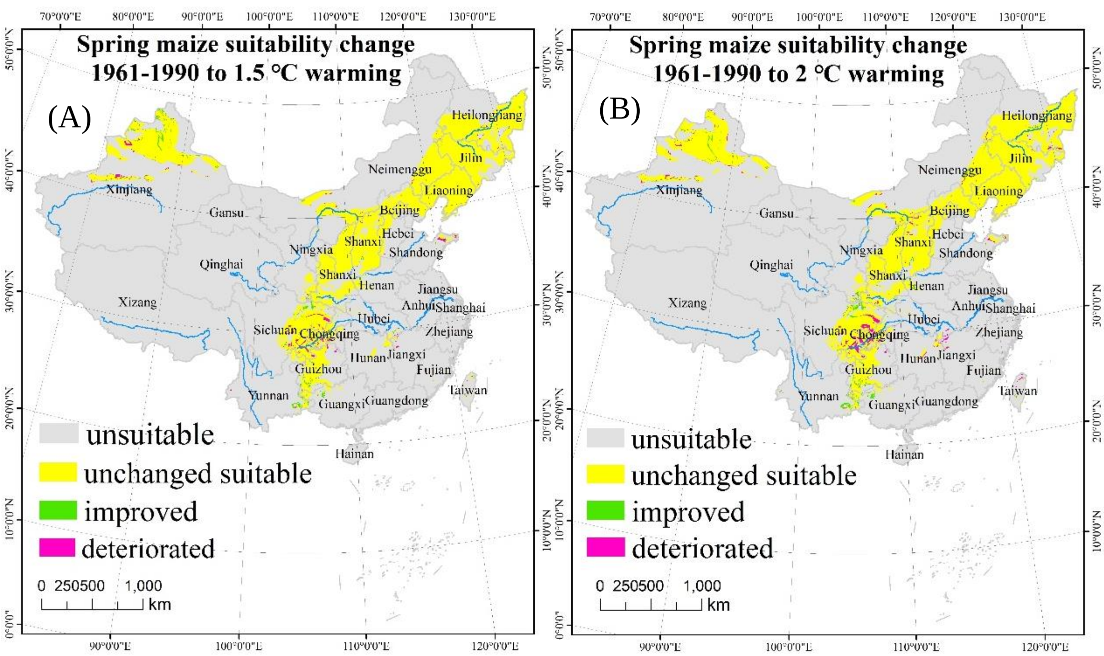

Figure 4. The change in suitable area for spring maize suitability from the baseline period 1961–1990 to 1.5 °C warming (**A**), and from the baseline period 1961–1990 to 2 °C warming (**B**).

After the affected area was divided into the improved area and the deteriorated area, the results showed that both the improved area and the deteriorated area accounted for 50% under warming scenarios of 1.5 °C, indicating hardly effect on spring maize suitability. Under warming scenarios of

2 °C, the improved area accounted for 47% while the deteriorated area accounted for 53%, indicating a slight adverse effect on spring maize suitability (Table 1).

The affected area, the improved area, and the deteriorated area revealed that there was no "tipping point" signal for spring maize suitability, indicating that warming alone is not enough to trigger a sudden "tipping point" after which abrupt collapse would occur for spring maize suitability, even if warming was 2 °C.

3.3. The Roles of Environmental Factors in Influencing Spring Maize Suitability

The relative role of environmental variables in influencing spring maize suitability was measured and displayed by the histogram of the Jackknife test. The results revealed that the warmest monthly temperature was the key variable influencing spring maize suitability, followed by annual radiation, mean annual temperature, elevation, annual precipitation, extreme low temperature, and the coldest monthly temperature (Figure 5).

It is easy to understand that the warmest monthly temperature played a key role in governing spring maize suitability, because spring maize is a thermophilic C_4 crop. In contrast, extreme low temperatures and the coldest monthly temperature played a relatively minor role, because they only affect soil moisture before spring maize is sown. In many cases of maize yields, annual precipitation played a key role in spring maize suitability under natural conditions without human interference. However, the role of annual precipitation was reduced significantly in our study, because the crop was disturbed by irrigating in some parts of the study area.

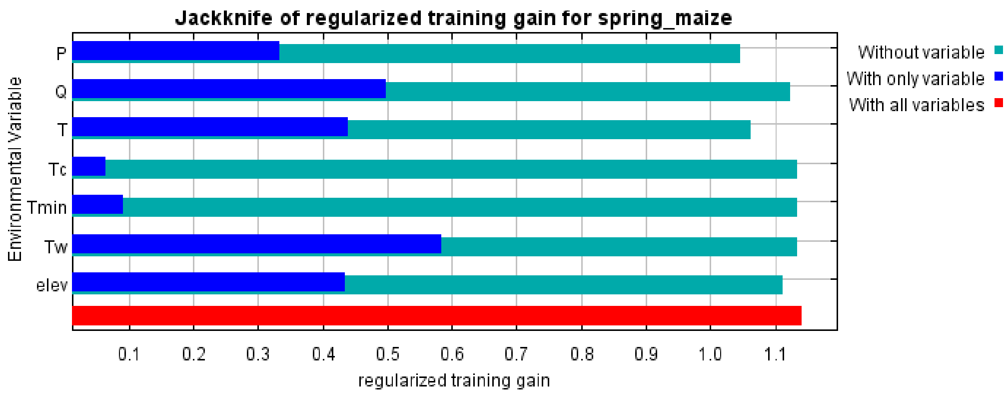

Figure 5. The relative roles of environmental variables influencing spring maize are displayed by the histogram of the Jackknife test. Tw is the warmest monthly temperature, P is annual precipitation, Q is the annual radiation, T is the mean annual temperature, Tc is the coldest monthly temperature, Tmin is extreme low temperature, and elev is elevation.

4. Discussion

Previous studies have suggested that climate change results in a negative impact on spring maize from analyzing extreme disasters from climate factors [8,10]. Our study drew the same conclusion as previous studies by predicting the probability of the potential distribution of spring maize during the period of 1961–2010. Our study provided some new evidence about negative impact from historical climate change, such as the reduced suitable area for spring maize, and a larger deteriorated area than improved area.

However, the shifted spatial patterns of spring maize in the paper did not agree with those of many previous studies, which showed a larger shift northward and expansion eastward in northeast China [5,6]. Previous studies ignored the effect of the topographic variable on spring maize suitability. Our study suggested that the topographic variable is a natural barrier which plays an important role in controlling spring maize suitability. As a result, our study confirmed no larger shift northward due to the topographic barrier in northeast China. Therefore, it is likely that previous studies overestimated the spatial shift of spring maize suitability due to neglecting the effect of the topographic variable.

No significant "tipping point" signal was discovered for spring maize suitability in our study. The "tipping point" is a threshold value after which an abrupt shifts occur in complex systems, reflecting a non-linear response to a gradual environmental change [19,29,30]. Our results revealed that warming scenarios of 1.5 °C and 2 °C would contribute to a slight expansion of spring maize. Our results also provided evidence that the affected area was smaller under these warming scenarios than that seen under historical climate change; the degradation area was the same as the improved area under warming scenarios of 1.5 °C and the degradation area was a little larger than the improved area under warming scenarios of 2 °C. Therefore, the hypothetical warming scenarios did not cause a clear "tipping point" signal for spring maize suitability.

The assumptions of warming scenarios of 1.5 °C and 2 °C in the paper were based on the observed data of 1961–1990, not the pre-industrial warming level at the reference period of 1850–1920 [18,19], because there was insufficient observed data over China during the pre-industrial period of 1850–1920. The observed data of 1961–1990 would set a credible base temperature to identify the role of warming by 1.5 and 2 °C in driving the temporal-spatial variations of spring maize suitability.

It has been reported that keeping global warming within 1.5 °C reduces maize yield loss risk compared with warming of 2 °C [12]. Global warming increases high-temperature stress, and was expected to cause significant maize yield losses in China, India, and the USA [31]. However, our results confirmed that the role of warming by 1.5 and 2 °C was limited if other climate factors remain unchanged, indicating that spring maize has a strong adaptability to global warming, and global warming alone is not likely to interrupt the sustainability of spring maize production.

Our paper provided a method to identify where benefits may occur from global warming, and where global warming may cause problems. The method can be easily extended to other regions and crops. The results in the paper not only benefit China in designing mitigation and adaptation strategies for coping with climate change, but also provide the theoretical perspective that the impact of global warming on crop ecosystems is not serious if other climate factors remain unchanged.

5. Conclusions

Compared with the baseline period of 1961–1990, the suitable area for spring maize was reduced and the deteriorated area was larger than the improved area under observed climate change. Therefore, historical climate change resulted in detrimental consequences for spring maize suitability. In contrast, warming scenarios of 1.5 °C and 2 °C would be helpful for the spatial expansion of spring maize. The affected area accounted for a small proportion compared with that seen under historical climate change. The degradation area was equal to the improved area under warming scenarios of 1.5 °C; the degradation area was a little larger than the improved area under warming scenarios of 2 °C. Signals of a "tipping point" were not detected for spring maize suitability under the hypothetical warming scenarios. The results confirmed theoretically that the impact of global warming on the maize crop ecosystem is not serious if other climate factors remain unchanged. Our results also revealed that spring maize suitability was controlled by multiple environmental factors, and the warmest monthly temperature was the key variable.

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Conflicts of Interest: The authors declare no conflict of interest.

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