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Impacts of climate change on agriculture: Evidence from China

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ABSTRACT

To move China's climate policy forward, improved analyses of climate impacts on economic sectors using rigorous methodology and high quality data are called for. We develop an empirical framework, using fine-scale meteorological data, to estimate the link between corn and soybean yields and weather in China. We find that (i) there are nonlinear and inverted U-shaped relationships between crop yields and weather variables; (ii) global warming has caused an economic loss of about $820 million to China's corn and soybean sectors in the past decade; and (iii) corn and soybean yields are projected to decline by 3–12% and 7–19%, respectively, by 2100.

Introduction

Development of effective strategies whereby agriculture can adapt to climate change over the coming decades requires farmers, agribusiness, crop scientists, and policy makers to understand potential climate risks posed by climate change (Howden et al., 2007). Existing studies have assessed the impacts of climate change on farmland value (Deschênes and Greenstone, 2007; Mendelsohn et al., 1994; Schlenker et al., 2006), and agricultural productivity (Lobell and Asner, 2003; McCarl et al., 2008; Olesen and Bindi, 2002; Ortiz-Bobea, 2013; Schlenker and Roberts, 2009) in the developed world. However, studies addressing similar issues in China, the world's largest developing economy, using a rigorous approach and high quality data, remain limited.

Over the past century, China has experienced some noticeable climate change. Annual average temperature has increased by about 0.5–0.8 °C during the past 100 years (Ding et al., 2007). The last century has also witnessed an increasingly uneven distribution of precipitation between the south with abundant water and the drier north, as well as some extreme climate events (Piao et al., 2010), such as the great flood in 1998 and the 2010–2011 drought. Although agriculture only accounts for a small share of GDP in China, it is an important industry, as it supports over 20% of the world's population with only 8% of global sown area. China has the world's largest agricultural economy, and is a major producer of cereal grains, meat, and vegetables (FAO Faostat-Agriculture, 2012). China is also a major importer of feed grains in the world market; it imported about 60% of the

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soybeans sold in the international market in 2010 (FAO Faostat-Agriculture, 2012). Therefore, how climate change affects China's agriculture can have important implications for the welfare of China's population of 1.3 billion and can generate profound impacts on world food/feed markets.

This issue is also highly relevant to the formation of China's national climate strategy. Agriculture is the most vulnerable economic sector under climate change, especially in developing countries like China. Different interpretations of climate change impacts on agriculture could lead to differences in a developing nation's strategy to address climate change. If the nation's agriculture is believed to suffer from severe climate change, it will be more likely to adopt an aggressive policy toward climate change mitigation. If, instead, the belief is that climate change is not going to have negative effects, or even will be beneficial to the nation's agriculture, the nation's response to climate change will not be strong. In this case, a conservative strategy would be developed and used by the nation in international climate negotiation. In fact, China's national climate strategy has been under the influence of agronomic studies (for example Xiong et al., 2007),[2] which found no adverse climate impacts on China's agriculture. As a result, China has been focusing on the costs of climate change mitigation instead of the benefits from mitigation, and has embraced a rather conservative national strategy to address climate change.[3] To affect the course of this strategic development, more analyses with high quality data and rigorous approaches are called for.

Currently, only two economic studies have investigated the impacts of climate change on China's agriculture with a particular focus on farmland value (Liu et al., 2004; Wang et al., 2009). However, due to the difference in the data used, they yielded mixed results. While Liu et al. (2004) found that warming had a positive impact on China's agriculture, Wang et al. (2009) showed that the climate effect on Chinese agriculture was negative. Both studies used cross-sectional data and thus relied on variations in weather across regions to identify the coefficients of weather variables. Therefore, they cannot capture the effects of year-to-year change in weather on agriculture. Crop simulation models have also been applied to assess the consequence of climate change on crop production in China (Lin et al., 2005; Xiong et al., 2007). However, these models apply agronomically optimal levels of inputs and ignore input prices, and thus tend to underestimate the true weather effects on crop yields (Schlenker et al., 2006).

Using a unique county-level panel on crop yields and newly available daily weather outcomes, we provide an empirical estimation on the relationship between weather variables and crop yields in China. The dataset contains county-specific crop yields in China during the period 2000–2009. The weather data consist of daily minimum, maximum, and average temperatures, precipitation, and solar radiation for most Chinese counties over the same period. The daily weather data facilitate accurate estimation of cumulative heat, precipitation, and radiation received by crops over their growing seasons. Here, we focus on corn and soybeans, because (1) China produces about 20% of the world's corn, second behind the U.S. (FAO Faostat-Agriculture, 2012); (2) soybean is the nation's predominant crop for edible oil production; (3) the two crops are widely produced across China and are important feed grains for livestock production; and (4) China heavily depends on imports to meet domestic demand for the two crops.

When estimating the relationship between corn and soybean yields and weather, we include temperature, precipitation, and radiation as weather variables. Using county-level crop yields and daily weather data in the U.S., Schlenker and Roberts (2009) found nonlinear temperature effects on corn, soybean, and cotton yields. In their regression analysis, they included temperature, precipication, and regional time trends as explanatory variables to explain the variations in crop yields. Agronomic literature has long suggested that temperature, precipitation, and radiation are three imporant factors for plant growth (Muchow et al., 1990; Szeicz, 1974). Radiation has also been emphasized as an important input for rice and wheat growth (see Auffhammer et al., 2006; Chameides et al., 1999; Welch et al., 2010). Therefore, omitting radiation as a weather variable in Schlenker and Roberts (2009) may lead to biased parameter estimates of the temperature and precipitation variables. This issue could be particularly serious if radiation was highly correlated with temperature or precipitation over crop growing seasons in their sample.

We construct two land-use-change (LUC) variables to reflect the change in soil quality under corn and soybeans stemming from the changes in regional land use patterns at the extensive and intensive margins, respectively. Most existing studies examining the impacts of climate change on crop yields assumed that soil quality remained constant over their study periods and used fixed-effect models to control for this unobservable heterogeneity across regions (see Schlenker and Roberts, 2009; Welch et al., 2010). Due to rising food prices in the past decade, corn and soybean production areas in China expanded by 8 and 1 million hectares (see Fig. 1), respectively, over the same period (NBS China, 2000–2009). Of the additional land under the two crops, some came from the reductions in land previously under other crops, such as rice, wheat, potato, cotton, sugarcane, and sugar beet, while the rest was converted from marginal lands. Because of the differences in soil quality of different land covers, regional land use changes may have affected county-average crop yields.

We also control for other factors that could affect county-average crop yields, such as input use and farmers' contemporaneous climate adaptation behaviors. Standard producer theory tells us that a rational farmer makes production decisions based on, among other factors, input and output prices, to maximize the net returns from crop production. The farmer may also make adaptations to climate change by adjusting cropping systems and altering irrigation water use in warmer growing seasons (Howden et al., 2007).

[2] The paper is the work of a team of agricultural scientists who were believed to be the most influential in China's climate strategy formation related to agriculture.

[3] For instance, China has stuck to performance-based environmental/climate policies for decades, such as energy-intensity and carbon-intensity targets rather than an overall greenhouse gas (GHG) emissions reduction target. Holland (2012)) showed that an intensity standard could be an inefficient instrument for reducing aggregate GHG emissions relative to an emissions target due to the provision of an implicit output subsidy.

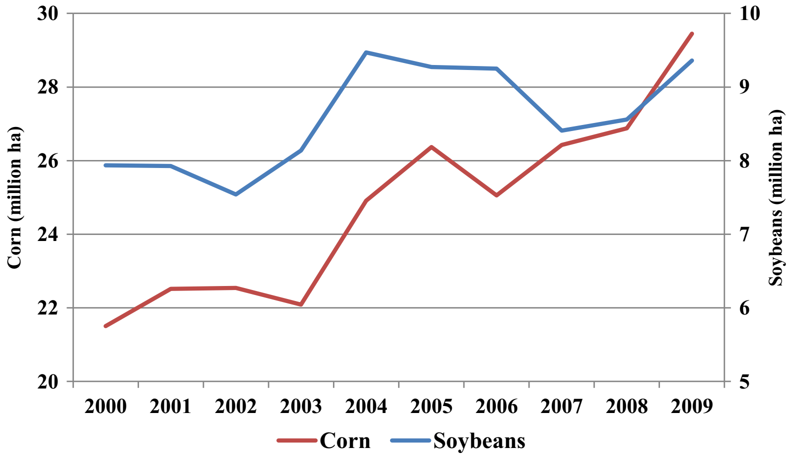

Fig. 1. Total planted acres of corn and soybeans in China over the period 2000–2009 in million hectares (ha).

Several studies in the literature have used fixed-effect models to estimate the total marginal effects of the changes in weather on crop yields, by regressing crop yields on weather variables only while controlling for other time-invariant variables (see McCarl et al., 2008; Schlenker and Roberts, 2009; Welch et al., 2010). The estimated total marignal effects of weather on yields in these studies can be interpreted as the sum of the direct effects of weather on yields (through the effects on crop physiology) and the indirect effects of weather on yields (through weather's influence on farmers' input use and climate adaptation actions) (see discussion in Welch et al. (2010)). Therefore, with the inclusion of socioeconomic variables in a regression model, estimated coefficients of weather on yields can be considered as the partial effects of weather on yields. That is because controlling for choices about input use and farmers' climate adaptation might absorb some of the overall effects of the changes in weather on yields. Here, because we are also interested in examining whether and how crop yields have reponded to the changes in regional land use patterns, input use, and farmer's climate adaptation behaviors in addition to weather variables, we will include these socioeconomic variables in some model specifications.

Our estimates indicate that there exist nonlinear relationships between corn and soybean yields and weather variables. Extremely high temperatures are very harmful for growth of the two crops. These findings are consistent with the only previous study with a comparable sample size in the U.S. (Schlenker and Roberts, 2009). Because precipitation was negatively correlated with radiation in our sample, we find that the omission of radiation in regression analysis would lead to an underestimation of the optimal amount of precipitation by 3.5–11.8% for corn and by 3.8–6.8% for soybeans, depending on model specifications. We also find that corn and soybean yields negatively responded to increased input prices, and that increased irrigation area effectively reduced the negative effect of high temperature on corn yields.

We use estimated coefficients of weather variables to quantify the net economic impact of changing climatic conditions on China's corn and soybean sectors over the sample period. Our results indicate that warming caused a net economic loss of $820 million in China's corn and soybean sectors in the past decade. We also use estimated weather coefficients to evaluate the potential impacts of future climate change on yields using the Hadley III model. We find that in the medium term (2040–2060) and in the long term (2090–2099), county-average corn and soybean yields in China are predicted to decrease in all warming scenarios considered by the Hadley III model. These findings are robust across different model specifications and data. Our results may have important public policy implications for the design of effective adaptation strategies for agriculture in China and the formation of China's global climate negotiation strategies.

Corn and soybean production in China

Corn and soybeans are two important feed crops in China's agricultural economy. Corn production area expanded from 22 million hectares in 2000 to 29 million hectares in 2009 (NBS China, 2000–2009). Currently, corn accounts for approximately 20% of the nation's grain area and 14% of the nation's total grain output (NBS China, 2000–2009). Soybean production in China has been relatively stable during the past decade with a total production area of 9 million hectares. China's corn and soybean sectors are also major components of the world agricultural economy, accounting for 20% and 6% of the world's corn and soybean production in 2010, respectively (FAO Faostat-Agriculture, 2012).

Despite the large amount of domestic corn and soybean production, China depends heavily on imports of the two crops to meet domestic demand for livestock production (mostly hogs, poultry, and dairy). China was self-sufficient in corn before 2009, but since then has become a major importer. In 2010, China imported 6 million metric tons (MT) of corn, which accounted for about 6% of the corn entering the international market (FAO Faostat-Agriculture, 2012). China is the world's largest soybean importer, currently with about 80% of domestic soybean consumption directly coming from imports, which account for about 57% of the soybeans sold in the international market in 2010 (FAO Faostat-Agriculture, 2012). With rapid

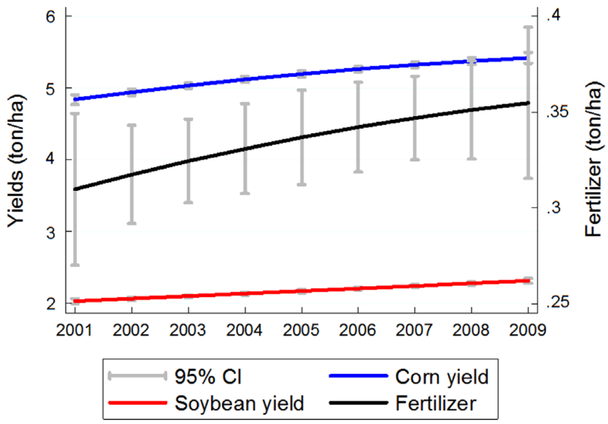

Fig. 2. Average corn and soybean yields (MT per ha) and fertilizer use (MT per ha) in China.

economic development and the demand for dietary improvement, China is expected to further increase its imports of the two crops in the next few decades.[4]

Corn and soybean sectors in China have experienced an impressive yield growth in the past several decades. Average corn and soybean yields grew at an annual rate of nearly 5% during the period 1980–1995 (Aunan et al., 2000); the annual growth rates declined to about 1% in the past decade (see Fig. 2). The rapid yield growth can be largely attributed to the government's increasing investment in agriculture in the past several decades with an aim to improve the nation's agricultural productivity (Stone, 1988). The widespread adoption of high-yielding and drought-tolerant seeds as well as the intensive use of fertilizers and pesticides has also contributed to yield increases in many areas of China (Huang et al., 2002).

Corn and soybeans are widely produced in China. As shown in Fig. 3, corn is primarily produced in the northern part of the country. Three Northeast provinces (Heilongjiang, Jilin, and Liaoning), Central China, and the Northwest inland area (including the Xinjiang Uygur Autonomous Region and Gansu) together account for more than 75% of the total corn production in China, while Southwest mountainous areas produce about 10% of the nation's corn (NBS China, 2000–2009). The three Northeast provinces are also the major soybean production regions, accounting for more than one-third of China's soybean production.

Due to the spatial differences in climatic conditions, corn and soybean growing seasons vary considerably across regions. According to their growing seasons, corn and soybeans in China can be divided into four types (Chinese Cropping System, 2005). Spring corn and soybeans, typically planted in April and harvested in late September, are mainly concentrated in the three Northeast provinces, Inner Mongolia, Ningxia, the Northwest inland, and several regions in the Southwest mountainous areas. Summer corn and soybeans have a slightly shorter growing season than spring corn and soybeans, and are primarily produced in the Huang-Huai plain area and the lower-middle reaches of the Yangtze River. Autumn corn and soybean production occurs mainly in the Southwest mountainous areas, including Guangdong, Fujian, Zhejiang and several regions in Yunnan province. China also has a small amount of winter corn and soybean production in tropical and subtropical areas.

Production areas of corn and soybeans in China have changed both spatially and temporally in the past decade. Fig. 1 shows that corn and soybean planted acres increased by 7.9 and 1.4 million hectares, respectively, during the period 2000–2009 (NBS China, 2000–2009). Of the additional land under the two crops (9.4 million hectares), about 2.5 million hectares came from the reductions in land previously under other food/feed and oil crops, such as rice, wheat, potato, oil seed, cotton, sugarcane, and sugar beet, while the rest (6.9 million hectares) were converted from marginal lands (NBS China, 2000–2009). Marginal lands used for the two crops mainly came from two sources. The primary source is the land that was originally under crop production but later abandoned by farmers. Due to high wages offered in manufacturing industries in urban areas and relatively low profit margins from agricultural production, many farmers moved to cities and abandoned their cropland.[5] The second source is reclamation of grassland and deforestation (Liu et al., 2005). Depending on the soil quality of the additional land used for the two crops, regional land use changes may have affected county-average corn and soybean yields.

A conceptual framework of crop yield

Consider a representative farmer who uses several inputs $k=1, \ldots, K$, such as fertilizer, chemicals, labor, and machinery, to produce crop $i=1, \ldots, I$. Let $X_{i,k}$ denote the use of input k for crop i per unit of land; ω_k the vector of input prices; c_i the vector of fixed costs associated with crop production (such as equipment renting for land preparation, planting, and

[4] http://www.chinadaily.com.cn/business/2013-01/07/content_16092446.htm.
[5] http://www.chinadaily.com.cn/china/2012-03/27/content_14918222.htm.

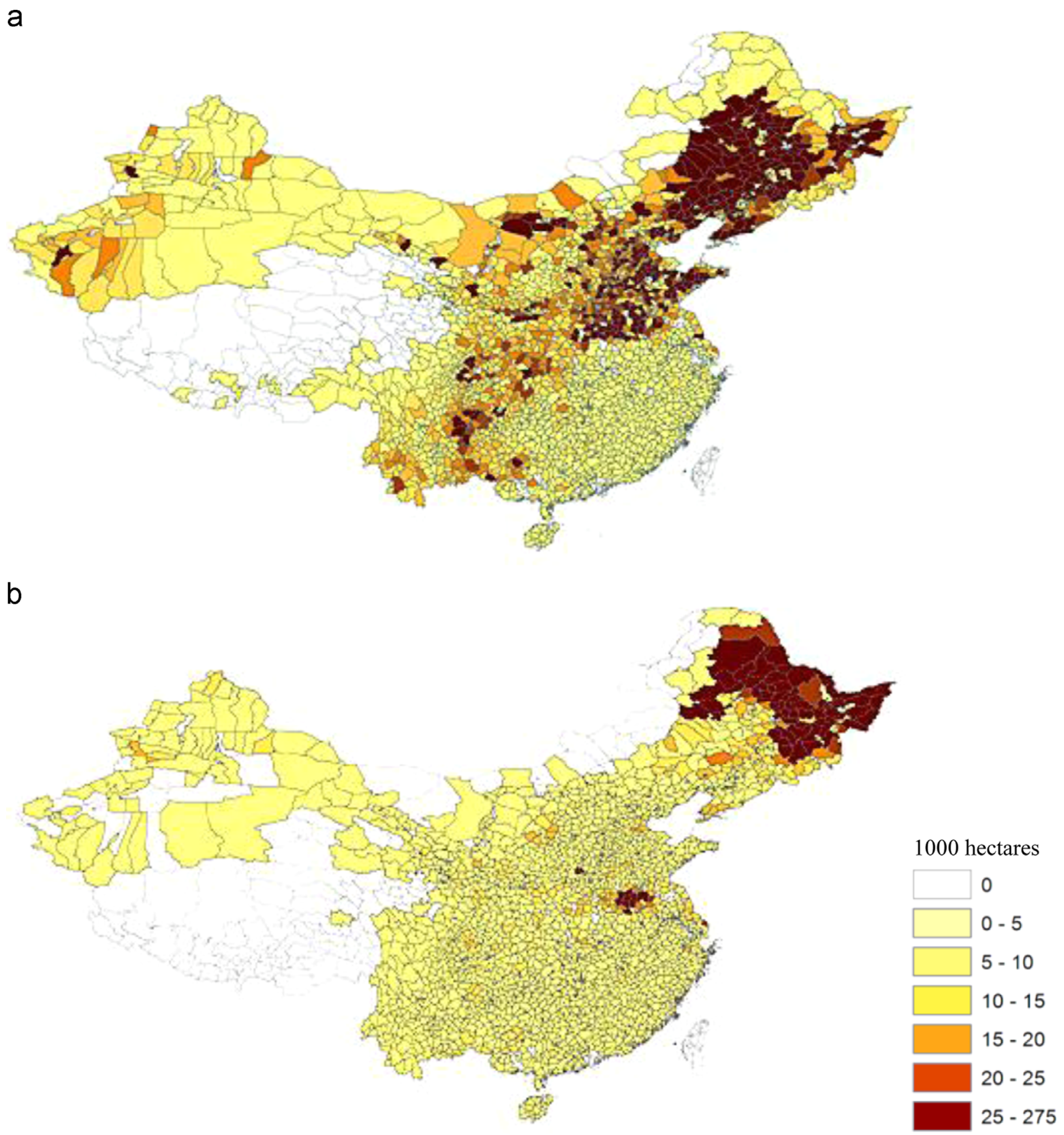

Fig. 3. Five-year (2005–2009) average planted acres of corn and soybeans in China (1000 hectares): (a) corn and (b) soybeans.

harvesting); and $E(p_i)$ the vector of expected crop prices by the end of the harvesting season. The total endowment of land is given by l, and A_i is used to denote the amount of land allocated to crop i. The land used to produce all crops should be less than the total land available, i.e., $\sum_{i \in I} A_i \le l$.

Following the standard agronomic literature (for example, see Cassman, 1999), we use $y_i(X_{i,k}, s_i, z, t)$ to denote the yield of crop i, which depends on input use ($X_{i,k}$), soil quality of the land under crop i (s_i), weather (z), and exogenous technological change stimulated by research and development (R&D) (represented by time t). Let π_i denote the profit associated with the production of crop i. The representative farmer's profit maximization problem can be formally formulated as follows:

$$\underset{X_{i,k},A_i}{Max} \sum_{i \in I} \pi_i = \sum_{i \in I} E(p_i) y_i(\cdot) A_i - \sum_{i \in I, k \in K} \omega_k X_{i,k} A_i - \sum_{i \in I} c_i \tag{1}$$

subject to $\sum_{i \in I} A_i \le l$. Assuming interior solutions of all decision variables exist, we can determine the optimal amount of input use ($X_{i,k}$) and planted area (A_i), using the first-order optimality conditions. The optimal use of input k can be expressed as $X_{i,k} = X(E(p_i), \omega_k, s_i, z, t)$. Substituting this expression into the yield function $y_i(X_{i,k}, s_i, z, t)$ suggests that crop yield can be expressed as a function of expected crop price, input prices, soil quality, weather variables, and exogenous technological change, as specified in Eq. (2):

$$y_i = y_i(E(p_i), \omega_k, s_i, z, t) \tag{2}$$

At the farm level, cropland can be considered to be homogenous in quality for each farm, especially in the Chinese agricultural setting, where the vast majority of farmers operate small farms.[6] Thus, when working with farm-level panel data, it is reasonable to use fixed-effect models to control for unobserved farm-specific characteristics that do not vary over time, such as soil quality. However, at a more aggregate level, such as a county, which is the spatial unit we deal with in this study, observed crop yields represent the outcomes of many heterogeneous profit-maximizing farmers in a county who make land use and other production decisions simultaneously in response to prices and weather conditions. For example, with expected high corn prices, many farmers may convert marginal lands or land previously under other crops with low profit margins to corn. By using additional new land, individual farmers' land use decisions could affect 'average' soil quality under corn in a county and thus county-average corn yields. Depending on the soil quality of the new land, county-average corn yields could be negatively or positively affected, which needs to be examined empirically.

In addition, farmers can take adaptation actions to mitigate the adverse effects of climate change (Howden et al., 2007), which could also affect crop yields. For example, farmers may adjust crop production practices, invest in new technology to save irrigated water, and change ground or surface irrigation usage in response to weather variations, to reduce the external effects of climate change on yields. With the lack of other relevant information on farmers' contemporaneous adaptation behaviors, we use the ratio of irrigated areas to total planted areas of all crops in a county as a proxy to control for the possibility of farmers' adaptation to climate change in the empirical analysis.

Empirical model

The empirical models assume that the climate effects on yields are cumulative and substitutable over crop growing seasons (as in Schlenker and Roberts, 2009), and are shown below:

$$\log Y_{r,t} = H_{r,t}\beta_0 + Z_{r,t}\beta_1 + S_{r,t}\beta_2 + c_r + \lambda_t + \varepsilon_{r,t} \tag{3}$$

$$\varepsilon_{r,t} = \rho \sum_{r'} W_{r,r'}\varepsilon_{r',t} + \phi_{r,t} \tag{4}$$

where $\log Y_{r,t}$ denotes log yield in county r and year t. $H_{r,t}$ represents heat accumulated in county r and year t over the crop growing season. $Z_{r,t}$ includes sums of precipitation and radiation in county r and year t over the growing season and their quadratic forms to capture the potential nonlinear effects on yields. Here, growing seasons are specified differently for spring, summer, autumn, and winter corn and soybeans. Because we do not have county-level information on planting and harvest dates for corn and soybeans by year, we assume that their growing seasons remained unchanged over the study period for each county and use regional-specific crop growing seasons provided by the Chinese Cropping System (2005) to construct our weather variables. This assumption is likely to lead to an overestimation of the true weather effects on yields, because it does not consider farmers' adjustments through changes in the planting and harvest dates in response to variations in weather conditions. $S_{r,t}$ contains socioeconomic variables, namely the two LUC variables, expected crop prices and input prices, and farmers' contemporaneous climate adaptation behaviors. A time-invariant county fixed effect c_r is used to control for regional heterogeneity, such as tradition of agricultural production. We also control for year-fixed effect (denoted by λ_t) to remove unobserved factors common to all counties in a given year, such as the introduction of high-yielding and drought-tolerant seeds, adoption of a new production technology, and other temporal shocks. Lastly, $\varepsilon_{r,t}$ are the error terms. β_0 and β_1 are the coefficients of interest. The main hypothesis is to test whether $\beta_0 = \beta_1 = 0$, namely that weather variables have no effect on crop yields.

Weather variables

We use two different approaches to represent the relationship between temperature and yields. Following the standard agronomic literature, we first capture this relationship using *growing-degree days* (GDD), which is defined as the sum of heat that crops receive between lower and upper temperature thresholds over the growing season. The appropriate temperature thresholds for computing GDD are still debated. Following Ritchie and NeSmith (1991) and Schlenker et al. (2006), we set the lower threshold at 8 °C and the upper threshold at 32 °C for corn and soybeans and use a fitted sine curve to estimate $GDD_{8,32}$ (Baskerville and Emin, 1969). A quadratic form of $GDD_{8,32}$ is also included to capture the potential nonlinear temperature effects on yields. Moreover, we construct a separate variable that indicates the length of time that each crop is exposed to temperatures above 34 °C (GDD_{34+}), which is considered to be very harmful for plant growth by agronomists (Ritchie and NeSmith, 1991).

[6] China's per capita farmland is about 0.13 ha, which is 40% less than the global average, see http://faostat.fao.org/site/377/default.aspxancor.

We then follow the approach introduced by Schlenker and Roberts (2009), and define the temperature variables using the number of days in 3 °C temperature bins. Thus, Eq. (3) can be re-written as

$$\log Y_{r,t} = \int_{\underline{a}}^{\overline{a}} g(a)\varphi_{r,t}(a)da + Z_{r,t}\beta_1 + S_{r,t}\beta_2 + c_r + \lambda_t + \varepsilon_{r,t} \tag{5}$$

In Eq. (5), $g(a)$ is the yield growth function that is a function of temperature a, and $\varphi_{r,t}(a)$ is the time distribution of temperature over the crop growing season in county r and year t. $\underline{a}$ and $\overline{a}$ are observed lower and upper temperature bounds, respectively, during the growing season. We estimate $g(a)$ using dummy variables for each 3 °C temperature bin. We use this model specification to examine whether nonlinear relationships between temperature and crop yields exist, and identify critical temperature thresholds above which are harmful for crop growth.

Socioeconomic variables

We use historical planted acres of major crops in each county to compute the two LUC variables that represent the conversion of marginal lands (marginal acre) and land previously under other crops (substitution acre), respectively, to corn and soybeans. The substitution acre for a crop is defined as the reduction in the sum of the land under all other crops relative to the previous year. If the sum of the land under all other crops increases relative to that in the previous year, the substitution acre for the crop is then equal to zero. The marginal acre for a crop is defined as the difference between the increase in acreage of the crop relative to the previous year and the substitution acre for the crop.

To capture the effects of the changes in crop prices and input prices on yields, we construct output–input price ratios as explanatory variables in the empirical analysis. We use crop prices in year t–1 as a proxy for expected crop prices in year t (Braulke, 1982; Nerlove, 1956). Because of the limited data on other input prices, we include fertilizer price index and wage as input prices. Other input prices (such as chemicals and machinery) are unlikely to be strongly correlated with weather. Thus, the exclusion of these variables is not expected to have a significant impact on coefficient estimates of β_0 and β_1. We use the ratio of irrigated acres to total planted acres of all crops in a county as a proxy to control for the possibility of farmers' contemporaneous adaptation to variations in weather.

Endogeneity of the socioeconomic variables

Because the two LUC variables reflect the response of farmers to future profits from crop production, they may be endogenous. Hence, we estimate the models (3) and (4) by using the instrumental variable approach. Drawing on the recent work by Roberts and Schlenker (2013), we use weather variables (including $GDD_{8,32}$, precipitation, and radiation) and crop prices in the previous year as instrumental variables for the two LUC variables. Lagged weather variables may influence the two LUC variables by affecting future prices of certain crops and changing suitable cropping areas (Olesen and Bindi, 2002). Lagged crop prices can also serve as good instruments for the two LUC variables because farmers' land use decisions are primarily driven by their expectations about future crop prices (Chavas and Holt, 1990; Nerlove, 1956).

As Roberts and Schlenker (2013) argued, the output–input price ratios are also endogenous. To address this endogeneity issue, in addition to lagged weather variables we also include crop inventories in the previous year as instruments for the two price ratios. Furthermore, the irrigation ratio variable is also potentially endogenous in that it reflects farmers' response to the changing weather conditions. We use irrigation ratio in the previous year as the instrumental variable for farmers' irrigation behavior in the current year. Past irrigation behavior is a good instrument because it affects irrigation behaviors in subsequent periods due to the large investment made on irrigation infrastructure, such as vertical wells and irrigation canals.

Error terms

As shown in Eq. (4), we allow the error terms $\varepsilon_{r,t}$ to be spatially correlated across counties. Here, $\phi_{r,t}$ are the error terms that are independently normally distributed with $E[\phi_{r,t}] = 0$ and $\text{var}[\phi_{r,t}] = \sigma_r^2$, ρ is the parameter of spatial correlation, and $W_{r,r'}$ is a pre-specified spatial weighting matrix that describes the spatial dependence of counties with their neighbors. Similar to Schlenker et al. (2006), we assume that the error terms $\phi_{r,t}$ are heteroskedastic. We also allow the error terms $\phi_{r,t}$ to be serially correlated.[7]

There are several reasons to believe that spatial correlation between counties could influence crop yields in Eq. (3). First, the error terms $\varepsilon_{r,t}$ may be spatially correlated because of the omission of other spatially correlated explanatory variables, such as agricultural policies/regulations implemented by different levels of government in certain areas to achieve specific policy goals. Second, counties located close to each other are likely to use the similar production practices, which could also influence yields. Third, we might expect that nearby counties may share the similar local characteristics, such as soil type, or experience with pest problems in a particular growing season. If any of these factors are omitted as explanatory variables, then $\varepsilon_{r,t}$ are expected to be spatially correlated. Our empirical analysis uses three different spatial weighting matrices. We

[7] We thank one referee for pointing out this issue and providing the solution to address it.

Table 1
Summary statistics.

Variable	Mean	Minimum	Maximum	Std. dev.
Crop yields				
Corn (MT per hectare)	5.19	0.04	16.92	1.95
Soybeans (MT per hectare)	2.15	0.03	10.81	1.03
Weather variables during corn growing season				
GDD_{8-32} (1000 D)	2.12	0.90	3.55	0.34
GDD_{34+} (D)	6.33	0	225.22	9.78
Solar radiation (1000 h)	0.89	0.41	2.08	0.33
Precipitation (1000 mm)	0.57	0.025	2.07	0.28
Weather variables during soybean growing season				
GDD_{8-32} (1000 D)	2.12	0.67	3.40	0.37
GDD_{34+} (D)	6.08	0	104.86	8.61
Solar radiation (1000 h)	0.90	0.40	2.08	0.33
Precipitation (1000 mm)	0.58	0.026	1.98	0.27

Notes: Numbers above are based on observations in years 2001–2009.

first use a spatial contiguity matrix because crop production in a county is more likely to be influenced by its neighboring counties that share the same boundary. Under the spatial contiguity matrix, the (r, r') element of the matrix is unity if counties r and r' share a common boundary, and 0 otherwise. We also consider two distance weighting matrices that weight either the six or four nearest counties relative to county r, according to their physical distance, and assign zero weights to other counties. The relative weights in each of the two distance weighting matrices are determined based on their distances to the centroid of county r.

In the following, we estimate the models (3) and (4) using a three-step procedure. We first address the endogeneity issue of the socioeconomic variables using the instrumental variable approach. Following the estimation strategy in Schlenker et al. (2006) we then estimate the parameter of spatial correlation $\hat{\rho}$ using the generalized method of moments (GMM) approach and pre-multiply the data by $I-\hat{\rho}W$. Lastly, we estimate the models using the approach introduced in Fetzer (2014) and Hsiang (2010) to allow for the heteroskedasticity and serial correlation of the error terms.

Data

We compile a county-level panel on crop yields, planted acres of major crops, and weather for years 2000–2009 in China. This section describes data sources and reports summary statistics.

County-specific total crop production and historical planted acres (including total and irrigated acres) of major crops are obtained from the National Bureau of Statistics of China (NBS), which covers 2570 Chinese counties. Yields for corn and soybeans are computed as total county-level production divided by their respective planted acres.[8] We exclude the Qinghai-Tibet plateau in the analysis because it is not a major agricultural production region for corn and soybeans. We use historical planted acres of major crops to compute the two LUC variables for corn and soybeans, namely marginal acre and substitution acre. With the inclusion of the two LUC variables, we lost the observations in 2000. To make results comparable across different model specifications, we use the data consistently for years 2001–2009 in the empirical analyses, which gives us 18,975 observations for corn yields and 19,575 observations for soybean yields. As shown in Table 1, corn yields varied substantially in the sample, ranging between 0.04 and 16.9 MT per hectare, with an average of 5.2 MT per hectare, while soybean yields changed from 0.03 to 10.8 MT per hectare, with a national average of 2.2 MT per hectare.

The weather data are obtained from the China Meteorological Data Sharing Service System (CMDSSS),[9] which records daily minimum, maximum, and average temperatures, precipitation, and solar radiation for 820 weather stations in China. The CMDSSS measures solar radiation using the number of hours in each day during which the sunshine is above 200 MW/cm^2. The dataset contains the exact coordinates of each weather station, enabling us to merge the weather data with our agricultural data. For counties with several weather stations, we construct weather variables by taking the simple average of the weather variables across these stations. For counties without a weather station, we impute the weather information from neighboring counties for these counties.

We obtain corn and soybean growing seasons from the Chinese Cropping System (2005). The growing season of spring corn and soybeans lies between April 1 and September 30. Summer corn and soybean have a relatively shorter growing season, spanning from June 1 to September 30. The growing season of autumn corn and soybean production is between August 1 and November 30. For winter corn and soybeans in tropical and subtropical areas, their growing season is typically between November 1 and February 28 in the following year.

[8] The lack of county-specific crop harvested acres may lead to an underestimation of true crop yields, especially in years with bad weather conditions.
[9] CMDSSS was developed and is currently managed by the Climatic Data Center, National Meteorological Information Center, China Meteorological Administration. See http://cdc.cma.gov.cn/home.do for details.

Table 2
Tests for the presence of spatial correlation of the error terms.

Spatial weighting matrix	Contiguity matrix	Distance matrix (six)	Distance matrix (four)
Corn yield regression			
Moran-I N(0,1)	28.92	30.12	26.67
LM-ERR $\chi^2(1)$	797.31	859.56	682.07
LR $\chi^2(1)$	571.50	569.87	537.48
Walds $\chi^2(1)$	19,425.21	12,533.43	15,376.71
Parameter of spatial correlation	0.63	0.62	0.54
Soybean yield regression			
Moran-I N(0,1)	27.25	29.13	25.64
LM-ERR $\chi^2(1)$	706.69	803.72	630.24
LR $\chi^2(1)$	545.54	555.86	514.96
Walds $\chi^2(1)$	20,462.79	13,261.80	15,773.54
Parameter of spatial correlation	0.63	0.61	0.54

Notes: Three spatial weighting matrices are used to examine the existence of spatial correlations of the error terms. Under the spatial contiguity matrix, the (r, r') element of the matrix is unity if counties r and r' share a common boundary, and 0 otherwise. Distance matrices are inverse distance weighting matrices that weight the six and four nearest neighbors, respectively, according to their physical distance, and assign zero to other counties. The distance matrices are then normalized to have row-sums of unity. Results presented in this table are based on the mean values of the variables over the sample period.

We collect province-level crop prices and fertilizer price index from the China Yearbook of Agricultural Price Survey for years 2000–2009 (NBS China, 2012). County-specific labor costs are not available. We use province-level average wage for farm labor from the NBS to control for the impacts of labor use on crop yields over the sample period.[10]

Empirical results

Before presenting our regression results, we first examine the presence of the spatial correlations of the error terms in the yield regression models by performing Moran's *I* test (Anselin, 1988) for each of our three spatial weighting matrices. We also supplement Moran's *I* test with three alternative tests, namely the Lagrange Multiplier (LM) ERR test, the Likelihood-Ratio (LR) test and the Wald test. We conduct these tests using the same set of explanatory variables as in the estimation of the yield equations, including weather and socioeconomic variables. As shown in Table 2, these test results indicate that the spatial correlations of the error terms in both yield equations are large and statistically significant. The parameters of spatial correlations are similar in magnitudes under the contiguity matrix and the distance matrix that weights the six nearest neighbors – they are 0.63 and 0.62, respectively – but become smaller (0.54) under the distance matrix that weights the four nearest neighbors. These test statistics provide strong evidence for the existence of the spatial correlations of the error terms. Therefore, omitting the spatial correlations is expected to lead to a significant overestimate of the true *t*-statistics (Schlenker et al., 2006). In the baseline analysis presented below, we employ the contiguity matrix as the spatial weighting matrix. We will examine the robustness of our results using other two spatial weighting matrices.

Regression results: GDD as temperature variables

We conduct the spatial error analysis using five different model specifications. In model (1), we include $GDD_{8,32}$, GDD_{34+} and precipitation as explanatory variables to examine the variations in yields over the sample period. In model (2), we add radiation and its quadratic form as additional explanatory variables. We consider this model specification mainly due to the concerns that the temperature and precipitation variables may be correlated with radiation and the omission of radiation in the regression analysis may lead to biased estimates of the true temperature and precipitation effects. Table 3 shows that $GDD_{8,32}$ and radiation were highly and positively correlated, and that both variables were negatively correlated with precipitation. This suggests that a failure to control for radiation will lead to biased parameter estimates of the temperature and precipitation variables. In model (3), we include the two LUC variables to examine whether they have played a significant role in influencing county-average crop yields. In model (4), we incorporate the two price ratios. Lastly, we add the irrigation ratio in model (5) and examine whether the inclusion of this variable will affect our coefficient estimates of weather variables. All model specifications include time-invariant county-fixed effects to control for unobserved characteristics within each county and year-fixed effects to remove the unobserved factors common to all counties in a given year.

As discussed above, we estimate the models (3) and (5) using the instrumental variable approach to address the endogeneity issues of the socioeconomic variables. We find that the *F*-statistics in the first stage are greater than 40, which indicates the strength of our instrumental variables. For brevity, they are not reported here.

[10] http://data.stats.gov.cn/workspace/index?m=fsnd.

Table 3
Correlations among weather variables over the growing season.

	Corn			Soybeans		
	$GDD_{8,32}$	Precipitation	Radiation	$GDD_{8,32}$	Precipitation	Radiation
$GDD_{8,32}$	1			1		
Precipitation	−0.3265*	1		−0.3119*	1	
Radiation	0.3680*	−0.3337*	1	0.3632*	−0.3288*	1

* $P < 1\%$.

Table 4
Spatial error estimations (dependent variable: log corn yields).

Model	Model (1): GDD and precipitation only	Model (2): add solar radiation	Model (3): add LUC variables	Model (4): add price ratios	Model (5): add irrigation ratio
$GDD_{8,32}$	0.3234** (2.54)	0.3363*** (2.65)	0.3515*** (2.63)	0.3375** (2.47)	0.3375** (2.47)
$GDD_{8,32}$ squared	−0.0733** (−2.19)	−0.0735** (−2.21)	−0.0801** (−2.31)	−0.0790** (−2.24)	−0.0789** (−2.24)
Square root of GDD_{34+}	−0.0120*** (−3.17)	−0.0130*** (−3.29)	−0.0122*** (−3.01)	−0.0115*** (−2.84)	−0.0115*** (−2.83)
Precipitation	0.0657** (2.08)	0.0653** (2.08)	0.0626* (1.92)	0.0723** (2.19)	0.0728** (2.20)
Precipitation squared	−0.0487*** (−2.59)	−0.0467** (−2.52)	−0.0436** (−2.34)	−0.0473** (−2.51)	−0.0476** (−2.53)
Radiation		0.3117*** (3.85)	0.2963*** (3.53)	0.3127*** (3.69)	0.3130*** (3.70)
Radiation squared		−0.1695*** (−4.10)	−0.1561*** (−3.30)	−0.1703*** (−3.47)	−0.1701*** (−3.46)
LUC: marginal acre			−0.0133 (−0.80)	−0.0193 (−1.13)	−0.0188 (−1.10)
LUC: substitution acre			−0.0140 (−0.31)	0.0155 (0.28)	0.0150 (0.27)
Ratio: corn price/fertilizer price index				0.0381** (2.48)	0.0397** (2.57)
Ratio: corn price/wage				0.0835 (1.16)	0.0869 (1.21)
Irrigation ratio					0.0347** (2.02)
Spatial correlation	0.3579*** (37.30)	0.3619*** (37.32)	0.3529*** (36.37)	0.3489*** (36.41)	0.3629*** (37.37)

Notes: The table lists coefficient estimates and asymptotic *t* statistics in parentheses with the contiguity matrix. Coefficients on time trends are suppressed. $N = 18{,}945$.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Estimated coefficients on the effects of temperature on yields indicate that there exists an inverted U-shaped relationship between corn and soybean yields and $GDD_{8,32}$ in all five model specifications (see Tables 4 and 5). Corn and soybeans achieved maximum yields with 2136–2287 D and 1480–1515 D of $GDD_{8,32}$, respectively, depending on model specifications. High temperatures above 34 °C had negative impacts on corn yields, but the effects on soybean yields were insignificant. The coefficients on precipitation show similar nonlinear patterns. To achieve maximum yields, corn required 67–76 cm of precipitation over the growing season, which are significantly higher than the precipitation requirement for soybeans, which needed 62–67 cm of precipitation. These nonlinear relationships indicate that $GDD_{8,32}$ and precipitation increased crop yields, but at declining rates. These results are consistent with the existing findings in other regions of the world (Lobell et al., 2011; Schlenker and Roberts, 2009).

Because precipitation was negatively correlated with radiation (see Table 3), omitting radiation in model (1) had a large influence on parameter estimate of precipitation. Specifically, the optimal amount of precipitation estimated in model (1) is

Table 5
Spatial error estimations (dependent variable: log soybean yields).

Model	Model (1): GDD and precipitation only	Model (2): add solar radiation	Model (3): add LUC variables	Model (4): add price ratios	Model (5): add irrigation ratio
$GDD_{8,32}$	0.4627*** (3.96)	0.4594*** (3.92)	0.3857*** (3.01)	0.3373** (2.55)	0.3362** (2.55)
$GDD_{8,32}$ squared	−0.1548*** (−4.56)	−0.1516*** (−4.48)	−0.1296*** (−3.45)	−0.1139*** (−2.95)	−0.1136*** (−2.94)
Square root of GDD_{34+}	−0.0013 (−0.33)	−0.0027 (−0.69)	−0.0030 (−0.76)	−0.0054 (−1.31)	−0.0053 (−1.30)
Precipitation	0.0888** (2.15)	0.0901** (2.20)	0.0965** (2.34)	0.0981** (2.39)	0.0982** (2.39)
Precipitation squared	−0.0712*** (−2.93)	−0.0695*** (−2.91)	−0.0740*** (−3.07)	−0.0734*** (−3.07)	−0.0734*** (−3.07)
Radiation		0.3172*** (3.63)	0.3642*** (3.85)	0.3433*** (3.64)	0.3426*** (3.63)
Radiation squared		−0.1658*** (−3.59)	−0.2085*** (−3.63)	−0.1910*** (−3.31)	−0.1907*** (−3.31)
LUC: marginal acre			0.0024 (0.12)	−0.0192 (−0.87)	−0.0191 (−0.86)
LUC: substitution acre			−0.0936 (−1.43)	−0.0900 (−1.32)	−0.0900 (−1.32)
Ratio: soybean price/ fertilizer price index				0.0308 (1.07)	0.0309 (1.07)
Ratio: soybean price/wage				0.0217** (2.45)	0.0216** (2.44)
Irrigation ratio					0.0058 (0.55)
Spatial correlation	0.2679*** (26.32)	0.2569*** (25.54)	0.2669*** (26.12)	0.2609*** (25.77)	0.2579*** (25.60)

Notes: The table lists coefficient estimates and asymptotic *t* statistics in parentheses with the contiguity matrix. Coefficients on time trends are suppressed. $N = 19{,}575$.
** $p < 0.05$.
*** $p < 0.01$.

3.5–11.8% smaller for corn and 3.8–6.8% smaller for soybeans relative to the corresponding estimates in models (2)–(5). The omission of radiation has a negligible effect on parameter estimates of $GDD_{8,32}$ and GDD_{34+}. Corn and soybean yields peaked with 918–949 and 873–957 h of radiation, respectively.

Parameter estimates of the weather variables change modestly with the inclusion of the LUC variables and price and irrigation ratios. We find that the LUC variables had insignificant impacts on county-average corn and soybean yields. These are expected results, given that the additional new lands brought into corn and soybean production were either abandoned cropland or land previously under other food and oil crops, both of which are suitable for crop production.

Parameter estimate of crop–fertilizer price ratio is positive and statistically significant for corn, indicating that the increase in fertilizer prices has resulted in reduced use of fertilizer and has had detrimental effects on county-average corn yields. This is an expected result because corn is a fertilizer-intensive crop. For soybeans, the coefficient is positive, but not statistically significant. Parameter estimate of crop–labor price ratio is positive and statistically significant for soybeans, which suggests that higher wages have led to reduced labor use and have negatively affected county-average soybean yields. The coefficient on crop–labor price ratio for corn has expected sign but not statistically significant. Increased irrigation area effectively reduced negative effect of high temperature on corn yields. The effect of this variable on soybean yields is positive but insignificant. It is not a surprising result, given that most soybean production in China occurs in rainfed regions, particularly in three Northeast provinces where precipitation is sufficient.

Regression results: temperature bins as temperature variables

Fig. 4 displays point estimates and the 95% confidence intervals of the temperature effects for the two crops when temperature bins for each 3 °C are used as temperature variables. Parameter estimates are obtained with the inclusion of the socioeconomic variables (model (5)). The horizontal axis in Fig. 4 is temperature, while the vertical axis in each figure denotes the log of yield (MT per hectare). Following Schlenker and Roberts (2009), we also normalize the exposure-weighted average predicted yields to zero. We find that corn and soybean yields increased with temperature up to 29 °C and 28 °C, respectively, and

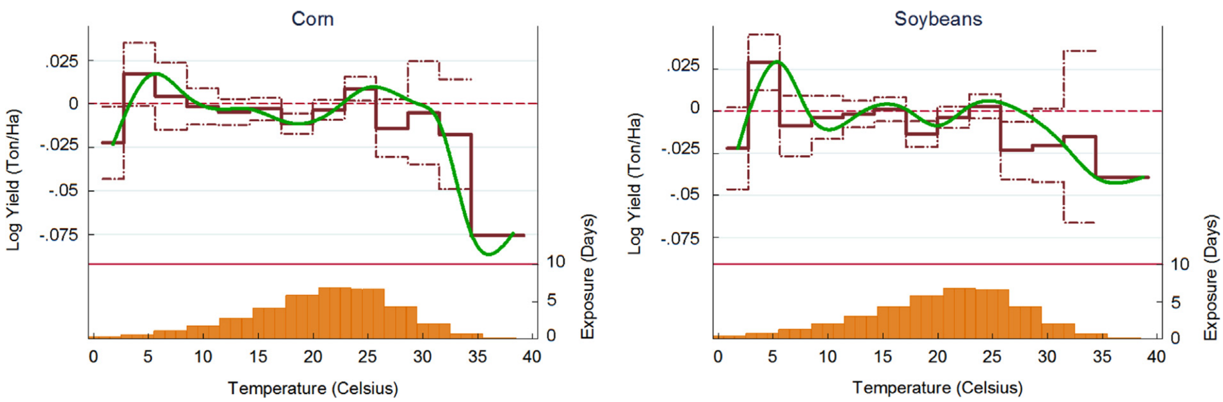

Fig. 4. Nonlinear relationship between temperature and crop yields. *Notes:* Results presented in the graphs are estimated using model specification (5)) with temperature bins as temperature variables. The 95% confidence intervals are also added (dark blue dash lines). The green line fits coefficient estimates of each 3 °C temperature range using an 8th-order polynomial function. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Sensitivity analysis: log corn yields.[a]

Scenarios	Baseline	Distance matrix (six)	Distance matrix (four)	Province-level time trend[b]	Non-irrigated subsample[b]
$GDD_{8,32}$	0.3375**	0.3362**	0.3917***	0.3146**	0.3314***
	(2.47)	(2.46)	(2.81)	(2.33)	(3.15)
$GDD_{8,32}$ squared	−0.0789**	−0.0764**	−0.0900**	−0.0720**	−0.0778**
	(−2.24)	(−2.16)	(−2.51)	(−2.01)	(−2.35)
Square root of GDD_{34+}	−0.0115***	−0.0115***	−0.0119***	−0.0122***	−0.0125***
	(−2.83)	(−2.80)	(−2.88)	(−3.02)	(−3.53)
Precipitation	0.0728**	0.0805**	0.0885***	0.0707**	0.0564*
	(2.20)	(2.46)	(2.65)	(2.21)	(1.66)
Precipitation squared	−0.0476**	−0.0520***	−0.0593***	−0.0476***	−0.0425**
	(−2.53)	(−2.77)	(−3.09)	(−2.57)	(−2.24)
Radiation	0.3130***	0.3152***	0.3548***	0.3250***	0.2207**
	(3.70)	(3.80)	(4.15)	(3.90)	(2.35)
Radiation squared	−0.1701***	−0.1706***	−0.1883***	−0.1774***	−0.1075*
	(−3.46)	(−3.54)	(−3.80)	(−3.80)	(−1.73)
Spatial correlation	0.3629***	0.3549***	0.2829***	0.3659***	0.2919***
	(37.37)	(36.83)	(36.21)	(36.96)	(34.70)

[a] Robustness checks are based on model specification (5). Coefficients of socioeconomic variables have expected signs and statistical significance. For brevity, they are not reported here. $N=16{,}965$ for non-irrigated subsample.
[b] Results are based on the contiguity matrix.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

temperatures above these thresholds had significant negative impacts on the growth of the two crops. For example, replacing a full day at 29 °C temperature with a full day at 35 °C temperature will decrease corn yields by about 9% (the left panel in Fig. 4), holding all else the same. The temperature thresholds identified here are comparable with the existing findings in the U.S. (Schlenker and Roberts, 2009). Coefficient estimates of other explanatory variables are consistent with the estimates when $GDD_{8,32}$ and GDD_{34+} are used as temperature variables. For brevity, they are not reported here.

In summary, our empirical results indicate the existence of nonlinear and inverted U-shaped relationships between weather variables and corn and soybean yields. The inclusion of radiation facilitates accurate estimates of the true temperature and precipitation effects on crop yields. While socioeconomic variables have expected signs and statistical significance, the inclusion of these variables only modestly affect parameter estimates of weather variables, which shows the robustness of our results.

Robustness check

Results presented above regarding the impacts of weather on crop yields make intuitive sense. In this section, we examine how robust they are across different spatial weighting matrices and estimation techniques in five different

Table 7
Sensitivity analysis: log soybean yields.[a]

Scenarios	Baseline	Distance matrix (six)	Distance matrix (four)	Province-level time trend[b]	Non-irrigated subsample[b]
$GDD_{8,32}$	0.3362**	0.3110**	0.3177**	0.3288**	0.3497***
	(2.55)	(2.40)	(2.42)	(2.28)	(2.90)
$GDD_{8,32}$ squared	−0.1136***	−0.1055***	−0.1063***	−0.1120***	−0.1122***
	(−2.94)	(−2.77)	(−2.77)	(−2.61)	(−3.26)
Square root of GDD_{34+}	−0.0053	−0.0058	−0.0070*	−0.0053	−0.0082**
	(−1.30)	(−1.42)	(−1.69)	(−1.28)	(−2.30)
Precipitation	0.0982**	0.1027**	0.1078***	0.0971**	0.0780**
	(2.39)	(2.49)	(2.58)	(2.39)	(2.29)
Precipitation squared	−0.0734***	−0.0756***	−0.0801***	−0.0751***	−0.0643***
	(−3.07)	(−3.12)	(−3.27)	(−3.14)	(−3.36)
Radiation	0.3426***	0.3498***	0.3762***	0.3682***	0.3941***
	(3.63)	(3.69)	(3.90)	(3.38)	(4.49)
Radiation squared	−0.1907***	−0.1950***	−0.2069***	−0.2168***	−0.2165***
	(−3.31)	(−3.39)	(−3.54)	(−2.76)	(−3.92)
Spatial correlation	0.2679***	0.2599***	0.1979***	0.2629***	0.2109***
	(25.60)	(25.72)	(22.08)	(25.69)	(24.19)

[a] Robustness checks are based on model specification (5). Coefficients of socioeconomic variables have expected signs and statistical significance. For brevity, they are not reported here. $N=18{,}918$ for non-irrigated subsample.
[b] Results are based on the contiguity matrix.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

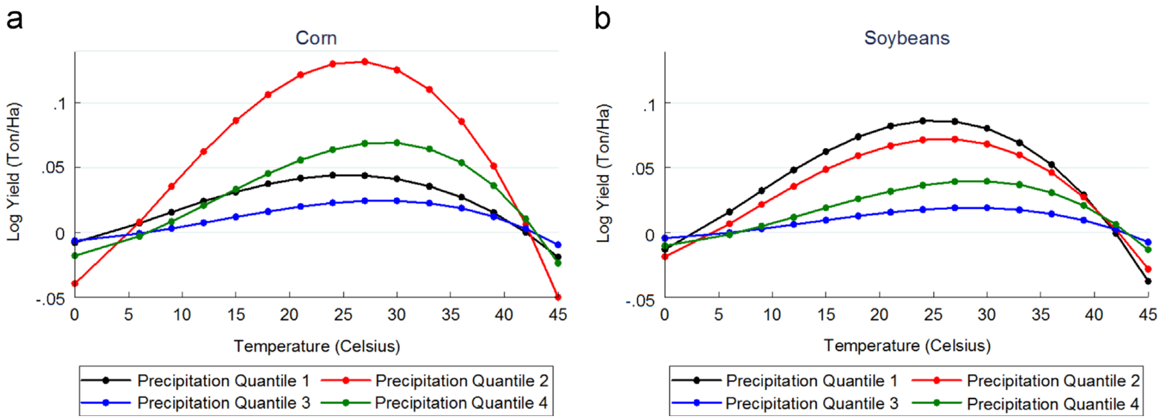

Fig. 5. Nonlinear relationship between temperature and corn and soybean yields with temperature–precipitation interactions. Notes: The full sample is divided into four quartiles based on the total precipitation over corn and soybean growing seasons. Results reported here are based on model specification (5) with $GDD_{8,32}$ and GDD_{34+} as temperature variables: (a) corn and (b) soybeans.

scenarios. Specifically, in Scenarios (1) and (2), we use two distance matrices that assign weights to the six and four nearest neighboring counties, and zero to other counties, respectively, as our spatial weighting matrix. In Scenario (3), we use time trends by province to capture exogenous technological change. In Scenario (4), we replicate the above analysis using a non-irrigated subsample. Lastly, in Scenario (5), we consider interactions between temperature and precipitation by dividing the sample into four quartiles based on total precipitation over crop growing season.

As shown in Tables 6 and 7, the nonlinear relationships between corn and soybean yields and weather variables still hold in Scenarios (1) and (2). Statistical significance, signs, and magnitudes of weather variables in both yield equations differ only slightly relative to the baseline estimates. Thus, the optimal numbers of $GDD_{8,32}$, precipitation, and radiation estimated for both crops in Scenarios (1) and (2) are almost identical to the baseline estimates. These results indicate that our results are not sensitive to the chosen spatial weighting matrix.

Regression results presented above included year-fixed effects to remove the unobserved factors common to all counties in a given year, including technology change that boosted crop yields. In Scenario (3), we replicate the above analysis using a time trend and its quadratic term by province to capture technological change due to R&D. Estimated coefficients on time variables are statistically significant at the 1% level, with positive signs on the linear terms and negative signs on the

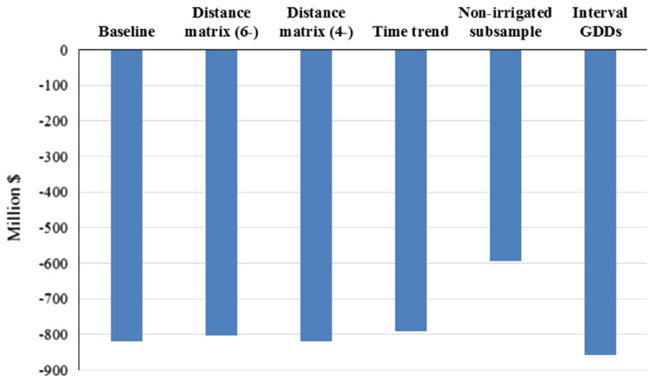

Fig. 6. Economic impact of climate change on China's corn and soybean sectors in the past decade ($ million). *Notes:* To compute the economic impact, we first calculate county-specific changes in corn and soybean yields for years 2001–2009 if weather conditions were maintained at the 2000 levels. We then multiply the changes in corn and soybean yields by their respective planted acreages in the corresponding years to estimate county-level production loss, summed across all counties and years in the sample, to get an estimate of the total production loss. We multiply the total production losses of corn and soybeans by their market prices in 2009 to obtain the economic loss in the two crop sectors due to climate change. National average corn and soybean prices in China were RMB 1.66 and 4.86 per kg, respectively, in 2009. The average exchange rate assumed here is RMB 6.8 per US$.

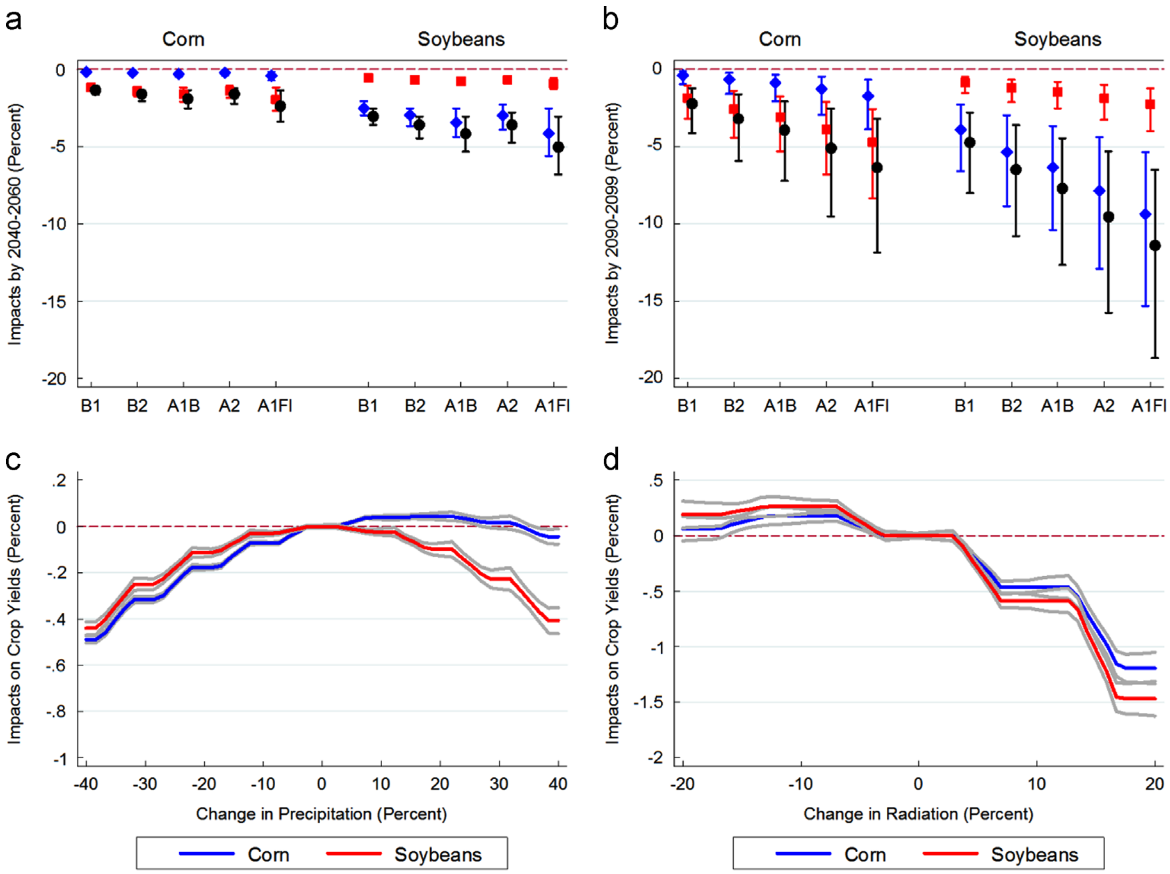

Fig. 7. Predicted impacts of climate change on corn and soybean yields in the baseline scenario. *Notes:* Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040–2060). Graph (b) displays the corresponding changes in the long term (2090–2099). A star indicates the point estimates in yield changes based on the most plausible changes in temperature, and whiskers represent ranges in yield changes based on lower and upper bounds in temperature change. The color represents the impact of different temperature intervals on yields. The blue represents the impact of $GDD_{8,32}$; the red denotes the impact of GDD_{34+}; and the black shows the total temperature impacts. Graphs (c) and (d) show the impacts of the uniform changes in precipitation and solar radiation on corn and soybean yields, respectively: (a) temperature (2040–2060), (b) temperature (2090–2099), (c) precipitation and (d) solar radiation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

quadratic terms, which indicate that exogenous technological change has boosted crop yields, but with a declining rate. Parameter estimates of weather variables are similar to our baseline results, suggesting that our results generally are not sensitive to the chosen method to represent exogenous technological change for yield growth.

Regression results presented above included all counties producing corn and soybeans in China (except the Qinghai-Tibet plateau). Because irrigation is a possible adaptation strategy to climate change, we would like to exclude the counties that heavily rely upon irrigation to grow the two crops to examine the sensitivity of our results. The lack of information on rainfed or irrigated corn and soybean production in Chinese counties prevents us from doing so. However, we know that some counties in the western provinces, such as Xinjiang Uygur Autonomous Region and Gansu Province, depend heavily on irrigation for crop production due to insufficient precipitation. We, therefore, exclude these western counties in the sample and replicate the above analyses in Scenario (4). As shown in the last columns of Tables 6 and 7, coefficient estimates of GDD_{8-32} and radiation have expected signs and statistical significance. As expected, parameter estimates of GDD_{34+} are statistically significant for both crops and are larger than the baseline results, while the effects of precipitation on yields now become smaller.

Fig. 5 displays the relationship between temperature and corn and soybean yields when the sample is divided into four quartiles based on the total precipitation over their growing seasons. The subsample coefficient estimates of temperature show similar inverted U-shaped relationships to parameter estimates obtained using the full sample. As precipitation increases, the critical temperature threshold associated with the subsample moves to the right, which indicates that, as precipitation increases, the two crops become more tolerant to high temperature.

Assessment of economic impact of climate change

We use coefficient estimates of weather variables obtained based on model specification (5) to get a rough estimate of the economic impact of changing weather conditions on China's corn and soybean sectors in the past decade. We first use these coefficient estimates to measure county-specific changes (δ_t) in yields for years 2001–2009 resulting from the changes in weather relative to year 2000:

$$\delta_t = E(\hat{Y}|H_{2000,}Z_{2000}, S_t) - E(\hat{Y}|H_{t,}Z_t, S_t) \quad (6)$$

where $E(\hat{Y}|H_{2000,}Z_{2000}, S_t)$ denotes the expected crop yields with the 2000 levels of weather outcomes and socioeconomic variables in year *t*; $E(\hat{Y}|H_{t,}Z_t, S_t)$ represents the expected crop yields when all explanatory variables are at their observed levels in year *t*. Therefore, δ_t measures the change in yields because of weather variations. Using Eq. (3), we can rewrite Eq. (6) as

$$\delta_t = \beta_0(H_{2000} - H_t) + \beta_1(Z_{2000} - Z_t) \quad (7)$$

where β_0 and β_1 measure the effects of weather on crop yields. Replacing β_0 and β_1 with their estimated coefficients can provide an estimate of δ_t.

We then multiply δ_t for both corn and soybeans in each county by their respective county-level planted acres in year *t*, summed across all counties and years, to get an estimate of the change in total corn and soybean production. We multiply the changes in total corn and soybean production by their market prices in 2009 to get a rough estimate of the economic impact of changing weather conditions on the two crop sectors over the sample period. Fig. 6 shows that the overall weather impact on China's corn and soybean sectors was negative in the past decade in the baseline analysis, and remains robust across the possible scenarios considered in the robustness checks, ranging between $594 million and $820 million. The economic loss becomes larger ($858 million) when temperature bins are used as temperature variables. Relative to annual production values of the two crops in China, the economic losses seem small. However, if other crop sectors are included, such as rice, the true social costs associated with climate change may become larger.

Future climate change impacts

In this section, we use the regression coefficients obtained based on model specification (5) to evaluate the potential impacts of future climate change on corn and soybean yields in China. The climate change scenarios we choose for this analysis are based on the Hadley III model, HadCM3, released by the UK Met Office and used in the fourth IPCC Assessment Report (IPCC, 2007). Specifically, we use the model's predicted changes in monthly minimum and maximum temperatures for five standard emissions scenarios (B1, B2, A1B, A2, and A1F1) for the medium term (2040–2060) and the long term (2090–2099). Each scenario represents different assumptions about population and economic growth, technological change, and use of fossil and alternative fuels. The B1 and A1F1 scenarios describe the slowest and fastest rates of warming by the end of this century, respectively. The Met Office also developed the Coupled Model Intercomparison Project (CMIP3) that predicts future precipitation change in China. According to CMIP3, precipitation is expected to increase between 0% and 20% over almost the entire country by the end of this century (IPCC, 2007). Here, we consider a broader range, from −40% to 40%, to fully reflect the possible future change in precipitation in China and examine the precipitation effects on crop yields. With the lack of long-term projections for radiation change, we also consider a uniform variation in radiation from –20% to 20% relative to 2009. Projected yield changes based on the baseline estimates are shown in Fig. 7, while predictions for scenarios considered in the robustness checks are shown in Appendix A.

We find that the increase in temperature will hurt crop yields, but the extent to which the yield reductions occur depends on warming scenarios. In the medium term, county-average corn yields in China are expected to decrease by 1–2%

under the B1 scenario and by 2–4% under the A1F1 scenario (see Fig. 7(a)). The corresponding reductions in soybean yields are larger, by 3–4% under the B1 scenario and by 3–7% under the A1F1 scenario. The yield reductions are expected to be considerably larger in the long term (see Fig. 7(b)). Specifically, county-average corn yields are expected to decrease by 1–4% and 3–12%, respectively, under the B1 and A1F1 scenarios, while soybean yields are likely to decline by 3–8% and 7–19% before the end of this century. These projected yield declines are smaller than projections from other settings (for example, see Schlenker and Roberts, 2009), possibly because of two reasons. First, we find that the differences between means of $GDD_{8,32}$ in the sample and the optimal amounts of $GDD_{8,32}$ estimated for corn and soybean yields are small, and that projected increases in $GDD_{8,32}$ and GDD_{34+} under different warming scenarios are also small (see Fig. A1). That implies that the negative impacts on yields because of rising temperatures are likely to be limited. Second, the projected yield declines displayed in Fig. 7 are based on parameter estimates of weather variables when $GDD_{8,32}$ and GDD_{34+} are used as temperature variables. When temperature bins are used as temperature variables, projected declines in corn and soybean yields in the long term are about 5% larger than our baseline projections (see Fig. A6). Changes in precipitation and radiation are expected to have a modest impact on yields (less than 1.5%) even with the wide range considered here (Fig. 7(c) and (d)).

Appendix A shows that the aggregate impacts of future climate change on corn and soybean yields are likely to be negative across the various scenarios considered. The primary driving force of the predicted yield reductions is the projected increase in frequency of high temperature (above 34 °C) for corn, and the increase in heat accumulated between temperature intervals of 8–32 °C for soybeans. However, one should note that the estimated impacts of future climate change on yields presented here are likely to be higher than the yield damage that will be actually caused by climate change in the long-term. That is because the coefficients of weather variables used for estimating the impacts of future climate change are based on the observed outcomes in the past decade, and thus they only reflect the short-term adaptions by farmers. In the long-term, farmers can take a variety of adaptations in response to changing climatic conditions, to reduce the external effects of climate change on crop yields (Mendelsohn et al., 1994).

Conclusion

Potential impacts of climate change on agricultural productivity and associated social and economic costs are at the core of the debate in China. Currently, China's climate policy has been based on inadequate analyses with apparent methodological and data issues. Therefore, more rigorous analyses based on better data and methodologies are called for. In this paper, we compiled a unique county-level panel on crop yields, combined with fine-scale daily weather data, to investigate the impact of climate change on corn and soybean yields in China.

Our analysis indicated that there are nonlinear and inverted U-shaped relationships between corn and soybean yields and weather variables. The optimal numbers of $GDD_{8,32}$, precipitation, and solar radiation estimated in all model specifications considered here are consistent with the existing literature. We find that temperatures above 34 °C had detrimental effects on crop growth. Socioeconomic variables also have expected signs and statistical significance. Results remain robust across various model specifications and variations in variables and data. We also used temperature bins to identify the potential nonlinearities in the relationship between temperature and crop yields. We find that yields increase with temperature up to 29 °C for corn and 28 °C for soybeans, and temperatures above these thresholds are very harmful for crop growth.

Using estimated weather coefficients, we show that global warming caused a net economic loss of $595–858 million in China's corn and soybean sectors in the past decade. Estimated weather coefficients are also used to predict the impacts of future global warming on corn and soybean yields in China. County-average corn and soybean yields could decrease by 3–12% and 7–19%, respectively, by 2100. The effects of the changes in precipitation and solar radiation on crop yields are expected to be small. These findings may provide valuable insights for the design of effective adaptation of agriculture to climate change and China's climate negotiation strategies.

Two major caveats apply. First, our data set covers observations for the past decade, yet our results are remarkably significant and robust. With a longer time period of observations, the net economic cost associated with climate change on the corn and soybean sectors could be even larger. Second, the coefficients of the weather variables used for estimating the future climate impacts are based on the short-term observations. Therefore, our estimates of the yield damages in future due to climate change are expected to be greater than the actual damages that will occur, because these coefficient estimates cannot capture the adaptation actions that farmers may take in the long-term in response to climate change.

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Appendix A. Impacts of future climate change on corn and soybean yields

See Fig. A1.

Scenario (1). Distance matrix (six)

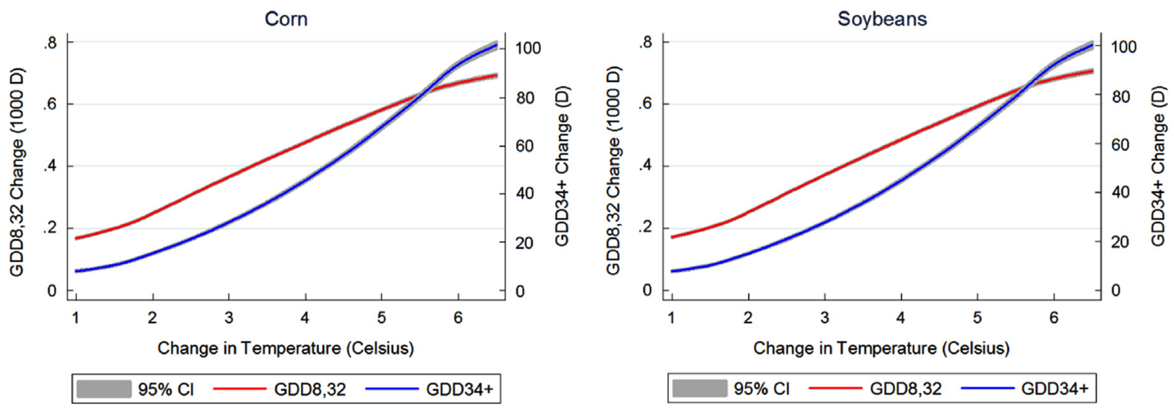

Fig. A1. Projected changes in $GDD_{8,32}$ and GDD_{34+} with temperature. *Notes:* Above figures are based on coefficient estimates of $GDD_{8,32}$ and GDD_{34+} in model specification (5) in the baseline case.

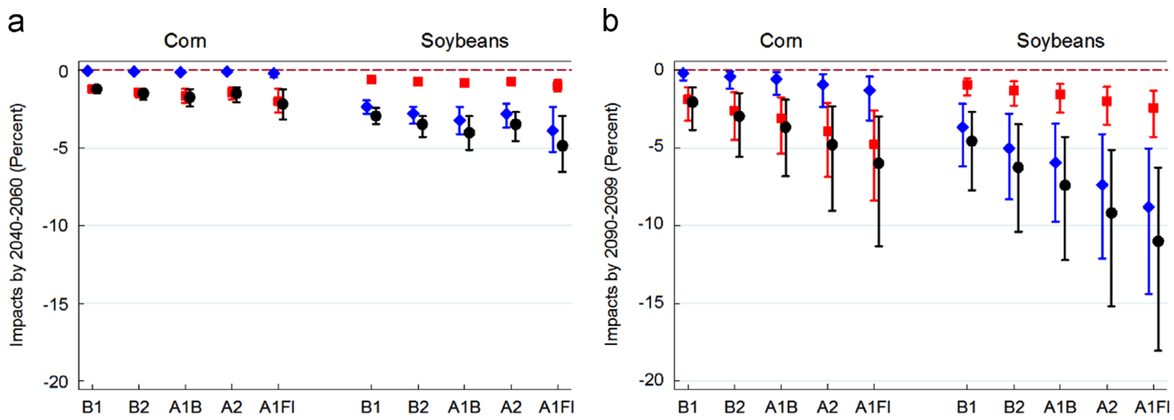

Fig. A2. Predicted impacts of climate change on corn and soybean yields. *Notes:* Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040–2060). Graph (b) displays the corresponding changes in the long term (2090–2099). A star indicates the point estimates in yield changes based on the most plausible changes in temperature, and whiskers represent ranges in yield changes based on lower and upper bounds in temperature change. The color represents the impact of different temperature intervals on yields. The blue represents the impact of $GDD_{8,32}$; the red denotes the impact of GDD_{34+}; and the black shows the total temperature impacts. (a)Temperature (2040–2060) and (b) Temperature (2090–2099). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

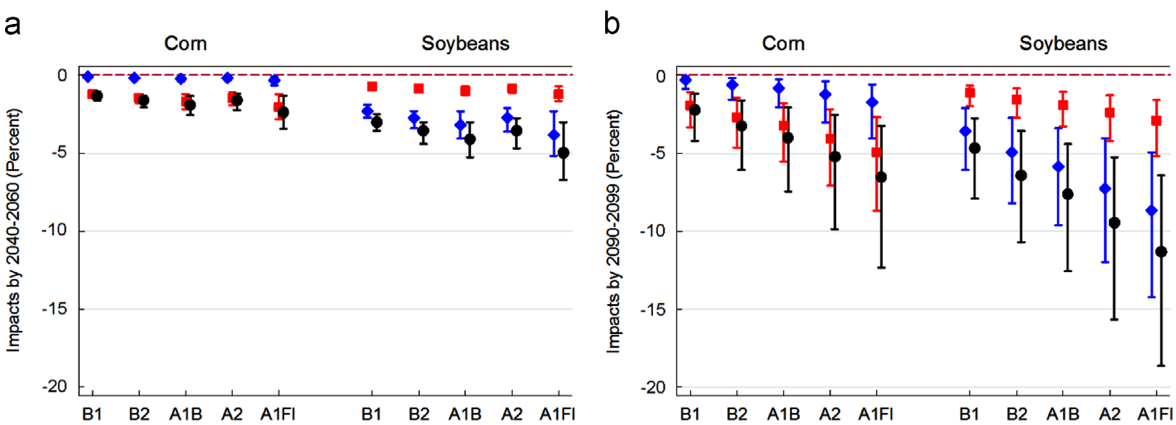

Fig. A3. Predicted impacts of climate change on corn and soybean yields. *Notes:* Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040–2060). Graph (b) displays the corresponding changes in the long term (2090–2099). A star indicates the point estimates in yield changes based on the most plausible changes in temperature, and whiskers represent ranges in yield changes based on lower and upper bounds in temperature change. The color represents the impact of different temperature intervals on yields. The blue represents the impact of GDD_{8-32}; the red denotes the impact of GDD_{34+}; and the black shows the total temperature impacts. (a)Temperature (2040–2060) and (b) Temperature (2090–2099). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

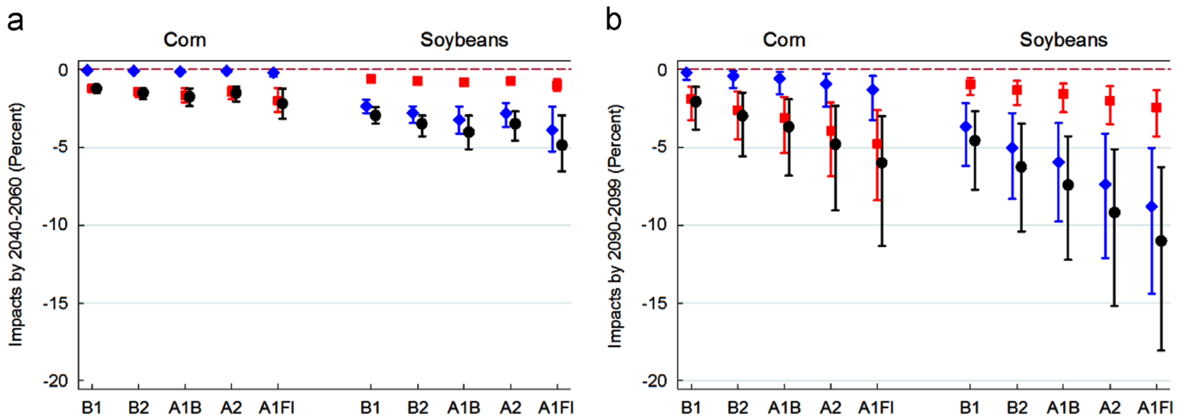

Fig. A4. Predicted impacts of climate change on corn and soybean yields. *Notes:* Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040–2060). Graph (b) displays the corresponding changes in the long term (2090–2099). A star indicates the point estimates in yield changes based on the most plausible changes in temperature, and whiskers represent ranges in yield changes based on lower and upper bounds in temperature change. The color represents the impact of different temperature intervals on yields. The blue represents the impact of GDD_{8-32}; the red denotes the impact of GDD_{34+}; and the black shows the total temperature impacts. (a) Temperature (2040–2060) and (b) Temperature (2090–2099). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

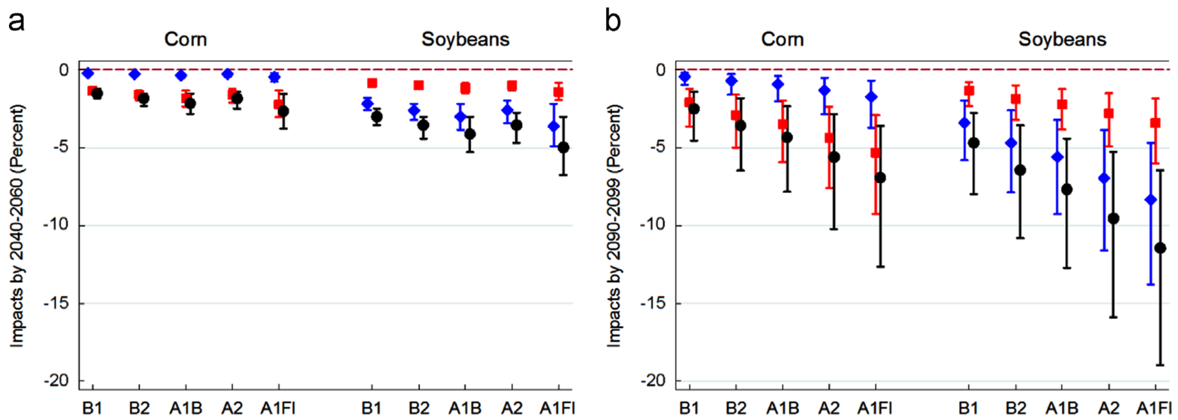

Fig. A5. Predicted impacts of climate change on corn and soybean yields. *Notes:* Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040–2060). Graph (b) displays the corresponding changes in the long term (2090–2099). A star indicates the point estimates in yield changes based on the most plausible changes in temperature, and whiskers represent ranges in yield changes based on lower and upper bounds in temperature change. The color represents the impact of different temperature intervals on yields. The blue represents the impact of GDD_{8-32}; the red denotes the impact of GDD_{34+}; and the black shows the total temperature impacts. (a) Temperature (2040–2060) and (b) Temperature (2090–2099). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

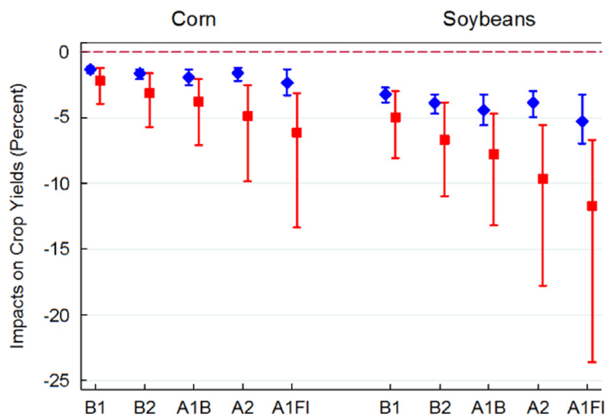

Fig. A6. Predicted impacts of climate change on corn and soybean yields. *Note:* Blue shows the predictions in the medium term (2040–2060) and the red denotes the predictions in the long term (2090–2099). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

See Fig. A2.

Scenario (2). Distance matrix (four)

See Fig. A3.

Scenario (3). Time trend

See Fig. A4.

Scenario (4). Non-irrigated subsample

See Fig. A5.

Scenario (5). Temperature bins as temperature variables

See Fig. A6.

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