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Impact of climate variability on grain yields of spring and summer maize

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A R T I C L E I N F O

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A B S T R A C T

Crop yield is greatly impacted by climate change, and a systemic assessment of its impacts on crop yields is essential. Aiming to investigate the impact of climate change on spring and summer maize yields in main maize growing areas of China, the observed meteorological and maize yield data over 1988–2017 at the 121 sites (including 85 sitess for spring maize and 36 sites for summer maize) in main maize growing areas of China were collected. The first-order difference, Sen's slopes and trend test, multi-collinearity detection, Pearson correlation, stepwise linear and nonlinear regression methods were used, and the best statistical regression models between maize yield and climate variables have been established. Of these, the Sen's slopes quantify the trend magnitude of the related climate variables and spring/summer maize yields during maize growth period. The Pearson correlation coefficients assess the relationship between pairs of climatic variables and maize yields, while the multi-collinearity analysis determines the mutually independent climatic variables with maize yields. The stepwise multi-variate linear and nonlinear regressions were conducted to obtain the best functions of the one-order-differences of spring (summer)maize yields at the 85 (36) sites. The results indicated that: (1) Generally, the precipitation and temperature during growth seasons was rising, while relative air humidity and sunshine hours was declining. Both the yields of spring and summer maize showed increasing trends. (2) Spring maize yields were more related to relative humidity, sunshine hours and precipitation, while summer maize yields were more related to precipitation and temperature. (3) The multivariate nonlinear functions performed better than the linear relationship. Based on the coefficient of determination, climate change has explained 5.8–87.6% variability of spring maize yield and 6.6–78.5% variability of summer maize yield. (4) The contribution importance rank of climate variables to yields of spring and summer maize was precipitation > relative humidity > sunshine hours > minimum temperature > maximum temperature > average temperature. The wet-cold and wet-warm climate, especially the former, had positive effects on maize yield. In conclusion, climate variables affect spring and summer maize yields and their best relationships were site-specific in China. Our research provides new insights for maize planting management under climate change.

1. Introduction

Climate change and variability has wide and far-reaching impacts on human and natural systems (Easterling et al., 2000; Wuethrich, 2000; Tao et al., 2006), and this impact will continue to spread. Climate change, characterized primarily by global warming, was one of the most serious challenges facing the global ecosystem (Alexandrov and Hoogenboom, 2000; Hussain et al., 2009). According to the fifth assessment report made by United Nations Intergovernmental Panel on Climate Change (IPCC) working group I, the global average temperature rose by 0.85 °C from 1880 to 2012, and 1983–2012 could be the warmest 30 years in the last 1400 years in the northern hemisphere (IPCC, 2013). Also, climate change in China has undergone obvious trend variation since last century (Chao et al., 2014). The average

Abbreviations: P_{re}, precipitation; S_{un}, sunshine hours; H_{um}, air relative humidity; T_{ave}, average temperature; T_{min}, minimum temperature; T_{max}, maximum temperature; Y, yield; Δ, the first-order difference; r, Pearson correlation coefficient; R^2_{adj}, adjusted coefficient of determination; RMSE, relative root mean square error.

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surface temperature in China from 2001– 2010 was 1.03 °C higher than 1961–1990, and the average temperature in China in 2015 was 1.46 °C higher than 1961–1990 with a warmer range higher than the global average (Wang et al., 2016). Global warming and climate fluctuation have comprehensively affected the growth of crops and threatened the stability of crop production. Therefore, it is necessary to evaluate the response mechanisms between climate change and crop growth.

The comprehensive effects of climate change on crop yields have been studied by using statistical methods based on historical data (Chmielewski and Potts, 1995; Isik and Devadoss, 2006; Tao et al., 2012), nested crop models and regional climate scenarios based on simulation data (Muchena and Iglesias, 1995; Tao and Zhang, 2011; Liu et al., 2012; Chen et al., 2020). The statistical models were used to represent the relationship between dependent variable (crop yield) and independent variables (climatic variables). Usually, crop simulation models were used to predict the impact of future climate change on crop yields, however the application of statistical analysis methods can provide more direct and accurate information for the assessment of the impact of climate change on crop production (Peng et al., 2004). The primary advantages of statistical models were its limited dependence on field calibration data and transparent evaluation of constructed model uncertainties through higher coefficient of determination (R^2) and lower confidence interval (P value) (Lobell and Burke, 2010).

From the statistical respects, many studies (Welch et al., 2010; Zhao et al., 2015; Adisa et al., 2018) focused on establishing linear regression models by combining the selected climate variables with the yield to quantify the roles of climate variables on explaining yield change. However, only a few studies (Feng et al., 2018; Liu et al., 2019) considered the multicollinearity characteristics of the climate variables. Without considering the multicollinearity of climatic variables, the statistical regression results would be exaggerated or weakened in explaining yield change based on temperature or other climate variables. Regarding statistical models, the linear regression models (including single variable or multiple variables) were used commonly (Peng et al., 2004; Lobell, 2007; Everingham et al., 2016), while few studies (Like Lobell et al., 2011; Gao et al., 2018; Li et al., 2020) have taken into account the non-linear characteristics of climate and crops. A key consideration in statistical analysis whether the linear regression model truly satisfies the interpretation of yield change or not. If not, the establishment of nonlinear regression model of yield may perform better, which needs to be clarified clearly.

Maize is one of the most important food crops in the world (Jones and Thornton, 2003; Niu et al., 2013; Yang et al., 2017; Abera et al., 2018). The increase of maize yield is crucial to the human life, human welfare, and development of national agriculture and animal husbandry. On the one hand, maize efficiency was sensitive to climate change from sowing to harvesting (Adams et al., 1998; Bassu et al., 2014). The effect of global warming on maize yield growth was mainly negative (Lobell and Field, 2007; Liu et al., 2013; Hawkins et al., 2013; Ureta et al., 2016). Climate change affected the growth days and phenology phase of maize through a combination of various climate variables (mainly temperature and precipitation play a major role), and these conditions shortened photosynthesis and grain filling processes and ultimately affected maize yields (Olesen and Bindi, 2002; Chen et al., 2010; Liu et al., 2013). From another hand, maize yield change can directly or indirectly reflect climate change. It is important to study the interactive and feedback between maize and climate change.

The impact of climate change on China's maize yield has not been well researched. Limitations of previous research include: (1) Some of the previous research focused on the provincial scale (Tao et al., 2008; Li et al., 2011; Zhang and Huang, 2012; Chen et al., 2014). The others were based on the site scale in the China's main maize planting belt, including the northeast (Zhao et al., 2015; Zhao et al., 2016), northwest (Wang et al., 2004), southwest (Li et al., 2014) and Huang-Huai-Hai regions (Liu et al., 2010; Chen et al., 2012; Xiao and Tao, 2016). (2) Spring and summer maize were two types. Due to data lacking, limited studies have selected the entire maize belt as study area to investigate the climate change effects on China's spring and summer maize yields. (3) The linear regression models (including single or multiple variables) were used commonly to study the relationships of climate change and crop yield (Peng et al., 2004; Lobell, 2007; Everingham et al., 2016), while only a few studies (Like Lobell et al., 2011; Gao et al., 2018; Li et al., 2020) have considered the non-linear characteristics of climate and crops.

Overall, there are still gaps in the research of climate variability effects on maize yields using both linear and nonlinear regression functions in China's main maize planting belt. Our objectives were: (1) to investigate the trends in climatic variables and spring/summer maize yields at different sites over 1988–2017 so as to supply an overall background for further establishment of regression functions for maize yields, (2) to determine the best linear and nonlinear relationships between the related climatic variables and maize yield after removal of variable multicollinearity, and (3) to compare the impacts of climate change on spring and summer maize yields based on the final best functions. Our study provide references to quantify climate variability on the spring and summer maize growth and yields.

2. Materials and methods

2.1. The studied area and data source

There are six main maize growing areas in China, namely the north spring maize area, the Huang-Huai-Hai Region, the southwest mountain area, the southern hilly area, the northwest inland area, and the Qianghai-Tibetan-plateau area. The largest maize planting area was located along the narrow belt from northeast to southwest (Wang, 2010; Yang et al., 2017). The daily climatic and maize yield data over 1988–2017 at the 121 sites (mainly distributed in the narrow maize belt where spring or summer maize are planted) were collected from the China Meteorological Data Sharing Service Network (http://data.cma.cn/) after strict quality control and inspection. There were 85 sites for spring maize and 36 sites for summer maize, respectively. The elevation and spatial distribution of the selected sites are mapped in Fig. 1.

The collected climatic variables include precipitation (P_{re}, mm), sunshine hours (S_{un}, h), air relative humidity (H_{um},%), average temperature (T_{ave}, °C), minimum temperature (T_{min}, °C) and maximum temperature (T_{max}, °C). The maize growth season was focused on and the growth period average value was used (rather than annual average) to further assess the impact of climate change on maize yields.

We classified the types of maize as spring and summer maize according to the sowing and maturity dates. The periods from planting to maturity were April to September for spring maize and June to October for summer maize. The basic geographical information, annual mean climate variables and yields during the maize growing period are referred to Tables S1 and S2.

2.2. Methods

2.2.1. Computation of the Sen's slope and variation coefficient

The magnitudes (overall rate) of the trend of the studied time series (climate variables and maize yields), namely the Sen's slope (β), were evaluated using the statistic proposed by Sen (1968). A positive (negative) β indicated increasing (decreasing) trend in time series. When $\beta = 0$, there was no trend. Sen's slope method calculated the median value of the sequence and was not affected by outliers. It was stricter than the linear slope of the time series. For the time series x_t ($t = 1, 2, \ldots, n$, $n = 30$ years), the formula for calculating Sen's slope (β) was as follows:

$$\beta = \text{Median}\left(\frac{x_j - x_i}{j - i}\right), \forall j > i \tag{1}$$

The variation coefficient C_V was the ratio of the mean value and standard deviation (Nielsen and Bouma,1985). C_V values were

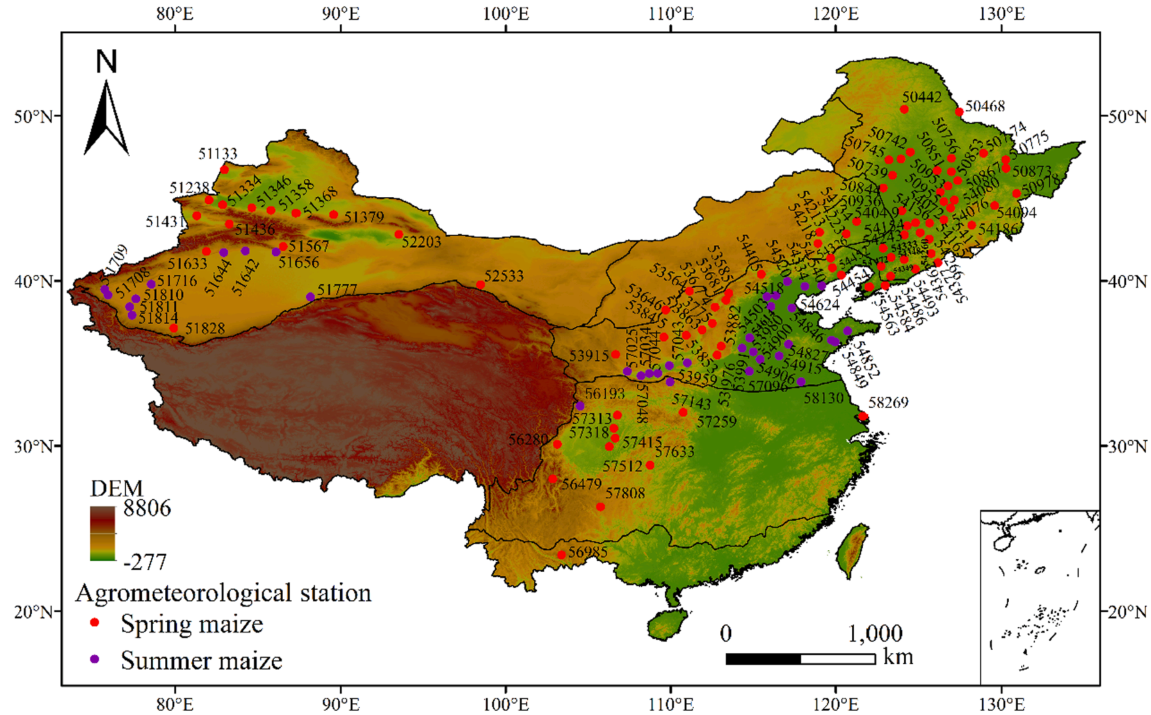

Fig. 1. Spatial distribution of the agrometeorological sites and digital elevation in the main maize growing areas of China.

calculated to show the temporal variability of yield or climatic variables. Variability levels were classified as weak, moderate, or strong with $C_v \leq 0.1$, $0.1 < C_v < 1.0$ and $C_v \geq 1.0$, respectively. β and C_V values were obtained for the annual mean climatic variables and maize yields versus time.

2.2.2. The best equations between maize yield and the related climatic variables

The first-difference value reflected directly the variation of a variable in the two consecutive years. The method of first-order difference can eliminate the mixed effects of non-climate factors such as crop variety, fertilizer and irrigation schedules on crop growth to the greatest extent (Nicholls, 1997). This approach has been applied popularly by Lobell et al. (2005), Lobell and Field (2007) and Bhatt et al. (2014) before assessing climate change effects on crop yields. This is an approved detrending analysis approach which minimized the confounding influences of long-term variations (such as cultivars, crop management practices, fertilizers and pesticides) in yields by calculating their first difference values (Prabnakorn et al., 2018). It was applied here before analyzing the relationship between maize yield and climatic variables. The subsequent regression models were established on the basis of the first differences of the climate variables and maize yields.

The relationship between crop yields and several climatic variables could be linear or non-linear. These quantitative equations can reflect how different climatic variables or climate change affected crop yields. For example, Li et al. (2020) applied both linear and non-linear regression methods to investigate the climate change effects on cotton growth and yield indices. Linear functions had limitations in revealing non-linear characteristics of climate change on crop yields and generally performed worse than non-linear equations (Malone et al., 2009; Lobell et al., 2007). Still, the multi-variable linear regressions were necessary for selecting the key climatic variables that affect maize yields before conducting non-linear multi-variate regressions.

The detail procedures for determining the best equations between maize yield and climatic variables are as follows.

First, the Pearson correlations between maize yield and each the related climatic variables (P_{re}, S_{un}, H_{um}, T_{max}, T_{min} and T_{ave}) were conducted at the significance level of 0.05. We obtained the Pearson correlation coefficient (r) which can reflect the degree of linear correlation between two variables. The rank of the importance of different climatic variables were elementary determined according to the r values.

Second, the multicollinearity among the studied six climate variables (P_{re}, S_{un}, H_{um}, T_{max}, T_{min} and T_{ave}) was analyzed using the variance inflation factor (VIF) (Mansfield and Helms, 1982). The formula of VIF is as follows:

$$VIF = \frac{1}{1 - R^2} \tag{2}$$

where R^2 is the coefficient of determination between pairs of variables x_i and x_j ($i, j = 1, 2, \ldots, 6, i \neq k$). The smaller the VIF values, the stronger the independence between the analyzed climate variables. Therefore, VIF < 10 indicated that the studied climatic variables had no statistical collinearity (Doetterl et al., 2015; Laubhann et al., 2009; Scheller and Mladenoff, 2008). The climatic variables with VIF > 10 was not considered further to establish regression models of maize yields due to their high collinearity. The VIF values of six climate variables were calculated at each site and we removed the climate variable which had the largest VIF value among the climatic variables that had VIF > 10. This procedure was repeated until the VIF value of all the remaining climate variables were less than ten. We kept the most representative set of climate variables that can affect maize yield by removing the climate variables with higher collinearity. The first collinearity test was conducted for six climate variables at the 85 sites for spring maize, and five independent climate variables were found for 42 sites. The second collinearity test was conducted for the rest of 43 sites, and we found that there were 38 sites which had four independent climate variables. The third collinearity test was conducted for the last five sites and three independent climate variables were retained. Finally, we selected the independent climate variables for each site (Table S3). Similar procedure was conducted for 36 sites of summer maize and the estimated VIF values are referred to Table S4.

Third, the remained climate variables with VIF < 10 were used further for multi-variate linear regression. The number of climatic variables increased from one to kk gradually (kk is the number of independent climate variables selected by multicollinearity method) for the multi-variate linear regression, described by the following equation (Nicholls, 1997):

$$\Delta Y = \sum \varepsilon_i \Delta x_i \tag{3}$$

where ΔY and Δx_i are the first-order differences of maize yield and climate variables ($i = 1, 2, \ldots, kk,$), ε_i represents the ith coefficients. The model stability was assessed by the adjusted coefficient of determination (R^2_{adj}). Greater R^2adj values indicated that the model was more stable (Zhang and Li, 2016) at a significance level (0.05 here). The model prediction ability was assessed by relative root mean square error (*RMSE*). Smaller *RMSE* values indicated better model prediction ability (Liu et al., 2013). The detail formula for estimating R^2_{adj} and *RMSE* were referred to Li et al. (2020) and will not be described in detail here. There were five, ten, ten, 15 and one equation (total 31 equations) during the one-, two-, …, to five-variable linear regression procedure at each site. The key climatic variables that played important roles in affecting maize yields could be selected with the largest R^2_{adj} and the smallest *RMSE* values among the 31 equations. Through this process, the invalid variables were removed and the best linear equation for maize yield was selected for each site.

Fourth, we conducted the nonlinear multi-variable regression by considering the first, second and third power and product of the climatic variables. We assumed the number of key climatic variables was m, then $2m + C_m^2$non-linear climatic variables could be considered to conduct nonlinear multi-variable regression, and total $3m + C_m^2$climatic variables or their combinations were used. The regression procedure with input climatic variable number of one-, two-, …, to $3m + C_m^2$contained $C^1_{3m+C_m^2}$, $C^2_{3m+C_m^2}$, $C^3_{3m+C_m^2}$, …, to $C^{3m+C_m^2}_{3m+C_m^2}$ equation(s), respectively. So, a total of $\sum_{j=1}^{3m+C_m^2} C^j_{3m+C_m^2}$ equations for maize yield were obtained at each site.

Finally, from all the available linear or non-linear equations, the equation with the largest R^2_{adj} and the smallest *RMSE* was chosen as the best equation of the maize yield. The best model showed the climate change effects during the growing season. The flow chart of this research is shown in Fig. 2.

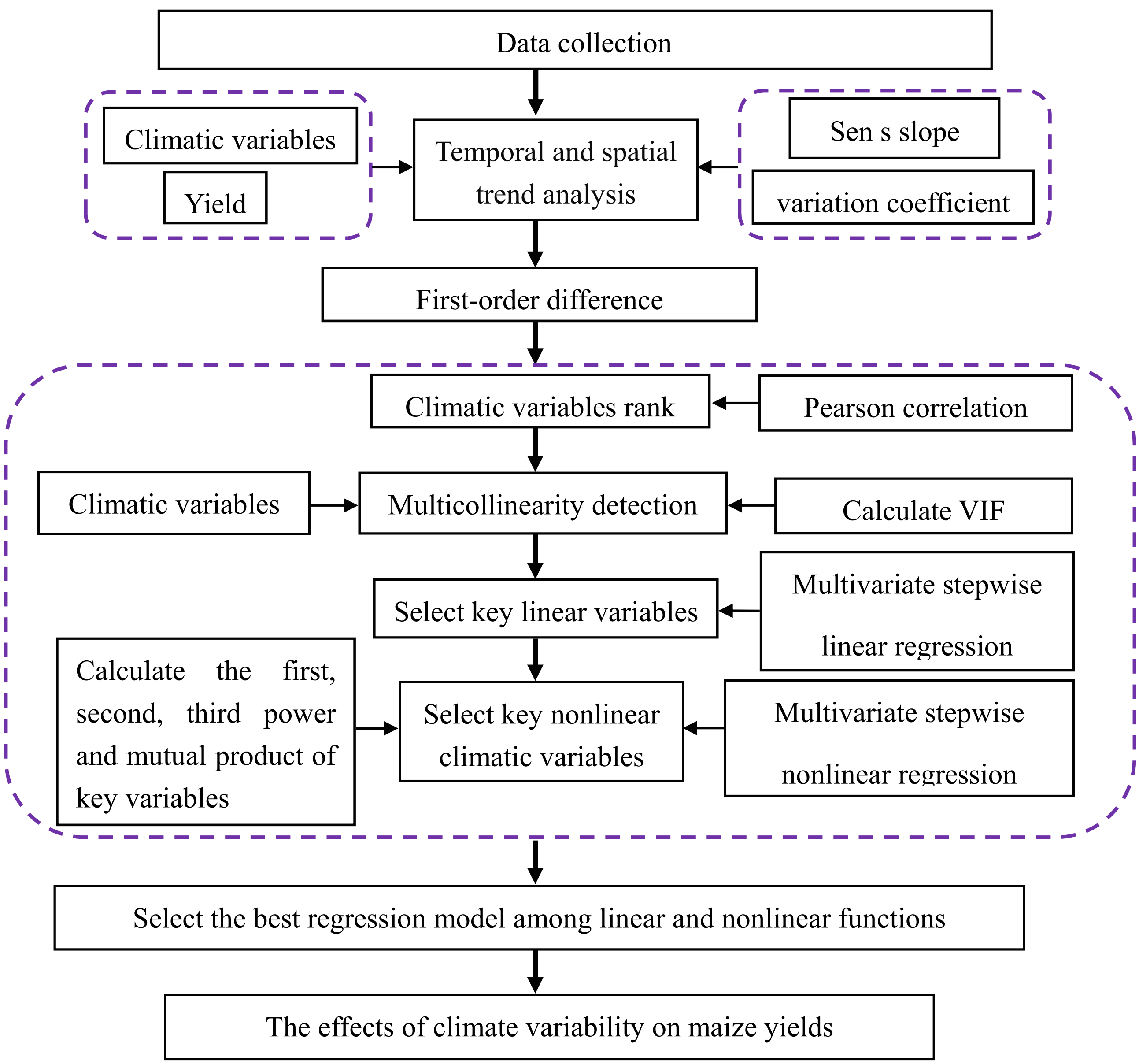

Fig. 2. The framework of this research.

3. Results

3.1. Temporal and spatial variations

3.1.1. Climatic variables

The box plots of temporal and spatial variations for P_{re}, S_{un}, H_{um}, T_{max}, T_{min} and T_{ave} during the maize growing seasons of spring maize over 1988 to 2017 at the 85 sites are illustrated in Fig. 3. The fluctuation ranges for P_{re}, S_{un}, H_{um}, T_{max}, T_{min}, and T_{ave} were 7–1717 mm, 458–2776 h, 28–87%, 15–29 °C, 2–20 °C and 8–24 °C, respectively. The C_V values of P_{re}, S_{un}, H_{um}, T_{max}, T_{min}, and T_{ave} ranged from 0.47 - 0.68, 0.18–0.23, 0.13–0.17, 0.10–0.16, 0.29–0.37 and 0.15–0.2, respectively. The variability levels of all climatic variables were moderate, and the rank of the variability level was $P_{re} > T_{min} > S_{un} > T_{ave} > H_{um} > T_{max}$. The differences and ranges in the climatic variables reflected the general climate conditions in the studied area of spring maize, and of summer maize.

The box plots of temporal and spatial variations in the P_{re}, S_{un}, H_{um}, T_{max}, T_{min} and T_{ave} during the summer maize growing seasons over 1988 to 2017 at the 36 sites are illustrated in Fig. 4. The fluctuation ranges for P_{re}, S_{un}, H_{um}, T_{max}, T_{min}, and T_{ave} were 2–1328 mm, 403–1946 h, 31–82%, 24–33 °C, 10–20 °C and 18–24 °C, respectively. The C_V values of P_{re}, S_{un}, H_{um}, T_{max}, T_{min}, and T_{ave} ranged from 0.53- 0.73, 0.12–0.29, 0.16–0.24, 0.03–0.06, 0.08–0.12, and 0.04–0.05, respectively. The variability levels of P_{re}, S_{un} and H_{um} were moderate and of T_{max}, T_{min}, and T_{ave} were weak. The variability extent of the climatic variables was $P_{re} > S_{un} > H_{um} > T_{min} > T_{ave} > T_{max}$.

3.1.2. Yields of spring and summer maize

The temporal and spatial variations in the yields during maize growing seasons of 1988 to 2017 at the total 121 sites in China, are illustrated as box plots in Fig. 5. Yields of spring maize and summer maize fluctuated within ranges of 1.2–16.7 t ha^{-1} and 0.3–11.6 t ha^{-1}, respectively. The variation range of the variation coefficient of yields of spring maize and summer maize were 0.15–0.58 and 0.21–0.55, respectively. The concentrated middle parts of the boxes show the general increase in the maize yields in the last 30 years, but the growth rate has slowed down in recent years. This may be due to i) global warming affected yield growth, and ii) the improvement space of the yield increasing technology were limited.

The doubled yield increase of spring maize yields in 2017 maybe combination effects of climate change and crop management practices.

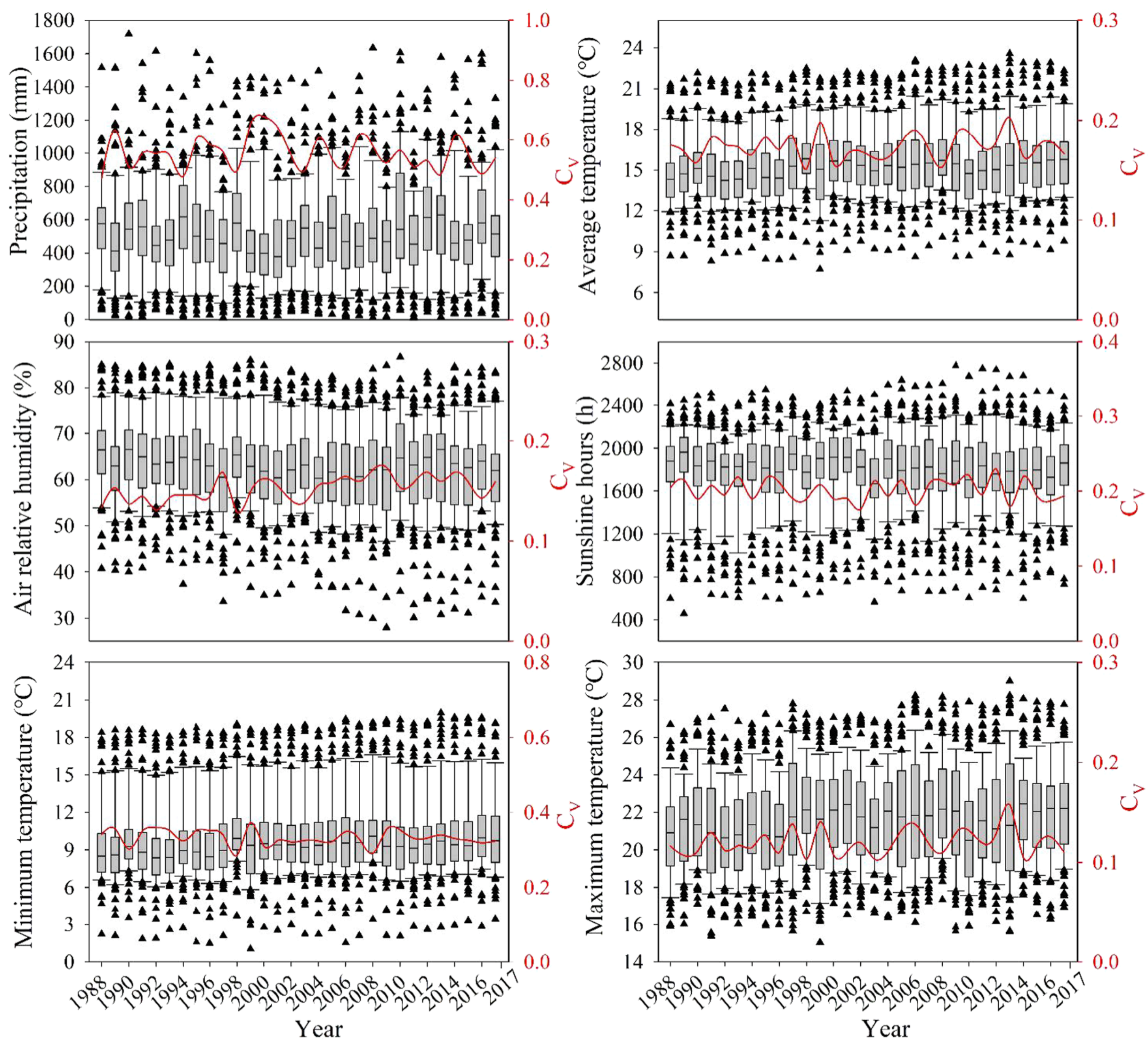

Fig. 3. The box plots and variation coefficient curves of the climatic variables during spring maize growth season over 1988–2017 at the 85 sites in China. Horizontal line: median; box-boundaries: 25th and 75th percentiles; whiskers: 10th and 90th percentiles; triangles: outliers; red lines: variation coefficient curve of the climatic variables (similar below). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

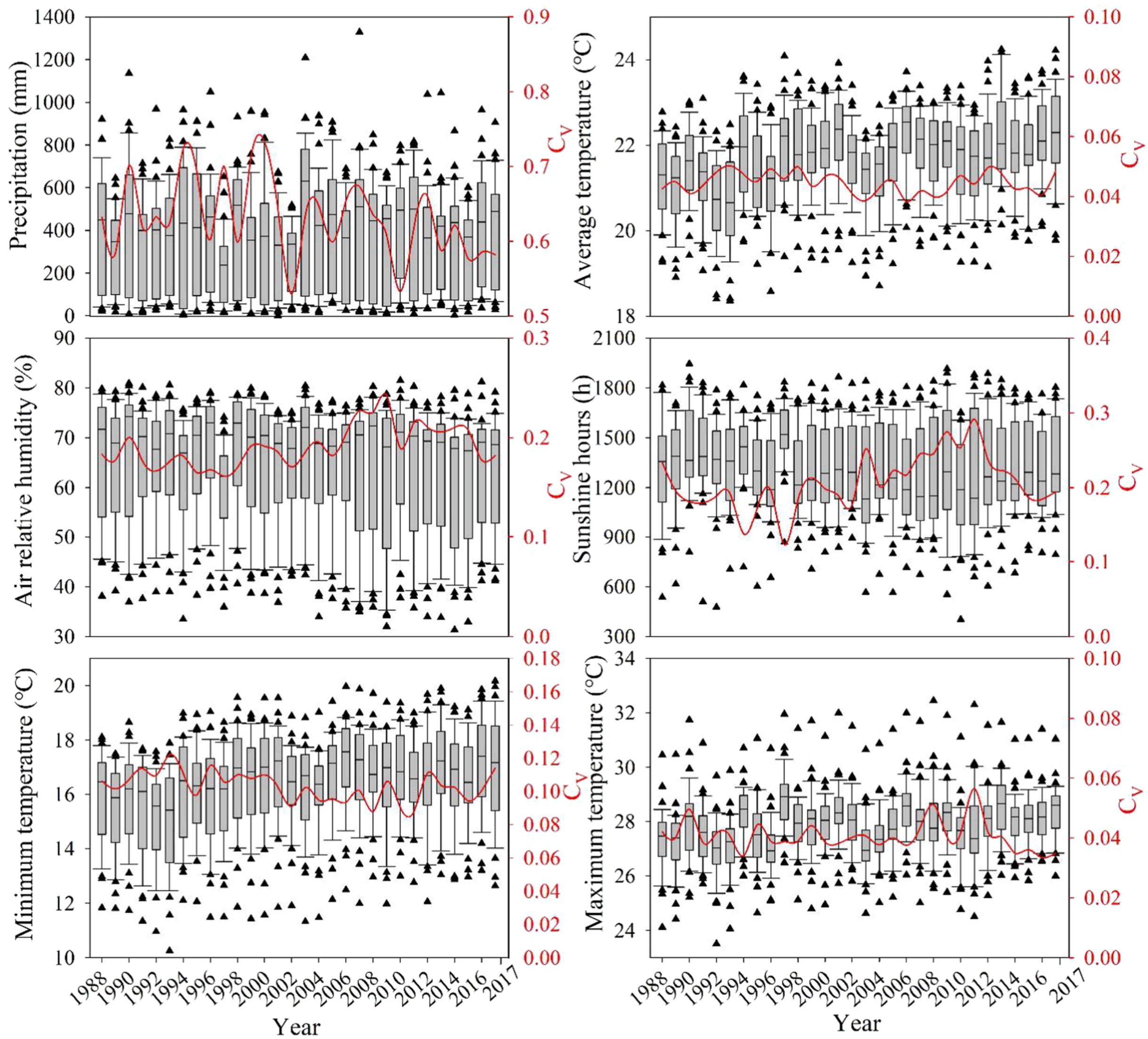

Fig. 4. The box plots and variation coefficient curve of the climatic variables during summer maize growth season over 1988–2017 at the 36 sites in China.

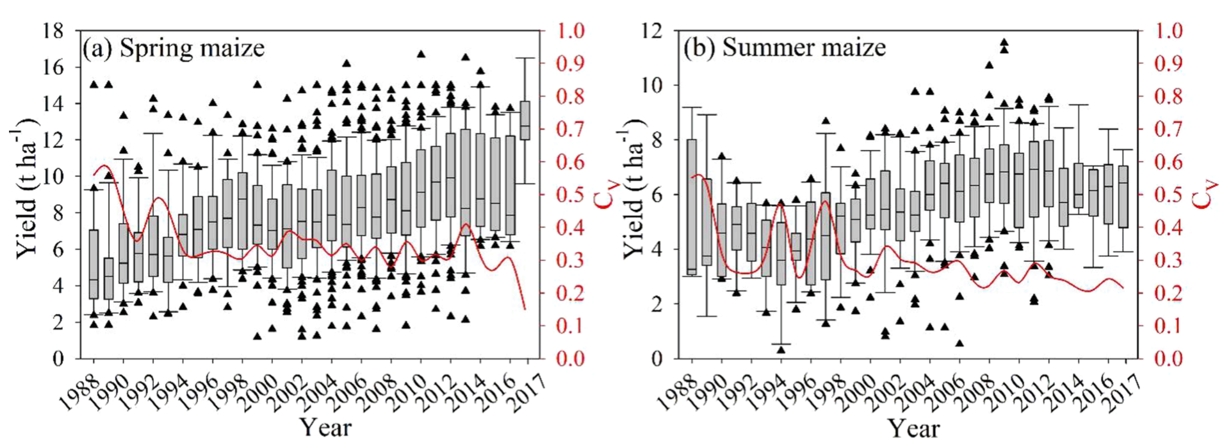

Fig. 5. The box plots and variation coefficient curve of maize yield over 1988 – 2017 at the 121 sites in China.

However, among the 85 spring maize sites, only 8 sites for spring maize contained the yield data in 1988–2017 and 1 site contained yield data in 1991–2017 (Table S5), which only represented 10.6% of the total sites. Nicholls (1997) showed that the fluctuations in wheat yield was caused by climate change and the slow increase in yield was caused by crop management practices. Although it is difficult to obtain and observe long-term crop management and to quantify its impacts on maize yields, we preliminary inferred that the doubled yield increase of spring maize yields in 2017 was more affected by crop management practices.

Among the 36 summer maize sites, yield data during 1988–1995 were only available at 11 sites, accounting for 30.6% of the total studied sites (Table S6). To reveal which climate variables contributed to the decrease of the summer maize yield in 1988–1995, the Pearson's correlation coefficients (r) between the first-order difference of maize yield (ΔY) and six related climate variables (ΔX_i) during the maize growing season in 1988–1995 are presented in Table 1. The results showed that: (1) The average r values between ΔY of summer maize and ΔP_{re}, ΔT_{ave}, ΔH_{um}, ΔS_{un}, ΔT_{mi}, ΔT_{max} were −0.13, 0.05, 0.18, −0.27, 0.09 and 0.007, respectively. (2) Among the 11 sites, ΔY were negatively correlated with ΔP_{re} at 7 and with ΔS_{un} at 8 sites, of which, 1 and 1 sites exhibited significant correlations, respectively. (3) Since P_{re} had a larger increase trends during the growth periods of summer maize than spring maize over the past 30 years (section 3.1.1), it indicated that the summer maize yield decrease in 1988–1995 may attribute to precipitation increase and sunshine hour decrease.

The feedback of spring maize and summer maize yields in 1988–1995 to precipitation is opposite. This is mainly due to the different sowing and growth periods of spring maize and summer maize. Spring maize is sown during April to early May, and when precipitation increases in the flourishing period (June to July) of spring maize, the growth and yield of spring maize will be promoted, and thus a positive feedback of precipitation effect on spring maize yield occurred. While summer maize is mainly sown during end of June to early July, when precipitation increases, the germination rate of summer maize and its growth will be decreased, which decrease summer maize yield, so the feedback of precipitation on summer maize yield is negative.

3.2. Variations of Sen's slope values

3.2.1. For the climatic variables

In Fig. 6, P_{re} showed an increasing trend, while S_{un} and H_{um} showed a decreasing trend during 1988–2017 at most sites of spring maize and summer maize, and T_{ave}, T_{min} and T_{max} at most sites showed significant increasing trends. For P_{re}, S_{un} and H_{um}, the Sen's slope values of spring and summer maize were 0.46 and 0.57 mm a^{-1}, −0.24 and −2.69 h a^{-1} and −0.12 and −0.13 % a^{-1}, and for T_{ave}, T_{min} and T_{max}, values were 0.03 and 0.03 °C a^{-1}, 0.04 and 0.05 °C a^{-1} and 0.04 and 0.02 °C a^{-1}, respectively.

3.2.2. For spring and summer maize yields

From 1988 to 2017, maize yields at most sites showed increasing trends, only 11 sites of spring maize sites and seven sites of summer maize showed insignificant decreasing trends (Fig. 7). Yield increased in most spring maize and summer maize sites and increase range of both ranged from 0.037 to 0.72 and 0.046 to 0.37 t ha^{-1} a^{-1}, respectively. The average yield growth of spring maize and summer maize was 0.21 and 0.12 t ha^{-1} a^{-1}, respectively. The increase of spring maize yield in northeast, northwest and south China was generally increasing. The increase of summer maize yield in Huang-Huai-Hai region and northwest China increased slowly.

Table 1
The Pearson's correlation coefficients (r) between the first-order difference of summer maize yield (ΔY) and the first-order difference of six climate variables (ΔX_i) during the maize growing season in 1988–1995. * and ** denote passing the significance test at levels of $P < 0.05$ and $P < 0.01$.

Site	ΔYield vs.					
	ΔP_{re}	ΔT_{ave}	ΔR_{hu}	ΔS_{un}	ΔT_{min}	ΔT_{max}
51656	0.321	0.079	0.058	−0.222	0.033	0.005
51708	−0.332	0.231	0.501	−0.258	0.344	0.137
51709	-0.76*	0.495	−0.444	−0.602	0.644	0.266
51716	−0.29	0.82*	−0.078	−0.227	0.904*	0.59
51777	0.558	−0.298	0.675	−0.418	−0.172	−0.427
51810	−0.549	0.22	0.124	0.485	0.042	0.295
51814	−0.16	−0.443	0.499	−0.945**	−0.234	−0.57
57025	−0.53	0.173	−0.204	0.239	0.166	0.168
57034	−0.28	0.647	−0.333	0.458	0.769	0.572
57043	0.371	−0.664	0.74	−0.81	−0.743	−0.446
57044	0.167	−0.685	0.417	−0.619	−0.747	−0.517

3.3. The best equations between maize yield and the related climatic variables

3.3.1. Pearson's correlation

The rank of the importance of different climatic variables were elementarily determined according to the Pearson correlation coefficient (r). The r values between the first differences of yields (ΔY) and climatic variables (Δx_i) during the maize growing season are shown in Fig. 8. The results showed that: (1)The average Pearson correlation coefficient values over 30 years of spring maize between ΔY and ΔH_{um}, ΔS_{un}, ΔP_{re}, ΔT_{min}, ΔT_{max} and ΔT_{ave} were 0.050, 0.048, 0.023, −0.007, 0.004 and −0.00051, respectively. Spring maize yields were most positively correlated with H_{um}, P_{re} and S_{un} at 47, 52 and 46 sites, with four, two and six sites exhibiting significant correlations (P-value ≤ 0.05), respectively. The correlations of spring maize yields with T_{mix} and T_{ave} were negative at 37 and 40 sites, respectively, with significant correlations at three and four sites. Spring maize yields were positively correlated with T_{max} at 47 sites, with three sites exhibiting significant correlations. Therefore, the ranking of climate variables affecting spring maize yields can be obtained by absolute values of r, i.e. $H_{um} > S_{un} >$ Pre $> T_{min} > T_{max} > T_{ave}$. (2)The average r values between ΔY of summer maize and ΔP_{re}, ΔT_{ave}, ΔT_{max}, ΔT_{min}, ΔS_{un} and ΔH_{um} were −0.055,0.033,0.025, 0.022, 0.011 and −0.007, respectively. The strongest positive correlations between summer maize yields and T_{ave}, T_{max}, T_{min} and S_{un} were found at 19,19,18 and 18 sites, respectively, being significant at two, one, two and one sites, respectively. Summer maize yields were most negatively correlated with P_{re} and H_{um} at 21 and 17 sites with three and one sites exhibiting significant correlations, respectively. Therefore, the ranking of climate variables affecting summer maize yields can be obtained by the absolute r values, i.e. $P_{re} > T_{ave} > T_{max} > T_{min} > S_{un} > H_{um}$.

In conclusion, the overall ranking of climate variables affecting spring and summer maize yields may vary due to maize type, geographical and technical differences. Ultimately, we concluded that P_{re}, H_{um}, S_{un}, T_{min}, T_{max} and T_{ave} were all key variables affecting maize yield. Their variations were random by nature although the r values had opposite signs at some adjacent sites (Figure S1).

3.3.2. The best equations of spring and summer maize yields

3.3.2.1. The best single and multivariate linear regression equations. We took the site 51709(Kashen) as an example for denoting the results of selecting the best single and multivariate linear regression equations. From the collinearity test, five climate variables of P_{re}, H_{um}, S_{un}, T_{min}, T_{max} were found to be independent from each other. The linear correlation function between ΔY and the selected five variables are given in Table 2. A best linear function $\Delta Y = 0.426\Delta T_{min}$ was selected (with the largest R^2_{adj} of 0.151 and the smallest $RMSE$ of 1.374).

The multivariate linear regression functions of ΔY, correlated with two-, three-, four- and five-climate variables, and their performance (shown by R^2_{adj} and $RMSE$) are given in Table 3. The best two-, three-, four-, and five-variate linear regression functions were selected (bold in Table 3). Of them, the two-variable equation ($\Delta Y = -0.29\Delta S_{un} + 0.381\Delta T_{min}$) had the largest R^2_{adj} and the smallest $RMSE$ values, therefore it was selected as the best multivariate linear equation for ΔY. In addition, S_{un} and T_{min} were the most important climatic variables affecting summer maize yield of the site 51709. By further comparing the performance of the best single and multivariate linear functions, the two-variable equation ($\Delta Y = -0.29\Delta S_{un} + 0.381\Delta T_{min}$) performed better than the best single-variate linear function for ΔY at the site 51709.

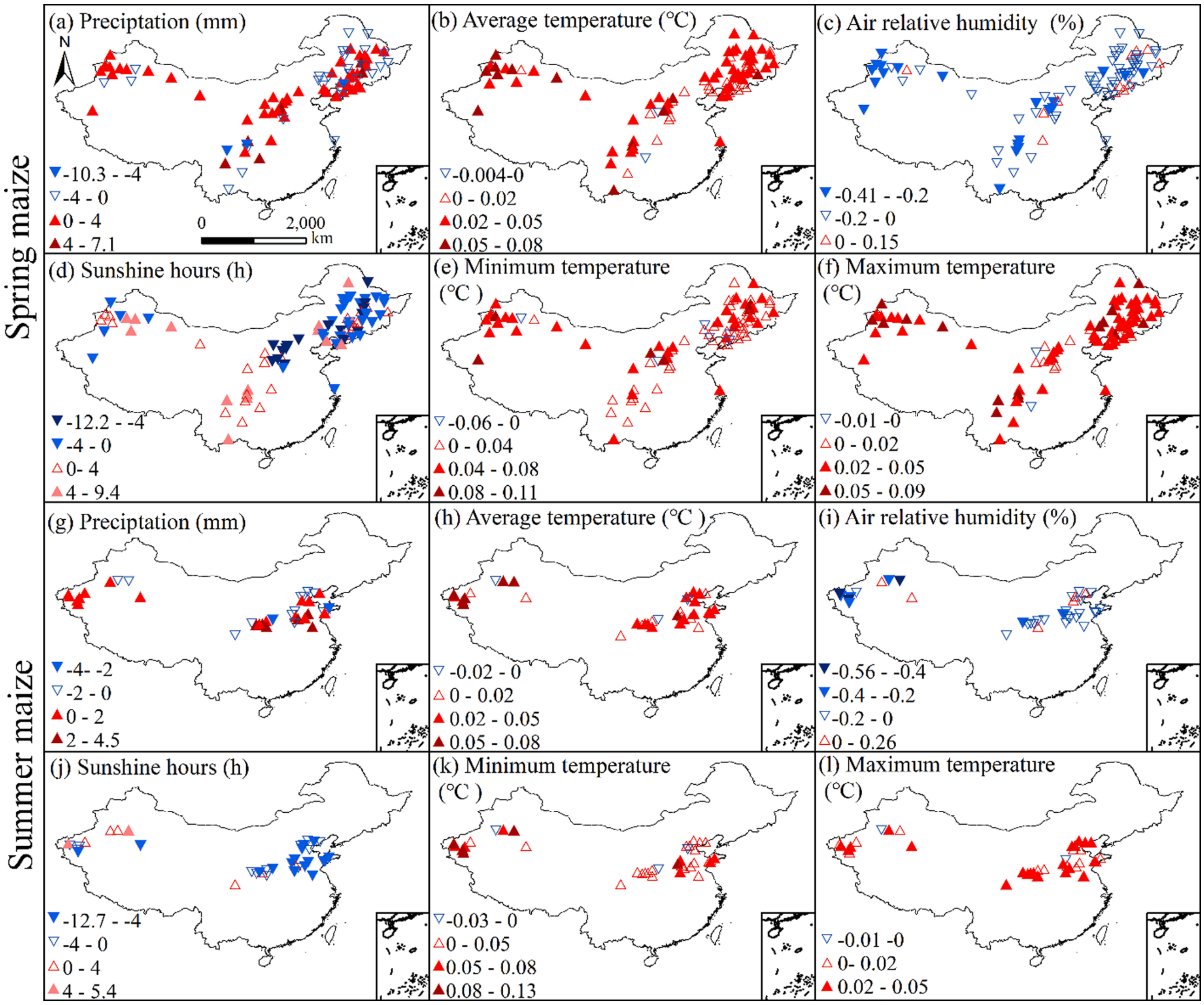

Fig. 6. Sen's slope values of the climatic variables during maize growth season over 1988–2017 at the 85 sites for spring maize and at the 36 sites for summer maize in China. Red and blue grids represent increase and decrease trends, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

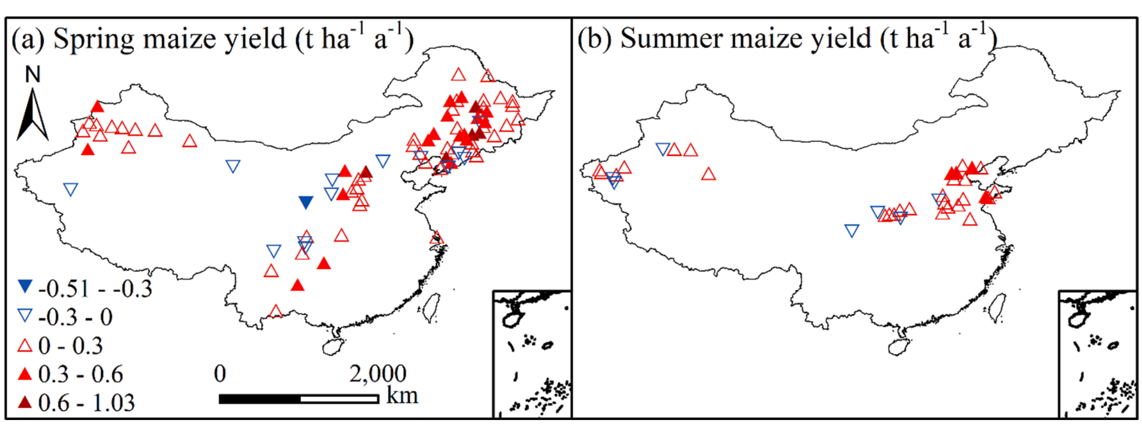

Fig. 7. Sen's slope of yields for spring and summer maize at the 121 sites in China.

3.3.2.2. The best multivariate nonlinear regression equations. After we obtained the key climate variables that affected maize yield at each site, we obtained the stepwise nonlinear regression functions. Also taking the site 51709 as the example, there were 5, 20, 35, 35, 21, 7 and 1 (total 124 equations) multivariate nonlinear equations for ΔY which were described by ΔS_{un} and ΔT_{min} with seven items of ΔS_{un}, ΔT_{min}, $\Delta S_{un} \times \Delta T_{min}$, ΔS_{un}^2, ΔT_{min}^2, ΔS_{un}^3 and ΔT_{min}^3 (Table 4). Finally, the performance of the best linear and nonlinear equations was compared for ΔY of

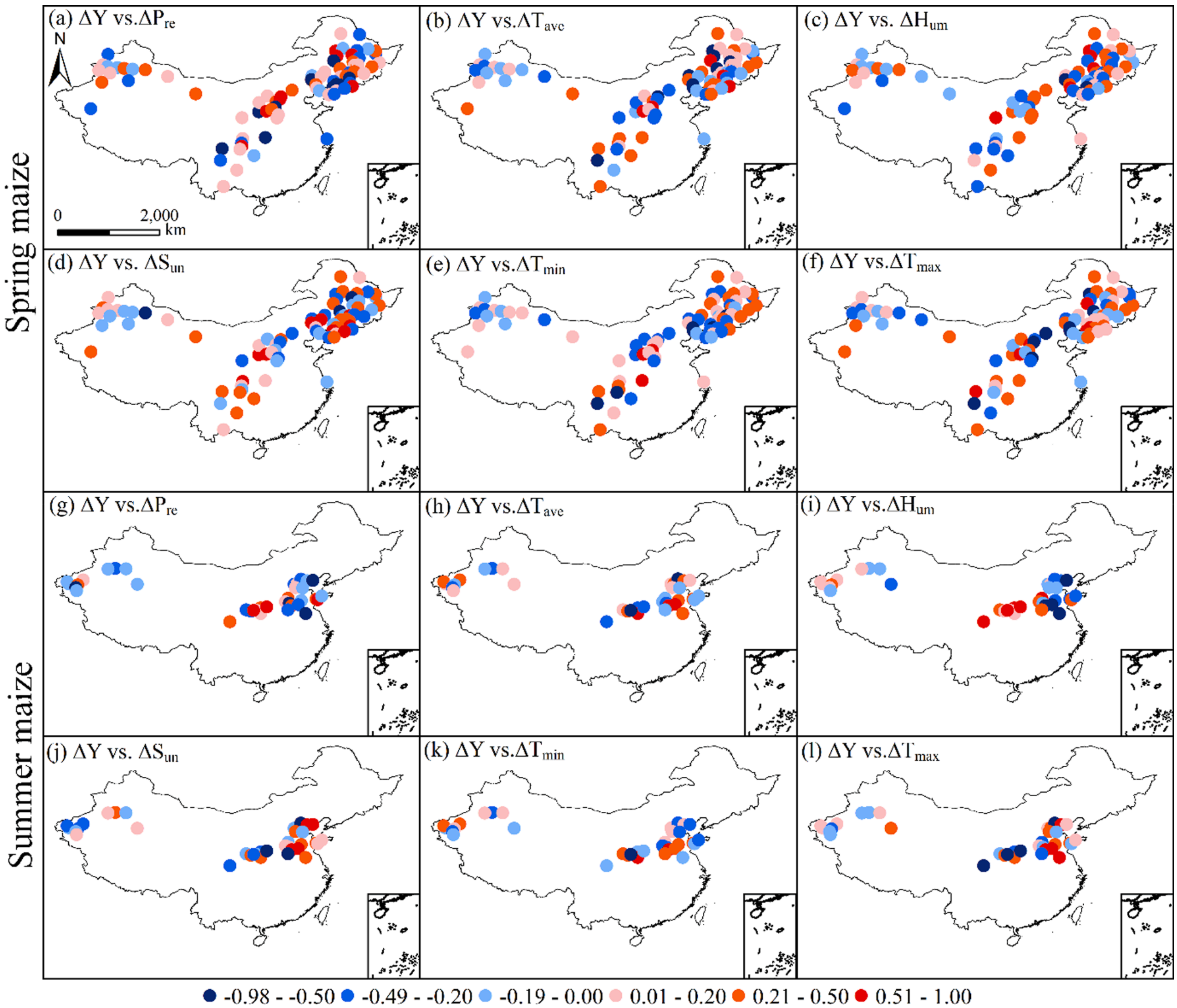

Fig. 8. Pearson's correlation coefficients between the first-order differences of maize yield (ΔY) and the related climatic variables (Δx_i).

Table 2
Fitted single variable correlation equations for ΔY and the performance at the site 51709.

No. of equation	Equation	R^2_{adj}	*RMSE*	*P*-value
1	$\Delta Y = -0.08\Delta P_{re}$	−0.03	1.514	0.679
2	$\Delta Y = 0.006\Delta H_{um}$	−0.037	1.519	0.975
3	$\Delta Y = -0.35\Delta S_{un}$	0.09	1.424	0.063
4	$\boldsymbol{\Delta Y = 0.426\Delta T_{min}}$	**0.151**	**1.374**	**0.021**
5	$\Delta Y = 0.131\Delta T_{max}$	−0.019	1.506	0.498

summer maize and the equation $\boldsymbol{\Delta Y = -0.405\Delta S_{un} + 0.631\Delta S_{un} \times \Delta T_{min} + 0.759\Delta T^3_{min}}$(with R^2_{adj} of 0.238 and *RMSE* of 1.253) was the best multivariate nonlinear equation for ΔY of summer maize at the site 51709.

We found that the single variate linear regression performed worse than multivariate linear regression, and the linear regression performed worse than the nonlinear regression. We implied that the crop growth, development and production were affected by climate change non-linearly to a great extent at the site 51709. This was reasonable since climate change is complex.

3.3.2.3. The site-specific best equations. Similarly, we compared the best single or multivariate linear and multivariate nonlinear functions and their performance to select the best functions for spring maize at the other 85 sites (Table 5). The number of best nonlinear equations was larger than the best linear equations. Among the 85 sites, 58 sites had the best nonlinear equations (linear at 27 sites). The climatic variables quantitatively explained the extent of yield change with 0.058 (site 50468) $< R^2_{adj} <$ 0.876 (site 53646). At the site 50468, yield change was only related P_{re} with a smallest R^2_{adj} among all sites. The site 53646 had the largest R^2_{adj} for nonlinearly correlating yield change with the related climatic variables in all sites.R^2_{adj} values of multivariate non-linear functions were generally larger (AverageR^2_{adj} = 0.51), which indicated the nonlinear attributions of the yield change. We found the selected best equations could be simple (single variable for 32 sites) or complex (multi-variate for 53 sites). Among the best equations of the 85 sites, yields at the 43 (or 40, 37, 29, 27 and 5) sites were related to P_{re} (or H_{um}, S_{un}, T_{min}, T_{max}, and T_{ave}, respectively). Yield was mostly related to P_{re}, H_{um} and S_{un}, followed by T_{min} and T_{max}, and the least related to T_{ave}. However, we were uncertain how much the role of P_{re} and H_{um} played on the development of maize yields.

The best functions for summer maize yields and their performance at the selected 36 sites are presented in Table 6. Similar to spring maize, there were more nonlinear equations (26 sites) than linear equations (10

Table 3
The fitted multivariate linear equations for ΔY correlating with two, three, four, to five climate variables and their performance at site 51709.

No. of climatic variables	No. of equation	Equation	R^2_{adj}	*RMSE*	*P*-value
2	1	$\Delta Y = -0.191\Delta P_{re} + 0.149\Delta H_{um}$	−0.059	1.507	0.808
2	2	$\Delta Y = -0.157\Delta P_{re} - 0.381\Delta S_{un}$	0.08	1.404	0.129
2	3	$\Delta Y = -0.006\Delta P_{re} + 0.425\Delta T_{min}$	0.119	1.374	0.074
2	4	$\Delta Y = -0.013\Delta P_{re} + 0.124\Delta T_{max}$	−0.058	1.506	0.797
2	5	$\Delta Y = -0.14\Delta H_{um} - 0.401\Delta S_{un}$	0.073	1.410	0.142
2	6	$\Delta Y = 0.128\Delta H_{um} + 0.46\Delta T_{min}$	0.135	1.361	0.058
2	7	$\Delta Y = 0.116\Delta H_{um} + 0.196\Delta T_{max}$	−0.048	1.499	0.706
2	**8**	$\boldsymbol{\Delta Y = -0.29\Delta S_{un} + 0.381\Delta T_{min}}$	**0.207**	**1.304**	**0.019**
2	9	$\Delta Y = -0.376\Delta S_{un} + 0.184\Delta T_{max}$	0.091	1.396	0.111
2	10	$\Delta Y = 0.535\Delta T_{min} - 0.185\Delta T_{max}$	0.143	1.356	0.052
3	11	$\Delta Y = -0.129\Delta P_{re} - 0.04\Delta H_{um} - 0.39\Delta S_{un}$	0.044	1.520	0.257
3	12	$\Delta Y = -0.217\Delta P_{re} + 0.291\Delta H_{um} + 0.466\Delta T_{min}$	0.124	1.344	0.1
3	13	$\Delta Y = -0.144\Delta P_{re} + 0.209\Delta H_{um} + 0.17\Delta T_{max}$	−0.081	1.492	0.822
3	**14**	$\boldsymbol{\Delta Y = -0.079\Delta P_{re} - 0.309\Delta S_{un} + 0.364\Delta T_{min}}$	**0.182**	**1.299**	**0.046**
3	15	$\Delta Y = -0.081\Delta P_{re} - 0.386\Delta S_{un} + 0.142\Delta T_{max}$	0.059	1.393	0.217
3	16	$\Delta Y = -0.129\Delta P_{re} + 0.564\Delta T_{min} - 0.271\Delta T_{max}$	0.121	1.346	0.104
3	17	$\Delta \mathrm{Y} = 0.002\Delta \mathrm{H}_{um} - 0.289\Delta \mathrm{S}_{un} + 0.382\Delta \mathrm{T}_{min}$	0.175	1.304	0.05
3	18	$\Delta Y = -0.046\Delta H_{um} - 0.389\Delta S_{un} + 0.16\Delta T_{max}$	0.056	1.396	0.227
3	19	$\Delta Y = 0.066\Delta H_{um} + 0.529\Delta T_{min} - 0.144\Delta T_{max}$	0.112	1.564	0.116
3	20	$\Delta Y = -0.269\Delta S_{un} + 0.436\Delta T_{min} - 0.088\Delta T_{max}$	0.181	1.300	0.047
4	21	$\Delta \mathrm{Y} = -0.169\Delta \mathrm{P}_{re} + 0.136\Delta \mathrm{H}_{um} - 0.273\Delta \mathrm{S}_{un} + 0.39\Delta \mathrm{T}_{min}$	0.156	1.293	0.089
4	22	$\Delta Y = -0.09\Delta P_{re} + 0.015\Delta H_{um} - 0.383\Delta S_{un} + 0.145\Delta T_{max}$	0.02	1.398	0.36
4	23	$\Delta Y = -0.284\Delta P_{re} + 0.245\Delta H_{um} + 0.574\Delta T_{min} - 0.223\Delta T_{max}$	0.113	1.325	0.145
4	**24**	$\boldsymbol{\Delta Y = -0.159\Delta P_{re} - 0.282\Delta S_{un} + 0.467\Delta T_{min} - 0.19\Delta T_{max}}$	**0.166**	**1.285**	**0.079**
4	25	$\Delta Y = -0.043\Delta H_{um} - 0.281\Delta S_{un} + 0.436\Delta T_{min} - 0.11\Delta T_{max}$	0.148	1.358	0.098
5	**26**	$\boldsymbol{\Delta Y = -0.225\Delta P_{re} + 0.11\Delta H_{um} - 0.255\Delta S_{un} + 0.48\Delta T_{min} - 0.176\Delta T_{max}}$	**0.135**	**1.281**	**0.138**

Table 4
The fitted multivariate nonlinear equations for ΔY and their performance at the site 51709.

No. of Equation	No. of climatic variables	Equation	R^2_{adj}	*RMSE*	*P*-value
1	1	$\Delta Y = -0.206\Delta S_{un} \times \Delta T_{min}$	0.007	1.487	0.285
2	1	$\Delta Y = 0.175\Delta S^2_{un}$	−0.005	1.496	0.364
3	1	$\Delta Y = 0.285\Delta T^2_{min}$	0.047	1.694	0.135
4	1	$\Delta Y = -0.312\Delta S^3_{un}$	0.064	1.444	0.1
5	**1**	$\boldsymbol{\Delta Y = 0.406\Delta T^3_{min}}$	**0.134**	**1.388**	**0.029**
6	2	$\Delta Y = -0.34\Delta S_{un} - 0.018\Delta S_{un} \times \Delta T_{min}$	0.055	1.424	0.183
7	2	$\Delta Y = -0.337\Delta S_{un} + 0.145\Delta S^2_{un}$	0.077	1.407	0.134
8	2	$\Delta Y = -0.292\Delta S_{un} + 0.201\Delta T^2_{min}$	0.095	1.393	0.105
9	2	$\Delta Y = -0.308\Delta S_{un} - 0.049\Delta S^3_{un}$	0.055	1.423	0.182
10	2	$\Delta Y = -0.227\Delta S_{un} + 0.318\Delta T^3_{min}$	0.148	1.352	0.048
11	2	$\Delta Y = 0.407\Delta T_{min} - 0.05\Delta S_{un} \times \Delta T_{min}$	0.121	1.373	0.071
12	2	$\Delta Y = 0.439\Delta T_{min} - 0.027\Delta S^2_{un}$	0.119	1.374	0.073
13	2	$\Delta Y = 0.375\Delta T_{min} + 0.112\Delta T^2_{min}$	0.129	1.366	0.063
14	**2**	$\boldsymbol{\Delta Y = 0.368\Delta T_{min} - 0.21\Delta S^3_{un}}$	**0.163**	**1.340**	**0.038**
15	2	$\Delta Y = 0.279\Delta T_{min} + 0.192\Delta T^3_{min}$	0.135	1.362	0.058
16	2	$\Delta Y = -0.162\Delta S_{un} \times \Delta T_{min} + 0.112\Delta S^2_{un}$	−0.02	1.479	0.493
17	2	$\Delta Y = -0.025\Delta S_{un} \times \Delta T_{min} + 0.268\Delta T^2_{min}$	0.011	1.457	0.332
18	2	$\Delta Y = 0.035\Delta S_{un} \times \Delta T_{min} - 0.337\Delta S^3_{un}$	0.028	1.443	0.263
19	2	$\Delta Y = 0.351\Delta S_{un} \times \Delta T_{min} + 0.69\Delta T^3_{min}$	0.147	1.352	0.048
20	2	$\Delta Y = -0.003\Delta S^2_{un} + 0.287\Delta T^2_{min}$	0.01	1.457	0.334
21	2	$\Delta Y = 0.097\Delta S^2_{un} - 0.285\Delta S^3_{un}$	0.037	1.678	0.234
22	2	$\Delta Y = -0.091\Delta S^2_{un} + 0.459\Delta T^3_{min}$	0.106	1.411	0.088
23	2	$\Delta Y = 0.176\Delta T^2_{min} - 0.228\Delta S^3_{un}$	0.054	1.646	0.186
24	2	$\Delta Y = -0.057\Delta T^2_{min} + 0.449\Delta T^3_{min}$	0.102	1.387	0.094
25	2	$\Delta Y = -0.108\Delta S^3_{un} + 0.342\Delta T^3_{min}$	0.109	1.382	0.086
…	…	…	…	…	…
124	**7**	$\boldsymbol{\Delta Y = -0.514\Delta S_{un} + 0.082\Delta T_{min} + 0.579\Delta S_{un} \times \Delta T_{min} - 0.106\Delta S^2_{un} + 0.114\Delta T^2_{min} + 0.172\Delta S^3_{un} + 0.69\Delta T^3_{min}}$	**0.114**	**1.239**	**0.216**

sites). The fitted performance varied with $0.066 < R^2_{adj} < 0.785$. The ΔY function of the site 51814 contained only a single nonlinear variable (T^2_{max}) and had the smallest R^2_{adj} among all sites. The ΔY function of the site 54534was a two-variables (S_{un} and $H_{um} \times T_{min}$) nonlinear expression with the largest R^2_{adj}.R^2_{adj} of non-linear multivariate functions were generally larger (Average$R^2_{adj} = 0.46$), which indicated the important climate change effects on yields. But at a few sites, the best equations also were kept linear. The selected best equations were simple at 15 sites but complex at 21 sites. Among the regressive equations of the 36 sites, yields at the 19 (or 17, 15, 11, 8 and 0) sites were related to P_{re} (or H_{um}, S_{un}, T_{min}, T_{max}, and T_{ave}, respectively). Like spring maize, yield of

Table 5
The best regression equation for spring maize yield and their performance at the 85 sites.

Site number	Equation	R^2 adj	*RMSE*	*P*-value
50442	$\Delta Y = 0.578\Delta T_{\min} + 0.267\Delta S_{un}^2 + 0.52\Delta S_{un}^3$	0.353	0.958	0.003
50468	$\Delta Y = -0.304\Delta P_{re}$	0.058	0.891	0.109
50739	$\Delta Y = 0.537\Delta S_{un} - 1.213\Delta T_{\max}$	0.764	1.110	0.001
50742	$\Delta Y = 0.476\Delta S_{un}$	0.116	3.478	0.195
50745	$\Delta Y = 0.403\Delta H_{um}^3$	0.132	1.123	0.03
50756	$\Delta Y = 0.792\Delta H_{um} + 1.167\Delta S_{un} + 0.642\Delta H_{um}^2 - 0.499\Delta S_{un}^2$	0.734	0.498	0.008
50774	$\Delta Y = 0.336\Delta H_{um} - 0.473\Delta S_{un} - 0.319\Delta P_{re} \times \Delta S_{un} + 0.279\Delta H_{um} \times \Delta S_{un} + 0.412\Delta P_{re}^2 - 0.745\Delta P_{re}^3$	0.459	0.493	0.002
50775	$\Delta Y = 0.518\Delta P_{re} \times \Delta T_{\min}$	0.242	0.981	0.004
50844	$\Delta Y = 0.601\Delta P_{re}$	0.282	1.737	0.066
50851	$\Delta Y = 0.875\Delta P_{re}^3$	0.688	0.241	0.052
50853	$\Delta Y = 0.315\Delta P_{re}$	0.066	0.952	0.096
50867	$\Delta Y = 1.197\Delta T_{ave} - 1.476\Delta H_{um} - 1.717\Delta T_{\max} + 0.607T_{\max}^2$	0.400	1.137	0.136
50873	$\Delta Y = 1.589\Delta H_{um} - 1.28\Delta T_{\min} + 0.581\Delta P_{re} \times \Delta H_{um} - 0.388\Delta H_{um} \times \Delta T_{\min} - 0.897\Delta S_{un} \times \Delta T_{\min} - 1.811\Delta H_{um}^3 + 0.963\Delta T_{\min}^3$	0.314	0.834	0.03
50936	$\Delta Y = 1.598\Delta S_{un} + 0.855\Delta T_{\min} + 1.62\Delta S_{un} \times \Delta T_{\min} + 1.412\Delta S_{un}^2$	0.717	0.483	0.054
50953	$\Delta Y = 0.797\Delta P_{re} - 0.597\Delta P_{re}^3$	0.171	0.643	0.033
50955	$\Delta Y = 0.444\Delta H_{um} + 0.445\Delta H_{um}^2$	0.261	0.856	0.122
50978	$\Delta Y = -0.31\Delta S_{un}^2 + 0.502\Delta T_{\max}^2 + 0.571\Delta S_{un}^3 + 0.353\Delta T_{\max}^3$	0.374	0.711	0.004
51133	$\Delta Y = -1.119\Delta P_{re} + 0.383\Delta P_{re} \times \Delta T_{\min} + 0.552\Delta T_{\min}^2 + 0.703\Delta P_{re}^3 - 0.485\Delta T_{\min}^3$	0.255	1.129	0.045
51238	$\Delta Y = 0.286\Delta S_{un} - 0.525\Delta H_{um} \times \Delta S_{un} - 0.537\Delta H_{um}^2$	0.169	2.536	0.05
51334	$\Delta Y = -0.404\Delta P_{re} \times \Delta S_{un}$	0.124	2.506	0.056
51346	$\Delta Y = 0.625\Delta S_{un} + 0.512\Delta T_{\min} + 1.163\Delta P_{re} \times \Delta T_{\min} - 2.167\Delta H_{um} \times \Delta T_{\min} - 0.384\Delta S_{un}^2 - 0.588\Delta T_{\min}^2 - 0.754\Delta S_{un}^3 - 0.593\Delta T_{\min}^3$	0.551	1.884	0.001
51358	$\Delta Y = 0.32\Delta H_{um}$	0.071	2.190	0.084
51368	$\Delta Y = -0.771\Delta H_{um} - 1.035\Delta S_{un} - 3.729\Delta P_{re} \times \Delta H_{um} - 0.457\Delta P_{re} \times \Delta S_{un} - 0.831H_{um} \times \Delta T_{\min} - 1.913H_{um} \times \Delta T_{\max} - 1.476\Delta T_{\min} \times \Delta T_{\max} + 1.898\Delta P_{re}^2 + 0.656\Delta S_{un}^2$	0.321	2.319	0.046
51379	$\Delta Y = 1.084\Delta H_{um} - 1.487\Delta S_{un} + 1.297\Delta T_{\max} - 1.489\Delta H_{um} \times \Delta T_{\max} + 0.674\Delta S_{un} \times \Delta T_{\max} - 0.815\Delta H_{um}^2 - 0.697\Delta T_{\max}^2 - 1.245\Delta H_{um}^3 + 0.638\Delta S_{un}^3 - 1.295\Delta T_{\max}^3$	0.566	1.574	0.002
51431	$\Delta Y = -0.633\Delta T_{\max} + 0.503\Delta S_{un}^3$	0.332	2.756	0.002
51436	$\Delta Y = -0.332\Delta P_{re} + 0.713\Delta T_{\min} - 0.269\Delta P_{re} \times \Delta S_{un} + 0.772\Delta P_{re} \times \Delta T_{\max} - 0.668\Delta S_{un} \times \Delta T_{\min} + 3.942\Delta T_{\min} \times \Delta T_{\max} - 2.539\Delta T_{\max}^2 + 1.032\Delta P_{re}^3 - 1.075\Delta T_{\min}^3$	0.56	1.147	0.001
51567	$\Delta Y = -2.076\Delta H_{um} - 1.127\Delta S_{un} + 2.596\Delta H_{um} \times \Delta S_{un} + 1.52\Delta H_{um} \times \Delta T_{\max} + 0.649\Delta S_{un} \times \Delta T_{\max} + 4.05\Delta H_{um}^2 + 1.902\Delta H_{um}^3 - 0.628\Delta S_{un}^3$	0.693	0.815	0.008
51633	$\Delta Y = 0.72\Delta \mathrm{H}_{um} + 0.666\Delta T_{\min} + 1.435\Delta T_{\max} - 0.917\Delta P_{re} \times \Delta \mathrm{H}_{um} + 0.933\Delta P_{re} \times \Delta T_{\min} - 0.799\Delta P_{re} \times \Delta T_{\max} - 0.885\Delta \mathrm{H}_{um} \times \Delta T_{\max} - 0.581\Delta T_{\min} \times \Delta T_{\max} + 0.452\Delta P_{re}^3 - 1.379\Delta T_{\min}^3 - 1.329\Delta T_{\max}^3$	0.582	1.628	0.002
51828	$\Delta Y = -0.488\Delta H_{um} - 0.364\Delta H_{um}^2$	0.262	1.088	0.029
52203	$\Delta Y = -0.329\Delta P_{re} \times \Delta T_{\min} - 0.599\Delta P_{re}^2 + 0.647T_{\min}^2 + 0.838\Delta P_{re}^3 - 0.486\Delta H_{um}^3 - 0.321\Delta T_{\min}^3$	0.522	1.241	0.001
52533	$\Delta Y = 0.724\Delta P_{re} + 0.714\Delta H_{um} + 0.814\Delta S_{un} + 0.933\Delta T_{\max}$	0.693	0.508	0.004
53564	$\Delta Y = 0.755\Delta P_{re} - 0.396\Delta S_{un} - 1.169\Delta T_{\min} + 1.23\Delta T_{\max}$	0.716	1.213	0.055
53585	$\Delta Y = 0.836\Delta P_{re}$	0.649	1.549	0.01
53646	$\Delta Y = -0.779\Delta P_{re} - 1.448\Delta H_{um} + 4.018\Delta S_{un} - 1.723\Delta T_{\max} + 0.421\Delta P_{re}^3 + 1.765\Delta H_{um}^3 - 3.799\Delta S_{un}^3 + 1.324\Delta T_{\max}^3$	0.876	0.357	0.096
53674	$\Delta Y = 0.949\Delta P_{re} - 0.768\Delta S_{un} - 0.351\Delta T_{\min} + 1.027\Delta T_{\max}$	0.52	1.311	0.054
53681	$\Delta Y = 0.687\Delta P_{re}$	0.396	2.854	0.041
53775	$\Delta Y = 3.264\Delta P_{re} - 3.504\Delta H_{um} - 2.815\Delta S_{un} + 2.841\Delta T_{\min}$	0.737	9.503	0.338
53845	$\Delta Y = -0.9\Delta P_{re}$	0.772	0.469	0.006
53853	$\Delta Y = 0.79\Delta T_{\min}^3$	0.561	2.097	0.02
53863	$\Delta Y = -0.914\Delta H_{um} + 0.518\Delta S_{un} + 0.703\Delta T_{\min} - 1.522\Delta T_{\max}$	0.082	0.930	0.392
53882	$\Delta Y = -0.493\Delta S_{un} - 0.673\Delta P_{re} \times \Delta T_{\min} - 0.763\Delta H_{um} \times \Delta S_{un}$	0.595	0.491	0.01
53915	$\Delta Y = -0.746\Delta P_{re} \times \Delta H_{um}$	0.482	1.612	0.034
53976	$\Delta Y = -1.456\Delta P_{re} + 0.553\Delta H_{um} + 0.476\Delta S_{un} + 0.705\Delta T_{\min} - 1.813\Delta T_{\max}$	0.46	0.754	0.149
54049	$\Delta Y = 0.877\Delta H_{um}$	0.736	1.636	0.002
54072	$\Delta Y = -0.67\Delta T_{ave} \times \Delta T_{\max} - 0.891\Delta T_{\max}^3$	0.492	11.16	0.027
54076	$\Delta Y = 0.649\Delta H_{um}^3$	0.356	1.024	0.031
54080	$\Delta Y = -3.064\Delta T_{\min} + 1.092\Delta P_{re} \times \Delta T_{\min} - 0.947\Delta H_{um} \times \Delta T_{\min} + 0.694\Delta P_{re}^2 + 3.449\Delta T_{\min}^3$	0.726	0.303	0.018
54094	$\Delta Y = 0.401\Delta T_{\max} + 0.344\Delta P_{re}^3 + 0.289\Delta H_{um}^3$	0.377	0.810	0.002
54134	$\Delta Y = 0.479\Delta T_{\min} + 0.482\Delta S_{un}^2 - 0.402\Delta T_{\min}^2$	0.288	1.041	0.098
54154	$\Delta Y = -0.688\Delta T_{\max}$	0.426	1.319	0.009
54156	$\Delta Y = 0.535\Delta P_{re}^3$	0.207	2.555	0.09
54165	$\Delta Y = -0.718\Delta T_{\min}$	0.446	3.657	

(*continued on next page*)

Table 5 (*continued*)

Site number	Equation	R^2 adj	*RMSE*	*P*-value
				0.03
54171	$\Delta Y = -0.863\Delta H_{um} + 1.524\Delta H_{um}^3$	0.735	0.817	0.002
54186	$\Delta Y = -0.465\Delta P_{re} - 1.017\Delta S_{un} - 0.57\Delta P_{re} \times \Delta S_{un}$	0.454	0.350	0.09
54213	$\Delta Y = -0.511\Delta T_{min}$	0.194	1.464	0.074
54218	$\Delta Y = -0.706\Delta P_{re}$	0.443	1.474	0.015
54223	$\Delta Y = 0.718\Delta P_{re} - 0.937\Delta H_{um} - 0.578\Delta T_{min}$	0.576	1.052	0.019
54243	$\Delta Y = -2.394\Delta H_{um} \times \Delta T_{max} - 2.323\Delta T_{max}^2 - 1.358\Delta H_{um}^3 - 1.008\Delta T_{max}^3$	0.11	1.484	0.365
54260	$\Delta Y = 0.701 T_{ave}^3$	0.418	1.135	0.035
54266	$\Delta Y = 1.176\Delta S_{un} + 1.079\Delta T_{ave} \times \Delta S_{un}$	0.745	0.925	0.002
54326	$\Delta Y = 0.324\Delta S_{un} - 0.887\Delta T_{min} + 0.359\Delta S_{un} \times \Delta T_{min}$	0.814	1.333	0.009
54333	$\Delta Y = -1.91\Delta S_{un} - 0.335\Delta T_{min} + 1.946\Delta T_{max} + 1.092\Delta S_{un} \times \Delta T_{min} - 1.557\Delta T_{min} \times \Delta T_{max} + 0.877\Delta T_{min}^2 - 0.809\Delta T_{max}^2$	0.541	0.746	0.224
54348	$\Delta Y = -0.793\Delta P_{re}^2$	0.554	1.736	0.033
54349	$\Delta Y = -0.825\Delta P_{re} + 0.789\Delta P_{re}^2 - 0.401\Delta H_{um}^2$	0.56	0.858	0.049
54362	$\Delta Y = 0.741\Delta S_{un}$	0.504	0.885	0.006
54377	$\Delta Y = 0.502\Delta P_{re} + 0.924\Delta T_{ave} + 0.669\Delta P_{re} \times \Delta T_{ave} - 0.63\Delta P_{re}^2 + 0.677\Delta T_{ave}^2$	0.746	0.259	0.027
54405	$\Delta Y = -1.943\Delta S_{un} + 1.564\Delta S_{un}^3$	0.278	1.11	0.133
54452	$\Delta Y = 0.651\Delta H_{um}$	0.36	1.985	0.03
54454	$\Delta Y = 6.25\Delta H_{um} \times \Delta T_{max} + 2.856\Delta H_{um}^2 + 3.652\Delta T_{max}^2 - 2.255\Delta H_{um}^3 - 2.281\Delta T_{max}^3$	0.102	0.988	0.475
54472	$\Delta Y = 2.747\Delta T_{max} - 1.275 T_{min}^2 - 3.069\Delta T_{max}^3$	0.769	0.714	0.008
54486	$\Delta Y = 0.615\Delta H_{um} + 2.434\Delta T_{max} - 0.931\Delta H_{um} \times \Delta T_{max} + 1.005\Delta H_{um}^2 - 2.221\Delta T_{max}^2 + 0.508\Delta H_{um}^3 - 2.22\Delta T_{max}^3$	0.745	0.651	0.102
54493	$\Delta Y = 0.576\Delta S_{un}$	0.257	0.833	0.064
54563	$\Delta Y = 0.624\Delta P_{re} \times \Delta H_{um}$	0.322	0.574	0.04
54584	$\Delta Y = -0.859\Delta P_{re} - 0.705\Delta H_{um}^3$	0.378	1.691	0.061
56280	$\Delta Y = 0.467\Delta S_{un}$	0.131	2.674	0.148
56479	$\Delta Y = -0.827\Delta P_{re}^3 + 1.715\Delta H_{um}^3 + 2.065\Delta S_{un}^3 - 1.016\Delta T_{max}^3$	0.845	0.327	0.261
56985	$\Delta Y = 0.377\Delta P_{re} + 2.67\Delta H_{um} + 2.983\Delta T_{max} + 0.405\Delta P_{re}^3 - 2.932\Delta H_{um}^3 - 2.666\Delta T_{max}^3$	0.76	0.355	0.169
57259	$\Delta Y = -0.924\Delta P_{re} - 0.65\Delta S_{un} + 0.515\Delta T_{min}$	0.545	0.235	0.115
57313	$\Delta Y = 1.303\Delta H_{um} \times \Delta S_{un} + 1.225\Delta H_{um}^2 + 0.529\Delta S_{un}^3$	0.313	0.808	0.118
57318	$\Delta Y = 2.06\Delta P_{re} - 3.826\Delta H_{um} - 0.328\Delta T_{min} + 3.171\Delta P_{re}^2 - 1.877\Delta H_{um}^2 - 0.92\Delta S_{un}^2$	0.742	0.359	0.181
57415	$\Delta Y = 0.536\Delta P_{re}$	0.208	0.631	0.089
57512	$\Delta Y = -0.803\Delta T_{min}^3$	0.555	1.496	0.055
57633	$\Delta Y = 0.661\Delta T_{max}^3$	0.366	1.059	0.038
57808	$\Delta Y = -0.424\Delta H_{um}^3 + 0.884\Delta T_{min}^3 - 1.042\Delta T_{max}^3$	0.827	0.189	0.042
58269	$\Delta Y = -0.526\Delta P_{re}^3$	0.217	1.270	0.053

summer maize was most closely related to P_{re}, H_{um} and S_{un}, followed by T_{min} and T_{max}, and least related to T_{ave}.

4. Discussions

4.1. The comparison of yield response to climate change between spring and summer maize

4.1.1. Climate background and yield response differences of spring and summer maize

In our study, spring maize was mainly planted in the northeast, north and northwest China (76 sites). Only 9 sites were located in the southwest China. The north of China was in the cold temperate zone characterized by low temperature, short frost-free period in winter with precipitation range of 400–800 mm. with 60% of precipitation concentrated in July to September (Wang, 2010). Such climatic conditions fitted a cropping system of one-harvest each year, in which spring maize was sown around April and harvested around September to October with an average growth period of about five months.

Summer maize was planted in the Huang-Huai-Hai region (20 sites, the warm temperate monsoon climate) and northwestern China (16 sites). The Huang-Huai-Hai region was characterized by high temperature ($8\,^{\circ}\mathrm{C} < T_{ave} < 15\,^{\circ}\mathrm{C}$), strong evaporation and uneven distribution of rainfall ranging from 500 to 900 mm (Xiao et al., 2020). Waterlogging was common in summer, and drought was common in spring (Wang, 2010). This climatic background fitted a cropping system of twice-harvest each year or intercropping of winter wheat with summer maize sown in June to July and harvested during September to October with an average growth period of about four months. The distinct differences in climate conditions during the growth period resulted in sensitive growth and yield responses of maize, which ultimately affected the yield change of spring and summer maize.

From our results, over the past 30 years, yields of spring maize increased more than yields of summer maize. It was expected since the planting area of spring maize gradually extended to the north under the global warming. The increment of spring maize yield decreased from northeast to north, northwest and southwest China, and the increment of summer maize yield decreased from Huang-Huai-Hai plain to northwest and southwestern China. Our results were consistent with Xu et al. (2017) who studied the impact of climate change on yield potential of maize across China using Global Agro-Ecological Zones (GAZA) model over 1960–2010. The variation trends of P_{re}, H_{um} and T_{min} had more adverse effects on the yields of spring and summer maize. This result was expected because the sowing dates, growth lengths and climatic conditions differed for spring and summer maize. Yields differed for spring and summer maize under different climate background even if two types of maize were planted in the same area at the same time (e.g. Gao et al., 2018).

Table 6
The best regression equation for summer maize yield and their performance at the 36 sites.

Site number	Equation	R^2 adj	RMSE	P-value
51642	$\Delta Y = -0.498\Delta P_{re}$	0.207	1.654	0.025
51644	$\Delta Y = 0.613\Delta P_{re} \times \Delta T_{max}$	0.332	0.783	0.012
51656	$\Delta Y = -0.381\Delta H_{um} \times \Delta T_{min}$	0.097	1.341	0.098
51708	$\Delta Y = 0.358\Delta H_{um}^2$	0.093	1.084	0.067
51709	$\Delta Y = -0.405\Delta S_{un} + 0.631\Delta S_{un} \times \Delta T_{min} + 0.759\Delta T_{min}^3$	0.238	1.253	0.02
51716	$\Delta Y = -0.307\Delta S_{un} + 0.481\Delta T_{min}^3$	0.318	0.943	0.003
51777	$\Delta Y = -0.743\Delta H_{um} \times \Delta S_{un} -0.519\Delta P_{re} \times \Delta H_{um} -0.445\Delta H_{um}^3$	0.471	1.203	0.002
51810	$\Delta Y = 0.352\Delta H_{um}$	0.092	0.879	0.061
51811	$\Delta Y = -1.925\Delta H_{um}^3 -1.888\Delta S_{un}^3 -0.604\Delta T_{min}^3$	0.577	1.837	0.154
51814	$\Delta Y = -0.313\Delta T_{max}^2$	0.066	0.819	0.093
53959	$\Delta Y = -0.701\Delta H_{um}^2 + 0.859\Delta T_{min}^2$	0.679	0.521	0.085
53980	$\Delta Y = 0.798\Delta P_{re} \times \Delta H_{um} + 0.67\Delta H_{um}^3$	0.610	0.338	0.015
53991	$\Delta Y = 0.803\Delta P_{re} -0.831\Delta T_{min} -0.594\Delta P_{re} \times \Delta T_{min}$	0.683	1.048	0.019
54503	$\Delta Y = 0.607\Delta H_{um} \times \Delta S_{un}$	0.305	0.609	0.036
54518	$\Delta Y = 0.744\Delta S_{un} \times \Delta T_{max}$	0.509	0.54	0.006
54520	$\Delta Y = -0.495\Delta P_{re} -0.615\Delta H_{um} -0.503\Delta T_{max}$	0.482	0.445	0.107
54534	$\Delta Y = 0.737\Delta S_{un} + 0.529\Delta H_{um} \times \Delta T_{min}$	0.785	0.799	0.009
54540	$\Delta Y = 0.583\Delta S_{un}$	0.257	1.198	0.077
54614	$\Delta Y = 0.491\Delta S_{un}$	0.165	1.544	0.105
54624	$\Delta Y = -1.531\Delta P_{re} -0.894\Delta T_{min} -0.857T_{max} + 0.87\Delta P_{re}^3 + 1.041\Delta T_{min}^3$	0.280	0.959	0.272
54827	$\Delta Y = 0.862\Delta P_{re}^3 + 1.128\Delta S_{un}^3$	0.213	0.945	0.275
54846	$\Delta Y = -0.642\Delta P_{re}^2 + 1.062\Delta S_{un}^2$	0.743	0.29	0.007
54849	$\Delta Y = -0.907\Delta S_{un} - 0.764\Delta P_{re} \times \Delta S_{un} + 0.706\Delta P_{re}^3 + 1.55\Delta S_{un}^3$	0.546	0.643	0.032
54852	$\Delta Y = 0.545\Delta P_{re} -1.264\Delta T_{min} + 1.024\Delta T_{max}$	0.479	0.821	0.108
54900	$\Delta Y = -0.746\Delta P_{re}$	0.52	0.699	0.002
54906	$\Delta Y = 1.642\Delta P_{re} - 0.883\Delta H_{um} + 0.754\Delta P_{re} \times \Delta H_{um} + 1.114\Delta P_{re}^2 - 0.993\Delta H_{um}^2 - 1.688\Delta P_{re}^3$	0.756	0.997	0.015
54915	$\Delta Y = 0.626\Delta S_{un}$	0.337	1.179	0.022
56193	$\Delta Y = 0.529\Delta H_{um}^3$	0.208	1.33	0.077
57025	$\Delta Y = -1.025\Delta P_{re} + 0.501\Delta H_{um} + 0.473\Delta P_{re}^2 -0.492\Delta H_{um}^2 + 0.662\Delta P_{re}^3$	0.268	1.190	0.049
57034	$\Delta Y = 0.549\Delta S_{un} - 0.602\Delta H_{um} \times \Delta T_{min} - 0.482\Delta S_{un} \times \Delta T_{min} +0.815\Delta H_{um}^2 - 0.573\Delta S_{un}^2 + 0.675\Delta H_{um}^3$	0.519	0.612	0.005
57043	$\Delta Y = -0.777\Delta P_{re} + 0.917\Delta H_{um} + 1.656\Delta P_{re} \times \Delta H_{um} -0.677\Delta P_{re} \times \Delta S_{un} + 1.788\Delta H_{um} \times \Delta S_{un} - 0.919\Delta P_{re}^2$	0.45	1.222	0.012
57044	$\Delta Y = -1.033\Delta P_{re} \times \Delta T_{min} + 0.947\Delta H_{um} \times \Delta T_{min}$	0.283	1.482	0.023
57048	$\Delta Y = -0.64\Delta T_{max}$	0.351	0.452	0.025
57096	$\Delta Y = 0.545\Delta P_{re} \times \Delta H_{um} + 1.165\Delta P_{re}^2 -1.42\Delta H_{um}^2$	0.552	0.618	0.035
57143	$\Delta Y = 0.555\Delta P_{re} + 1.528\Delta T_{max} -0.847\Delta T_{max}^3$	0.278	0.704	0.142
58130	$\Delta Y = -0.832\Delta P_{re}$	0.665	1.074	0

4.1.2. *Sensitivity of spring and summer maize yield to climate variables*

According to our Pearson correlation results, we concluded that spring maize was more sensitive to H_{um} and S_{un}, and summer maize was more sensitive to P_{re} and temperature (T_{min}, T_{max} and T_{ave}). For spring maize, the sensitivity of yield was ranked as $H_{um} > S_{un} > P_{re} > T_{min} > T_{max} > T_{ave}$. H_{um} played a key role in maize yields, however, often it's roles were overlooked because of its proper coordination with other climatic factors (Hsiao et al., 2019). When H_{um} increased, pollen was inactivated during silk therefore affected the maize yield (Matsuda and Higuchi, 2015). The sensitivity of spring maize to S_{un} were stronger than that of P_{re} and temperature. This result was inconsistent with Zhao et al. (2015) who studied the relationships between climatic variables and climate-induced yield of spring maize in Northeast China from 1978 to 2010. And they indicated that S_{un} was not the major limiting factor to yield of spring maize compared with temperature and P_{re}. We suggest that the reason for this difference may be that solar radiation was reduced due to severe environmental pollution over past years. Compared with P_{re}, S_{un} was the most influential factor affecting maize photosynthesis which played key role for forming maize dry matter.

The sensitivity of spring maize to P_{re} was stronger than that of temperature. This result was consistent with Xu et al. (2017) who found that the arable land in the northern regions of China where natural rainfall did not meet the water demands for the production of spring maize both in terms of volume and frequency, and annual Pre change and water stress more serious on maize yield than other meteorological factors.

For summer maize, we ranked the sensitivity of yield as $P_{re} > T_{ave} > T_{max} > T_{min} > S_{un} > H_{um}$. The sensitivity of summer maize to P_{re} was stronger than that of temperature, which agreed with Chen et al. (2012) who explored factors affecting summer maize yield under climate change in Shandong Province of China in 1957–2007. Chen et al. (2012) concluded that P_{re} had a greater influence than light and temperature on yield. Gao et al. (2018) conducted comparison analysis of climate factor to maize productivity in the North China Plain based on experimental data from 2009 to 2016. They found that summer maize yield was more sensitive to P_{re} in silking stage but more sensitive to temperature and solar radiation in the later growth stages. High temperature and strong sunshine in the main producing areas of summer maize accelerated evaporation of water in the soil, which affected the yield. The sensitivity of summer maize yield to air humidity was not obvious because of the strong opposite effect of precipitation and temperature on air humidity.

Maize yields were sensitive to T_{ave}, especially in summer maize, but T_{ave} performed worst in interpreting yield change. Also, Prabnakorn et al. (2018) showed that the use of T_{ave} to assess rice yield variations provided greater uncertainty than the use of T_{min} and T_{max}. From our results, since T_{ave} had high collinearity with T_{min} and T_{max} thus was removed from the regression process. However, the effects of T_{ave} could be judged roughly from that of T_{min} and T_{max} considering its high connection with T_{min} and T_{max}.

4.1.3. Contribution of warmer climate on increasing spring maize yield

Our results also showed that the variation trend of T_{min} in the past 30 years were larger than that of T_{max}, this may have promoted to increased yields. Nicholls (1997) found that the increase in yields of Australian wheat was caused more by the increased T_{min} than the increased T_{max} and P_{re}. Our results agreed with Nicholls (1997) in that the spring maize yield was more sensitive to T_{min} compared to T_{max}. However, summer maize yield was more sensitive to T_{max} than T_{min} due to the high temperature and rainy weather during the growth period of summer maize.

Warming may have negative or positive impacts on crop production at low or high latitudes, depending on whether the overall temperature of the studied region is above the optimal temperature for crop production (IPCC 2001). Bhatt et al. (2014) reported that warming had positive impacts on maize yields at some high latitudes areas in the Koshi basin of Nepal, benefiting from favorable available water and soil fertility conditions. Chen et al. (2014) found that average temperature had a positive effect on maize yields in northeast and northwest China at high latitudes, and maize yield increased 0–7.5% with 1 °C increase in temperature. Our results showed that spring maize yield in the northeast and northwest China at high latitudes also increased with rising temperatures (especially the minimum temperatures), which was partially consistent with Bhatt et al. (2014) and Chen et al. (2014).

4.1.4. Maize yields formation processes and mechanisms under climate change

The accumulation of dry matter of maize was formed by daily accumulation of carbon through photosynthesis throughout the growth period (Dong et al., 1993). Therefore, the material source of maize yield was photosynthesis. Photosynthetic characteristic shown that moderate temperature and sufficient sunshine could promote photosynthesis to some extent. There was evidence that inappropriately increased temperature had negative effects on photosynthesis (Ruiz and Ursula, 2014), consistent with our results. In our study, over the past 30 years, sunshine hours had a larger decline trends during the growth periods of summer maize than spring maize, this may lead to a smaller increase in summer maize yield than spring maize. Furthermore, on the basis of the shorter growing periods of summer maize than spring maize, the growing periods of summer maize was shorter due to the rising temperature.

Water was one of the raw materials for photosynthesis. When water stress occurred in plants, the photosynthetic reaction was blocked, thus weaken the accumulation of dry matter. Our results shown that P_{re} had a larger increase trends during the growth periods of summer maize than spring maize over the past 30 years, while the summer maize yield increase range was smaller than spring maize. There are three reasons for this: (1) when P_{re} increased, S_{un} was reduced and decreased photosynthesis; (2) when P_{re} increased, H_{um} was increased and restricted the pollen germination, which would affect maize yield; (3) During the period of maize grain filling, increased P_{re} would affect the filling rate. The specific effects of H_{um} on photosynthesis was not well determined and was often combined with other climate variables (such as P_{re}).

At our 121 studied sites, the contribution of climatic variables to account for yield change was ranked as $P_{re} > H_{um} > S_{un} > T_{min} > T_{max} > T_{ave}$. Our results were consistent with earlier research (Pedram et al., 2011; Waha et al., 2013; Bhatt et al., 2014) that P_{re} was more powerful in explaining the variability of maize yields. Also, P_{re} affected H_{um} and S_{un}. When P_{re} increased, H_{um} increased and solar radiation decreased, affected photosynthesis and dry matter accumulation.

4.2. Evaluation of applicability of the best regression model

The responses of crop yield to climate change are very complex. The regression functions established in our research are very useful to quantitatively understand the response of crops to climate. Nicholls (1997) estimated the contribution of climate trends to Australian wheat yields from 1952 to 1992 with linear regression model, and found that 30–50% of the increase in wheat yields was caused by increase in climate trends. Lobell and Field (2007) found that variations in the annual yields of global six crop yields (wheat, rice, maize, soybean, barley and sorghum) from 1961 to 2002 were explained at least 29% by climatic variations. Chen et al. (2011) conducted linear regression analyses of climate factors (T_{ave}, T_{min}, T_{max} and P_{re}) of 72 meteorological sites in Northeast China and maize yield over the period 1965–2008. They showed that the daily T_{min} was the dominant factor to maize yield compared other climatic factors. Linear regression models can be used to capture the net climate effect of multivariate climate variables.

However, there was complex feedback of crop yield to climate change and climate change has a non-monotonic effect on crop yield. Therefore, nonlinear equations performed much better than linear equations. There were different shapes of the nonlinear regression equations, for example, the second order polynomial function (Lobell et al., 2007), quadratic type (Almaraz et al., 2008), mixed linear and nonlinear (Li et al., 2020), or combining linear, quadratic terms with interaction terms (Malone et al., 2009). The effects of climate variables varied in explaining the yield variability, which were 46–80% of 12 crops in California from 1980 to 2003 (Lobell et al., 2007), 62% of maize in the Montergie region of south-western Quebec over 1973–2005 (Almaraz et al., 2008), 8.5–75.3% for seed cotton yield in Xinjiang, China over 1986–2017 (Li et al., 2020), and 54% of maize yield in six counties of Iowa over 1995–2005 (Malone et al., 2009). We added a cubic item to linear, quadratic and interaction term by considering the multicollinearity of climatic variables. We found varying explanation ability of climatic variables on maize yields (5.8–87.6%) since the climate and yield variability occurred. The introduced cubic terms and interaction terms played important roles in explaining maize yield variation than the square terms and linear.

We found that the key climatic factors in the best regression model of spring and summer maize yields had spatial variability. This was consistent with Li et al. (2020) who investigated the spatial variable cotton yields and climate variables in Xinjiang, China. From the adjusted R^2 values, the climate change explained 5.8–87.6% of spring maize yields variability and explained 6.6–78.5% of summer maize yields variability. We found that maize yield was sensitive to climate change at a great extent. Climate variables that affect maize yields may differ even at adjacent sites. Therefore, our results are useful as a reference for maize breeding scientists to develop new high-yielding varieties according to yield associated factors in different regions.

The feedback of climate change and crop growth are complex. We introduced the best linear and nonlinear regression models, but there may be other selective equations. Further research is needed to find even better equations that could explain higher variability in maize yields affected by climate change. Due to many constraints, the effects of extreme weather events on maize yields were not considered. Future studies should consider the effects of climate change and extreme weather on maize yields, and use more appropriate optimal regression models to assess the dual feedback mechanism between climate and maize growth.

5. Conclusions

In the maize planting belt of China, the P_{re}, H_{um} and S_{un} during crop growth periods and spring/summer maize yields had moderate variability over 1988–2017, so did T_{ave}, T_{min} and T_{max} of spring maize. Whereas T_{ave}, T_{min} and T_{max} of summer maize had low variability. The P_{re}, T_{ave}, T_{min} and T_{max} series of spring (summer) maize at 53 (22), 83 (33), 79 (33) and 83 (34) out of 85 (36) sites had increasing trends, while H_{um} and S_{un} of spring (summer) maize at 73 (30) and 47 (28) out of 85 (36) sites exhibited decreasing trends. Spring/summer maize yields both showed increasing trends, of which the trend magnitudes of spring maize yields were greater.

The climate variables contributed to the variability of maize yields to different extents. P_{re}, H_{um}, S_{un}, T_{min}, T_{max} and T_{ave} accounted for 2.3%, 5%, 4.8%, 0.7%, 0.3%, and 0.05% of spring maize yield variability according to the Pearson correlation coefficients between the climatic variables and maize yield. Similarly, P_{re}, H_{um}, S_{un}, T_{min}, T_{max} and T_{ave} accounted for 5.5%, 0.7%, 1.1%, 2.2%, 2.5%, and 3.3% of summer maize yield variability. Spring maize yield was more sensitive to H_{um}, S_{un} and P_{re} and summer maize yield was more sensitive to P_{re} and temperature.

The contribution of climatic variables to spring/summer yields variability ranked as $P_{re} > H_{um} > S_{un} > T_{min} > T_{max} > T_{ave}$. Both the wet-cold and wet-warm climate, especially the wet-cold climate, had positive effects on maize yield. However, the dry-warm climate had negative effects on maize yield. Climate change explained 5.8–87.6% of variability in spring maize yields and 6.6–78.5% of variability in summer maize yields, respectively, which were also site-specific. The multivariate nonlinear functions (especially cubic and interaction terms) performed better than the linear ones in explaining maize yield variability. Future research would focus on prediction of maize yields under climate change using some global climate models and downscaling methods.

Author contribution

Tianxue Wang, Na Li and Yi Li made c onceptualization. Tianxue Wang contributed to data curation and writing - original draft. Yi Li contributed to Writing review & editing. Na Li, Haixia Lin and Ning Yao conducted visualization. Xinguo Chen and Qiang Yu provided resources. De Li Liu and Hao Feng improved methodology and provided software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

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References

Abera, K., Crespo, O., Seid, J., Mequanent, F., 2018. Simulating the impact of climate change on maize production in Ethiopia, East Africa. Environ. Syst. Res. 7 (1), 1–12.
Adams, R.M., Hurd, B.H., Lenhart, S., Leary, N., 1998. Effects of global climate change on agriculture: an interpretative review. Clim. Res. 11 (1), 19–30.
Adisa, O.M., Botai, C.M., Botai, J.O., Hassen, A., Darkey, D., Tesfamariam, E., Adisa, A.F., Adeola, A.M., Ncongwane, K.P., 2018. Analysis of agro-climatic parameters and their influence on maize production in South Africa. Theor. Appl. Climatol. 134 (3–4), 991–1004.
Alexandrov, V.A., Hoogenboom, G., 2000. The impact of climate variability and change on crop yield in Bulgaria. Agric. For. Meteorol. 104 (4), 315–327.
Almaraz, J.J., Mabood, F., Zhou, X., Gregorich, E.G., Smith, D.L., 2008. Climate change, weather variability and corn yield at a higher latitude locale: Southwestern Quebec. Clim. Change 88 (2), 187–197.
Bassu, S., Brisson, N., Durand, J.L., Boote, K., Lizaso, J., Jones, J.W., et al., 2014. How do various maize crop models vary in their responses to climate change factors? Glob. Change Biol. 20 (7), 2301–2320.
Bhatt, D., Maskey, S., Babel, M.S., Uhlenbrook, S., Prasad, K.C., 2014. Climate trends and impacts on crop production in the Koshi River basin of Nepal. Reg. Environ. Change 14 (4), 1291–1301.
Chao, C., Guang-sheng, Z., Li, Z., 2014. Impacts of climate change on rice yield in China from 1961 to 2010 based on provincial data. J. Integr. Agric. 13 (7), 1555–1564.
Chen, C., Lei, C., Deng, A., Qian, C., Hoogmoed, W., Zhang, W., 2011. Will higher minimum temperatures increase corn production in Northeast China? An analysis of historical data over 1965–2008. Agric. For. Meteorol. 151 (12), 1580–1588.
Chen, C., Wang, E., Yu, Q., Zhang, Y., 2010. Quantifying the effects of climate trends in the past 43 years (1961–2003) on crop growth and water demand in the North China Plain. Clim. Change 100 (3–4), 559–578.
Chen, C., Zhou, G.S., Pang, Y.M., 2014. Impacts of climate change on maize and winter wheat yields in China from 1961 to 2010 based on provincial data. J. Agric. Sci. 153 (5), 825–836.
Chen, G., Liu, H., Zhang, J., Liu, P., Dong, S., 2012. Factors affecting summer maize yield under climate change in Shandong Province in the Huanghuaihai Region of China. Int. J. Biometeorol. 56 (4), 621–629.
Chen, X., Wang, L., Niu, Z., Zhang, M., Li, C., Li, J., 2020. The effects of projected climate change and extreme climate on maize and rice in the Yangtze River Basin, China. Agric. For. Meteorol. 282, 107867.
Chmielewski, F.-M., Potts, J.M., 1995. The relationship between crop yields from an experiment in southern England and long-term climate variations. Agric. For. Meteorol. 73 (1–2), 43–66.
Dong, S., Hu, X., Gao, R., 1993. Rates of apparent photosynthesis, respiration and dry matter accumulation in maize canopies. Biol. Plant. 35 (2), 273–277.
Doetterl, S., Stevens, A., Six, J., Merckx, R., Van Oost, K., Casanova Pinto, M., Casanova-Katny, A., Muñoz, C., Boudin, M., Zagal Venegas, E., Boeckx, P., 2015. Soil carbon storage controlled by interactions between geochemistry and climate. Nat. Geosci. 8 (10), 780–783.
Easterling, D.R., Meehl, G.A., Parmesan, C., Changnon, S.A., Karl, T.R., Mearns, L.O., 2000. Climate extremes: observations, modeling, and impacts. Science 289 (5487), 2068–2074.
Everingham, Y., Sexton, J., Robson, A., 2016. A statistical approach for identifying important climatic influences on sugarcane yields. Int. Sugar J. 118 (1405), 46–50.
Feng, P., Wang, B., Liu, D.L., Xing, H., Ji, F., Macadam, I., Ruan, H., Yu, Q., 2018. Impacts of rainfall extremes on wheat yield in semi-arid cropping systems in eastern Australia. Clim. Change 147 (3–4), 555–569.
Gao, Z., Feng, H.Y., Liang, X.G., Zhang, L., Lin, S., Zhao, X., Shen, S., Zhou, L., Zhou, S. 2018. Limits to maize productivity in the North China Plain: A comparison analysis for spring and summer maize. Field Crops Res., 228: 39-47.
Hawkins, E., Fricker, T.E., Challinor, A.J., Ferro, C.A.T., Ho, C.K., Osborne, T.M., 2013. Increasing influence of heat stress on French maize yields from the 1960s to the 2030s. Glob. Change Biol. 19 (3), 937–947.
Hsiao, J., Swann, A.L.S., Kim, S.H., 2019. Maize yield under a changing climate: The hidden role of vapor pressure deficit. Agric. For. Meteorol. 279, 107692.
Hussain, O., Perdomo, A., Dillon, T., Chang, E., 2009. A digital information ecosystem structure for regional climate change assessment and adaptation. Int. Conf. Digital Ecosyst. Technol. 2009 (3), 199–204.
IPCC. 2001. Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment report of the Intergovernmental Panel on Climate Change. Vol. 2. UK: Cambridge University Press.
Ipcc, 2013. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (AR5). Climate change 2013: The Physical Science Basis. Cambridge University Press, Cambridge.
Isik, M., Devadoss, S., 2006. An analysis of the impact of climate change on crop yields and yield variability. Appl. Econ. 38 (7), 835–844.
Jones, P.G., Thornton, P.K., 2003. The potential impacts of climate change on maize production in Africa and Latin America in 2055. Global Environ. Change 13 (1), 51–59.
Laubhann, D., Sterba, H., Reinds, G.J., de Vires, W., 2009. The impact of atmospheric deposition and climate on forest growth in European monitoring plots: an individual tree growth model. For. Ecol. Manage. 258, 1751–1761.
Li, N., Lin, H., Wang, T., Li, Y., Liu, Y., Chen, X., Hu, X., 2020. Impact of climate change on cotton growth and yields in Xinjiang, China. Field Crops Res. 247, 107590.
Li, X., Takahashi, T., Suzuki, N., Kaiser, H.M., 2011. The impact of climate change on maize yields in the United States and China. Agric. Syst. 104 (4), 348–353.
Li, X., Takahashi, T., Suzuki, N., Kaiser, H.M., 2014. Impact of climate change on maize production in Northeast and Southwest China and risk mitigation strategies. APCBEE Procedia 8, 11–20.
Liu, D.L., Wang, B., Evans, J., Ji, F., Waters, C., Macadam, I., Yang, X., Beyer, K., 2019. Propagation of climate model biases to biophysical modelling can complicate assessments of climate change impact in agricultural systems. Int. J. Climatol. 39 (1), 424–444.
Liu, S., Li, Y., He, C., 2013a. Spectral analysis and estimations of soil salt and organic matter contents. Soil Sci. 178 (3), 138–146.
Liu, Y., Wang, E., Yang, X., Wang, J., 2010. Contributions of climatic and crop varietal changes to crop production in the North China Plain, since 1980s. Glob. Change Biol. 16 (8), 2287–2299.
Liu, Z., Hubbard, K., Lin, X., Yang, X., 2013b. Negative effect of climate warming on maize yield are reversed by the changing of sowing date and cultivar selection in Northeast China. Glob. Change Biol. 19 (11), 3481–3492.
Liu, Z., Yang, X., Hubbard, K.G., Lin, X., 2012. Maize potential yields and yield gaps in the changing climate of northeast China. Glob. Change Biol. 18 (11), 3441–3454.
Lobell, D.B., 2007. Changes in diurnal temperature range and national cereal yields. Agric. For. Meteorol. 145 (3–4), 229–238.
Lobell, D.B., Burke, M.B., 2010. On the use of statistical models to predict crop yield responses to climate change. Agric. For. Meteorol. 150 (11), 1443–1452.
Lobell, D.B., Cahill, K.N., Field, C.B., 2007. Historical effects of temperature and precipitation on California crop yields. Clim. Change 81 (2), 187–203.

Lobell, D.B., Field, C.B., 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2 (1), 014002.
Lobell, D.B., Ortiz-Monasterio, J.I., Asner, G.P., Matson, P.A., Naylor, R.L., Falcon, W.P., 2005. Analysis of wheat yield and climatic trends in Mexico. Field Crops Res. 94 (2–3), 250–256.
Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate trends and global crop production since 1980. Science 333 (6042), 616–620.
Malone, R.W., Meek, D.W., Hatfield, J.L., Mann, M.E., Jaquis, R.J., Ma, L., 2009. Quasi-biennial corn yield cycles in Iowa. Agric. For. Meteorol. 149 (6–7), 1087–1094.
Mansfield, E.R., Helms, B.P., 1982. Detecting multicollinearity. Am. Statistic. 36, 158–160.
Matsuda, H., Higuchi, H., 2015. Effects of temperature and humidity conditions on anthesis and pollen germinability of cherimoya (Annona cherimola Mill.). Trop. Agricult. Devel. 59 (2), 57–62.
Muchena, P., Iglesias, A., 1995. Vulnerability of maize yields to climate change in different farming sectors in Zimbabwe. Climate Change Agric.: Anal. Potential Int. Impacts 59, 229–239.
Nicholls, N., 1997. Increased Australian wheat yield due to recent climate trends. Nature 387 (6632), 484–485.
Nielsen, D.R., Bouma, J., 1985. Soil Spatial Variability. Pudoc Press, Wageningen, pp. 1–243.
Niu, X., Xie, R., Liu, X., Zhang, F., Li, S., Gao, S., 2013. Maize yield gains in Northeast China in the last six decades. J. Integr. Agric. 12 (4), 630–637.
Olesen, J.E., Bindi, M., 2002. Consequences of climate change for European agricultural productivity, land use and policy. Eur. J. Agron. 16, 239–262.
Pedram, R., Lobell, D.B., Linderman, M., Ramankutty, N., 2011. Climate variability and crop production in Tanzania. Agric. For. Meteorol. 151, 449–460.
Peng, S., Huang, J., Sheehy, J.E., Laza, R.C., Visperas, R.M., Zhong, X., Centeno, G.S., Khush, G.S., Cassman, K.G., 2004. Rice yields decline with higher night temperature from global warming. Proc. Natl. Acad. Sci. 101 (27), 9971–9975.
Prabnakorn, S., Maskey, S., Suryadi, F.X., De Fraiture, C., 2018. Rice yield in response to climate trends and drought index in the Mun River Basin, Thailand. Sci. Total Environ. 621, 108–119.
Ruiz, V., Ursula, M. 2014. Impacts of global warming and rising atmospheric CO_2 concentrations on physiology, development and productivity of Midwestern crops. Dissertations and Theses Gradworks. University of Illinois at Urbana-Champaign.
Scheller, R.M., Mladenoff, D.J., 2008. Simulated effects of climate change, fragmentation, and interspecific competition on tree species migration in northern Wisconsin, USA. Clim. Res. 36, 191–202.
Sen, P.K., 1968. Estimates of the Regression Coefficient Based on Kendall's Tau. J. Am. Stat. Assoc. 63 (324), 1379–1389.
Tao, F., Yokozawa, M., Liu, J., Zhang, Z., 2008. Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends. Clim. Res. 38 (1), 83–94.
Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y., Zhang, Z., 2006. Climate changes and trends in phenology and yields of field crops in China, 1981–2000. Agric. For. Meteorol. 138 (1–4), 82–92.
Tao, F., Zhang, Z., 2011. Impacts of climate change as a function of global mean temperature: maize productivity and water use in China. Clim. Change 105 (3–4), 409–432.
Tao, F., Zhang, Z., Zhang, S., Zhu, Z., Shi, W., 2012. Response of crop yields to climate trends since 1980 in China. Clim. Res. 54 (3), 233–247.
Ureta, C., Martinez-Meyer, E., González, E.J., Alvarez-Buylla, E.R., 2016. Finding potential high-yield areas for Mexican maize under current and climate change condition. J. Agric. Sci. 154 (5), 782–794.
Waha, K., Mueller, C., Rolinski, S., 2013. Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid- to late-21st century. Global Planet. Change 106, 1–12.
Wang, R., Zhang, Q., Wang, Y., Yang, X., Han, Y., Yang, Q., 2004. Response of corn to climate warming in arid areas in Northwest China. Acta Botanica Sinica 46 (12), 1387–1392.
Wang, S.P., 2010. The division of corn growing areas in China. Breeding Technical Consultant 6, 74 in Chinese with English abstract.
Wang, Y., Zhou, B., Ren, Y., Sun, C., 2016. Impacts of global climate change on China's climate security. J. Appl. Meteorol. Sci. 27 (6), 750–758 in Chinese with English abstract.
Welch, J.R., Vincent, J.R., Auffhammer, M., Moya, P.F., Dobermann, A., Dawe, D., 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. Proc. Natl. Acad. Sci. 107 (33), 14562–14567.
Wuethrich, B., 2000. How climate change alters rhythms of the wild. Science 287 (5454), 793–795.
Xiao, D., Liu, D.L., Wang, B., Feng, P., Waters, C., 2020. Designing high-yielding maize ideotypes to adapt changing climate in the North China Plain. Agric. Syst. 181, 102805.
Xiao, D., Tao, F., 2016. Contributions of cultivar shift, management practice and climate change to maize yield in North China Plain in 1981–2009. Int. J. Biometeorol. 60 (7), 1111–1122.
Xu, X., Wang, L., Sun, D., Liu, L., Banson, K.E., 2017. The impact of climate change on yield potential of maize across China. Int. J. Plant Prod. 11 (1), 47–64.
Yang, D., Xiong, W., Xu, Y., Feng, L., Zhang, M., Liu, H., 2017. Analysis of reason for recent slowing maize yield increase under climate change in China. Trans. t Chin. Soc. Agric. Eng. 33 (Supp. 1), 231–238 in Chinese with English abstract.
Zhang, P., Li, Y., 2016. Study on the comparisons of the establishment of two mathematical modeling methods for soil organic matter content based on spectral reflectance. Spectrosc. Spect. Anal. 36 (3), 903–910.
Zhang, T., Huang, Y., 2012. Impacts of climate change and inter-annual variability on cereal crops in China from 1980 to 2008. J. Sci. Food Agric. 92 (8), 1643–1652.
Zhao, J., Guo, J., Mu, J., 2015. Exploring the relationships between climatic variables and climate-induced yield of spring maize in Northeast China. Agric. Ecosyst. Environ. 207, 79–90.
Zhao, J., Yang, X., Liu, Z., Lv, S., Wang, J., Dai, S., 2016. Variations in the potential climatic suitability distribution patterns and grain yields for spring maize in Northeast China under climate change. Clim. Change 137 (1–2), 29–42.