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Abstract

Corn is one of most important agricultural products in China. Understanding impacts of regional climate change, as well as agricultural management practices, on corn yields is critical for maintaining stable corn production. Using the DayCent model and observed climatic data in Sichuan province (a humid and hot environment) and Hebei province (a cold and dry environment) in China, corn yields in 1948-2010 were simulated. The spatial variations of simulated corn yields and the relationship between regional climate variability and warming with corn yields in these two environments were analyzed. The results demonstrated that: (1) corn yields in Zhangjiakou of Hebei and most regions of Sichuan decreased significantly after 2000 compared to other regions; (2) relative humidity and precipitation exhibit a significant negative correlation with observed crop yields in the growing season in Hebei province; (3) air temperature from 23.33 °C to 29 °C constitutes the ideal range influencing the increase of corn yields in Sichuan; (4) the planting of the large amount of silage maize in Sichuan compensated the negative impact of the rising air temperature on corn yields; (5) sensitivity tests for different fertilization levels and OMAD suggest that an increasing fertilization level significantly affects corn yields in Hebei province, a cold and dry environment, while a decreasing fertilization level has a significant negative effect in Sichuan province, a hot and humid environment. The overarching goal of these analyses is to provide the theoretical basic for maintaining stable corn production under regional climate warming and different agricultural management practices.

Keywords: corn yields, DayCent model, climate variability and change, fertilization level, organic matter additions

1. Introduction

Corn is one of the most important crops globally, and its production has increased continuously from 2008 to 2015 in China, reaching 22 trillion kg in 2016. This increase of corn production has been attributed to enlargement of cultivated areas and advancements in production technology (B. Chen & G. Chen, 2007; Peng, Tang, & Zou, 2009; Yu, Huang, & Zhang, 2012; Bryan, King, & Zhao, 2014; Nendel, Kersebaum, Mirschel, & Wenkel, 2014). Effects of climate factors on corn yields have also been widely studied. Some extant literature has investigated the effect of air temperature (Wolfram & Michael, 2009; Yin et al., 2016; Lobell & Field, 2007; Basche et al., 2016; S. Chen, X. G. Chen, & J. T. Xu, 2016; Lee & Durmaz, 2016; Meng, Carew, Florkowski, & Klepacka, 2016), while others have focused on the effect of other climatic factors, such as precipitation and wind (Yin et al., 2016; Lee & Durmaz, 2016; Wang, Bocoling, & Cherkauer, 2016). A number of studies found that rising air temperature in the growing season, especially in July or in the seeding and maturity phases, increased corn yields (Wolfram & Michael, 2009; Yin et al., 2016). However, scholars have also reported that climate change has resulted in the reduction of corn yield over several countries in the past few decades (Wolfram &

Michael, 2009; Lobell & Field, 2007; Basche et al., 2016; S. Chen, X. G. Chen, & J. T. Xu, 2016; Lee & Durmaz, 2016; Almarza, Mabood, Zhou, Gregorich, & Smith, 2008). In fact, Chen et al. (2016) reported that corn yield is projected to decline by 3-12% by 2100 in China due to rising air temperature. In the U.S., it was found that after the average growing-season air temperature exceeded 29 °C, corn yield would decrease sharply (Wolfram & Michael, 2009). Warming since 1981 has resulted in annual combined losses of crops representing roughly 40 Mt or USD $5 billion per year, as of 2002 (Lobell & Field, 2007). A 1% increase in the growing season air temperature reduces corn yield per acre by 9% (Lee & Durmaz, 2016). Increases in minimum and maximum air temperatures were attributed to reduced yields of 1.6-2.7% by decade (Basche et al., 2016). Although different climate characteristics among the study areas explain some temperature responses in corn yields, there is a general lack of comprehensive research on the effect of air temperature on crop yield. In this study, we thoroughly investigate this issue by studying the relationship between air temperature and corn growth in two different regions in China.

To analyze the impact of climate on corn yield, various models have been utilized, such as empirical frameworks (S. Chen, X. G. Chen, & J. T. Xu, 2016), regression models (Wolfram & Michael, 2009), statistical models (Basche et al., 2016; Almarza, Mabood, Zhou, Gregorich, & Smith, 2008), climatic models (IHadRM3, C4I, REMO-MPI, ETHZ, CNRM, DMI-HIRHAM, KNMI, SMHI) (Voloudakis et al., 2015), the Agricultural Production Systems sIMulator (APSIM) (Basche et al., 2016), crop simulation models (Morell et al., 2016), and crop growth models (Silva, Reidsma, Laborte, & van Ittersum, 2017). These approaches possess respective strengths and weaknesses. For example, although the DNDC model considers the cropping system, fertilizer and straw return in its crop simulations, it only employs a few key management practices (Morell et al., 2016). A crop growth model (ORYZA v3) was able to simulate rice yield relatively well, but tended to overestimate other crops' yields (Silva, Reidsma, Laborte, & van Ittersum, 2017). APSIM and HERMES address the agricultural management practice factor in analyzing the impact of climate change on corn yield, but only limited numbers of management factors were considered. In this study, we employ the DayCent model (Parton, Hartman, Ojima, & Schimel, 1998; Parton et al., 2001) to test the effects of key climatic factors, warming air temperatures, and various agricultural management practices on crop yield.

DayCent is a process-based biogeochemical model, and is a useful tool to predict yields as it integrates crop growth, carbon and nutrient dynamics, hydrology, management, and climate. Many studies have utilized DayCent to simulate changes in soil C, soil N, and greenhouse gas emissions (Wieder, Bonan, & Allison, 2014; Sheehan et al., 2013; Frey, Lee, Melillo, & Six, 2015; Cheng, Ogle, Parton, & Pan, 2014; Robertson, Grace, Izaurralde, Parton, & Zhang, 2014; Rafique, Fieneu, Parkin, & Anex, 2013; Reay et al., 2012; Mangalassery et al., 2014). Only a few previous studies have examined grain yield change under different climatic conditions and agricultural management practices using this model in China (Campbell et al., 2014; Lee, De, & Six, 2011). Cheng et al. (2014) used the DayCent model to successfully simulate crop yields in China, but focused on analyzing greenhouse gas mitigation potential and not the response of crop yields to future climatic change. In this study, variability in corn yields within each study region and the response to future climatic change were analyzed.

We selected Hebei province (a dry and cold environment) and Sichuan province (a warm and humid environment) in China as study areas, which possess quite different climate backgrounds (Figure 1). The spatial variation of simulated corn yields and the relationship between regional climate change, regional warming, and corn yield are reported in this study. The sensitivity of agricultural management practices in simulating corn yields by DayCent is also discussed.
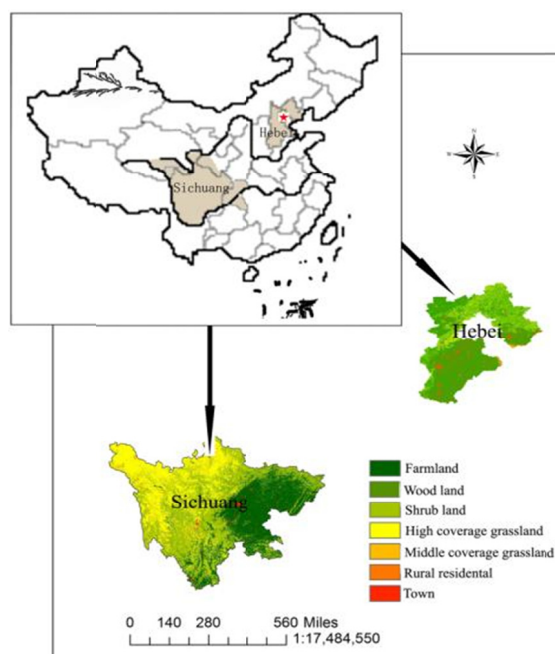
Figure 1. The geographic locations of the study area in China

2. Methods

2.1 Study Area

The geographic areas in this study, Hebei (E 113°04′ to 119°53′, N 36°01′ to 42°37′) and Sichuan (E97°21′ to 108°33′, N26°03′ to 34°19′) provinces in China are located in the northeast and southwest of China, respectively (Figure 1). Although they exhibit different climate characteristics, both have high corn acreage and production. Hebei has a temperate monsoon climate/warm temperate, humid-semi–arid continental monsoon climate, with an annual mean air temperature of 4-13 °C and an annual mean precipitation of 400-800 mm/yr (based on 63 years (1948-2010) of data). Climate is characterized by cold winters with little snow, hot summers with substantial rainfall, and windy springs and autumns with less rainfall. Climate in Sichuan is characterized by warm winters, dry springs, hot summers, rainy autumns, substantial fog, and less sunshine in the east, and by cold and long winters, short summers, abundant sunshine, and concentrated rainfall in the west.

Hebei is located in northern China, with an area of 188 thousand km^2. It encompasses 11 prefecture-level cities, 22 county-level cities, 108 counties, and six autonomous counties. The province's terrain slopes upward from the northwest to southeast. Hills, mountains and plateaus are in the northwest, with an average altitude of 1200-1500 m; plains are in central and southeast China, with an average altitude of less than 50 m.

Sichuan is located in the upper reaches of Changjiang River in southwest China, with an area of 99 thousand km^2. It is covered by plateaus in the west and basins in the east. The terrain is higher in the west with an altitude of 4000-5000 m, and lower in the east.

2.2 Selection of Study Locations

In Sichuan, we selected 18 counties (Figure 2a), including Abazhou, Bazhong, Chengdu, Dazhou, Deyang, Guangan, Guangyuan, Leshan, Xiaojin, Luzhou, Meishan, Mianyang, Nanchong, Neijiang, Yaan, Yibin, Zigong and Ziyang as study areas, which constitute the primary agricultural regions in the province. In Hebei, we selected 17 grid locations (Figure 2b) that were uniformly distributed within the boundary ranges of latitude and latitude covered by Hebei province and were not based on counties. This method ensured the broadest range of surface conditions and crop yields within the province, since conditions within individual counties are quite variable. Some locations in the boundary and out of the boundary were discarded because they were not representative of farmland. The latitude or longitude of the interval between adjacent two grid locations is 1° and are marked with letters "a" to "q", respectively, in Figure 2b.
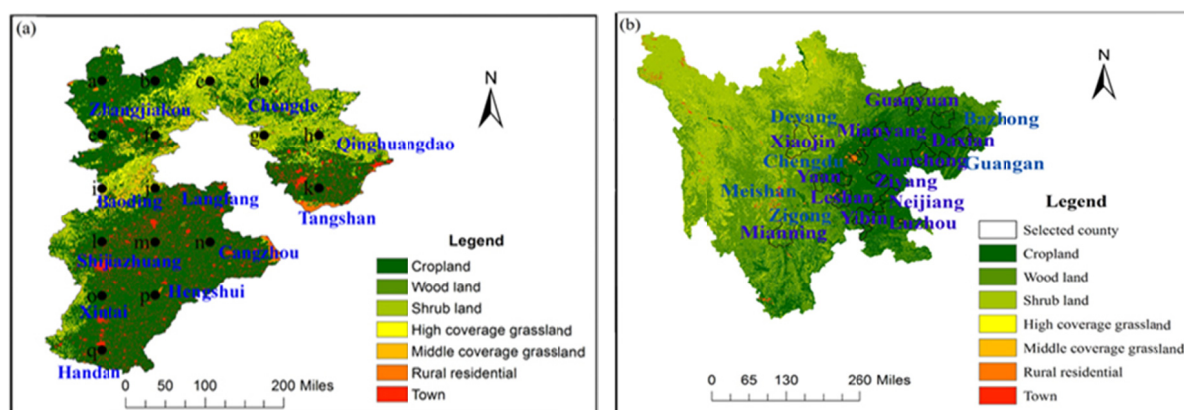
Figure 2. Land cover and selected locations in Hebei (a) and selected counties in Sichuan (b) in 2013. In selected locations of Hebei, a, b, c, e, and f represents Zhangjiakou. d, g, and h represent Chengde. k represents Tangshan. i represents Baoding. j represents langfang. l and m represent Shijiazhuang. n represents Cangzhou. o represents Xintai. p represents Hengshui. q represents Handan

2.3 DayCent Model

DayCent is a daily time-step version of the Century model that simulates plant production, trace gas fluxes (N_2O, NOx, CH_4), and the dynamics of carbon and nitrogen in grassland, forest, savanna, and agricultural systems (Wieder, Bonan, & Allison, 2014; Sheehan et al., 2013; Frey, Lee, Melillo, & Six, 2015; Cheng, Ogle, Parton, & Pan, 2014; Robertson, Grace, Izaurralde, Parton, & Zhang, 2014). The model has been widely utilized to simulate the impact of environmental changes (elevated CO_2 and climatic changes, management practices) on production and yield in agro-ecosystems globally (Cheng et al., 2014; Robertson, Grace, Izaurralde, Parton, & Zhang, 2014; Reay et al., 2012; Mangalassery et al., 2014).

2.3.1 Model Inputs and Data Collection

Model inputs are daily weather data, soil properties, and agricultural management practices (e.g., crop type, cultivation/planting schedules, amount and timing of nutrient amendments, irrigation, and tillage). The crop-specific parameter PRDX(1), a coefficient for calculating potential aboveground daily production as a function of solar radiation outside the atmosphere, is a critical important parameter. The values of PRDX(1) for the types of corn (C1, C2, C3, C4, C5, and C6) increased in value according to the various corn productivity levels and were different for each province. This set of corn parameters for Hebei and Sichuan provinces was the same for all simulations, respectively. Measured corn yields from 1978 to 2010 were obtained from the Hebei Economic Year Book (2008-2011) and the Sichuan Statistical Year Book (2000-2011).

(1) *Weather data*: Daily weather data, which include daily maximum and minimum air temperature (T_{min} and T_{max}), daily precipitation (Prcp), daily solar radiation (Dswrf), daily relative humidity (RH), and daily wind speed (Wind), are necessary forces to drive ecosystem processes in DayCent. The weather data from 1948 to 2010 for this study were derived from the Princeton University Hydroclimatology Group Bias Corrected Meteorological Forcing Dataset (Sheffield, Goteti, & Wood, 2006). The units of these data were converted according to the format required by DayCent.

(2) *Soil data*: Soil property data, specified by soil layer, comprised bulk density (g/cm^3), field capacity, wilting point, evaporation coefficient, fraction of roots, fraction of sand and clay, saturated hydraulic conductivity, and pH. All of these data were obtained by field survey and sample measurement in the study areas in 2016. Specifically, three plots of corn planted in 2016 in each county or location were selected in 18 counties of Sichuan province and 17 locations of Hebei province from August to September. Soil samples in each corn plot were collected using plastic bags. Fresh weight was determined at that time, and the samples were brought to the laboratory and dried at 105 ℃. Dry weight was then obtained, and then soil water content was calculated.

(3) *Crop management data*: Agricultural management options, which are specified in the DayCent schedule file, include crop types, irrigation intensity, cultivation practices, residue removal during harvest, organic matter additions, inorganic fertilizer additions, and planting and harvest dates (Cheng et al., 2014). Corn growth in Hebei province is mainly dependent on irrigation, while corn growth in Sichuan province relies on irrigation and rainfall. Assuming ample water for irrigation, corn production is not limited by water availability in these two provinces. We define five periods according to production technology levels during the periods of 1948-2010 in

China: 1948-1965, 1966-1975, 1976-1985, 1986-1995, and 1996-2010. The management options for these five periods were obtained through reports from local farmers and relevant literature (Liang, 2015; Liang et al., 2008; Luo et al., 2016; Liu et al., 1998; Chen, 2013).

2.3.2 Evaluation Method

Performance of the DayCent model was assessed using several quantitative methods (Janssen & Heuberger, 1995). First, the main difference between the simulated and observed values was assessed by calculating the root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \left(S_i - O_i\right)^2 / n} \tag{1}$$

where, O_i and S_i denote the observed and simulated values, respectively; and n is the number of measurements. Second, the accuracy of the simulations was evaluated based on modeling efficiency (EF):

$$\text{EF} = \frac{\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{2}$$

where, $\bar{O}$ denotes the mean of the observed data; and O_i and S_i denote the observed and simulated values, respectively. A positive value of EF indicates good modeling efficiency, in which the closer the value is to +1, the better is the modeling efficiency. Negative values of EF indicate poor modeling efficiency, in which the farther the value is from +1, the worse is the modeling efficiency. Third, bias constitutes the main difference between the simulated and observed values, and was determined by calculating the relative error (E):

$$\text{E} = \frac{100}{n}\sum_{i=1}^{n}\left(O_i - S_i\right)^2 / O_i \tag{3}$$

An E value closer to 0 suggests a better model fit to the measurements. When both measurements and observations are positive numbers, a positive E value indicates that the model underestimates the observations, and a negative E value indicates that it overestimates the observations.

We also analyzed the spatial variation and temporal correlation between simulated and observed corn yields from 1978-2010 by the Pearson correlation analysis method using SPSS 13.0 software.

2.4 Factors that Affect Corn Yields and Experimental Designs

Simulated corn yield was affected by numerous factors, including climate forcing and specified agricultural management practices. In this paper, we analyze the general relationship between climate variables and crop yields based on observation and model simulation. We also present the sensitivity of crop yields to management. Since we possessed no detailed information regarding crop management, we performed several sensitivity studies to test how each factor affects corn yield simulation. In the sensitivity tests, one factor at a time was changed (Figure 3). The sensitivity tests were designed as follows:
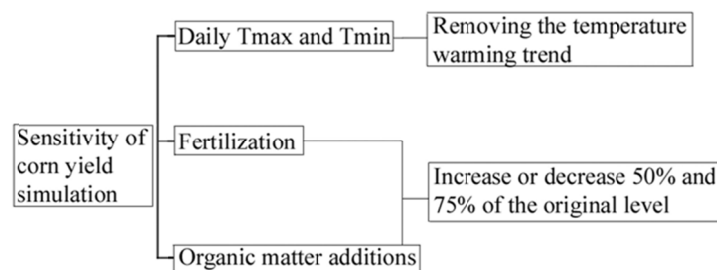

Figure 3. Schematic diagram of sensitivity analysis. (A) factors and (B) methods

(1) *Sensitivity to air temperature*. In the sensitivity study, we removed the trend of elevated air temperature from 1978 to 2010 in Hebei and Sichuan provinces (*i.e.*, de-trending) by subtracting the annual mean values, which were derived from original daily T_{max} and T_{min}. Comparisons between the actual and detrended mean growing season temperatures for each province are briefly presented in Figure 4. From Figure 4, it can be seen that the mean growing season T_{max} in Hebei and Sichuan decreased by 0.08 °C and 0.43 °C, respectively, after detrending; The mean growing season T_{min} in Hebei and Sichuan decreased by 0.09 °C and 0.44 °C, respectively, after detrending. All of these findings indicate that the mean growing season T_{max} and T_{min} in Hebei increased slightly in the past 23 years, but greatly in Sichuan.

(2) *Sensitivity to fertilizer and organic matter additions*. Fertilizer management includes different fertilization timing and levels. In this paper, only fertilizer level was considered. The application of organic matter (OMAD) in the field after harvest maintains soil fertility for the following year. In the sensitivity tests, we added or decreased fertilization and OMAD level by 50% and 75% compared with the original setting. These fertilizer or OMAD amounts did not vary spatially in Hebei or Sichuan in this experiment. Organic matter (*e.g.*, manure) is widely available in China so that applications can be increased (Zhao et al., 2017).

To assess sensitivity, we calculated the average simulated corn yields in the sensitivity simulation minus the average of the control simulated corn yields in the study period.
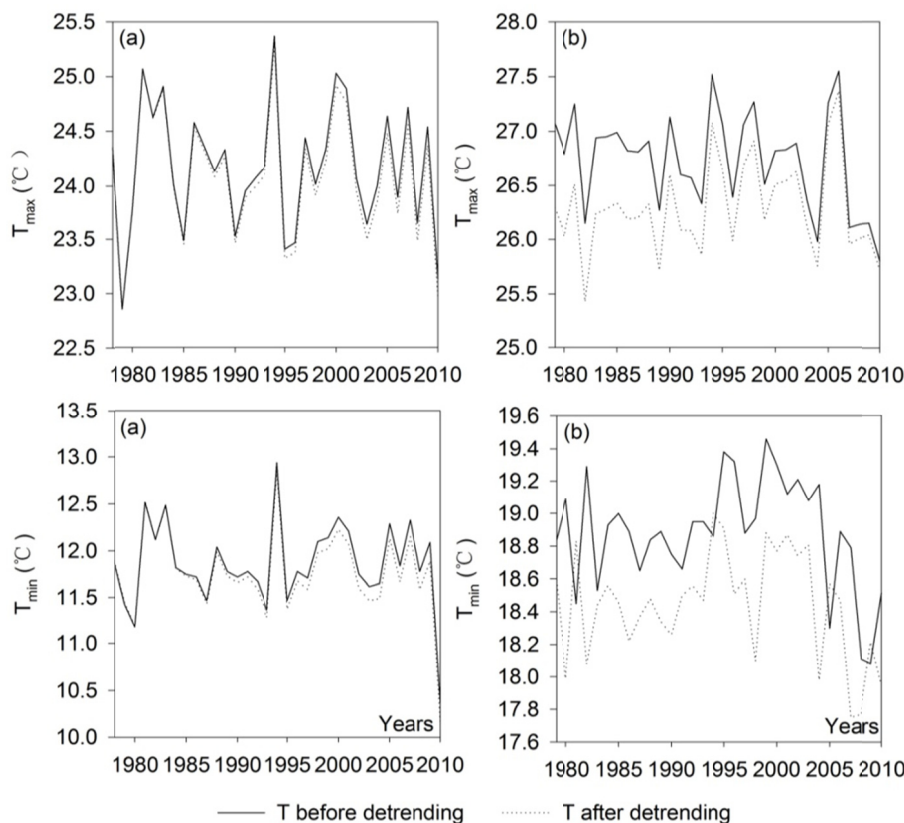

Figure 4. Change in mean growing season T_{max} and T_{min} before and after detrending in 1978-2010 in the province of (a) Hebei and (b) Sichuan

2.5 Data Availability

Weather data derived from the Princeton University Hydroclimatology Group Bias Corrected Meteorological Forcing Dataset. Soil data were obtained by field work in the study area. Crop management data were provided by the local farmers and Statistic Yearbook of the Sichuan and Hebei provinces.

3. Results

3.1 Relationship Between Climate Variables and Corn Yields

In this paper, corn yield only refers to grain yield, and does not include corn stalk. The simulated results are compared with measured corn yields for 1978-2010 (Figure 5). A strong correlation was found between mean simulated and observed corn yields, with R^2 values of 0.842 in Hebei and 0.751 in Sichuan. These results are in agreement with Cheng et al. (2014), who also reported that the DayCent model was reasonably accurate in simulating crop yields with R^2 values ranging from 0.71 to 0.85 in 350 cropland experiments in China. The values of RMSE, EF, and E are 875.12, -0.76, and 3.39 in Hebei, and 1173.28, -0.24, and 0.22 in Sichuan, respectively. RMSE in Hebei is lower than in Sichuan. The value of EF in Sichuan is closer to 1 than in Hebei. Moreover, the relative error, E, in Sichuan is lower and closer to 0 than in Hebei, which reflects the better simulation efficiency in Sichuan.
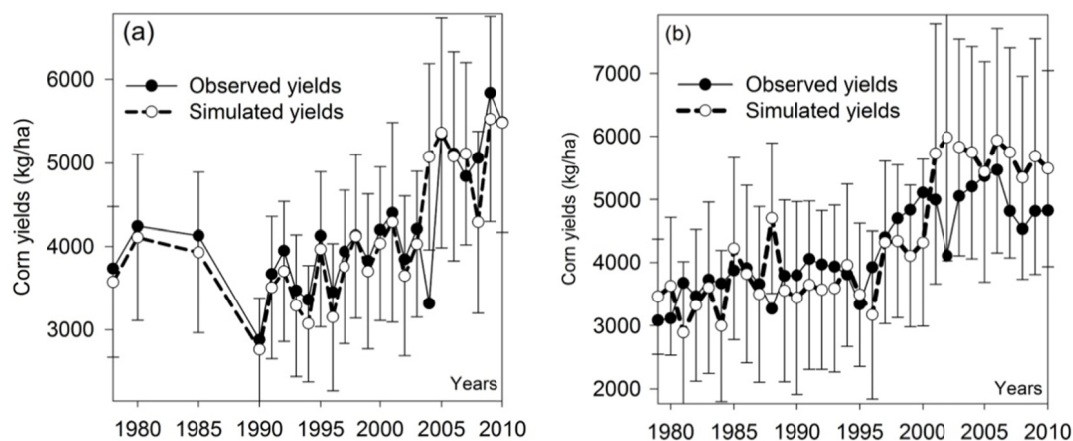
Figure 5. Mean observed and simulated corn yields in the province of (a) Hebei and (b) Sichuan. The bars represent plus and minus one standard deviation for simulated value

Figure 6 presents the variation of six meteorological variables (T_{max}, T_{min}, Dswrf, RH, Wind, and Prcp) over the past 33 years (1978-2010) in these two provinces. T_{max} and T_{min} increased at a rate of 0.22 °C/10 yr and 0.23 °C/10 yr (the method: estimation of linear trend (Fu et al., 2013) in Sichuan, respectively, and 0.34 °C/10 yr and 0.55 °C/10 yr in Hebei, respectively).

Downward shortwave radiation (Dswrf) increased at a rate of 1.92 (langleys/day)/10 yr in Sichuan, and decreased at a rate of -0.82 (langleys/day)/10 yr in Hebei. RH decreased at a rate of -0.06%/10 yr in Sichuan, and increased at a rate of -0.45%/10 yr in Hebei. Wind decreased at a rate of -0.11 (miles/hour)/10 yr in Sichuan, and increased at a rate of 0.08 (miles/hour)/10 yr in Hebei. Precipitation decreased at a rate of -0.01 cm/10 yr in both Sichuan and Hebei. The Z values (the method: Mann-Kendall nonparametric statistical test (Kahya & Kalayci, 2004) of the change in six meteorological variables were all more than 1.78 ($\alpha < 0.05$), indicating significant change trends of six climatic factors over the past 33 years.

To elucidate how each of the climatic factors affected corn yield, we analyzed the relations of six meteorological variables averaged over the growing season (April-September) from 1948-2010 with observed and simulated corn yields. Table 1 shows the correlation coefficients. In general, simulated and observed correlations are consistent with each other. However, in a few cases, the observations show significant results that were not confirmed by the simulations. In Hebei province, RH and Prcp exhibited a significant negative correlation with observed crop yields in the growing season. This is likely because the continuous rainfall in the pollination period seriously impacted the growth of maize (Liu, 2008). In Sichuan province, only T_{min} was negatively correlated with observed crop yields. There was no impact for T_{max} on observed corn yield in Sichuan. This is probably because the mean air temperature in Sichuan is relatively high, which usually met the needs of corn growth. The rising of T_{min} in Sichuan could cause the seeding time and the end of the growing season appear earlier and shorten the growing season of corn (Liu, Qin, Ge, Dai, & Chen, 2017), thus decreasing corn production.
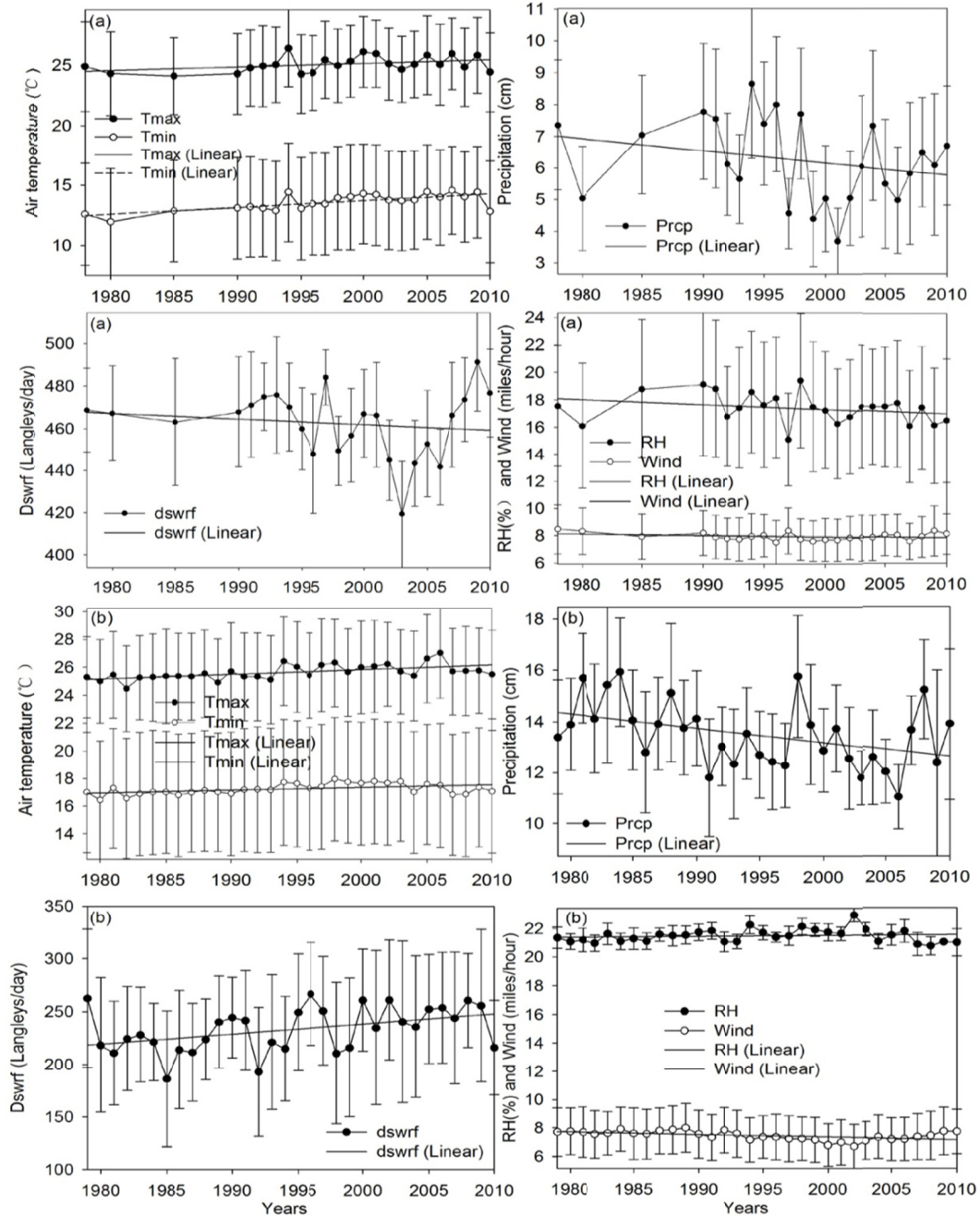
Figure 6. The annual change of six climatic factors (a) from 1978 to 2010 in Hebei and (b) from 1979 to 2010 in Sichuan. The bars represent plus and minus one standard deviation

Table 1. Pearson correlation between the average values of six meteorological factors from April to September, and crop yields in 1978-2010 in Hebei and in 1979-2010 in Sichuan provinces

Province	Variables		April-September		Province	Variables		April-September	
			Simulated	Observed				Simulated	Observed
Hebei	T_{max}	Pearson Correlation	0.172	-0.060	Sichuan	T_{max}	Pearson Correlation	-0.258	-0.133
		Sig.(2-tailed)	0.421	0.781			Sig.(2-tailed)	0.153	0.469
		N	24	24			N	33	33
	T_{min}	Pearson Correlation	0.299	0.059		T_{min}	Pearson Coefficient	-0.363**	-0.508**
		Sig.(2-tailed)	0.156	0.299			Sig.(2-tailed)	0.041	0.003
		N	24	24			N	33	33
	dswrf	Pearson Correlation	-0.010	0.105		dswrf	Pearson Coefficient	-0.166	-0.027
		Sig.(2-tailed)	0.961	0.625			Sig.(2-tailed)	0.364	0.884
		N	24	24			N	33	33
	RH	Pearson Correlation	-0.603**	-0.590**		RH	Pearson Coefficient	-0.056	0.073
		Sig.(2-tailed)	0.002	0.002			Sig.(2-tailed)	0.760	0.692
		N	24	24			N	33	33
	Wind	Pearson Correlation	0.323	0.303		Wind	Pearson Coefficient	0.024	0.181
		Sig.(2-tailed)	0.124	0.151			Sig.(2-tailed)	0.897	0.321
		N	24	24			N	33	33
	Prcp	Pearson Correlation	-0.373	-0.450*		Prcp	Pearson Coefficient	--0.379*	-0.295
		Sig.(2-tailed)	0.073	0.028			Sig.(2-tailed)	0.032	0.102
		N	24	24			N	33	33

Note. *. Correlation is significant at the 0.05 level (2-tailed); **. Correlation is significant at the 0.01 level (2-tailed).

3.2 Spatial Variations of Corn Yield Simulation

The spatial distribution of simulated corn yields in 1948-2010 in Hebei revealed that corn yields in central and north Hebei were more than yields in the south (Figure 7a). Corn yields in Chengde, Baoding and Shijiazhuang were the greatest in the whole province, while corn yields in Tangshan, Hengshui, Langfang, and Xintai were the least. Corn yields in the entire province increased from 1948 to 2010. North of Zhangjiakou, yields increased from 1948 to 1999, but decreased substantially after 2000 compared to other regions. Additionally, corn yields in the north of Chengde decreased substantially compared to other regions from 1948 to 2010. Reduction of corn production that occurred after 2000 was observed in Zhangjiakou and Chengde, which could be due to continuous rainfall in the pollination period and drought in the grain formation-mature period (Liu, 2008; Zhang, 2014; Liu, 2013).

In Sichuan province (Figure 7b), high-yield corn is mainly located east of Sichuan, especially in the northeastern and southeastern regions of the province, which is associated with topographic features and agriculture distribution. Corn yields in Guangyuan, Bazhong, Deyang, Ziyang and Daxian were the greatest in the whole province, while those in Xiaojin, Yaan, and Mianning distributed in the central of Sichuan were the least. After 2000, corn yields in Bazhong, Daxian, Ziyang, Nanchong, Guangan, Yibin, Luzhou, Neijiang, and Zigong decreased substantially compared to other regions (Figure 8). Zhu and Yang (2007) found that corn yields have continued to decline since 2000 due to large-scale adjustment of planting areas of maize under the policy of returning farmland to forest in Sichuan. This simulated yield reflected the declination of corn yields, in agreement with Zhu and Yang (Zhu & Yang, 2007).
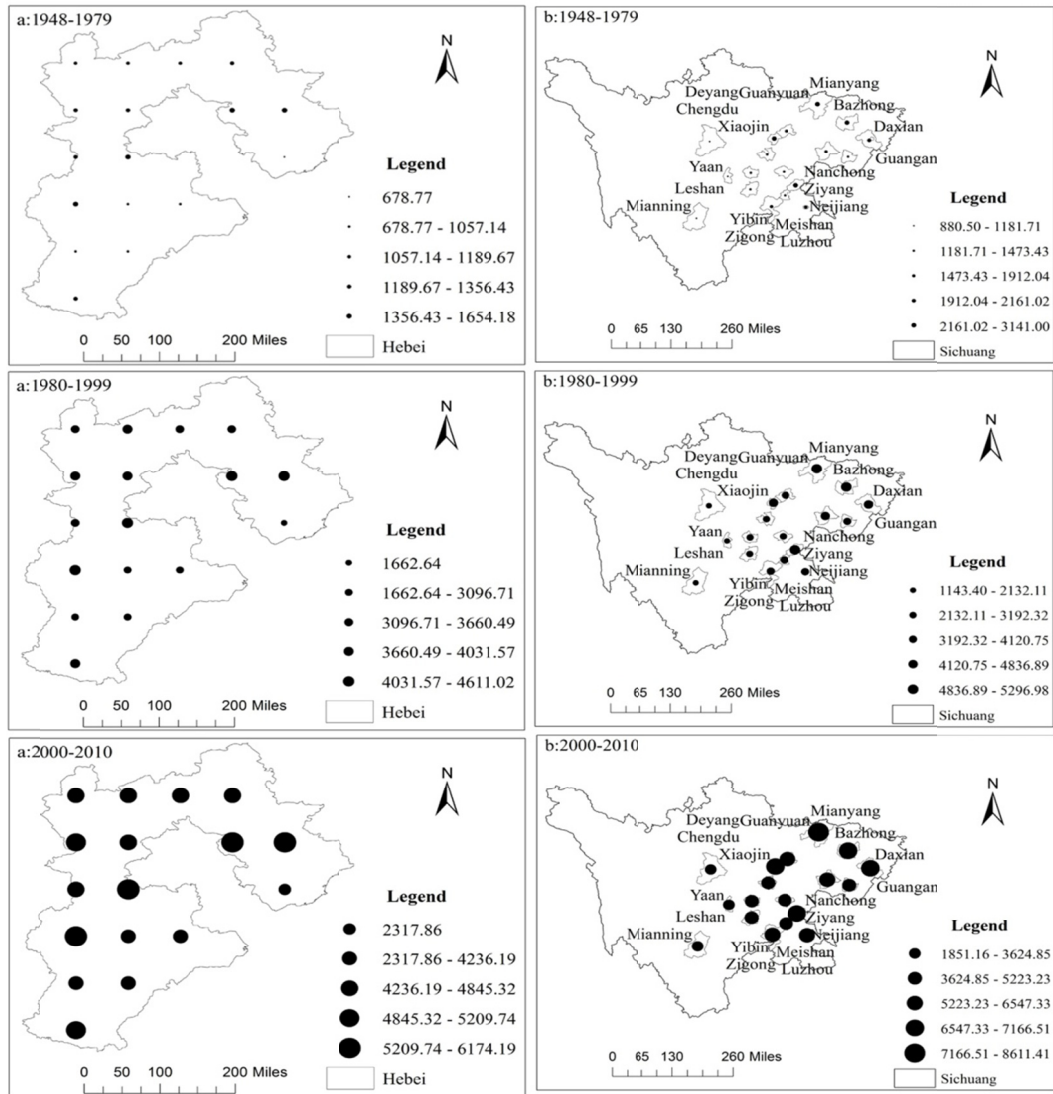
Figure 7. Spatial variations on simulated corn yields in 1948-1979, 1980-1999, and 2000-2010 in the province of (a) Hebei and (b) Sichuan
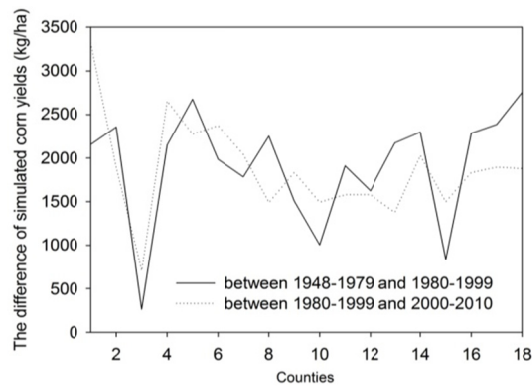

Figure 8. The differences of simulated corn yields between 1980-1999 and 1948-1979, and between 2000-2010 and 1980-1999 in Sichuan. Thereinto, in horizontal ordinate, 1-18 represents Guangyuan, Bazhong, Xiaojin, Mianyang, Daxian, Deyang, Chengdu, Guangan, Meishan, Yaan, Ziyang, Leshan, Zigong, Yibin, Mianning, Luzhou, Neijiang and Nanchong, respectively

3.3 Impact of Regional Warming on Corn Yield

To test the regional warming effect, we removed the daily air temperature warming trend of the forcing meteorological data from 1978 to 2010 in the experiment. Figure 9 shows that, the variations of simulated corn yields with regional warming compared to those without regional warming were different during various phases of 1978-2010. In Hebei province, the annual mean corn yield in the controlled experiment after de-trending was 3794 kg/ha in 1978-2003, 4590 kg/ha in 2004-2007 and 5385 kg/ha in 2008-2010. Compared to the original simulated annual mean corn yields of 3684 kg/ha in 1978-2003, 5156 kg/ha in 2004-2007 and 5097 kg/ha in 2008-2010, mean corn yields increased by 110 kg/ha in 1978-2003 and 288 kg/ha in 2008-2010, respectively, decreased by 565 kg/ha in 2004-2007, with removing the warming trend. The change of mean simulated corn yields in Hebei was not significant (Z = 0.0095, α > 0.05, resulting from Mann-Kendall test (Fu et al., 2013)).
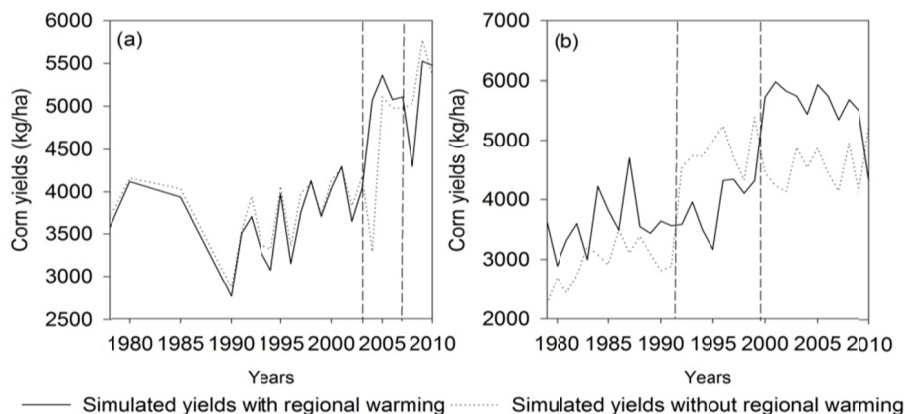

Figure 9. Changes of corn yields with/without regional warming in the province of (a) Hebei and (b) Sichuan

In Sichuan, the simulated mean corn yields before and after de-trending were 3604 kg/ha/yr and 2931 kg/ha/yr in 1979-1991, 3909 kg/ha/yr and 4832 kg/ha/yr in 1992-1999, 5567 kg/ha/yr and 4540 kg/ha/yr in 2000-2010 respectively, which shows that rising air temperature enhanced corn yields in 1979-1991 and 2000-2010, increasing them by 674 kg/ha/yr and 1027 kg/ha/yr on average in these two periods, affected corn growth in 1992-1999, decreasing them by 923 kg/ha/yr. These change were significant (Z = 1.53, α < 0.05). The reason why rising air temperature has a significant impact on corn yields in Sichuan is that the warming of air temperature extends the summer and increased solar radiation, which allows to plant spring corn, summer corn and silage corn in more regions in a year under the condition of enough precipitation (Figure 6) in 1979-1991 and 2000-2010, so corn yields were increased. In the 1990s, precipitation was the least compared to other periods in Sichuan (Zhou et al., 2011). Therefore, the drought degree intensified in the 1990s in Sichuan with the rising of air temperature and the decrease of precipitation (Figure 6), which led to the reduction of corn yields. However, in Hebei, the warming of air temperature intensified drought and increased evapotranspiration. Sufficient irrigation can compensate for the need of more water in corn growth. Therefore, the rising air temperature did not lead to the significantchange of corn yield in Hebei.

From this, we can see that the sensitivity of simulated corn yields to elevated air temperature was greater in hot and humid environments than in cold and dry environments. In contrast, Liu (2008) reported that the adaptation of crops to the warming of air temperature was low, revealing the inhibition effect on yield in a warm province, and founding that area growth and development of crops were accelerated, but the growth period was shortened, and total dry weight was reduced with rising air temperature. The results in this paper were not controversial to that reported by Liu (Liu, 2008). The increase of corn yields with the rising air temperature is mainly because the enlargement of two bifurcation corn plant area in Sichuan, especially silage corn in large quantities (Duan, 2014). The negative correlation between T_{min} and corn yields (Table 1) also showed that the negative impact of air temperature warming on corn yields, which is in agreement with the report by Liu (Liu, 2008).

The variation of simulated corn yields among different mean growing season air temperature in 1978-2010 in Hebei and in 1979-2010 in Sichuan were calculated and analyzed using the least significant difference (LSD) by SPSS 13.0 software (Table 2). The annual mean growing season air temperature in 1978-2010 in Hebei and in 1979-2010 in Sichuan are taken as control factors, and simulated annual corn yields as the dependent variables. After the control factors were sorted in ascending order, and the dependent variables were correspondingly

sorted with the control factors, the control factors in the different provinces were divided into three levels from small to large, respectively (Table 2). Then, the significance of the difference between the dependent variables among these three levels of the control factors was analyzed using the LSD method. The results showed that, in Hebei, when the mean growing season air temperature increased from 18.69 °C to 19.41 °C, and then to 20.21 °C, there was no significant difference between simulated corn yields, which indicates that there was not a critical threshold value of air temperature influencing corn yields when the growing season air temperature varied in the range of 18.69 °C-20.21 °C. In Sichuan, when the air temperature rose from 22.29 °C to 22.68 °C, simulated corn yields varied non-significantly, but at 23.33 °C, simulated corn yields changed significantly, which shows that 23.33 °C may constitute a critical threshold value influencing simulated corn yields. The change in the growing season air temperature was positively associated with simulated corn yields with the correlation coefficient of 0.456 (sig. = 0.009 < 0.05) (Table 3). Therefore, when the mean growing season air temperature was over 23.33 °C, simulated corn yields increased with the rising of air temperature in Sichuan province. Wolfram and Michael (2009) also found that annual mean air temperature affects corn yields. They indicated that crop yield would increase with elevated air temperature up to 29 °C. Moreover, above this threshold value of air temperature, further warming would have a detrimental effect on yield. The results of this study are not contradictory to those of Wolfram and Michael (2009), and provide a minimum value of air temperature influencing and increasing corn yields. The annual mean air temperature in the growing season of corn (April to September) in Sichuan and Hebei are 22.83 °C and 19.34 °C, respectively. Therefore, when the mean growing season air temperature reaches 23.33 °C-29 °C in Sichuan, corn yields increase with the rising air temperature. It has been found that the 1990s are the warmest 10 years in 1948-2010 because the number of days over 29 °C of actual air temperature in the growing season was more than 190 days in each year of seven years of 1990s. This long period and continuous high temperature are also probably the factors leading to the reduction of corn yields in the 1990s.

Table 2. The least significant difference (LSD) analysis on simulated corn yields among the different growing season air temperature levels in Hebei and Sichuan provinces

Provinces	Air temperature (I) (°C)	Air temperature (II) (°C)	Mean difference (I-J)	Std. Error (°C)	Significance
Hebei	18.69	19.41	998.71*	464.27	0.043
		20.21	120.71	439.25	0.786
	19.41	18.69	-998.71*	464.27	0.043
		20.21	-878.00**	308.16	0.010
	20.21	18.69	-120.71	439.15	0.786
		19.41	878.00**	308.16	0.010
Sichuan	22.29	22.68	-1046.71**	323.42	0.003
		23.33	-1442.88**	526.99	0.010
	22.68	22.29	1046.71**	323.42	0.003
		23.33	-396.16	550.43	0.477
	23.33	22.29	1442.88**	526.99	0.010
		22.68	396.16	550.43	0.477

Note. *. LSD is significant at the 0.05 level (2-tailed); **. LSD is significant at the 0.01 level (2-tailed).

Table 3. Pearson correlation coefficients between the mean growing season air temperature and simulated corn yields in Hebei and Sichuan provinces

Provinces	Correlation coefficients	Significance (2-tailed)
Hebei	0.294	0.163
Sichuan	0.456**	0.009

3.4 Sensitivity Analysis

Anandhi (2016) also analyzed the impact of management decisions, such as plant water use, fertilizer application and hybrids on corn yields, and found inadequate N fertility results in lower yields, whereas over-fertilization results in higher emissions of nitrous oxide. Here, we examine the changes in yields that result from increasing or decreasing inorganic and organic N applications.

3.4.1 Sensitivity to Inorganic N Fertilization Levels

The original fertilization levels (Table 4) were increased or decreased by 50% and 75% without changing other factors. In Hebei province, when the fertilization level was increased by 50% and 75%, mean annual yields from 1979 to 2010 increased by 2136 kg/ha (52%) and 2448 kg/ha (59%), respectively; when the fertilizer level was decreased by 50% and 75%, mean annual yields decreased by 2130 kg/ha (52%) and 3095 kg/ha (75%), respectively (Figure 10a). In Sichuan province, the mean annual yields from 1978 to 2010 were higher by 1467 kg/ha (34%) and 2346 kg/ha (55%) after a 50% and 75% increase in fertilization level, respectively; yields were lower by 2354 kg/ha (55%) and 3369 kg/ha (78%), respectively, when the fertilization level decreased by 50% and 75% (Figure 10b). Fertilization level increases in a cold and dry environment (in Hebei) were more beneficial than in a humid and hot environment (in Sichuan) in terms of percentage change. However, when the fertilization levels were decreased, crop yield in Sichuan suffered more than in Hebei. These results indicated that the sensitivity of the fertilization level influencing corn yield simulation was great in these two provinces. This is probably associated with the original soil fertility condition. It has been reported that the soil in Sichuan was more fertile than that in Hebei because of the humid and hot environment in Sichuan (Zhang, 2014), and because of the higher N fertilization level in Sichuan than that in Hebei (Table 4). In addition, corn yields in Hebei increased slightly with the mean increase amount of 312 kg/ha/yr when the fertilization levels increased from 50% to 75%, which was less than the mean increase amount of 879 kg/ha/yr in Sichuan (Figure 10). This demonstrates that crop yield increases are not proportional to N fertilizer increases, and that fertilizer addition above +50% produces diminishing returns (Zhang, 2014; Luo, 2009).
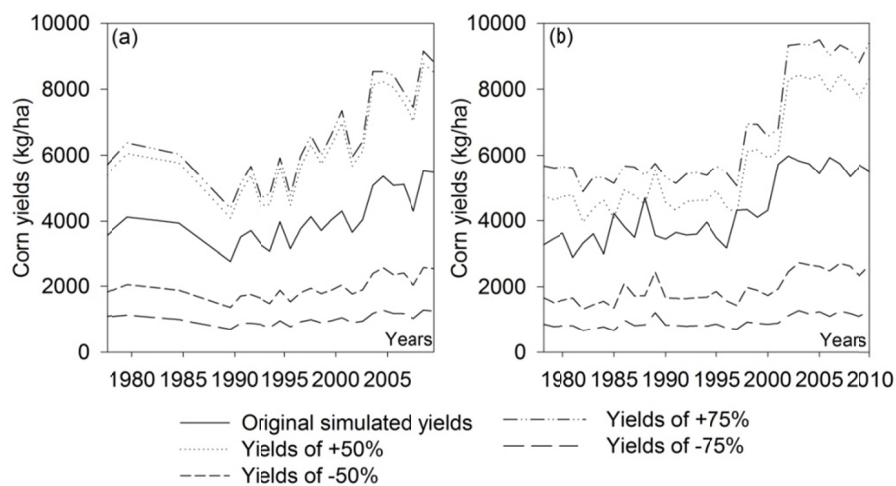

Figure 10. Changes on original simulated corn yields and yields of the control experiment when adding and extracting 50% and 75% of fertilization in the province of (a) Hebei and (b) Sichuan
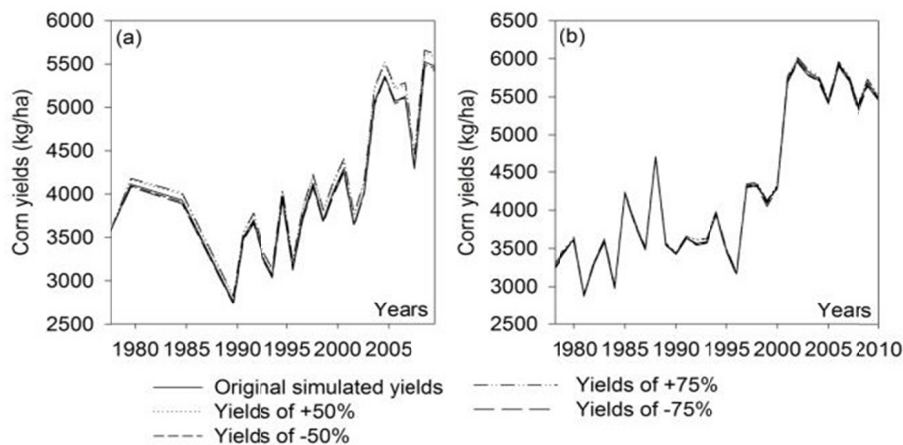

Figure 11. Changes on original simulated corn yields and yields of the control experiment when adding and extracting 50% and 75% of OMAD in the province of (a) Hebei and (b) Sichuan

Table 4. N fertilization levels and OMAD in the control run

Provinces	Phrases set in schedule file	N fertilization level I (kg N/ha/yr)	N fertilization level II (kg N/ha/yr)	Organic C (kg C/ha/yr)
Sichuan	1701-1900	60	60.5	23.1
	1901-1960	60	60.5	23.1
	1961-1970	93	94	57.7
	1971-1980	112	117	69.0
	1981-1996	117	118	81.0
	1997-2000	142	146	92.0
	2001-2010	142	146	92.0
Hebei	1701-1900	18.6	18.6	23.1
	1901-1960	18.6	18.6	23.1
	1961-1976	60.5	63	46.1
	1977-1996	66	66.9	57.7
	1997-2002	66.9	67	57.7
	2003-2010	66.9	67	57.7

3.4.2 Sensitivity to OMAD

After corn is harvested each year, soil fertility needs to be replenished to benefit corn growth in the following year. The amount of organic N that was applied in the control runs was 20 kg/ha/yr. The C:N ratio of the organic matter applied was 15. We conducted sensitivity studies by adding or decreasing 50% and 75% of the original OMAD level. There was no difference in the mean control and experimental simulations yields in 1979-2010 in Sichuan (Figure 11b); whereas, there was a slight increase in 1978-2010 mean yields (59.05 kg/ha/yr) in Hebei (Figure 11a). This is also probably related to the original soil fertilization condition. The higher inorganic N soil fertilization amounts in Sichuan meet the needs of corn growth. There was no need for additional organic N fertilizer in the field. In addition, the reason that OMAD increases are not important to either province is probably different. In Hebei, when corn is harvested in autumn, OMAD cannot efficiently improve soil fertility for drier soil; in Sichuan, OMAD can improve soil fertility for humid soil due to ample precipitation and irrigation.

Generally, fertilization level and OMAD have a larger impact in Hebei (cold and dry environment), where there is less active biophysical activity due to lower soil moisture and warmth. Increased soil fertilization can improve soil biophysical activities and meet the needs of corn growth (Tan et al., 2002).

4. Conclusions

The DayCent model is used to simulate corn yields under different environmental conditions in China. The model reproduced the inter-annual variation of crop yield with a R^2 of 0.71 and 0.85 in Hebei and Sichuan, China, respectively, demonstrating that the DayCent model is capable of accurately simulating corn yield in these two environments.

The annual mean T_{max} and T_{min} increased at a rate of 0.22 °C/10 yr and 0.23 °C/10 yr in Sichuan, respectively, and 0.34 °C/10 yr and 0.55 °C/10 yr in Hebei, respectively. The annual mean downward shortwave radiation (Dswrf) increased at a rate of 1.92 (langleys/day)/10 yr in Sichuan, and decreased at a rate of -0.82 (langleys/day)/10 yr in Hebei. The annual mean RH decreased at a rate of -0.06 %/10 yr in Sichuan, and increased at a rate of -0.45 %/10 yr in Hebei. The annual mean wind decreased at a rate of -0.11 (miles/hour)/10 yr in Sichuan, and increased at a rate of 0.08 (miles/hour)/10 yr in Hebei. The annual mean precipitation decreased at a rate of -0.01 cm/10 yr in both Sichuan and Hebei.

In this paper, the impacts of climatic factors and management amendment levels on corn yields were explored. The results showed that RH and Prcp negatively affected corn yields in Hebei (a cold and dry environment). That impacts of the rising of T_{max} and T_{min} on corn yields were not significant is because corn growth in Hebei mainly depends on irrigation, and is not constrained by the drought resulting from the rising air temperature. Only T_{min} negatively affected corn yields in Sichuan.

Simulated corn yields decreased significantly after de-trending the warm air temperature in Sichuan. There was no critical threshold value of air temperature influencing corn yield simulation in Hebei; whereas, 23.33 °C was the critical threshold value influencing simulated corn yields in Sichuan.

The sensitivity study suggests that crop yield is more sensitive to fertilization level in a cold and dry environment as compared to that in a humid and hot environment. Fertilizer application can remedy the shortage of soil fertility, and accelerate crop growth in a cold and dry environment.

In Sichuan province (a humid and hot environment), current air temperature is limiting to corn production. 23.33 °C-9 °C constitutes the ideal scale of air temperature influencing increase of corn yields.

Acknowledgements

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