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Impacts of Climate Change on Agriculture

Evidence from China

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Impacts of Climate Change on Agriculture: Evidence from China

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Abstract

We estimate the link between corn and soybean yields and weather in China, while controlling for other variables that could affect crop yields, such as socioeconomic and climate adaptation variables. We find that: (i) there are nonlinear and asymmetric relationships between corn and soybean yields and weather variables; (ii) expansion of corn and soybean production to land types not previously used for these two crops had detrimental effects on average yields for both crops; (iii) climate change led to a net economic loss of about $200 million to China's corn and soybean sectors in the past decade; (iv) corn and soybean yields are projected to decline by 4-14% and 8-21% by 2100.

Key Words: climate, China, corn, soybean, yields, land

JL Codes: Q54, Q10

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Introduction

Development of effective strategies whereby agriculture can adapt to climate change over the coming decades requires farmers, agribusiness, 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 (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, particularly in the United States (US). However, studies to address similar issues in China, the largest developing economy in the world, using a rigorous approach and high quality data, remain limited.

China has experienced noticeable climate change over the past century. Annual average air temperature has increased by 0.5-0.8°C during the past 100 years, which was slightly greater than the average global temperature rise over the same period (Ding et al. 2007). The last century has also witnessed an increasingly uneven distribution of precipitation between the south, where water is abundant, and the drier north, as well as increasing frequency and intensity of extreme climate events (Piao et al. 2010). Although agriculture accounts for only a small share of GDP in China, it is a vital industry, as it employs more than 300 million farmers and supports over 20% of the world's population with only 8% of global sown area. China has the world's largest agricultural economy, producing 18% of the world's cereal grains, 29% of the world's meat, and nearly 50% of the world's vegetables (FAO 2012). China is also a major importer of feed grains in the world market; it imported 57% of the soybeans sold in the international market in 2010 (FAO 2012). Hence, how climate change affects China's agriculture can have broad implications for food security in China, as well as prices worldwide.

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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 such as China. Different interpretations of climate change impacts on agriculture would 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 will even 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 negotiations. In fact, China's national climate strategy has been influenced by agronomic studies in the past decade (for example, Xiong et al. 2007), which found no adverse impacts of climate change on China's agricultural production. 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. To affect the course of this strategic development requires more analysis with high quality data and rigorous approaches.

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 differences 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 warming negatively affected farmland value in China. Both studies used cross-sectional data and thus relied on variations in weather between regions to identify weather coefficients. Thus, they cannot capture the effects of year-to-year change in weather on agriculture. Crop simulation models have also been applied to derive the predicted change for irrigated and rainfed corn, rice, and wheat yields in China (Lin et al. 2005; Xiong et al. 2007). The predicted yield change is combined with socio-economic models to assess the consequence of climate change on crop production in China. However, fundamental aspects of these crop simulation models have been questioned (Lobell et al. 2011; Schlenker et al. 2006), because they apply agronomically optimal levels of input but ignore the linkages with the rest of the economy.

Using a unique county-level panel on crop yields and daily weather outcomes, this paper provides the first empirical evidence on the impacts of climate change on crop yields in China. The dataset contains county-specific crop yields in China over the period 2001-2009. The daily weather data consist of minimum and maximum temperatures, precipitation, and solar radiation for all counties in China over the same period. The daily weather data facilitate accurate calculation of cumulative heat, precipitation, and solar 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 US (FAO 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.

When estimating the link between corn and soybean yields and weather variables, we control not only for temperature and precipitation, but also solar radiation. Using county-level crop yields and daily weather data in the US, Schlenker and Roberts (2009) found nonlinear temperature effects on corn, soybean and cotton yields; yields increase with temperature up to 29°C for corn, 30°C for soybeans and 32°C for cotton, while temperatures above these thresholds are found to be very harmful. Their regression analysis includes only temperature, precipitation, and regional time trends to explain the variations in crop yields. As agronomic literature has long suggested that temperature, precipitation, and solar radiation are three imporant factors for plant growth (Muchow et al. 1990; Szeicz 1974), their model specifications may lead to biased parameter estimates of temperature and precipitation due to the omission of solar radiation. The endogeneity issue could be particularly serious if radiation is highly correlated with temperature or precipitation over crop growing seasons.

We also construct two land-use-change (LUC) variables to reflect the change in soil quality 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 assume that soil quality remained constant over their study periods and used fixed-effect models to control for this unobservable heterogeneity across regions (Auffhammer et al. 2006; Schlenker and Roberts 2009). However, due to rising corn and soybean prices, corn production area in China increased by seven million hectares (ha) and soybean production area increased by two million ha during the 2001-2009 period (NBS 2001-2009). Of the additional land under the two crops, some came from reductions in land previously under other crops, such as rice, wheat, potatoes, oil seed, cotton, sugarcane, and sugar beet, while the rest was converted from marginal lands. Because of the difference in soil quality, the changes in land use patterns could have affected area-weighted corn and soybean yields.

Furthermore, we control for other factors that could affect the two crop yields, such as input use and farmers' 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 return from crop production. The farmer may also make adaptations to climate change by adjusting cropping systems and using more irrigation in warmer growing seasons (Howden et al. 2007). Exclusion of these factors may lead to biased estimates of the true effect of weather on crop yields.

We use estimated coefficients of weather variables to quantify the net economic impact of climate change on China's corn and soybean sectors over the sample period. This analysis provides some perspective on the sign and magnitude of the effect of climate change on China's two important crop sectors. Our estimates indicate that there exist nonlinear and asymmetric relationships between corn and soybean yields and weather variables. Extremely high temperatures are always harmful for growth of the two crops. These findings are consistent with the existing studies for the US (Schlenker et al. 2006; Schlenker and Roberts 2009). We also find that the rapid expansion of corn and soybean production areas on marginal land and other cropland in China has negatively affected area-weighted average corn and soybean yields. Furthermore, farmers have actively undertaken adaptation to mitigate the adverse impacts of high temperature on crop yields.

Our results indicate that climate change led to a net economic loss of about $200 million in China's corn and soybean sectors in 2009 alone, relative to 2001. In the medium term (2040-2050), area-weighted average corn yield in China is predicted to decrease by 1-2% under the slowest warming scenario and by 2-4% under the fastest warming scenario. The reductions in soybean yield are found to be more pronounced, about 3-4% and 4-8%, respectively, in the medium term. Yield reductions are expected to be considerably larger in the long term: corn and soybean yields are predicted to decrease by 2-5% and 3-9%, respectively, before the end of this century under the slowest warming scenario, and by 4-14% and 8-21% under the fastest warming scenario. Our results are robust across various model specifications and variations in variables and data. Our results may have important public policy implications for the design of effective adaptation strategies for agriculture in China. They are also important for 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. During the past decade, corn production area increased from 22 million ha in 2000 to 31 million ha in 2010 (see Fig. 1). Currently, corn accounts for approximately 20% of the total grain area and 14% of grain output in China. China's corn sector is also a major component of the world corn economy, producing over 20% of the world's corn (FAO 2012). China's soybean production has been relatively stable during the past decade with a total production area of 9 million ha, accounting for about 6% of the world's soybean production in 2010.

Despite the large amount of 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 2012). China persists in being the largest soybean importer in the world, with about 80% of domestic soybean consumption directly coming from imports, which accounts for about 57% of the soybeans sold in the international market (FAO 2012). With rapid economic growth and the demand for dietary improvement, China is expected to further increase its imports of the two crops in the next few decades.[1] Therefore, the future performance of China's corn and soybean sectors are of critical importance to the welfare of China's population of 1.3 billion and can have profound impacts on world food/feed markets.

Corn and Soybean Yields

Yield performance of the corn and soybean sectors has been impressive in the past three decades. During 1980-1995, average corn and soybean yields in China grew at an annual rate of nearly 5% (Aunan et al. 2000). During 2001-09, the annual growth rates declined to about 1% (see Fig 2). The yield growth can be largely attributed to the government's continued effort to invest in agriculture and modernize the nation's agricultural sector (Stone 1988). For example, with the widespread adoption of high-yielding and drought-tolerant seeds, many farmers in China have substantially increased their crop yields (Huang et al. 2002). The intensive use of inorganic fertilizers and chemical pesticides, resulting from the rapid expansion in fertilizer and chemical manufacturing capacity, has also contributed to yield increases in many areas of China (Huang et al. 2002).

Corn and Soybean Production Areas

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

Production areas of corn and soybeans in China changed both spatially and temporally during the period 2001-2009. As Fig. 1 displays, corn and soybean planted acres increased by 6.9 and 1.4 million ha, respectively, over this period (NBS 2001-2009). Of the additional land under

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[1] http://www.chinadaily.com.cn/business/2013-01/07/content_16092446.htm

the two crops (8.3 million ha), about 4.8 million ha came from 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 (3.5 million ha) were converted from marginal land (NBS 2001-2009). Marginal land used for corn and soybean production mainly came from two sources. The primary source is 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.[2] The second source is reclamation of grassland and deforestation (Liu et al. 2005). Depending on the soil quality of the additional land used for corn and soybean production, the regional land use changes may have affected area-weighted average corn and soybean yields.

Corn and Soybean Growing Seasons

Because of 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 are divided into four types (Chinese Cropping System 2005). Spring corn and soybean, typically planted in April and harvested in late September, are mainly concentrated in three northeastern provinces, Inner Mongolia, Ningxia, the Northwest inland area, and several regions in the southwestern mountainous areas. Summer corn and soybeans have a slightly shorter growing season compared to 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 southwestern 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/subtropical areas.

Conceptual Framework

Agronomic studies suggest that input use, soil quality, and weather are three main factors affecting crop yields at the field level (Cassman 1999). These experimental studies are based on field trials and typically apply agronomically optimal levels of fertilizer and chemicals to minimize nutrient, water, pest, and other stresses. In a real agricultural setting, however, farmers make decisions based on weather conditions they observe and prices they pay for inputs and receive for harvested crops. Therefore, it is essential to control for input use, among other factors, to obtain

2 http://www.chinadaily.com.cn/china/2012-03/27/content_14918222.htm

true weather effects on crop yields. However, such data on crop-specific input use are generally not available in public datasets and even in farmer surveys. In this section, we develop a conceptual model to deal with this data issue.

Consider a representative farmer who uses several inputs $k = 1,..., K$, such as fertilizer, chemicals, labor, and machinery, to produce crop $i = 1,..., I$. 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 renting equipment for land preparation, planting and 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 *A*, and we use A_i 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., $\sum_{i\in I} A_i \le A$.

Following the standard agronomic literature (for example, Cassman 1999), we assume yield of crop *i*, denoted by $y_i(x_{i,k}, s_i, z, t)$, to depend on input use ($x_{i,k}$), soil quality (s_i), weather (*z*), and exogenous technological change stimulated by research and development (R&D), which is 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:

$$\underset{x_{i,k}, A_i}{Max} \sum_{i\in I} \pi_i = \sum_{i\in I} E(p_i) y_i(x_{i,k}, s_i, z, t) A_i - \sum_{i\in I, k\in K} \omega_k x_{i,k} A_i - \sum_{i\in I} C_i \quad (1)$$

subject to $\sum_{i\in I} A_i \le A$. Assuming that interior solutions exist for all decision variables, the first-order optimality conditions with respect to input demand ($x_{i,k}$) and planted area (A_i) lead to:

$$E(p_i)\frac{\partial y_i}{\partial x_{i,k}} - \omega_k = 0 \qquad \text{for } \forall k = 1,..., K \text{ and } \forall i = 1,..., I \quad (2)$$

$$E(p_i) y_i(.) - \sum_{i\in I, k\in K} \omega_k x_{i,k} - \lambda = 0 \qquad \text{for } \forall i = 1,..., I \quad (3)$$

where λ is the Lagrangian multiplier of the land constraint (a measure of the land rent). With a binding land availability constraint, λ is positive. The first term of equation (2) is the marginal benefit from an additional use of input *k* (through the impact on yield, represented by $\frac{\partial y_i}{\partial x_{i,k}}$). Thus, the optimal use of input k is determined when the marginal benefit from the additional input use is equal to its market price, and can be expressed as a function of $E(p_i), \omega_k, s_i, z$ and t ,

$$x_{i,k} = x(E(p_i), \omega_k, s_i, z, t) . \tag{4}$$

Equation (3) can be rewritten as follows:

$$\lambda = E(p_i)y_i(.) - \sum_{i \in I, k \in K} \omega_k x_{i,k} = E(p_j)y_j(.) - \sum_{j \in I, k \in K} \omega_k x_{j,k} \ \ \forall i \neq j \tag{5}$$

Equation (5) states that, at the margin, profits obtained from producing crop i or j should be the same, and are equal to the land rent (λ). Substituting Equation (4) into 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 Equation (6):

$$y_i = y_i(E(p_i), \omega_k, s_i, z, t) \tag{6}$$

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.[3] 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, including soil quality and management practices (rotation and tillage). 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 who make land use and input decisions simultaneously in response to input and output prices. For example, with expected high corn prices, many farmers may convert idle land and/or land previously under other crops with low profit margins to corn. By using additional new land for corn production, an individual farmer's land use decisions could affect "average" soil quality under corn in a county and thus county-

[3] 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.aspx#ancor

average corn yield. Depending on the soil quality of the new land, area-weighted average corn yield 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 on crop yields (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 conditions. These adaptation behaviors can affect crop yields, and the necessity of these behaviors is largely dependent on local weather variations. Therefore, omitting them from a regression model could cause biased estimates of weather on crop yields. With the lack of other relevant information on farmers' adaptation behaviors, we use the ratio of irrigated area to total planted area of all crops in a county as a proxy to control for the possibility of farmers' adaptation to climate change. Even with the inclusion of this variable, we can only capture part of climate adaptation behaviors. However, if contemporaneous adaptation behavior is positively related to high temperatures, and if adaptation behavior lowers the negative impacts of high temperatures on crop yields, omitting it will yield a lower bound of the true effect.

Empirical Model

The empirical models are presented in Equations (7)-(8). We assume that crop growing seasons remain unchanged and that climate effects on crop yields are cumulative and additively substitutable over time (as in Schlenker and Roberts 2009):

$$\log Y_{r,t} = Z_{r,t}\beta_0 + LUC_{r,t}\beta_1 + P_{r,t}\beta_2 + A_{r,t}\beta_3 + c_r + \varepsilon_{r,t} \tag{7}$$

$$\varepsilon_{r,t} = \rho \sum_{r'} W_{r,r'}\varepsilon_{r',t} + \phi_{r,t} \tag{8}$$

where $\log Y_{r,t}$ denotes log crop yields in county r and year t. $Z_{r,t}$ includes the three weather variables (temperature, precipitation, and solar radiation) in county r and year t and their quadratic forms to capture the potential nonlinear effects of weather on crop yields over the growing season, which is defined differently for spring, summer, autumn and winter corn and soybeans. $Z_{r,t}$ also includes a time trend, to represent the exogenous technological change due to R&D, and a quadratic form of the time trend, to denote the speed at which the technological change occurred.[4] $LUC_{r,t}$ are two LUC variables by county, representing changes in soil quality due to regional land use changes in county r and season-year t relative to t-1. Expected crop prices and input prices are denoted by $P_{r,t}$. We use crop prices in year t-1 as a proxy for expected crop prices in year t (Braulke 1982; Nerlove 1956). $A_{r,t}$ represents farmers' contemporaneous climate adaptation behavior. A time-invariant county fixed effect c_r is used to control for heterogeneity, such as different agricultural production practices (rotation or tillage, for example). Lastly, $\varepsilon_{r,t}$ are the error terms. β_0 is the coefficient of interest. The main hypothesis is to test whether $\beta_0 = 0$, namely that weather variables have no effect on crop yields.

Following the standard agronomic literature, we represent the relationship between temperature and crop yields through the concept of *growing-degree days* (GDD), which is defined as the sum of heat that crops receive between lower and upper temperature thresholds during the growing season. The appropriate temperature thresholds for GDD are still debated. Here, 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 (Baskerville and Emin 1969). We also construct a separate variable that indicates the length of time that each crop is exposed to temperatures above 34°C, which are considered to be very harmful for plant growth (Ritchie and Nesmith 1991). A recent study by Schlenker and Roberts (2009) uses the number of days in 1°C temperature bins to calculate GDD and identify critical temperature thresholds which are beneficial to crop growth. They find that corn and soybean yields increase with temperature up to 29°C and 30°C, respectively, in the US, and that temperatures above these thresholds are very harmful. As a sensitivity check, we will draw on their work to identify temperature thresholds for corn and soybeans in China, and examine how this will affect our coefficient estimates of weather variables and the economic impact of climate change on China's corn and soybean sectors. We also compute cumulative precipitation and solar radiation over the growing season of corn and soybeans.

We use historical planted acres of major crops in each county to compute the two LUC variables that represent the conversion of marginal land (marginal acres) and land previously under other crops (substitution acres), respectively, to corn and soybean production. The substitution acre for a crop is defined as the reduction in aggregate acreage of all other crops relative to the previous

[4] As mentioned in Section 2, corn and soybean production in China is primarily concentrated in the north, and these major production regions are geographically close. Therefore, in the empirical regression models, we assume technological change does not vary across regions, but differs by crops.

year. 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 if the difference is positive. Therefore, the substitution acre for the crop would equal zero if the aggregate acreage of all other crops increases relative to the previous year. In this case, the marginal acre for the crop is the acreage increase of the crop relative to the previous year. The underlying assumption made here is that marginal land will be brought into crop production only if the demand for total cropland increases. Because the two LUC variables reflect the response of farmers to future profits from crop production, they may be endogenous, which could lead to a biased estimate of β_0 . However, the bias is expected to be small for two reasons. First, farmers' land use decisions are primarily driven by their expectations about future crop prices (Chavas and Holt 1990; Nerlove 1956). With the inclusion of Pr,t as explanatory variables in Equation (7), the correlation between the LUC variables and the error terms is likely to be small. Second, given the small scale of farm production in China (see footnote 5), individual farmers are unlikely to consider the potential impact of their land use decisions on crop yields, which makes the LUC variables less endogenous. However, when many heterogeneous profit-maximizing farmers in a county make land use decisions simultaneously, their decisions could affect area-weighted average crop yields.

To capture the effects of the changes in output and input prices on crop yields, we use input-output price ratios as explanatory variables in the empirical analysis (as in Welch et al. 2010), and include fertilizer price index and wage as input prices. Because other input prices (such as chemicals and machinery) are unlikely to be strongly correlated with weather, the exclusion of these variables only leads to a slightly less precise estimate of β_0. When identifying agricultural commodity supply and demand elasticities, Roberts and Schlenker (2013) argue that commodity prices are endogenous. To address the potential endogeneity issue of the two price ratios, we use observed weather outcomes and crop inventories in the previous year as instruments for the two variables, and use two-stage least square (2SLS) to estimate the yield equations.

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' adaptation to climate change. This variable is also potentially endogenous in that it reflects farmers' response to the changing climate. Here, we use the irrigation ratio in the previous year to serve as the instrument for farmers' irrigation behavior in the current year. Past irrigation behavior is a good instrument because it affects irrigation behavior in subsequent periods due to the large investment made on irrigation infrastructure, such as vertical wells and irrigation canals. But it has zero covariance with unobserved factors affecting crop yields in the current period. Unobserved factors might stem from the omission of input use, recurrent or unanticipated pest problems, agricultural production practices, and perhaps other factors.

As shown in Equation (8), we allow the error terms $\varepsilon_{r,t}$ to be spatially correlated across counties. $\phi_{r,t}$ are the error terms that are independently normally distributed with $E[\phi_{r,t}]=0$ and $\text{var}[\phi_{r,t}]=\sigma^2$, 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 on their neighbors. There are several reasons why spatial correlation between counties could influence crop yields in Equation (7). First, the error terms $\varepsilon_{r,t}$ may be spatially correlated due to the omission of spatially correlated explanatory variables. It is well known that agricultural policies may be subject to local variations if, for instance, governments at different levels implement regulatory policies in certain areas in a bid to achieve specific policy goals. Second, counties located close to each other are likely to use the same or similar production practices, which could influence crop yields. Third, we might also expect that closely related counties will share the same or similar local characteristics, such as soil type and seed varieties, 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 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 spatial matrix is unity if counties *r* and *r'* share a common boundary, and 0 otherwise. The contiguity matrix is then normalized so that the elements in each row sum to unity. However, the spatial contiguity matrix allows the possibility that counties share only a single boundary point (such as a shared corner point on a grid of counties). Thus, we consider two alternative 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 the county *r*. All spatial panel models are estimated using maximum likelihood (Anselin 1988; Elhorst 2010).

Data

We compiled a county-level panel on crop yields, planted acres of major crops, and weather for years 2001-2009 in China. This section describes data sources and reports summary statistics.

Crop Yields and Land Use Change Variables

County-specific total crop production, historical planted acres (including total and irrigated acres) of all crops in all counties are obtained from National Bureau of Statistics of China (NBS), which covers 2570 counties in China over the period 2001-2009. Yields for corn and soybeans are computed as total county-level production divided by planted acres.[5] We exclude the Qinghai-Tibet plateau in the analysis because it is not a major agricultural production region for corn and soybeans in China (accounting for less than 1% of total crop production in China). This gives us 18975 observations with corn yields and 19575 observations with soybean yields. As shown in Table 1, corn yields varied substantially in the sample, ranging between 0.04-16.9 MT per ha, with an average of 5.2 MT per ha, while soybean yields changed from 0.03-10.8 MT per ha, with a national average of 2.2 MT per ha. We use historical planted acres of major crops in China to compute the two LUC variables, namely marginal acres and substitution acres.

Weather

The weather data are obtained from the China Meteorological Data Sharing Service System (CMDSSS),[6] which records daily minimum and maximum 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 Megawatts/cm^2. The dataset also contains the exact coordinates of each weather station, enabling the weather data to be merged with our agricultural data. Fig. 4 shows spatial distribution of the weather stations along with county boundaries. For counties with several weather stations, we construct weather variables by taking the simple average of these weather variables across these stations. We impute the climatic information from the contiguous counties for counties without a station.

Crop Growing Seasons

Based on *The Chinese Cropping System* (2005), we assume that 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 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/subtropical areas, their growing season is typically between November 1 and February 28 in the following year.

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5 The lack of county-specific crop harvested acres may lead to an underestimation of true crop yields because farmers may choose not to harvest during extremely bad years. Schlenker and Roberts (2009) find that results are generally insensitive to the chosen yield definition.

6 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 more details.

Economic Variables

We obtain province-level data on corn and soybean prices from the China Yearbook of Agricultural Price Survey (NBS 2012). County-specific labor costs are not available. We obtain province-level average wage for farm labor from the National Bureau of Statistics of China.[7] Because of the prevalence of compound fertilizers, nutrient-specific fertilizer prices are also not available. For this, we compile a fertilizer price index at the province level from the China Yearbook of Agricultural Price Survey (NBS 2012).

Empirical Results

Before presenting our regression results, we first examine the presence of the spatial correlations of the error terms in corn and soybean 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, economic, LUC and climate adaptation variables. As shown in Table 2, these test results indicate that spatial correlations of the error terms in both yield equations are quite large. 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 considerably 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 will 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 spatial weighting matrices.

Baseline Results

We conduct the spatial error analysis using five different model specifications. In Model (1), we include GDD, precipitation, a time trend and their quadratic forms as explanatory variables to examine the changes in corn and soybean yields over the sample period. In Model (2), we add solar radiation and its quadratic form as additional explanatory variables. We consider this model

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7 http://data.stats.gov.cn/workspace/index?m=fsnd

specification mainly due to the concern that temperature and precipitation may be correlated with solar radiation and the omission of solar radiation in the regression analysis may lead to biased estimates of the true temperature and precipitation effects on corn and soybean yields. As shown in Table 3, we find that the correlation of the three weather variables is notable: GDD and solar radiation were highly (and positively) correlated, and both variables were negatively correlated with precipitation. These results suggest that a failure to control for solar radiation will lead to biased coefficient estimates of temperature and precipitation. In Model (3), we include the LUC variables to examine whether they have played a significant role in influencing area-weighted average corn and soybean 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.[8] All model specifications include time-invariant county fixed effects to control for the possibility of unobserved characteristics within each county. Regression results are reported in Tables 4-5.

Our empirical results show that weather had a significant impact on both corn and soybean yields over the sample period. Estimated coefficients on the effects of temperature on the two crops indicate the existence of an inverted U-shaped relationship between corn and soybean yields and GDD in all five model specifications. The optimal numbers of GDD in the range of 8-32°C for corn and soybean yields peak at 2090-2130 and 1380-1400, respectively, depending on model specifications. High temperatures above 34°C had detrimental effects for corn, but are found to be insignificant for soybeans. The coefficients on precipitation show similar nonlinear patterns. To achieve maximum yields, corn requires 68-73 cm of precipitation over the growing season, which is significantly higher than the amount for soybeans, which need 58-62 cm of precipitation. This nonlinear relationship indicates that precipitation increased corn and soybean yields, but at a declining rate. These results are consistent with the only previous study with a similar sample size, which focuses on temperate corn and soybeans in the US (Schlenker and Roberts 2009). Because of the omission of solar radiation, the optimal amounts of precipitation estimated in Model (1) (68 cm for corn and 58 cm for soybeans) are 5-8% and 4% smaller, respectively, relative to those estimated in Models (2)-(5), while the difference in GDD estimation across these models is negligible. Solar radiation also had significant impacts on corn and soybean yields, which peak with 1060-1090 and 1000-1020 hours of solar radiation, respectively. Estimated coefficients on

[8] With the inclusion of the LUC variables in Models (3)-(5), we lose the observations in 2001. To make results comparable across different model specifications, we used the data for years 2002-2009 in Models (1)-(2).

time trends are statistically significant at the 1% level, indicating that exogenous technological change boosted corn and soybean yields, but with a declining rate.

Coefficient estimates of the two LUC variables in Models (3)-(5) are both statistically significant at the 1% level and have negative signs, which indicates that the rapid expansion of corn and soybean production on marginal land and other cropland reduced county-average yields of the two crops, holding all else the same. However, the magnitudes of the yield reductions due to the land expansion are small, less than 1% relative to average corn and soybean yields in the sample. 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.

Coefficients on crop-labor price ratio are positive and statistically significant in Models (4)-(5), which suggests that higher wages have led to reduced labor use and have negatively affected area-weighted average corn and soybean yields. Likewise, the coefficient on crop-fertilizer price ratio for soybeans is positive and statistically significant, which indicates that the increase in fertilizer prices has resulted in reduced use of fertilizer and has had detrimental effects on soybean yield. For corn, the coefficient on crop–fertilizer price ratio is positive, but not significant.

To control for the effect of possible climate adaptation on crop yields, we add to the model the ratio of irrigated acres to total planted acres in a county in Model (5). The results from including this variable, reported in the last columns of Tables 4-5, show that irrigation has a positive effect on corn yield, suggesting that the adaptation of corn production to climate change is actively undertaken. The effect of this variable on soybean yield is positive but insignificant. It is not a surprising result, given that most soybean production in China occurs in rainfed regions, particularly in the three Northeast provinces, where precipitation is sufficient.

In summary, our empirical results indicate the existence of nonlinear and asymmetric relationships between weather variables and corn and soybean yields. The inclusion of other explanatory variables, including solar radiation, LUC, and economic and climate adaptation variables, facilitates more accurate estimates of the true weather effects on corn and soybean yields than otherwise, particularly with the consideration of solar radiation. While the LUC, economic, and adaptation variables have expected signs and statistically significant impacts on corn and soybean yields, the addition of these variables does not significantly affect coefficient 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, data, and estimation strategies. Specifically, in Scenarios (1)-(2), we use two distance matrices that assign weights to the six and four nearest neighboring counties, and zero to other counties, as our spatial weighting matrix. In Scenario (3), we consider year-fixed effects rather than a smooth time trend, in order to capture exogenous technological change. In Scenario (4), we replicate the above analysis using a non-irrigated subsample. Results for Scenarios (1)-(4) are presented in Tables 6-7.

When examining the impacts of future climate change on crop yields in the US, Schlenker and Roberts (2009) defined temperature variables differently. Rather than using GDD between pre-specified lower and upper temperature thresholds over the growing season as an explanatory variable, they calculated heat received by crops for each 1°C temperature interval, with the relationship fitted either linearly or with flexible polynomials, and use that to identify critical temperature thresholds for crop yields. Drawing on their work, we examine the sensitivity of our results in Scenario (5) and also identify the critical temperature thresholds that are beneficial for corn and soybeans in China. Lastly, in Scenario (6), we consider interactions between temperature and precipitation by dividing the sample into five quartiles based on total precipitation over the corn and soybean growing seasons.

In Scenarios (1)-(2), we find that the nonlinear relationships between corn and soybean yields and weather variables still hold, regardless of the spatial weighting matrix used. Statistical significance, signs, and magnitudes of weather variables in both yield equations differ only slightly as compared to the baseline estimates. Thus, the optimal numbers of GDD, precipitation, and solar radiation estimated for corn and soybeans in the two scenarios are very close to the baseline estimates.

All regressions so far have included a time trend and a quadratic time trend. However, this smooth trend cannot capture sudden discrete jumps, such as the introduction of a new crop variety with a significant yield boost, adoption of new production technologies, or other temporal shocks (such as drought, flood, or pest problems). We therefore replicate the above analysis with year fixed effects in Scenario (3). As show in Tables 6-7, regression results for both the corn and soybean yield equations are similar to our baseline estimates, indicating that our results are generally insensitive to the chosen interpolation method.

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, to examine the sensitivity of our results we would like to exclude the counties that heavily rely upon irrigation to grow the two crops. The lack of information on rainfed or irrigated corn and soybean production in counties in China 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 from the sample and replicate the above analyses in Scenario (4). As shown in the last columns of Tables 6-7, coefficient estimates of temperatures in the range of 8-32°C and above 34°C are larger than the baseline results. Effects of precipitation on the two crop yields now become smaller. Coefficients of solar radiation still have the expected signs and are statistically significant.

Following Schlenker and Roberts (2009), we consider two different approaches to calculate GDD with temperature bins in Scenario (5). Specifically, we first approximate GDD using dummy variables for each three-degree temperature interval. We then use an 8th order Chebychev polynomial to compute GDD. Point estimates and 95% confidence bands of temperature effects for corn and soybeans are displayed in Fig. 5. Results confirm the nonlinear relationships between corn and soybean yields and temperature, which shows that corn and soybean yields increase modestly up to a critical temperature and then decrease sharply. The critical threshold temperature is 30° C for corn and 29° C for soybeans, above which is harmful for corn and soybean growth. These results are consistent with those found in the US (Schlenker and Roberts 2009). Coefficient estimates of other weather variables show similar nonlinear patterns with the crop yields.

Fig. 6 displays the relationship between temperature and the two crop yields when the sample is divided into five quartiles based on total precipitation over the growing season. The subsample coefficient estimates of temperature have similar inverse U-shaped relationships to those estimated 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.

Economic Impact of Climate Change

We use the coefficient estimates of weather variables presented above to get a rough estimate of the economic impact of climate change on China’s corn and soybean sectors. We first use these coefficient estimates to measure the percentage change (δ) in crop yields in 2009 that have resulted from changes in weather over time:

$$\delta = \frac{E(Y \mid Z_{2001}, LUC, P, A) - E(Y \mid Z_{2009}, LUC, P, A)}{E(Y \mid Z_{2009}, LUC, P, A)} \tag{9}$$

where $E(Y \mid Z_{2001}, LUC, P, A)$ denotes the expected crop yields with 2001 levels of weather conditions and 2009 levels of technology, socioeconomic, and climate adaptation variables; and $E(Y \mid Z_{2009}, LUC, P, A)$ represents the expected crop yields with 2009 levels of all variables. In other words, δ measures the percentage change in crop yields because of the changing climate conditions over 2001-2009. Using Equation (7), we can rewrite (9) as:

$$\delta = \frac{\beta_0 (Z_{2001} - Z_{2009})}{E(Y \mid Z_{2009}, LUC, P, A)} \tag{10}$$

where β_0 is the coefficient of the effect of weather on crop yields. Replacing β_0 with its estimated coefficient will provide an estimate of δ.

We then multiply the changes in crop yields in each county over the sample period by their respective county-specific planted acres in 2009 to get an estimate of the changes in crop production resulting from climate change. We multiply the changes in corn and soybean production by their respective market prices in 2009 to get a rough estimate of the economic impact of climate change on the two crop sectors. As shown in Fig. 7, changing climate conditions over the period 2001-2009 led to a net economic loss of approximately \$203 million in China's corn and soybean sectors in 2009 alone. We also compute the economic impact of climate change using the coefficients estimated in Models (1)-(4), which range between \$80 million and \$216 million. The lower bound of that range is obtained using Model (1), which excludes solar radiation as an explanatory variable. Furthermore, we use the coefficients estimated in the robustness checks to quantify the economic impacts of climate change on the two crop sectors. Consistent with our baseline estimate, we find that the net economic impact is always negative for the past decade across all possible scenarios considered here, ranging between \$121-261 million, depending on scenarios (see Fig. 7). Relative to annual production values of corn and soybeans in China, the economic losses seem small. However, if we include other crop sectors, such as rice,[9] the true social costs associated with climate change could be larger.

[9] Welch et al. (2010) find that higher minimum temperature reduced rice yields in tropical/subtropical Asia, including China.

Future Climate Change Impacts

In this section, we use the regression coefficients obtained above 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 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 average monthly 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, respectively, by the end of this century. 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 corresponding impacts on corn and soybean yields. With the lack of long-term projections for solar radiation change, we also consider a uniform variation in solar radiation from -20% to 20% relative to 2009. We evaluate the impacts of future climate change on corn and soybean yields using parameter estimates based on Model (5), in both the baseline case and the scenarios considered in the robustness checks. Predictions based on the baseline case are shown in Fig. 8. We present the predictions under other scenarios in Appendix A.

Across the scenarios considered here, we find that increase in temperature will hurt corn and soybean yields, but the extent to which the yield reductions occur depends on warming scenarios. In the medium term, area-weighted average corn yield in China is expected to decrease by 1-2% under the B1 scenario and by 2-4% under the A1F1 scenario (see Fig. 8(a)). The corresponding reductions in soybean yield are larger: 3-4% under the B1 scenario and 4-8% under the A1F1 scenario. The yield reductions are expected to be considerably larger in the long term (see Fig. 8(b)). Specifically, corn yield is expected to decrease by 2-5% and 4-14% under the B1 and A1F1 scenarios, respectively, while soybean yield is likely to decline by 3-9% and 8-21% before the end of this century. Figures 8 (c)-(d) present predicted yield impacts with the changes in precipitation and radiation. We find that changes in precipitation and solar radiation would have a modest impact on corn and soybean yields (less than 1%) even with the wide range considered here.

As shown in Appendix A, we find that aggregate impacts of future climate change on corn and soybean yields would be negative across the various scenarios considered. Among the three weather variables considered in this analysis, the primary driving force of the predicted yield reductions is the projected increase in frequency of extremely high temperature (above 34°C) for corn, and the increase in heat accumulated between temperature intervals of 8-32°C for soybeans.

Concluding Remarks

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 investigated the impact of climate change on corn and soybean yields in China. We compiled a unique county-level panel on crop yields, combined with fine-scale daily weather data. Other socioeconomic variables and variables representing farmers' climate adaptation are also included in the regression analysis. This is the first county-level analysis estimating the relationship between weather and crop yields for a country other than the US.

Our analysis indicated the existence of nonlinear and asymmetric relationships between corn and soybean yields and weather variables. The optimal numbers of GDD, precipitation, and solar radiation estimated in the preferred model are consistent with existing literature. Other variables have intuitive signs and magnitudes. For example, temperatures above 34°C are always harmful to corn and soybean growth. Acreage expansion on marginal land or land under other crops had negative impacts on area-weighted average corn and soybean yields. Estimated coefficients of the time trend suggest that recent adoption of new seed varieties has led to renewed increases in corn and soybean yields over the sample period, but with declining rates. Results remain robust across various model specifications and variations in variables and data.

Using estimated coefficients from yield equations, we found that climate change led to a net economic loss of $121-261 million in China's corn and soybean sectors in 2009 alone relative to 2001. These coefficient estimates are also used to predict the impacts of future global warming on corn and soybean yields in China. In the medium term, area-weighted average corn yield in China is expected to decrease by 1-2% under the slowest warming scenario and by 2-4% under the fastest warming scenario. The corresponding reductions in soybean yield are larger, by 3-4% and 4-8%, respectively. Yield reductions are expected to be considerably larger in the long term. Corn and soybean yields could decrease by 4-14% and 8-21%, respectively, before the end of this century. The effects of the changes in precipitation and solar radiation on corn and soybean 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 could be even larger. Second, our analysis focuses on the impacts of changes in temperature, precipitation, and solar radiation on crop yields, and does not consider the impact of CO_2 fertilization on crop yields. Laboratory studies have found that higher CO_2 fertilization may offset yield reductions due to warmer climate (Long et al. 2006). However, it is impossible in a regression analysis to account for CO_2 effects on crop yields because CO_2 concentrations quickly dissipate throughout the atmosphere.

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Tables and Figures

Table 1: Summary Statistics: Crop Yields and Weather Variables

Variable	Mean	Minimum	Maximum	Std. Dev.
Crop yields				
Corn yield (MT per ha)	5.19	0.04	16.92	1.95
Soybean yield (MT per ha)	2.15	0.03	10.81	1.03
Weather variables for corn				
GDD (8-32°C) (thousand D)	2.12	0.90	3.55	0.34
GDD ($\geq$ 34°C) (D)	6.33	0	225.22	9.78
Solar radiation (thousand hours)	0.89	0.41	2.08	0.33
Precipitation (thousand mm)	0.57	0.025	2.07	0.28
Weather variables for soybeans				
GDD (8-32°C) (thousand D)	2.12	0.67	3.40	0.37
GDD ($\geq$ 34°C) (D)	6.08	0	104.86	8.61
Solar radiation (thousand hours)	0.90	0.40	2.08	0.33
Precipitation (thousand mm)	0.58	0.026	1.98	0.27

Table 2: Tests for the Presence of Spatial Correlation

Spatial weighting matrix	Contiguity matrix	Distance matrix(6)	Distance matrix(4)
	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 $\chi^2(1)$	19425.21	12533.43	15376.71
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 $\chi^2(1)$	20462.79	13261.80	15773.54
Parameter of spatial correlation	0.63	0.61	0.54

Notes: We use three spatial weighting matrices to examine the sensitivity of our results to proposed weighting matrices. 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. The matrix is then normalized so that the elements in each row sum to unity. 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.

Table 3: Correlations among Weather Variables over the Growing Season

	Corn			Soybeans		
	GDD	Precipitation	Radiation	GDD	Precipitation	Radiation
GDD	1			1		
Precipitation	-0.3265*	1		-0.3119*	1	
Radiation	0.3680*	-0.3337*	1	0.3632*	-0.3288*	1

Notes: GDD are calculated based on a temperature interval of 8-32°C. Correlations were calculated using residual variations in the variables after demeaning them by county and years to remove the time trend and fixed effects of unobserved factors unique to each county. Number of observations = 18,945 for corn and 19,575 for soybeans. * denotes $P < 1\%$.

Table 4: Spatial Error Estimations (Dependent Variable: Log Corn Yield)

Model	Model (1): GDD and precipitation only	Model (2): add solar radiation	Model (3): add LUC variables	Model (4): add economic variables	Model (5): add climate adaptation variable
GDD (8-32°C)	0.3509***	0.3703***	0.3888***	0.3673***	0.3646***
	(2.84)	(2.98)	(3.18)	(2.95)	(2.93)
GDD (8-32°C) squared	-0.0824**	-0.0871***	-0.0932***	-0.0874***	-0.0868***
	(-2.53)	(-2.68)	(-2.91)	(-2.67)	(-2.65)
Square root of GDD	-0.0093***	-0.0120***	-0.0113***	-0.0135***	-0.0135***
(≥ 34°C)	(-2.94)	(-3.66)	(-3.53)	(-4.14)	(-4.15)
Precipitation	0.0900***	0.0927***	0.0921***	0.0968***	0.0958***
	(2.95)	(3.02)	(3.04)	(3.15)	(3.13)
Precipitation squared	-0.0666***	-0.0653***	-0.0642***	-0.0658***	-0.0657***
	(-3.47)	(-3.42)	(-3.41)	(-3.45)	(-3.45)
Radiation		0.3165***	0.3089***	0.2960***	0.2996***
		(5.17)	(5.11)	(4.81)	(4.87)
Radiation squared		-0.1492***	-0.1417***	-0.1373***	-0.1383***
		(-5.04)	(-4.84)	(-4.64)	(-4.68)
LUC: marginal acre			-0.0051***	-0.0053***	-0.0054***
			(-7.68)	(-7.88)	(-8.01)
LUC: substitution acre			-0.0059***	-0.0058***	-0.0059***
			(-5.19)	(-5.17)	(-5.25)
Ratio: corn price/fertilizer				0.1568	0.1325
price index				(1.37)	(1.15)
Ratio: corn price/wage				0.4818**	0.4742***
				(2.09)	(2.06)
Irrigation ratio					0.0439***
					(3.04)
Spatial correlation	0.3819***	0.3809***	0.3729***	0.3699***	0.3689***
	(37.57)	(37.16)	(35.73)	(35.03)	(35.09)
N	16840	16840	16840	16840	16840
R^2	0.8087	0.8095	0.8105	0.8110	0.8110

Notes: Table lists coefficient estimates and asymptotic *t* statistics in parentheses with the contiguity matrix. Results presented in the last two columns (Models (4)-(5)) are estimated using instrumental variables and 2SLS. *F-statistics* in the first-stage for the three endogenous variables (two price ratios and irrigation ratio) are greater than 40, indicating the validity of the instrumental variables. For brevity, they are not reported here. Coefficients on time trends are suppressed. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 5: Spatial Error Estimations (Dependent Variable: Log Soybean Yield)

Model	Model (1): GDD and precipitation only	Model (2): add solar radiation	Model (3): add LUC variables	Model (4): add economic variables	Model (5): add climate adaptation variable
GDD (8-32°C)	0.3942***	0.3936***	0.3873***	0.3417***	0.3442***
	(3.57)	(3.59)	(3.54)	(3.09)	(3.14)
GDD (8-32°C) squared	-0.1413***	-0.1406***	-0.1396***	-0.1241***	-0.1250***
	(-4.57)	(-4.56)	(-4.53)	(-4.02)	(-4.05)
Square root of GDD	-0.0007	-0.0028	-0.0028	-0.0046	-0.0044
(≥ 34°C)	(-0.19)	(-0.78)	(-0.79)	(-1.28)	(-1.24)
Precipitation	0.0927***	0.0946***	0.0960***	0.0900**	0.0892**
	(2.64)	(2.68)	(2.73)	(2.56)	(2.55)
Precipitation squared	-0.0783***	-0.0768***	-0.0775***	-0.0770***	-0.0763***
	(-3.52)	(-3.49)	(-3.53)	(-3.50)	(-3.47)
Radiation		0.2891***	0.2866***	0.3111***	0.3081***
		(4.16)	(4.14)	(4.49)	(4.45)
Radiation squared		-0.1418***	-0.1399***	-0.1545***	-0.1534***
		(-4.26)	(-4.21)	(-4.64)	(-4.62)
LUC: marginal acre			-0.0038***	-0.0039***	-0.0039***
			(-4.62)	(-4.74)	(-4.75)
LUC: substitution acre			-0.0048***	-0.0047***	-0.0047***
			(-2.63)	(-2.59)	(-2.58)
Ratio: soybean price/fertilizer				0.1360***	0.1419***
price index				(2.77)	(2.89)
Ratio: soybean price/wage				0.0771***	0.0779***
				(4.34)	(4.39)
Irrigation ratio					0.0190
					(1.11)
Spatial correlation	0.2869***	0.2799***	0.2819***	0.2749***	0.2719***
	(25.46)	(25.90)	(25. 27)	(24.93)	(24.82)
N	17400	17400	17400	17400	17400
R^2	0.8128	0.8132	0.8136	0.8139	0.8139

Notes: Table lists coefficient estimates and asymptotic *t* statistics in parentheses with the contiguity matrix. Results presented in the last two columns (Models (4)-(5)) are estimated using instrumental variables and 2SLS. *F-statistics* in the first-stage for the three endogenous variables (two price ratios and irrigation ratio) are greater than 40, indicating the validity of the instrumental variables. For brevity, they are not reported here. Coefficients on time trends are suppressed. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 6: Sensitivity Analysis: Corn Yield (Dependent Variable: Log Corn Yield)[1]

Scenarios	Distance matrix(6)	Distance matrix(4)	Year fixed effect[2]	Non-irrigated subsample[2]
GDD (8-32°C)	0.3531***	0.3968***	0.3786***	0.4047***
	(2.79)	(3.20)	(3.06)	(3.01)
GDD (8-32°C) squared	-0.0816**	-0.0917***	-0.0939***	-0.0892***
	(-2.44)	(-2.84)	(-2.88)	(-2.58)
Square root of GDD(≥ 34°C)	-0.0135***	-0.0150***	-0.0089***	-0.0136***
	(-4.06)	(-4.79)	(-2.66)	(-4.24)
Precipitation	0.1040***	0.1093***	0.1269***	0.0671***
	(3.36)	(3.62)	(3.87)	(2.13)
Precipitation squared	-0.0717***	-0.0781***	-0.0800***	-0.0491***
	(-3.72)	(-4.14)	(-4.08)	(-2.57)
Radiation	0.2949***	0.3368***	0.3045***	0.2022***
	(4.77)	(5.61)	(4.96)	(2.89)
Radiation squared	-0.1365***	-0.1541***	-0.1494***	-0.0743**
	(-4.58)	(-5.34)	(-5.08)	(-1.94)
Spatial correlation	0.3799***	0.2999***	0.3619***	0.3789***
	(34.16)	(32.94)	(35.44)	(33.64)
N	16840	16840	16840	15080
R^2	0.8110	0.8111	0.8123	0.8114

1. Robustness checks are based on model specification (5). Coefficients for other variables have expected signs and are statistically significant. For brevity, they are not reported here. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

2. Results are based on spatial contiguity matrix.

Table 7: Sensitivity Analysis: Soybean Yield (Dependent Variable: Log Soybean Yield)[1]

Scenarios	Distance matrix(6)	Distance matrix(4)	Year fixed effect[2]	Non-irrigated subsample[2]
GDD (8-32°C)	0.3221***	0.3324***	0.3684***	0.3633***
	(2.93)	(3.06)	(3.35)	(3.29)
GDD (8-32°C) squared	-0.1171***	-0.1195***	-0.1316***	-0.1249***
	(-3.78)	(-3.96)	(-4.22)	(-4.01)
Square root of GDD(≥ 34°C)	-0.0045	-0.0055	-0.0016	-0.0062*
	(-1.25)	(-1.61)	(-0.43)	(-1.81)
Precipitation	0.0961**	0.0991***	0.0929***	0.0664*
	(2.72)	(2.88)	(2.65)	(1.84)
Precipitation squared	-0.0802***	-0.0842***	-0.0765***	-0.0659***
	(-3.63)	(-3.89)	(-3.49)	(-2.95)
Radiation	0.3147***	0.3479***	0.2755***	0.3534***
	(4.53)	(5.17)	(3.97)	(4.98)
Radiation squared	-0.1576***	-0.1717***	-0.1482***	-0.1753***
	(-4.73)	(-5.32)	(-4.47)	(-4.98)
Spatial correlation	0.2759***	0.2089***	0.2689***	0.2309***
	(25.10)	(22.84)	(24.79)	(20.12)
N	17400	17400	17400	16816
R^2	0.8142	0.8143	0.8149	0.8093

1. Robustness checks are based on model specification (5). Coefficients for other variables have expected signs and statistical significance. For brevity, they are not reported here.*p< 0.1, **p< 0.05, ***p< 0.01.

2. Results are based on spatial contiguity matrix.

Figure 1. Total planted acres of corn and soybeans in China over 2001-2009 (million ha)

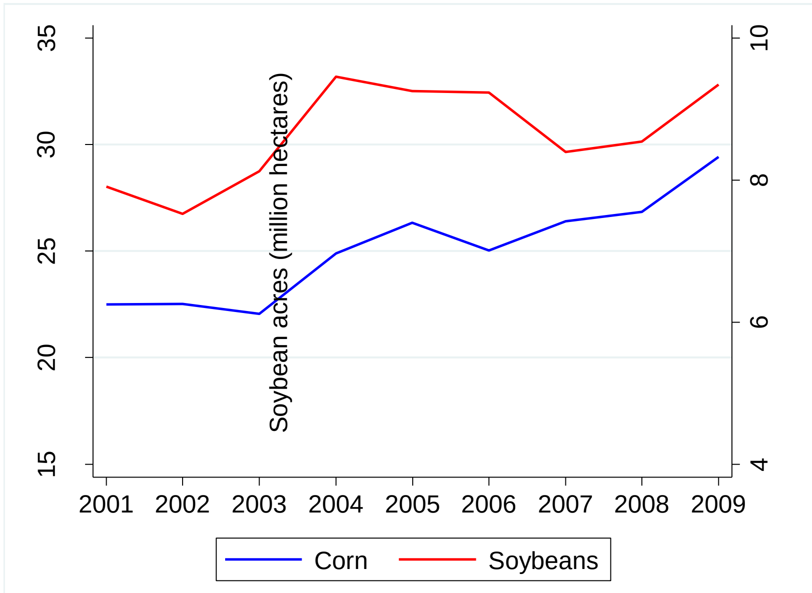


Figure 2. Average corn and soybean yields (MT per ha) and total fertilizer use (MT per ha) in China over 2001-2009

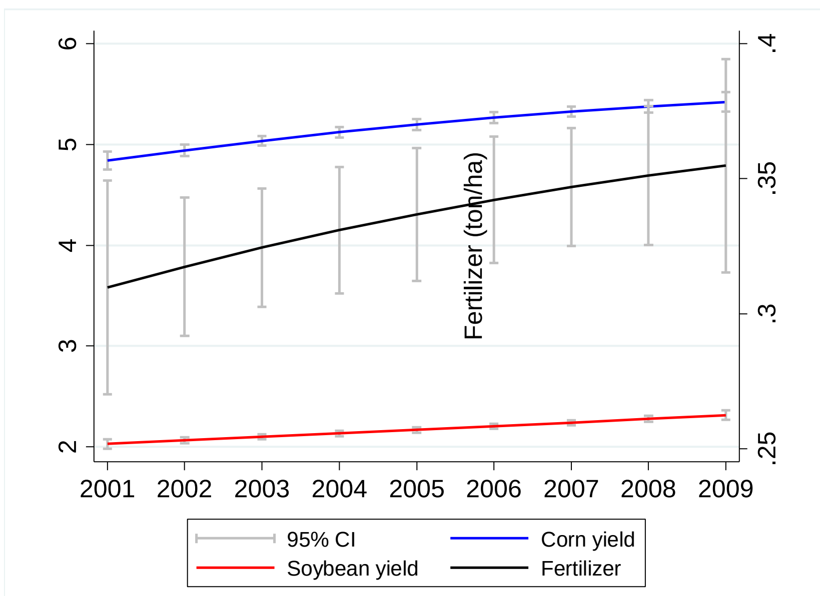
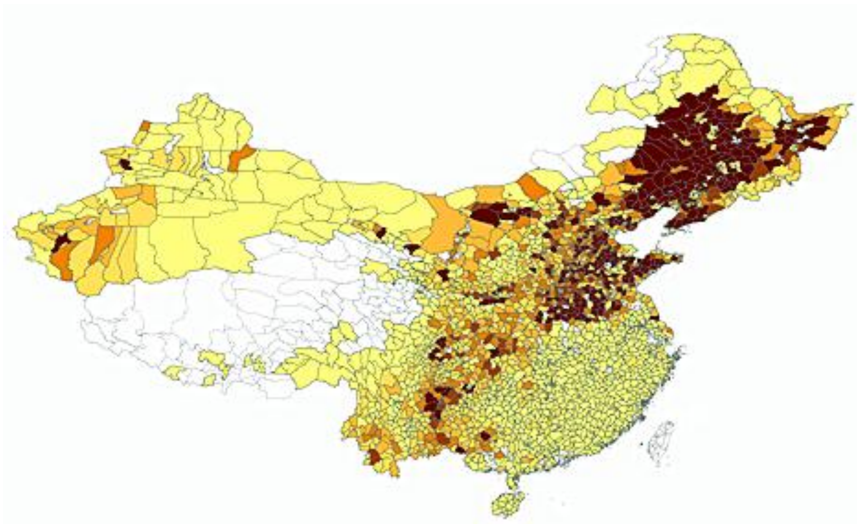
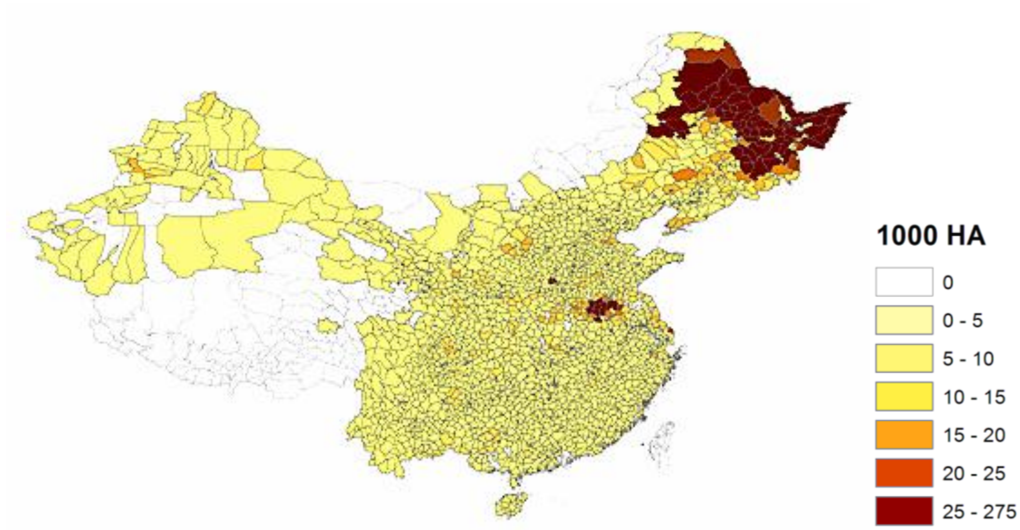


Figure 3. Five-year (2005-2009) average planted acres of corn and soybeans in China (1000 ha)



(a) Corn



(b) Soybeans

Figure 4. Weather stations in China

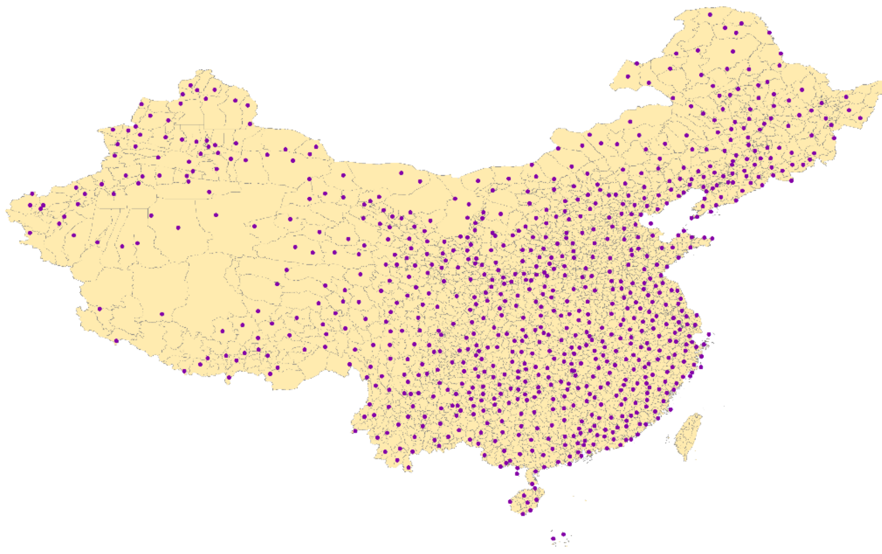
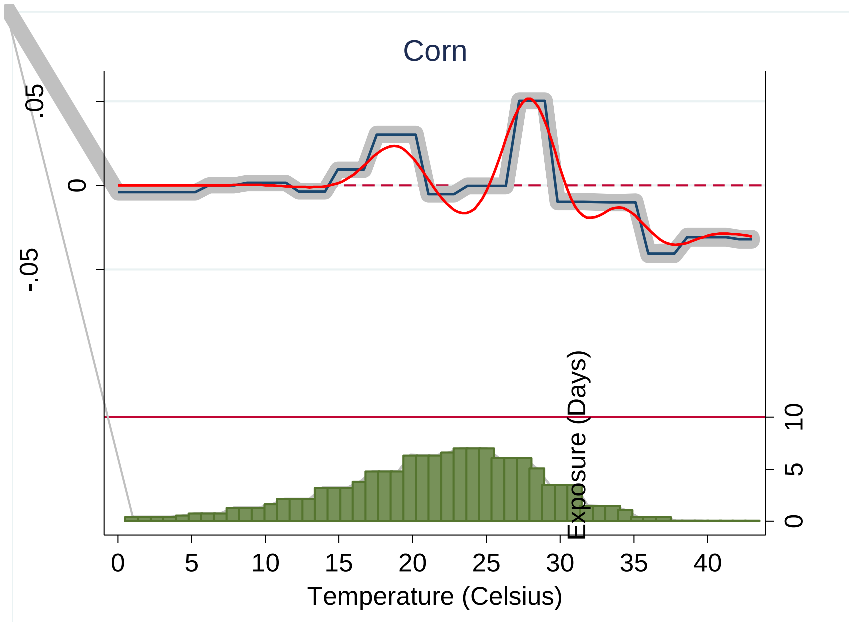
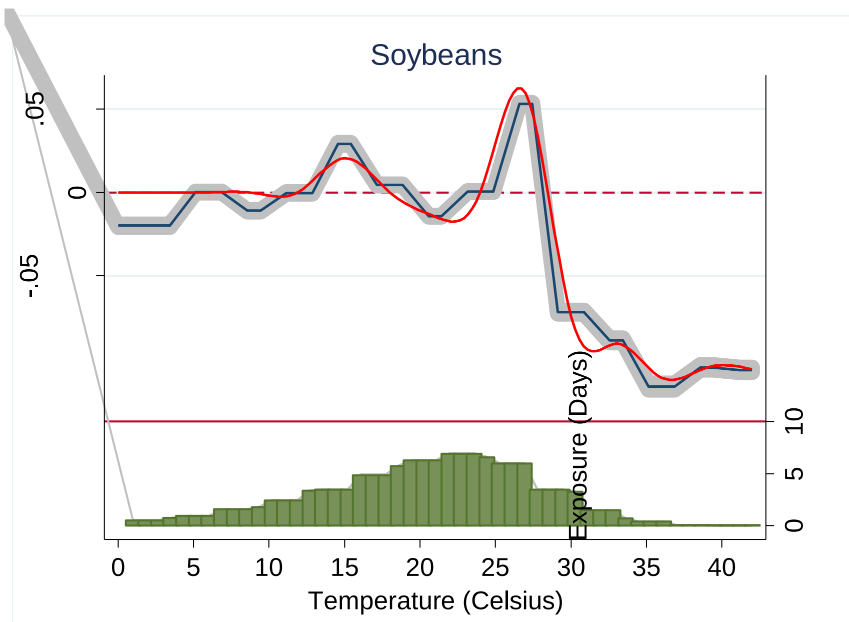


Figure 5. Nonlinear Relation between Temperature and Crop Yields



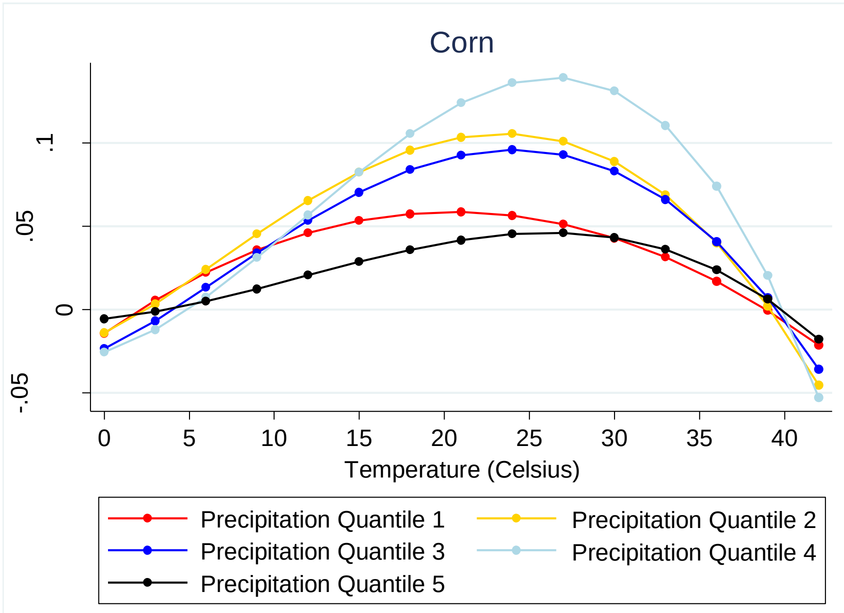
(a) Corn



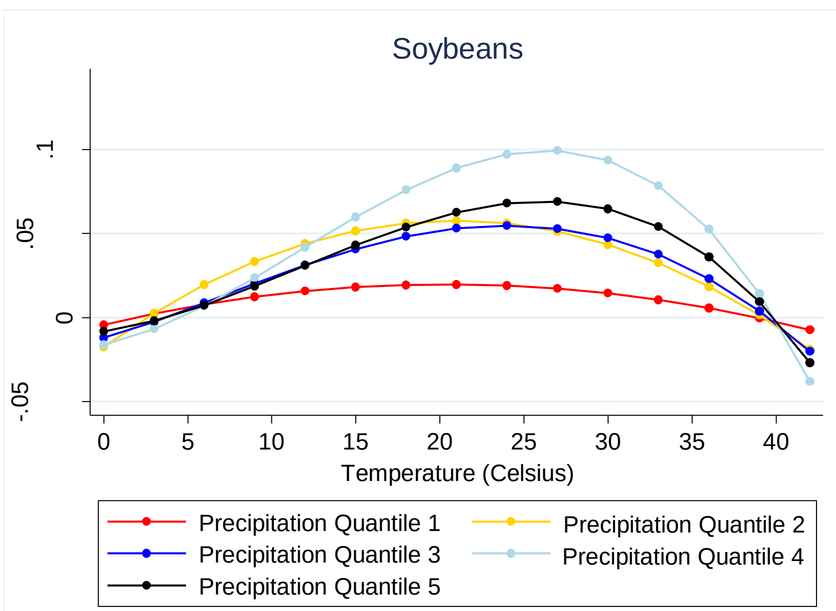
(b) Soybeans

Notes: Solid lines represent point estimates. The 95% confidence bands are denoted as gray area for the three-degree Celsius temperature interval regression.

Figure 6. Nonlinear Relationship between Temperature and Crop Yields with Temperature-Precipitation Interactions



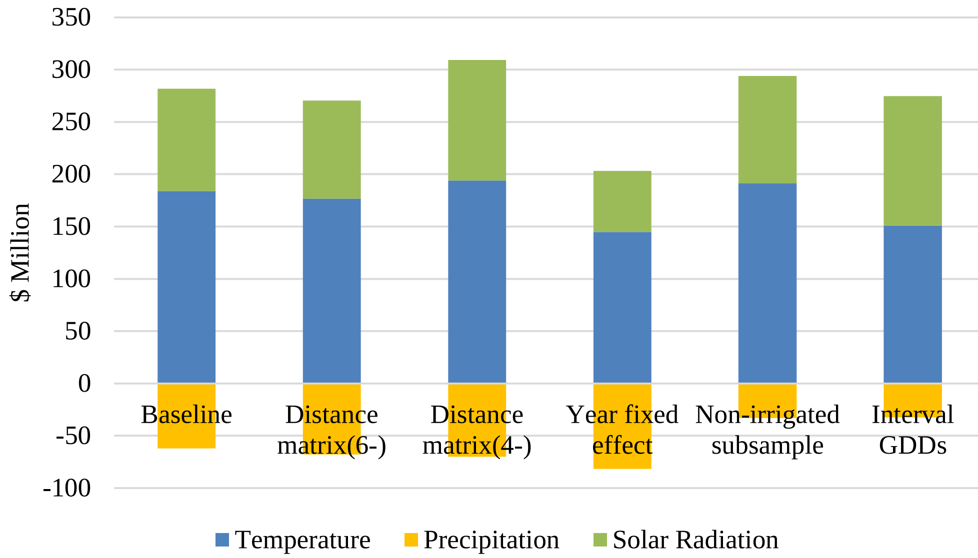
(a) Corn



(b) Soybeans

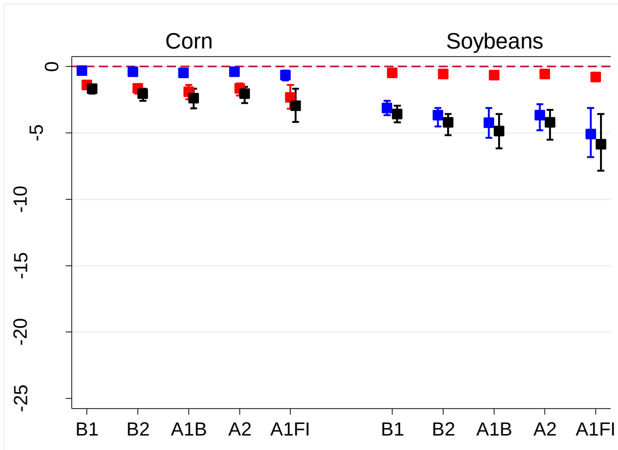
Notes: The full sample is divided into five quartiles based on total precipitation over the growing season. Results reported here are based on Model (5).

Figure 7. Net economic loss in China's corn and soybean sectors due to climate change ($ million)

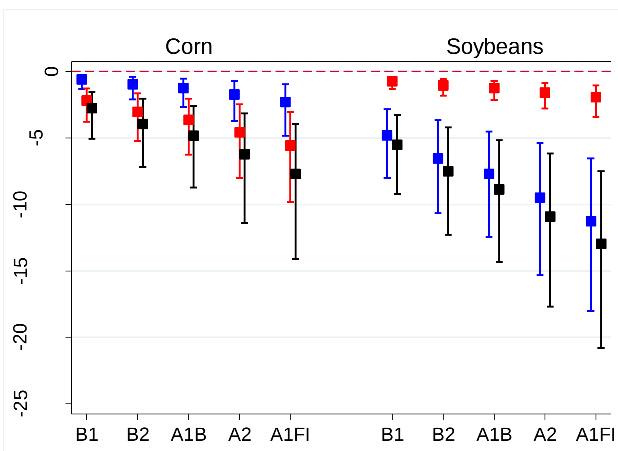


Notes: To compute economic loss in corn and soybean sectors resulting from climate change, we first calculate percentage changes in crop yields in 2009 if climate conditions were at their 2001 levels. We then multiply the changes in crop yields by corn and soybean planted acreages in 2009, respectively, to estimate county-level production loss, and sum across all counties in the sample to get total production loss. We multiply total production loss by crop prices in 2009 to obtain total economic loss 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$. Different colors represent the economic impacts of different weather variables.

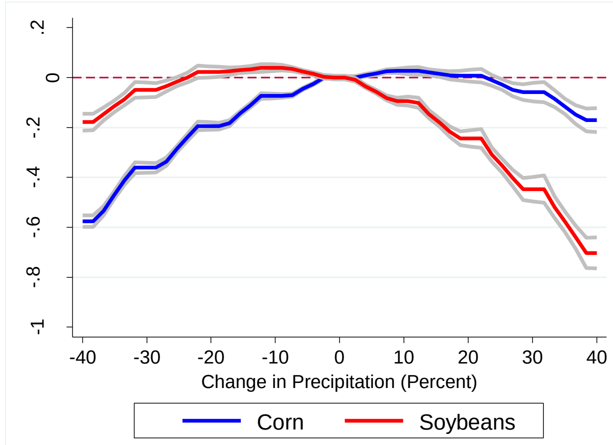
Figure 8. Predicted impacts of climate change on corn and soybean yields in the baseline scenario



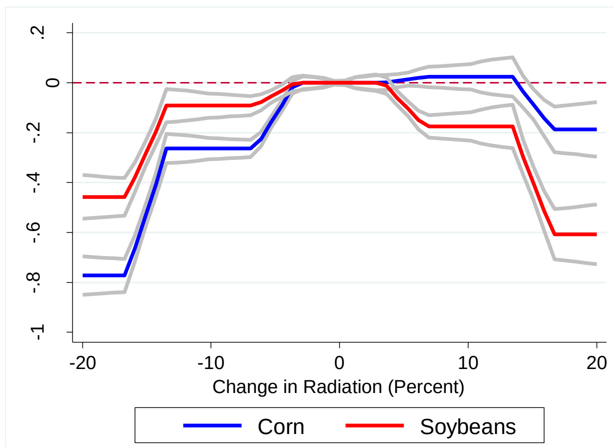
(a) Temperature (2040-2060



(b) Temperature (2090-2099)



(c) Precipitation



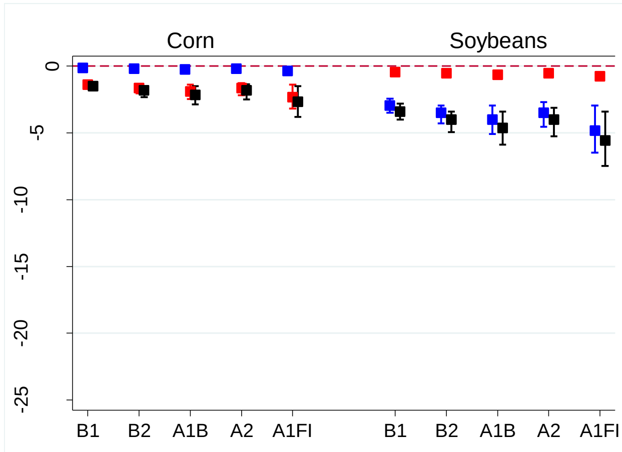
(d) Solar Radiation

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 crop yields. The blue represents the impact of GDD in the range of 8-32°C; the red denotes the impact of GDD in the range above 34°C; 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.

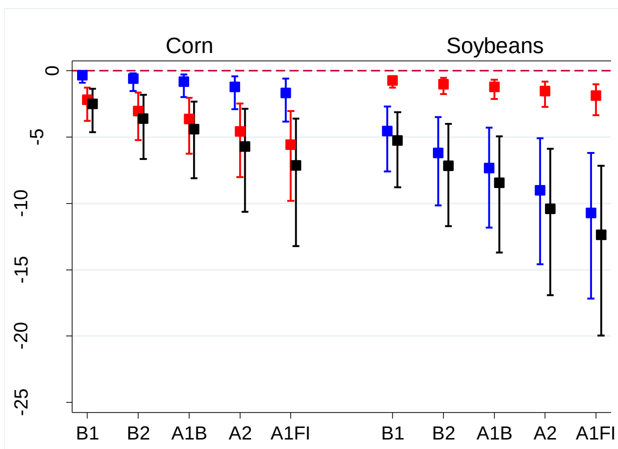
Appendix A. Impacts of future climate change on crop yields

Figure A1. Predicted impacts of climate change on corn and soybean yields

Scenario (1): Distance matrix (6)



(a) Temperature (2040-2060)

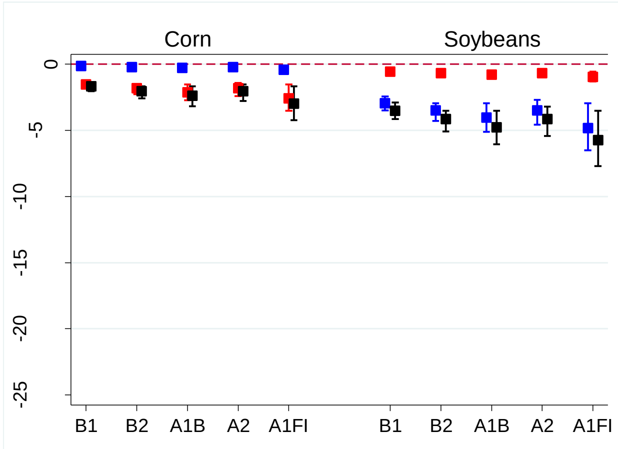


(b) Temperature (2090-2099)

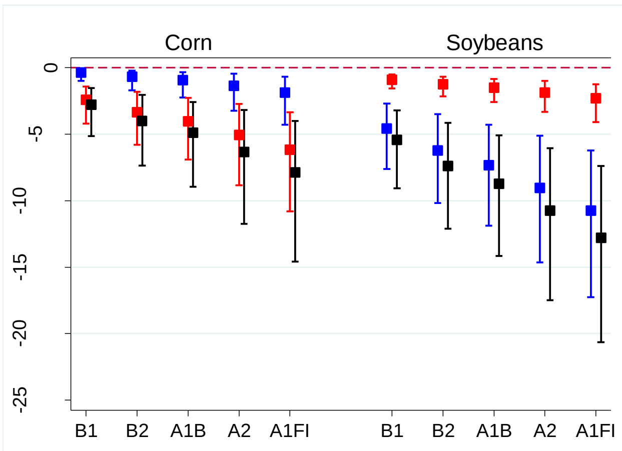
Notes: Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040-2060). Graph (b) displays the corresponding changes in the long term (2090-2099). A star indicates the point 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 crop yields. The blue represents the impact of GDD in the range of 8-32°C; the red denotes the impact of GDD in the range above 34°C; and the black shows the total temperature impacts.

Figure A2. Predicted impacts of climate change on corn and soybean yields

Scenario (2): Distance matrix (4)



(a) Temperature (2040-2060)

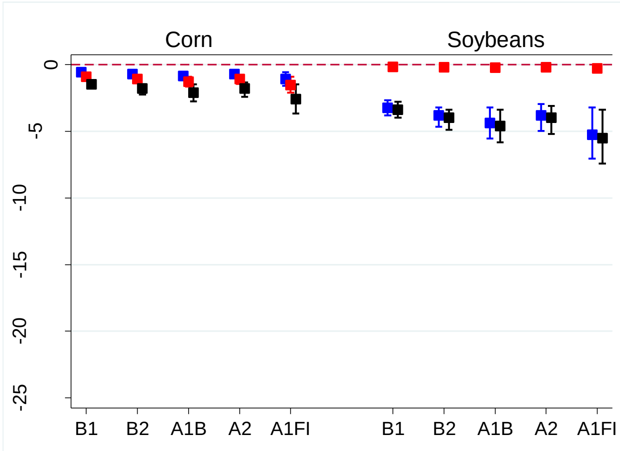


(b) Temperature (2090-2099)

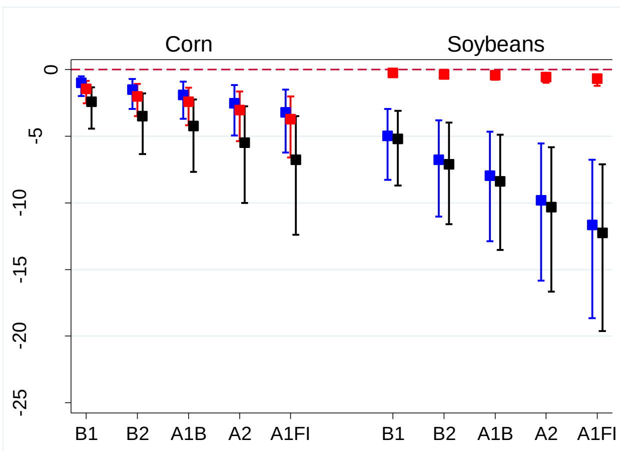
Notes: Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040-2060). Graph (b) displays the corresponding changes in the long term (2090-2099). A star indicates the point 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 crop yields. The blue represents the impact of GDD in the range of 8-32°C; the red denotes the impact of GDD in the range above 34°C; and the black shows the total temperature impacts.

Figure A3. Predicted impacts of climate change on corn and soybean yields

Scenario (3): Year-fixed effects



(a) Temperature (2040-2060)

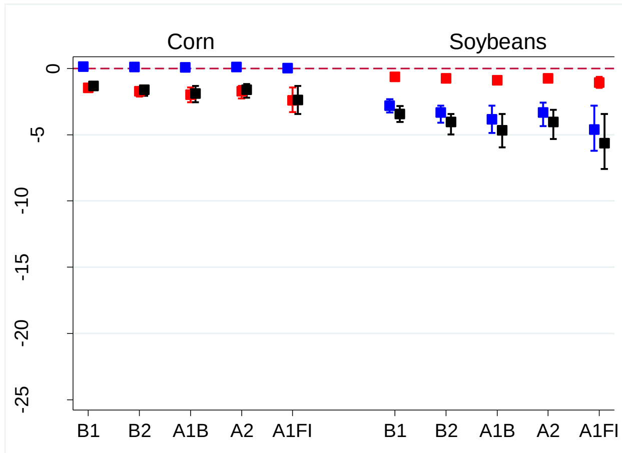


(b) Temperature (2090-2099)

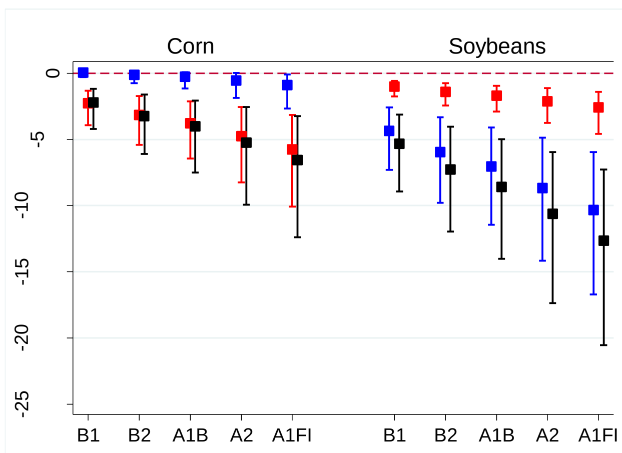
Notes: Graph (a) displays predicted percentage changes in corn and soybean yields due to higher temperatures under five emissions scenarios of the Hadley III climate model in the medium (2040-2060). Graph (b) displays the corresponding changes in the long term (2090-2099). A star indicates the point 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 crop yields. The blue represents the impact of GDD in the range of 8-32°C; the red denotes the impact of GDD in the range above 34°C; and the black shows the total temperature impacts.

Figure A4. Predicted impacts of climate change on corn and soybean yields

Scenario (4): Non-irrigated subsample



(a) Temperature (2040-2060)

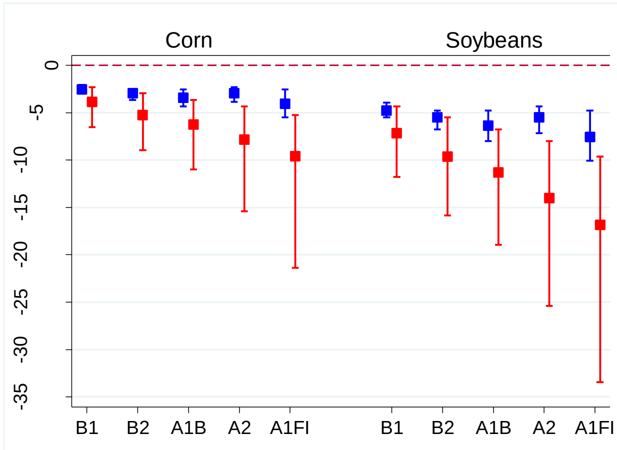


(b) Temperature (2090-2099)

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 crop yields. The blue represents the impact of GDD in the range of 8-32°C; the red denotes the impact of GDD in the range above 34°C; and the black shows the total temperature impacts.

Figure A5. Predicted impacts of climate change on corn and soybean yields

Scenario (5): Temperature Bins



Note: Blue shows the predictions in the medium term (2040–2060) and the red denotes the predictions in the long term (2090-2099).