Impacts of Climate Change on Corn and Soybean Yields in China

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Abstract

Using a unique county-level panel on crop yields and daily weather dataset over the past decade, we estimate the impact of climate change on corn and soybean yields in China. Our results suggest the existence of nonlinear and asymmetric relationships between corn and soybean yields and climate variables. We find that extreme high temperatures are always harmful for crop growth. Moreover, the rapid expansion of corn and soybean acreages at both intensive- and extensive margins had detrimental effects on corn and soybean yields. Using estimated coefficients, we estimate changing climate conditions over the study period has led to an economic loss of $220 million in 2009 alone in China's corn and soybean sectors. Corn yields in China are predicted to decrease by 2-5% under the slowest warming scenario and by 5-15% under the fastest warming scenario by the end of the century. The reductions in soybean yields are found to be more pronounced, about 5-10% and 8-22%, respectively.

Key words: Climate change, Corn and soybean yields, China

JEL code: Q54, Q10

1. Introduction

Growing concentrations of greenhouse gases (GHG) in the atmosphere have raised the global average temperature by roughly 0.13°C per decade since 1950 (IPCC 2007). Due to increased water evaporation, warmer climates have led to frequent extreme precipitation events globally (Allan and Soden 2008, Christensen and Christensen 2003, Diffenbaugh et al. 2005). As the largest emitter of GHG in the world, China is responsible for a large (24%) and growing share of global emissions (United Nations 2012). That has attracted many studies examining China's influence on world's climate and predicting the future path of GHG emissions in China (Auffhammer and Carson 2008, Weber et al. 2008, Yunfeng and Laike 2010). Although China also experienced climate extremes in the past several decades (Piao et al. 2010), studies examining the impact of climate change on China's economy are very limited.

In this paper, we examine the impact of climate change on China's agriculture. Although agriculture only accounts for a small share of domestic GDP in China, it persists in being a vital industry as a supplier of food for consumers and a primary source providing inputs for agro-industries. China's agriculture employs more than 300 million farmers and supports over 20% of the world's population with only 8% of the global sown area. Moreover, China produces 18% of the world's cereal grains, 29% of the world's meat, and 50% of the world's vegetables, which makes China the world's largest agricultural economy (FAO 2012). Despite the enormous significance of the subject, only a few studies have examined the impacts of climate change on China's agriculture (Liu et al. 2004, Wang et al. 2009). These two studies primarily focus on estimating the impacts of temperature and precipitation on farmland values using the Richardian approach (see Mendelsohn et al. 1994). However, due to the cross-sectional data utilized in their analysis, they reply on variation in weather between regions in the identification of the weather coefficients and therefore cannot capture the effects of year-to-year change in climate on agriculture.

The purpose of this paper is to estimate the impact of changing climate conditions on yields for two major crops in China, namely corn and soybeans. As the second largest corn producing country in the world next to the United States (U.S), China produces 20% of the world's corn (FAO 2012). Soybean is the nation's predominant crop for edible oil production. These two crops are also important sources of feed grains for livestock production. To conduct the analysis, we first developed a simple conceptual framework of a representative profit-maximizing farmer that produces a given crop with multiple inputs to illustrate the factors that affect crop yields. We then compiled a unique county-level panel on crop yields and climate variables to identify the impact of climate change on corn and soybean yields. The panel data contain county-level corn and soybean yields in China over the period 2001-2009. Our daily weather data consist of minimum and maximum temperature, precipitation, and solar radiation for each county in China over the past decade. The daily temperature data allow us to calculate the length of time that each crop is exposed to 1°C temperature interval for each day of the growing season, which is used to compute the cumulative heat received for plant growth.

Several studies have examined the effect of climate change on crop yields (see, for example Deschênes and Greenstone 2007, Lobell and Asner 2003, McCarl et al. 2008, Ritchie and NeSmith 1991, Schlenker and Roberts 2009). Even though these studies all focus on estimating the relationship between weather and crop yields in the U.S., they differ substantially in their scope (crops and time periods considered), the level of disaggregation of data, climate and economic variables incorporated, and econometric estimation methods. Therefore, they reach mixed conclusions about the impact of climate change on crop yields. For example, using U.S. county-level panel for the period of 1950-2005, Schlenker and Roberts (2009) find the nonlinear effects of climate variables on corn and soybean yields. Based on estimated coefficients of climate variables, they predict that a warmer climate would lead to a reduction in crop yields by 30-82% depending on global warming scenarios. In a parallel study, Deschênes and Greenstone (2007) use U.S. census data for the periods 1987, 1992, 1997, and 2002 to examine the relationship between climate and corn and soybean yields and find that higher temperatures have resulted in a negative impact on the crop yields, but the magnitudes of the effect are very small (less than 5%). Deschenes and Greenstone (2007) also find that an increase in precipitation is beneficial for corn and soybean yields while McCarl et al. (2008) suggest that increased precipitation had no significant impact on corn and soybean yields. In contrast to above studies that only use climate variables and a time trend as explanatory variables, Welch et al (2010) incorporate both climate and economic variables, such as crop and input prices, to isolate the effects of temperature on rice yields in tropical/subtropical Asia. They find that rice yields are sensitive to changes in minimum and maximum temperatures over the growing season, but their results remain robust even with the inclusion of economic variables.

Only few studies have looked at the impact of climate change on crop yields in China. Lobell et al. (2011) examine the impacts of recent climate change (1980-2008) on corn, rice, wheat and soybean yields at the global-scale, and calculate national estimates for China. They find that a warmer climate has led to a small but negative impact on corn yield, with no substantial effects on rice, wheat or soybean yields. Using a crop simulation model, Iglesias and Rosenzweig (2009) predict that the reduction in corn yields in China due to higher temperatures would be small (no more than 10%) by 2080 as compared to the baseline scenario (1970-2000).

This paper contributes to the existing literature examining the impacts of climate change on crop yields in six major aspects. First, we estimate the impact of climate change on corn and soybean yields in China using a detailed county-level panel on crop yields and climate variables rather than exploiting time series variation at the national level. Second, in addition to tempetarue and precipation, we include solar radiation as an additional explanatory variable to explain the change in crop yields. Agronomic literature suggests that temperature, precipitation, and radiation are three imporant factors for plant growth (Muchow et al. 1990, Szeicz 1974). With a few exceptions (Auffhammer et al. 2006, Welch et al. 2010), however, prior literature has ignored the impacts of radiation on crop yields. This ommision may lead to omitted-variable and endogeneity biases if radiation is correlated with temperature and precipitation over crops' growing season (Welch et al. 2010). Third, we construct two land-use-change (LUC) variables to reflect the change in cropland quality due to land use pattern at both extensive- and intensive- margins. Previous studies have used county fixed effect to control for heterogeneity, such as soil type and quality (Auffhammer et al. 2006, Schlenker and Roberts 2009). However, by converting marginal lands and cropland under other food/feed crops for corn and soybean production, the two LUC variables may have affected soil quality of land under corn and soybean production and therefore corn and soybean yields. Fouth, we allow for spatial dependence in crop yields across counties, which has been shown to be particularly important if there is suifficient heterogeneity at lower levels of aggregation and some variables, such as crop production practices and agricultural subsidies, can not be included as explanatory variables in econometric estimations (Cole et al. 2013, Elhorst 2010). Fifth, we present several sensitivity checks and examine the robustness of our results across alternative model specifications, weighting matrices, climate variables and data. Based on our regression results, we calculate the economic losses in corn and soybean sectors due to the changing climate conditions in the sample period. Finally, we evaluate potential impacts of future global climate change on corn and soybean yields in China using scenarios projected by major global climate models.

This paper is organized as follow. Section 2 provides background information about corn and soybean production in China. Section 3 presents the conceptual framework and empirical estimation strategy. Section 4 describes the data used for the analysis. In Section 5, we present our econometric results and predicted impacts of climate change on corn and soybean yields in China. Section 6 concludes with a discussion.

2. Background: Corn and Soybean in China

2.1 Corn and soybean production

Corn has long been an important food crop in China's agricultural economy. In 2010, China planted about 30 million hectare (ha) of corn, which accounted for approximately 20% of the total grain area and 14% of grain output in China (FAOSTAT 2013). As the second largest corn producing country in the world next to the U.S, China supplied over 20% of the world's corn in 2010 (FAOSTAT 2013). Despite the large amount of corn production, China has become a major corn importer since 2009 due to increasing domestic demand as fodder for livestock production (mostly hogs, poultry, and dairy) and for industrial use (primarily for fuel ethanol production). In 2010, China imported 6 million tonnes of corn, which accounted for about 6% of corn entering international markets (FAOSTAT 2013).

Soybean is another important crop in China. China is the fourth largest soybean producing country in the world (after the U.S., Brazil and Argentina) with a total production area of 9 million ha in 2010, but only producing 6% of world's soybean. To meet domestic demand for soybean for livestock production, China heavily replies upon imports with about 80% of domestic soybean consumption directly coming from imports, which makes China the world's leading soybean importer. With the rapid growth in income and dietary improvement, China is expected to continue to increase imports of corn and soybeans from international markets to satisfy rising domestic demand 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 domestic population of 1.3 billion and could have profound impacts on world food markets.

2.2 Corn and soybean yields

Yield performance of the corn and soybean sectors has been impressive in the past few decades. During the period 1980-95, the average yields of corn and soybeans in China grew at an annual rate of nearly 5% (Aunan et al. 2000); during the period 2001-09, their growth rates declined to about 1% (see Fig 1). The growth in corn and soybean yields can be largely attributed to the government's continual 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). Moreover, the intensive use of inorganic fertilizers and chemical pesticides (see Fig 1), 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).

2.3 Corn and soybean production areas

Corn and soybean are widely produced in many areas of China. Fig 2 shows the five-year (2005-2009) average planted acres of corn and soybeans in China. As can be seen, corn is primarily produced in the northern part of the country. Northeast three provinces (Heilongjiang, Jilin and Liaoning), Central China, and Northwestern inland (including Xinjiang Uygur

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

Autonomous Region and Gansu Province), together account for more than 75% of total corn production in China, while Southwest mountain hills produce about 10% of the nation's corn. Northeast three provinces are also the major soybean production regions in China, accounting for more than one-third of China's soybean production.

Over the period 2001-2009, resulting from rising global food prices and domestic demands, corn and soybean planted acres increased by 7 and 1 million ha, respectively (National Bureau of Statistics of China, 2001-2009). Of the additional land under corn and soybean production (8 million ha in total), about 4.3 million ha came from the reduction in land previously under other food/feed and oil crops, such as rice, wheat, potato, oil seed, cotton, and sugarcane, while the rest were converted from marginal idle land.

The regional land use changes at intensive- and extensive- margins may have affected soil quality of cropland used for corn and soybean production and thus county-averaged corn and soybean yields. Land use change at the intensive margin may increase or decrease corn or soybean yields depending on the quality of cropland that was previously under other food/feed and oil crops and converted to corn or soybean production. Land use change at the extensive margin may negatively affect corn or soybean yields, but the effects are expected to be small. Marginal idle land converted for corn and soybean production in China comes from two major sources. The primary source is regular cropland that was used for crop production, but 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 the land released under the Requisition-Compensation (RC) policy. To enhance food security and strictly control the conversion of farmland into non-farmland, Chinese government implements the RC policy that requires the occupancy (construction) has to add new land with the

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

same quantity and quality as that of the farmland occupied for non-agricultural uses. To achieve this, local governments promote merging villages and encourage farmers to live together to save the homestead occupation. Other methods, such as turning graveyards into farmland, are also implemented. Lands under homestead and graveyards were historically regular cropland. In the empirical analysis presented below, we will examine statistical significance and signs of the effects of the LUC variables on corn and soybean yields.

2.4 Corn and soybean growing seasons

Due to the spatial differences in climatic conditions in major agricultural production regions, corn and soybeans production in China can be further divided into four types based on their growing seasons (Chinese Cropping System, 2005). Spring corn and soybean, typically planted in April and harvested in late September, are mainly concentrated in northeast three provinces, Inner Mongolia, Ningxia, the Northwest inland, and several regions in Southwest mountain hills. Summer corn and soybean have a slightly shorter growing season as compared to spring corn and soybeans, and are primarily produced in Huang-Huai plain area and the lower-middle reaches of the Yangtze River. Autumn corn and soybean production occurs in Southern Hills, 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 area.

3. Model

In this section, we first develop a conceptual model of a representative profit-maximizing farmer who produces a given crop with multiple inputs. We use this framework to illustrate the factors that affect crop yields and build our hypotheses. We then present our empirical regression models and estimation strategy.

3.1 Conceptual Framework

Consider a representative farmer who uses several inputs, such as fertilizer, chemicals, labor, and seed, to produce a given crop, say corn. We assume the input and output markets are competitive and the farmer is a price-taker. Let π denote the profit associated with the production of corn; $E(p)$ expected market price of corn; ω_k market price of input $k = \{1, ...K\}$; and C the fixed cost associated with corn production (such as the purchase of planting and/or harvesting machines). Let $y(x_k, s, z)$ denote corn yield per ha, which is assumed to depend on input uses (x_k), which will be determined as endogenous variables, soil quality of the cropland under corn (s), and climatic conditions (z) (including temperature, precipitation and radiation). We assume $\frac{\partial y(.)}{\partial s} > 0$.

Let A be the planted acre of corn, which will be determined as another endogenous variable. We assume soil quality of the cropland under corn $s = s(\Delta A, c)$, where c is the average soil condition of the cropland under corn in previous period, and $\Delta A = A - A_{-1}$ represents the change in land under corn relative to previous period with A_{-1} denoting the planted acre of corn in previous period. Hence, soil quality of the cropland used for corn production is affected not only by c, but also regional land use changes which could occur at intensive and/or extensive margins.

Depending on the quality of additional new land used for corn production, $\frac{\partial s(.)}{\partial \Delta A}$ could be positive or negative. It is also possible that corn acreage shrinks compared to previous period, which will lead to $\frac{\partial s(\Delta A, c)}{\partial \Delta A} = 0$. For ease of illustration, we do not consider this possibility and assume that $\frac{\partial s(\Delta A, c)}{\partial \Delta A} \neq 0$ in the following discussion.

With above notations, the farmer's profit maximization problem from producing corn can be formally formulated as follows:

$$\underset{A,x_k}{Max}\ \pi = E(p)y(x_k, s, z)A - \sum_k \omega_k x_k A - C \tag{1}$$

The first-order optimality conditions with respect to input demand (x_k) and planted acre (A) lead to:

$$E(p)\frac{\partial y(.)}{\partial x_k} - \omega_k = 0 \qquad \text{for } \forall\ k = \{1, ...K\} \tag{2}$$

$$E(p)y(.) + E(p)A\frac{\partial y(.)}{\partial s}.\frac{\partial s(\Delta A, c)}{\partial \Delta A} - \sum_k \omega_k x_k = 0 \tag{3}$$

The first term of equation (2) is the marginal benefit due to an additional use of input k (through the impact on yield, represented by $\frac{\partial y(.)}{\partial x_k}$). 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 $E(p), \omega_k, z, c$ and ΔA:

$$x_k = x(E(p), \omega_k, z, c, \Delta A) \tag{4}$$

The first term of equation (3) is the per-ha revenue from corn production, while the second term represents the marginal impact of land expansion on farmer's revenue through the impact on soil quality and crop yield. The last term is the total cost of input uses. From equation (3), we know that the optimal crop planted acre will depend on several factors as shown in (5).

$$A = A(E(p), \omega_k, z, c, A_{-1}) \tag{5}$$

Substituting equations (4) and (5) into yield function $y(x_k, s, z)$ suggests that crop yields can be expressed as a function of expected crop price, input prices, climate variables, soil quality, and regional land use changes, as specified in equation (6):

$$y = y(E(p), \omega_k, z, c, \Delta A) \qquad (6)$$

3.2 Empirical Estimation Strategy

Based on the equation (6), we develop the following semi-log regression models to estimate the relationship between climate variables and crop yields:

$$\log Y_{it} = Z_{it}\beta + LUC_{it}\gamma + P_{it}\delta + c_i + \varepsilon_{it} \qquad (7)$$

$$\varepsilon_{it} = \rho \sum_j W_{i,j} \varepsilon_{jt} + \phi_{it} \qquad (8)$$

where $\log Y_{it}$ denotes log crop yield in county *i* and year *t*. Z_{it} includes weather variables, such as temperature, precipitation, solar radiation, and their respective quadratic forms to capture the potential nonlinear effects of climate variables on crop yields. Z_{it} also includes a time trend to represent the exogenous technological change due to R&D and a quadric form of the time trend to denote the speed at which the technological change occurred in the sample period. LUC_{it} represents regional land use changes at both intensive and extensive margins in county *i* and season-year *t* relative to *t*-1; this variable is used to capture the change in soil quality due to regional variations in land use patterns. Other control factors, such as crop prices and input prices, are denoted by P_{it}. We use crop price in year *t*-1 as a proxy to denote expected crop price in year *t* (Braulke 1982). A time-invariant county fixed effect c_i is used to control for heterogeneity, such as soil type and regional crop production practices. Lastly, ε_{it} is the error term.

We represent the relationship between temperature and crop yields through the concept of *growing degree-days* (GDD), which is defined as the total amount of heat that crops received between lower and upper temperature thresholds during the growing season. Following Ritchie and NeSmith (1991) and Roberts and Schlenker (2009), we set the lower threshold at 8°C and the upper threshold at 32°C for corn and soybeans. Several studies have used the simple average of daily minimum and maximum temperatures to compute daily mean temperature, which is summed over the growing season to obtain GDD (see Deschênes and Greenstone 2007). As Zalom et al. (1983) point out, this approach may not produce an accurate estimate of degree days since it ignores the upper temperature threshold and extreme high temperatures. To estimate GDD, we first use the *single sine curve* method proposed by Baskerville and Emin (1969) and daily low and high temperatures to generate a sine curve over a 24-hour period over crop growing seasons. This step is to estimate hourly temperature for each day of crops' growing seasons. We then estimate GDD by calculating the area above the lower threshold and below the curve for each day of entire growing seasons. Using the same approach, we also construct a separate variable that indicates the length of time that each crop is exposed to temperature above 34°C which is considered to be very harmful for plant growth (Ritchie and NeSmith 1991). As shown in Table 1, we find that although the two approaches produce similar estimates of GDD for temperatures between 8°C and 32°C, the simple averaging method leads to a significant underestimation of GDD when temperatures are above 34°C. As a sensitivity check, we will examine how this will affect our coefficient estimates of climate variables. Due to the spatial difference in growing seasons of corn and soybeans in China, we use cumulative precipitation and radiation over growing seasons of each crop to examine the impact of precipitation and radiation on crop yields.

We use historical planted acres of major crops in each region to compute LUC variables at both the intensive and extensive margins for corn and soybeans. The intensive margin for a crop is defined as the reduction in aggregate acreage of all other crops relative to previous year. The extensive margin for a crop is the difference between the increase in acreage of the crop relative to previous year and the intensive margin for the crop if the difference is positive. Therefore, the intensive margin for a crop would equal zero if the aggregate acreage of all other corps increases relative to previous year. In this case, the extensive margin for the crop is the increase in acreage of the crop relative to previous year. The underlying assumption made here is that marginal lands would be brought into crop production if the demand for total cropland increases. Since the LUC variables reflect the response of farmers to expected crop prices and future profits of crop production, they are potentially endogenous and estimates of β and γ may be biased. However, the bias is expected to be small with the inclusion of P_{it} for two reasons. First, farmers' land use decisions are mainly driven by their expectations about future crop prices (Chavas and Holt 1990, Nerlove 1956). If expected crop prices are incorporated as explanatory variables, the correlation between the LUC variables and the error terms is likely to be insignificant. Second, given the small-scale of farms' crop production in China,[3] spatial differences in land quality and crop yields for each farm are expected to be small. Therefore, when making land use decisions among alternative crops farmers are unlikely to consider the potential impact on crop yields, which makes the LUC variables less endogenous (or even exogenous) to crop yields.

Crop yields are also affected by the amount of production inputs used, such as labor, fertilizer and chemicals. However, due to the lack of data, we only include fertilizer price index and wage as input prices in our econometric regressions. The exclusion of other economic variables can bias estimates of β if the variables are significantly correlated with the weather variables. However, when the correlations are small, the bias is expected to be small and the exclusion of these variables only leads to a slightly less precise estimate of parameters. Consistent estimates of β also require that the price variables are not simultaneously determined with crop yields. This condition is met in our data, since farmers in China operate small farms (0.13 ha in average) and are price takers in corn, soybeans, labor and fertilizer markets. To capture the effects of relative price

[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

changes in output and input prices, we use price ratio as explanatory variables in our empirical analysis.

In rainfed areas, the water supply for crop growth mainly comes from direct precipitation before and during crop growing seasons. However, in irrigated areas, farmers may take adaptation behaviors, such as investing on new technology to save irrigated water and adjusting ground or surface irrigation based on climatic conditions, to reduce the externality effects of climate change on crop yields. Since irrigation plays a key role in affecting crop yields in irrigated areas and irrigation is largely dependent on regional climate conditions, such as temperature and precipitation, the exclusion of this variable may lead to biased coefficient estimates of climate variables. With the lack of the data on crop-specific irrigated acres in each county, 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 farms' adaptation behaviors to climate change.

As shown in equation (8), we allow the error term ε_{it} to be spatially correlated across counties. Here, ϕ_{it} are the error terms that are independently normally distributed with $E[\phi_{it}] = 0$ and $\mathrm{var}[\phi_{it}] = \sigma^2$, ρ is the parameter of spatial correlation, and $W_{i,j}$ is a pre-specified spatial weighting matrix that describes the spatial dependence of counties with their neighbors in the sample. There are several reasons in which spatial correlation between counties could influence crop yields in equation (7). First, the error term ε_{it} 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 may 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/similar production practices (irrigation, rotation, and tillage), which could influence crop yields. Third, we might also expect counties closely related will share the same/similar local characteristics such as soil quality and seed varieties. If any of these factors are omitted as explanatory variables then ε_{it} is expected to be spatially correlated.

Our empirical analysis uses three different spatial weight 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 (i, j) element of the spatial matrix is unity if counties i and j share a common boundary, and 0 otherwise.[4] However, this 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 weigh 6- and 4- nearest counties relative to county i, respectively, 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 i. All spatial panel models are estimated using maximum likelihood (Anselin 1988, Elhorst 2010).

4. Data

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

4.1 Crop Yields and LUC Variables

County-specific total crop production, historical planted/harvested acres, and total and irrigated acres of all crops in all counties, are obtained from National Bureau of Statistics of China

[4] The contiguity matrix is then normalized so that the elements in each row sum to unity. Other weight matrices, such as Queen Standardized matrix and distance weights, are essentially the same as the contiguity matrix, for a discussion see Kelejian and Prucha (1999) and Schlenker et al.(2006).

(NBSC), 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 harvested acres. We exclude Qinghai-Tibet plateau in the analysis since it is not a major agricultural production area of corn and soybean in China (accounting for less than 1% of the total crop production in China). This gives us 18975 observations with corn yields and 19575 observations with soybean yields. We use historical planted acres of major crops in China to compute the two LUC variables both at the intensive and extensive margins for corn and soybeans.

4.2 Climate Variables

We merge the climate data with the crop production and land use data. The climate data are obtained from China Meteorological Data Sharing Service System (CMDSSS).[5] The climate data are available for the period 2001-2009, including daily measures of minimum and maximum temperatures, precipitation and radiation from 820 weather stations in China. The dataset also contains the exact coordinates of each station, enabling them to be merged with our agricultural data. Fig 3 shows spatial distribution of the weather stations in 2010 along with county outlines. These stations are mainly located in major agricultural production regions and densely populated areas. We use Geographic Information System (GIS) software to place each of the weather stations into the 2570 counties in China. For counties with several weather stations, we construct climate variables by taking the simple average of these climate variables across these stations. We impute the climatic information from the contiguous counties for counties without a station.

4.3 Identification of Crop Growing Seasons

According to Chinese Cropping System (2005), growing seasons of spring corn and soybeans lie between April 1 and September 30. Summer corn and soybean have a relatively short

[5] CMDSSS was developed and is currently managed by Climatic Data Center, National Meteorological Information Center, China Meteorological Administration. See http://cdc.cma.gov.cn/home.do for further details.

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 soybean in Tropical/subtropical area, their growing season is typically between November 1 and February 28 in the following year. We compute GDD, total precipitation, and radiation for corn and soybeans for each county by summing the daily measures over their respective growing seasons.

4.4 Price Data

We obtain province-level data on corn and soybeans prices from China Yearbook of Agricultural Price Survey (2012). County-specific labor costs are not available. We use hourly compensation costs in manufacturing industry as a proxy for opportunity cost of farm labor, which is obtained from U.S. Bureau of Labor Statistics (2012). Because of the prevalence of compound fertilizers, nutrient-specific fertilizer prices are also not available. For this, we compile fertilizer price index at the province level from China Yearbook of Agricultural Price Survey (2012).

5. Regression Results

Before presenting the 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 weighting matrices. We also supplement the Moran's *I* test with three alternative tests, namely Lagrange Multiplier (LM) ERR test, LR ratio test and the Wald test. The test results are reported in Table 2.[6] These test results indicate that the 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 weighting matrix (W1) and the distance weighting matrix (W2) that weighs 6-nearest neighbors, but become significantly smaller under the distance weighting matrix (W3) that weighs 4-nearest neighbors only. For example, the parameters

[6] Results presented in Table 2 are based on the pooled sample.

of the spatial correlations for corn and soybean yield models under W1 are 0.69 and 0.68, respectively, but decline to 0.60 under W3. We will examine the sensitivity of our results to alternative weighting matrices. Nevertheless, the test statistics provide strong evidence indicating 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).

5.1 Baseline results

The baseline spatial panel analysis employs the contiguity matrix (W1) as the spatial weighting matrix. We conduct the spatial error analysis with five different model specifications. In model (1), we only include GDD, precipitation, a time trend and their quadric 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 quadric form as additional explanatory variables, while in model (3) we include the two LUC variables to examine if they have played a role in influencing corn and soybean yields. In model (4), in addition to the climate and LUC variables we incorporate price ratios. Lastly, in model (5) we add the ratio of irrigated acres to total planted acres of all crops in a county and examine if the inclusion of this variable will affect our coefficient estimates of climate variables. Time-invariant county fixed effects are used to control for the possibility of unobserved characteristics within each county. Regression results under these model specifications are reported in tables 3-4, while Fig 4 illustrates the difference in coefficient estimates of climate variables graphically.

The estimated coefficients on time variables in models (1)-(5) show that exogenous technological progress stimulated by R&D increased corn and soybean yields. The quadratic time terms are statistically significant at the 1% level, suggesting that growth rates of corn and soybean yields declined over the sample time period. However, they differ in coefficient estimates of climate variables. Consistent with the Moran *I* and other residual tests, the spatial correlation coefficients are statistically significant under the contiguity weighting matrix.

Our estimated coefficients on the effects of climate variables on crop yields indicate the existence of an inverted U-shaped relationship between corn and soybean yields and GDD in model (1). The optimal numbers of GDD for corn and soybean yields peak at 2742 and 1611, respectively. This is consistent with the agronomic literature and the nonlinear effects of the climate variables on corn and soybean yields found in the literature (for example, see Deschênes and Greenstone 2007, Schlenker and Roberts 2009). High temperatures above 34°C had detrimental effects on corn yields, while it is found to be insignificant for soybean yields. The coefficients on precipitation show the similar nonlinear effects on the two crops over their growing seasons. To achieve maximum yields, corn requires 74 cm of precipitation over the growing season, which is significantly higher than that for soybeans that need 54 cm. The nonlinear relationship between precipitation and crop yields indicate that precipitation increased crop yields but at a decreasing rate.

The addition of the solar radiation variables in model (2) does not lead to a significant difference in coefficient estimates of GDD, precipitation and the time variables relative to those in model (1). However, we find that the coefficients of solar radiation are statistically significant at the 1% level, indicating that radiation had affected corn and soybean yields over the sample period (see the second columns of tables 3-4). Corn and soybean yields peak at 1059 and 997 hours of radiation, respectively. These results are similar to the solar radiation requirements of many crops (Daughtry et al. 1983). With the inclusion of radiation, the coefficient of high temperatures above 34°C in soybean yield regression now is statistically significant and has a negative sign, which suggests that high temperatures could have negatively affected soybean yields.

The third columns of tables 3-4 report regression results with the inclusion of the LUC variables in model (3). It first can be seen that although the signs and statistical significance of the climate variables are similar to those in models (1)-(2), magnitudes differ quite substantially. As shown in Fig 4(a), the optimal numbers of GDD estimated by model (3) are 2190 and 1461 for corn and soybeans, respectively, which are 20% and 9% smaller as compared to those estimated in model (1). Moreover, estimated precipitation requirements for corn and soybeans are 10% and 4% higher, respectively, relative to models (1)-(2), while the signs and statistical significance of radiation are close to that in model (2). Coefficient estimates of the two LUC variables are both statistically significant and have negative signs, indicating that the rapid expansion of corn and soybean production areas on marginal lands and land previously under other crops reduced county-average corn and soybean yields, holding all else the same. However, magnitudes of the reductions are small. For example, with every 1000 ha increase in corn and soybean acres on marginal lands, average corn and soybean yields only decline by 30 and 10 kilograms (kg) per ha, respectively, which can be translated into a yield loss of 0.5% and 0.4% relative to average crop yields over the sample period. These are expected results since additional marginal lands used for corn and soybean production were previously regular cropland and/or released under the RC policy, both of which are suitable for crop production. Acreage expansion at the intensive margin also had a negative but negligible impact on corn and soybean yields.

In model (4) with the inclusion of economic variables, the coefficient on the crop-labor price ratio is positive and statistically significant in the soybean yield equation, which suggests that higher wage led to reduced labor use and thus negatively affected soybean yields. However, it is found to be insignificant in the corn yield equation. Similarly, the coefficients of the crop-fertilizer price ratio have expected signs in both yield equations, but are not statistically significant. The results are in also agreement with the observation of Welch et al. (2010) who find that the addition of economic variables does not lead to a significant change in coefficient estimates of climate variables on rice yields in Asia. Parameter estimates of climate variables are almost identical to those in model (3). As shown in Fig 4, the optimal numbers of GDD, precipitation and radiations differ slightly between the two models.

While climate change has negatively affected crop yields, farmers may respond by taking adaptation behaviors, such as adjusting cropping practices and utilizing available ground or surface irrigation, to mitigate the external effects of climate change (Howden et al. 2007). Since irrigation can effectively affect crop yields and the necessity of irrigation largely depends on local climate conditions, omitting this variable could yield biased effects of climate variables on crop yields. To test the impact of climate adaptation behaviors, 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 3-4, show that irrigation has a positive effect on corn yields, suggesting that the climate adaptation behavior is actively undertaken. The effect of this variable on soybean yields has a positive sign but not significant. That is because most of soybean production in China occurs in rainfed regions with sufficient precipitation, particularly in northeast three provinces. Coefficient estimates of other climate and economic variables are similar to those in model (4), which indicates the robustness of our model results.

5.2 Marginal Impacts of Climate

To further compare the differences in coefficient estimates of models (1)-(5), we use both estimated linear and the squared coefficients of each climate variable to calculate their marginal impacts ($\frac{\partial \log Y_{it}}{\partial Z_{it}}$), at the sample mean. The marginal impact measures how changes in climate variables (Z_{it}) affect log crop yields ($\log Y_{it}$). Table 5 reports the marginal impact of each climate variable in our baseline analysis. We find that these models differ not only in the magnitudes of the effect of a marginal increase in GDD on corn yields, but also the signs of the effects. Models (1)-(2) suggest that at the sample mean higher temperatures increase corn yields. In contrast, with the inclusion of the LUC and economic variables in models (3)-(5) results show that higher temperatures would hurt corn yields. Although these model results suggest that at the sample mean a small increase in precipitation raises corn and soybean yields, they differ in magnitudes of the yield increases. Models (3)-(5) show that an increase in precipitation by 100 mm raises average corn yields by 10 kg per ha, while the increases in yields are much modest in models (1)-(2) by 3-5 kg per ha. Likewise, the estimated marginal impacts of radiation on crop yields also differ across alternative model specifications (see table 5).

5.3 Robustness Check

Results presented above about the impacts of climate change on corn and soybean yields make intuitive sense. However, how robust are they across alternative model specifications, spatial weighting matrices, variables and data? Here, we conduct several robustness checks to examine the sensitivity of our coefficient estimates of climate variables using model specification (5). Results are presented in tables 6-7.

We first test the stability of the climatic coefficients under alternative spatial weighting matrices. As discussed above, the spatial distance weighting matrix W2 is very similar in spirit to the spatial contiguity matrix used in the baseline analysis. Hence, we find parameter estimates of climatic variables under W2 are not significantly different from the benchmark results. Under the spatial distance weighting matrix W3, although parameters of the spatial correlations in both yield models become smaller than that under weighting matrices W1 and W2, statistical significance, signs and magnitudes of climate variables in both yield equations only differ slightly from the baseline estimates. As a result, the optimal numbers of GDD, precipitation and radiation estimated in the two scenarios are very similar to the baseline estimates.

All regressions so far 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 or other temporal shocks. We therefore replicate the above analysis with year fixed effects. As show in the second columns of tables 6-7, regressions results for both corn and soybean yield equations are similar to our baseline estimates, indicating that our results are generally insensitive to the chosen interpolation method.

In all regression results presented above, we use daily low and high temperatures and the *single sine curve* method to estimate hourly temperature for each day of crops' growing seasons and calculate GDD. Here, we replicate the above analysis with GDD computed based on daily mean temperatures as in Deschênes and Greenstone (2007). Although statistical significance, signs and magnitudes of coefficient estimates of precipitation and radiation are close to our baseline results, the estimated temperature effects are quite different. Specifically, we find that the optimal numbers of GDD required for corn and soybean become 20% and 17% smaller, respectively, relative to the baseline results. The coefficient of the squared term of GDD for corn yields is much larger than the baseline estimate, suggesting that with the same level of increase in temperatures between 8-32°C it would lead to a much larger reduction in corn yields than otherwise. The role of high temperatures above 34°C now is found to be insignificant in affecting corn yields.

Above regressions included all counties producing corn and soybeans (except Qinghai-Tibet plateau). Because irrigation is a possible mitigation strategy to climate change, we want to exclude irrigated counties in the analysis to examine the sensitivity of our results. However, the lack of information on rainfed or irrigated counties for corn and soybean production precludes us from doing so. There are some counties in the western provinces, such as Xinjiang Uygur Autonomous Region and Gansu Province, which heavily rely on irrigation for crop production due to insufficient precipitation. Therefore, we exclude these western counties in the sample and replicate the above analysis. As shown in the last columns of tables 6-7, temperatures between 8-32°C now have larger impacts on corn and soybean yields relative to the results estimated with the full sample, which are expected results since corn and soybean production in selected counties is relatively more sensitive to higher temperatures due to the lack of efficient mitigation strategies. On the other hand, the effects of precipitation on crop yields become smaller due to relatively sufficient precipitation in these regions. Moreover, with the exclusion of western counties that have sufficient solar radiation, regression results now indicate the optimal numbers of radiation for corn and soybean are considerably larger relative to our baseline results.

5.4 Magnitude of Findings

To get a sense of the magnitude of these findings, we measure the percentage change (δ) in crop yields in 2009 that have resulted from changes in climate over time:

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

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

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

where β is the coefficient of the effect of climate variables on crop yields. Replacing β with its estimated coefficient will provide an estimate of δ. Table 8 shows that changes in temperatures and solar radiation over the period 2001-2009 have negatively affected corn and soybean yields. On the other hand, the change in precipitation over this period raised crop yields. Overall, the changes in climate conditions since 2001 led to reductions in average corn and soybean yields by 0.5% and 0.4%, respectively.

To get a rough estimate of economic losses due to the changing climate conditions, we first multiply the changes in crop yields between 2001 and 2009 by their harvested acres in 2009 to get an estimate of the change in crop production. We then multiply the numbers by their market prices in 2009. As reported in table 8, we find the changing climate conditions over the period 2001-2009 led to an economic loss of approximately $220 million in China's corn and soybean sectors in 2009 alone in 2009 price. Compared to annual production values of corn and soybean in China, this estimate seems small. However, it only represents a lower bound of the true social costs associated with the changing climate conditions, since it only includes economic losses in corn and soybean sectors, thus ignoring the negative effects on other crops.[7]

6. Climate Change Impacts

We use the regression coefficients obtained in model (5) to evaluate the impacts of future climate change on corn and soybean yields in China. The climate change scenarios we choose for this analysis are based on Hadley model, HadCM3, released by the U.K. 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,

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

and A1F1) for years 2070-2099. 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 over the next century, respectively. The Met Office also developed the Coupled Model Intercomparison Project (CMIP3) that provides predictions for future precipitation change in China. According to CMIP3, precipitation is projected to increase between zero and 20% over almost the entire country by the end of this century (IPCC 2007). We consider a broader range from (-)40% to (+)40% to fully reflect the possible change in precipitation in China and evaluate associated impacts on corn and soybean yields. With the lack of long-term projections on change in solar radiation, we consider a range from (-)20% to (+)20% in changes in solar radiation and examine the impacts on corn and soybean yields.

Impacts of the temperature changes under all five emissions scenarios on corn and soybean yields for the 2070-2099 are presented in Fig 5. Across all scenarios considered here, we find that higher temperatures would hurt corn and soybean yields by the end of the century, but the extent to which the reduction occurs vary by emissions scenarios. Specifically, corn yields are expected to decrease by 2-5% under the slowest warming scenario (B1), and by 5-15% under the fastest warming scenario (A1F1). The corresponding reductions in soybean yields are larger, by 5-10% under the B1 scenario and 8-22% under the A1F1 scenario. Our predicted impacts of climate change on corn and soybean yields in China are comparable with those obtained by Lobell et al. (2011) and Rosenzweig (2009) who forecast that by the end of this century changing climate conditions will lead to negative but small (no more than 10%) impacts on corn and soybean yields in China. Since our model results are sensitive to the method about how GDD are calculated, we also make predictions on corn and soybean yields using coefficients estimated when GDD are computed based on daily mean temperatures. As shown in Fig 6, even though these two approaches differ in impacts of different temperature groups on crop yields, estimated total impacts of higher temperatures on crop yields are similar to each other.

Fig 7 presents predicted yield impacts under a range of uniform precipitation changes for the full sample and non-irrigated sample. In line with the existing literature (see Deschênes and Greenstone 2007, Schlenker and Roberts 2009), we find that the change in precipitation would have a small (less than 1%) impact on corn and soybean yields even with the wide range considered here. Fig 8 shows the impacts on corn and soybean yields under a range of uniform changes in radiation. Similar to the impact of precipitation, the impacts on corn and soybean yields due to solar radiation changes are also expected to be small, less than 1%.

7. Concluding Remarks

In this paper, we investigate the impact of climate change on corn and soybean yields in China. We compiled a unique county-level panel on crop yields over the period 2001-2009, combined with a fine-scale weather dataset that includes daily measures of minimum and maximum temperatures, precipitation and solar radiation for each day over crops' growing seasons. In addition to climatic variables, other socioeconomic variables and variable representing farmers' adaptation behaviors to the warmer climate are also included. This is the first county-level analysis estimating the relationship between weather and crop yields for a country other than the U.S., and the first to do so using spatial panel econometric techniques.

Our statistical results indicate the existence of nonlinear and asymmetric relationships between corn and soybean yields and climate variables. The optimal numbers of GDD in the range 8–32°C, precipitation and radiation in the preferred model are consistent with the agronomic literature. Other variables also have intuitive signs and magnitudes. For example, GDD above 34°C are always harmful to corn and soybean growth, and acreage expansion of crops occurred at both intensive- and extensive margins had negative impacts on crop yields. Estimated coefficients of the time trend suggest that recent adoption of new varieties has led to renewed increases in corn and soybean yields over the sample period, but with declining rates of growth. Results remain robust across various spatial weighting matrices, model specifications, variables and data.

Using estimated coefficients from the preferred yield equations, we estimate changing climate conditions have led to an economic loss of $220 million in 2009 alone over the period 2001-2009 in China's corn and soybean sectors. These coefficient estimates are also used to predict the impacts of global warming on corn and soybean yields in China. Corn yields are predicted to decrease by 2-5% under the slowest warming scenario and by 5-15% under the fastest warming scenario. The corresponding reductions in soybean yields are larger, which are 5-10% and 8-22%, respectively, depending on warming scenarios. The effect of the change in precipitation and solar radiation on corn and soybean yields is expected to small. These findings may provide valuable insight for global collaboration on climate change initiatives.

Two major caveats apply. First, our data set covers observations for the past decade, yet our results are remarkably significant and robust. The negative effect of extreme high temperatures on soybean yields could be more robust if we had a longer period of observations. Second, our analysis focuses on the impact of changes in temperature, precipitation and radiation, and did not consider the impact of CO2 fertilization (that is affected by climate change) on crop yields. Erda et al.(2005) suggest that increased CO2 fertilization can effectively offset yield reductions caused by higher temperatures. Future research should take into account the interaction between climate change and CO2 fertilization in analyzing the impacts of climate change on crop yields.

Table 1. Summary Statistics

Variable	Mean	Min	Max	SD
Corn yield regression				
Corn yield (Ton/ha)	5.19	0.04	16.92	1.95
Degree days (8-32°C), daily min and max temperatures (thousand D)	2.12	0.90	3.55	0.34
Degree days (8-32°C), daily mean temperature (thousand D)	2.06	0.66	3.63	0.35
Degree days (34°C), daily min and max temperatures (D)	6.33	0	225.22	9.78
Degree days (34°C), daily mean temperature (D)	2.68	0	864.00	20.94
Radiation (thousand hours)	0.89	0.41	2.08	0.33
Precipitation (thousand mm)	0.57	0.025	2.07	0.28
Soybean yield regression				
Soybean yield (Ton/ha)	2.15	0.03	10.81	1.03
Degree days (8-32°C), daily min and max temperatures (thousand D)	2.12	0.67	3.40	0.37
Degree days (8-32°C), daily mean temperature (thousand D)	2.05	0.41	3.28	0.39
Degree days (34°C), daily min and max temperatures (D)	6.08	0	104.86	8.61
Degree days (34°C), daily mean temperature (D)	2.41	0	432.00	17.28
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	W1	W2	W3
Corn yield regression model			
Moran-I N(0,1)	33.85	35.81	31.37
LM-ERR $\chi^2(1)$	1106.35	1232.54	954.97
LRatio $\chi^2(1)$	763.12	769.43	729.57
Walds $\chi^2(1)$	26967.56	17604.99	22856.24
Parameter of spatial correlation	0.69	0.67	0.60
Soybean yield regression model			
Moran-I N(0,1)	35.21	37.60	32.18
LM-ERR $\chi^2(1)$	1197.74	1360.75	1005.37
LRatio $\chi^2(1)$	810.75	820.05	758.29
Walds $\chi^2(1)$	28939.62	18547.55	24361.16
Parameter of spatial correlation	0.68	0.67	0.60

We use three spatial weighting matrices to examine the sensitivity of our results to proposed weighting matrices. Spatial weight matrix W1 is a spatial contiguity matrix. Under the spatial contiguity matrix, the (*i*, *j*) element of W1 is unity if counties *i* and *j* share a common boundary, and 0 otherwise. The matrix W1 is then normalized so that the elements in each row sum to unity. Spatial weight matrices W2 and W3 are inverse distance weight matrices that weigh 6- and 4- nearest neighbors, respectively, according to their physical distance and assign zero to other counties. W2 and W3 are then normalized to have row-sums of unity. Results presented here are based on the 9-year's average of the sample.

Table 3: Spatial Error Estimations (Dependent Variable: Log Corn Yield)

Model	Model (1): degree days and precipitation only	Model (2): add radiation	Model (3): add LUC variables	Model (4): add economic variables	Model (5): add irrigation variable
Time trend	0.0267***	0.0260***	0.0377***	0.0400***	0.0411***
	(6.99)	(6.78)	(6.92)	(7.32)	(7.39)
Time trend squared	-0.0009**	-0.0008**	-0.0017***	-0.0017***	-0.0017***
	(-2.37)	(-2.09)	(-3.54)	(-3.46)	(-3.53)
Degree days (8-32°C)	0.2923**	0.3091**	0.3939***	0.3988***	0.3937***
	(2.30)	(2.44)	(3.18)	(3.22)	(3.18)
Degree days (8-32°C) squared	-0.0604*	-0.0628*	-0.0945***	-0.0966***	-0.0953***
	(-1.84)	(-1.92)	(-2.92)	(-2.98)	(-2.94)
Square root of degree days(>34°C)	-0.0143***	-0.0161***	-0.0114***	-0.0120***	-0.0121***
	(-4.52)	(-5.00)	(-3.54)	(-3.72)	(-3.73)
Precipitation	0.0559*	0.0575*	0.0930***	0.0927***	0.0923***
	(1.84)	(1.89)	(3.05)	(3.04)	(3.02)
Precipitation squared	-0.0445**	-0.0425**	-0.0651***	-0.0650***	-0.0648***
	(-2.34)	(-2.24)	(-3.42)	(-3.42)	(-3.41)
Radiation		0.3246***	0.3124***	0.3128***	0.3128***
		(5.31)	(5.12)	(5.13)	(5.13)
Radiation squared		-0.1643***	-0.1430***	-0.1438***	-0.1436***
		(-5.58)	(-4.85)	(-4.88)	(-4.87)
LUC: extensive margin			-0.0051***	-0.0052***	-0.0052***
			(-7.69)	(-7.73)	(-7.82)
LUC: intensive margin			-0.0059***	-0.0059***	-0.0059***
			(-5.19)	(-5.20)	(-5.25)
Ratio: corn price/fertilizer				0.0180	0.0170
				(1.16)	(1.09)
Ratio: corn price/wage				0.1438	0.1437
				(1.43)	(1.42)
Ratio: irrigated acres/total planted acre					0.0253***
					(2.88)
Spatial correlation	0.3660***	0.3620***	0.3710***	0.3690***	0.3710***
	(37.57)	(37.16)	(35.74)	(35.68)	(35.67)
N	18945	18945	16840	16840	16840
R^2	0.7828	0.7836	0.8105	0.8106	0.8107

Table lists coefficients estimates and asymptotic t statistics in parenthesis with the contiguity weight matrix (W1).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Model	Model (1): degree days and precipitation only	Model (2): add radiation	Model (3): add land use change	Model (4): add economic variables	Model (5): add irrigation variable
Time trend	0.0304***	0.02972***	0.0419***	0.0444***	0.0447***
	(7.74)	(7.48)	(7.36)	(7.62)	(7.64)
Time trend squared	-0.0010***	-0.0009**	-0.0019***	-0.0018***	-0.0018***
	(-2.60)	(-2.33)	(-3.76)	(-3.52)	(-3.53)
Degree days (8-32°C)	0.4298***	0.4296**	0.3873***	0.3715***	0.3718***
	(3.98)	(3.97)	(3.54)	(3.38)	(3.38)
Degree days (8-32°C) squared	-0.1392***	-0.1380***	-0.1396***	-0.1336***	-0.1335***
	(-4.68)	(-4.62)	(-4.54)	(-4.30)	(-4.29)
Square root of degree days(>34°C)	-0.0038	-0.0058*	-0.0028	-0.0039	-0.0040
	(-1.12)	(-1.68)	(-0.79)	(-1.09)	(-1.11)
Precipitation	0.0848**	0.0880**	0.0960***	0.0890**	0.0899**
	(2.47)	(2.54)	(2.73)	(2.53)	(2.56)
Precipitation squared	-0.0708***	-0.0685***	-0.0775***	-0.0739***	-0.0748***
	(-3.28)	(-3.17)	(-3.53)	(-3.37)	(-3.40)
Radiation		0.3289***	0.2866***	0.2942***	0.2983***
		(4.85)	(4.14)	(4.25)	(4.31)
Radiation squared		-0.1601***	-0.1399***	-0.1458***	-0.1476***
		(-4.93)	(-4.21)	(-4.39)	(-4.44)
LUC: extensive margin			-0.0038***	-0.0039***	-0.0039***
			(-4.63)	(-4.76)	(-4.76)
LUC: intensive margin			-0.0048***	-0.0047***	-0.0048***
			(-2.63)	(-2.62)	(-2.63)
Ratio: soybean price/fertilizer				0.0363	0.0352
				(1.59)	(1.53)
Ratio: soybean price/wage				0.0693***	0.0694***
				(3.08)	(3.08)
Ratio: irrigated acres/total planted acre					0.0083
					(0.78)
Spatial correlation	0.2720***	0.2760***	0.2800***	0.2790***	0.2790***
	(26.46)	(26.63)	(25.73)	(25.69)	(25.41)
N	19575	19575	17400	17400	17400
R^2	0.7944	0.7949	0.8136	0.8139	0.8139

Table lists coefficients estimates and asymptotic t statistics in parenthesis with the contiguity weight matrix (W1).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Marginal Effects of Climate Variables on Log Crop Yields*

Model	Model (1): degree days and precipitation only	Model (2): add radiation	Model (3): add land use change	Model (4): add economic variables	Model (5): add irrigation variable
Corn yields					
GDD	0.036	0.042	-0.008	-0.012	-0.011
	(18.6)	(22.0)	(-3.9)	(-6.0)	(-5.8)
Precipitation	0.005	0.009	0.018	0.018	0.018
	(2.5)	(4.5)	(9.5)	(9.4)	(9.4)
Radiation		0.032	0.058	0.057	0.574
		(16.8)	(30.2)	(29.7)	(29.9)
Soybean yields					
GDD	-0.161	-0.156	-0.205	-0.195	-0.195
	(-34.2)	(-33.3)	(-43.7)	(-41.6)	(-41.5)
Precipitation	0.003	0.009	0.007	0.004	0.004
	(0.7)	(1.9)	(1.4)	(0.8)	(0.8)
Radiation		0.041	0.035	0.032	0.033
		(8.9)	(7.6)	(6.9)	(7.1)

*Marginal effects are calculated at the sample mean, and statistically significant at the $p < 0.01$ level. Numbers in parenthesis represent the effect of the increases in GDD, precipitation, and radiation by 100D, 100 mm and 100 hours, respectively, on county-average corn and soybean yields (kg per ha).

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

Scenarios	Weight matrix W1	Weight matrix W2	Year fixed effect	Mean temperature for degree days calculation	Non-irrigated subsample
Degree days (8-32°C)	0.3849***	0.4336***	0.3928***	0.3942***	0.4304***
	(3.06)	(3.51)	(3.16)	(3.78)	(3.20)
Degree days (8-32°C) squared	-0.0909***	-0.1034***	-0.0921***	-0.1146***	-0.0949***
	(-2.76)	(-3.24)	(-2.84)	(-4.18)	(-2.74)
Square root of degree days(>34°C)	-0.0122***	-0.0133***	-0.0093***	-0.0006	-0.0122***
	(-3.71)	(-4.30)	(-2.81)	(-0.48)	(-3.84)
Precipitation	0.1024***	0.1072***	0.1044***	0.1082***	0.0673**
	(3.32)	(3.56)	(3.44)	(3.58)	(2.13)
Precipitation squared	-0.0711***	-0.0770***	-0.0707***	-0.0724***	-0.0495***
	(-3.71)	(-4.08)	(-3.73)	(-3.83)	(-2.59)
Radiation	0.3047***	0.3533***	0.2928***	0.2737***	0.2220***
	(4.96)	(5.94)	(4.82)	(4.55)	(3.19)
Radiation squared	-0.1406***	-0.1606***	-0.1476***	-0.1299***	-0.0866***
	(-4.73)	(-5.59)	(-5.04)	(-4.43)	(-2.26)
Spatial correlation	0.3810***	0.3000***	0.3580***	0.3750***	0.3780***
	(36.28)	(34.43)	(34.98)	(35.22)	(34.33)
N	16840	16840	16840	16840	15080
R^2	0.8107	0.8108	0.8123	0.8103	0.8110

Notes: Robustness checks are based on Model (5). Coefficients for other variables have expected signs and statistical significance. For brevity, they are not reported here. Table lists coefficients estimates and *Asymptot t* statistics in parenthesis with the contiguity weight matrix.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Scenarios	Weight matrix W1	Weight matrix W2	Year fixed effect	Mean temperature for degree days calculation	Non-irrigated subsample
Degree days (8-32°C)	0.3551***	0.3673***	0.3740***	0.3073***	0.3947***
	(3.22)	(3.34)	(3.40)	(3.34)	(3.58)
Degree days (8-32°C) squared	-0.1274***	-0.1303***	-0.1343***	-0.1246***	-0.1364***
	(-4.08)	(-4.24)	(-4.31)	(-4.80)	(-4.39)
Square root of degree days(>34°C)	-0.0039	-0.0048	-0.0010	-0.0008	-0.0065*
	(-1.09)	(-1.39)	(-0.27)	(-0.58)	(-1.89)
Precipitation	0.0964***	0.0998***	0.0940***	0.0931***	0.0622*
	(2.73)	(2.88)	(2.69)	(2.68)	(1.74)
Precipitation squared	-0.0783***	-0.0822***	-0.0764***	-0.0762***	-0.0624***
	(-3.54)	(-3.78)	(-3.49)	(-3.50)	(-2.82)
Radiation	0.3031***	0.3362***	0.2711***	0.2854***	0.3470***
	(4.36)	(4.95)	(3.91)	(4.18)	(4.96)
Radiation squared	-0.1511***	-0.1651***	-0.1456***	-0.1414***	-0.1721***
	(-4.53)	(-5.07)	(-4.39)	(-4.28)	(-4.95)
Spatial correlation	0.2780***	0.2220***	0.2690***	0.2800***	0.2290***
	(25.35)	(23.85)	(24.87)	(25.21)	(23.96)
N	17400	17400	17400	17400	16816
R^2	0.8139	0.8139	0.8148	0.8138	0.8093

Notes: Robustness checks are based on Model (5). Coefficients for other variables have expected signs and statistical significance. For brevity, they are not reported here. Table lists coefficients estimates and *Asymptot t* statistics in parenthesis with the contiguity weight matrix.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Magnitude of Estimates

A. Effects of change in climatic conditions from 2001 to 2009 on corn yield in 2009

Climate variables	δ (%)	Production loss (thousand tons)	Cost (Million $)
Temperature	0.4	547.3	123.7
Precipitation	-0.1	-225.2	-51.2
Radiation	0.3	402.1	91.2
Total	0.5	722.0	163.2

B. Effects of change in climatic conditions from 2001 to 2009 on soybean yield in 2009

Climate variables	δ (%)	Production loss (thousand tons)	Cost (Million $)
Temperature	0.4	85.5	53.4
Precipitation	-0.1	-14.8	-9.3
Radiation	0.1	20.7	12.9
Total	0.4	91.1	57.1

Notes: δ is the percentage change in crop yields in 2009 only if climate conditions were at their 2001 levels. Negative numbers indicate gains due to climate changes, while positive numbers are losses due to chaning climates. To calculate total production loss, we first compute county-level production loss using the change in crop yields multiplied by corn and soybean harvested acreages in 2009, and then sum across all counties in the sample. We multiply total production loss by crop price in 2009 to value total economic costs due to climate change. Average corn and soybean prices were RMB 1.66 and 4.86 per kg, respectively, in 2009. The average exchange rate assumed here is RMB6.8 per US$.

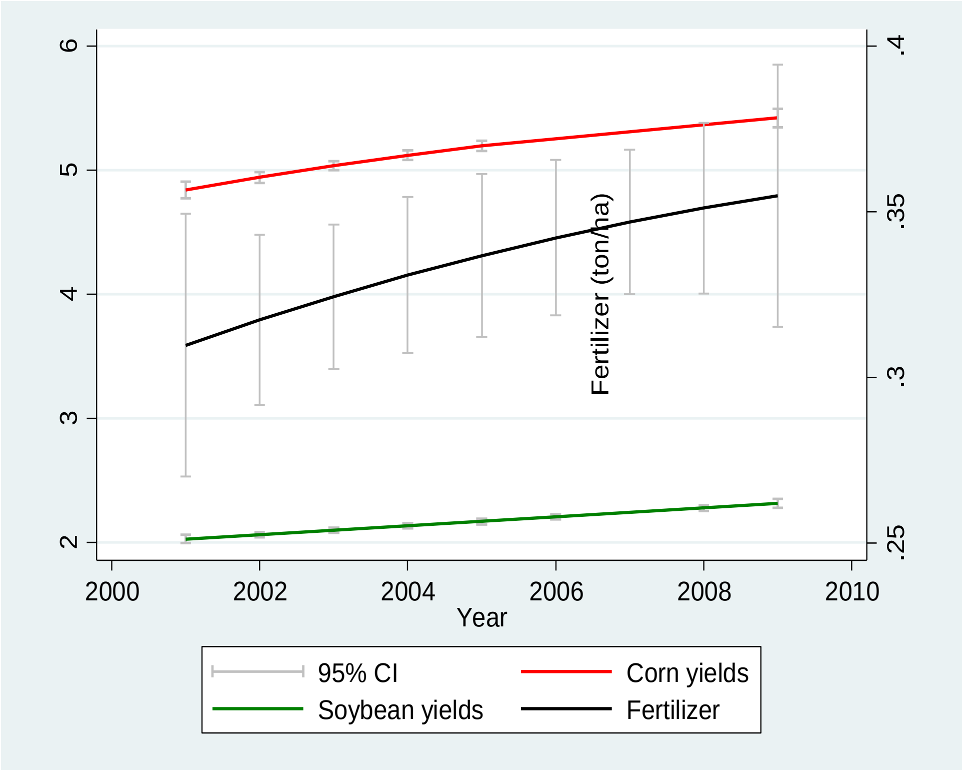
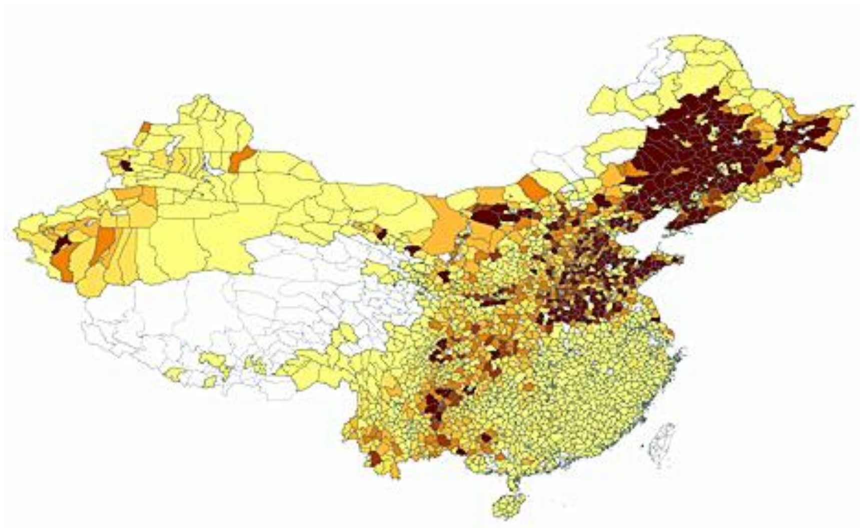
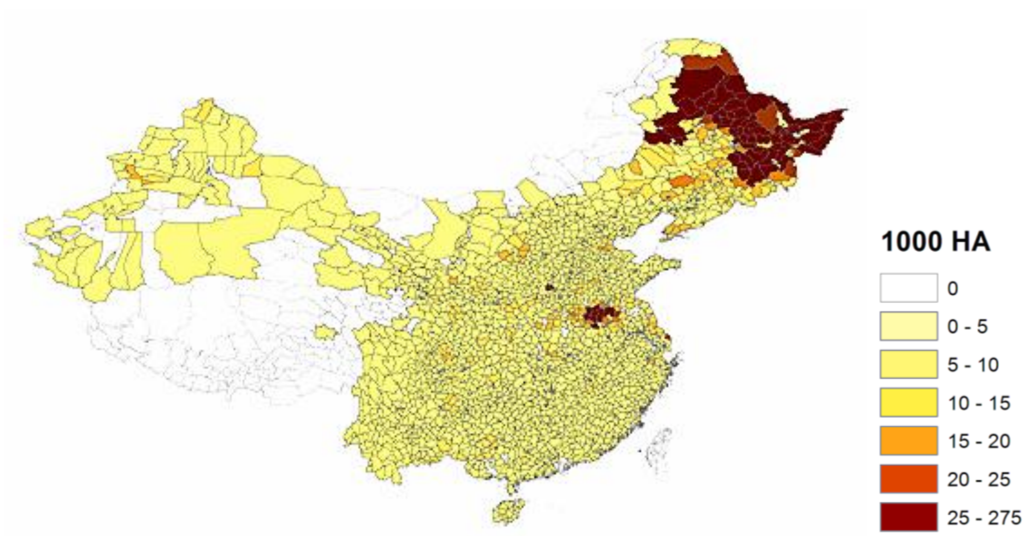


Fig 1. Average yields (tonnes ha^{-1}) of corn and soybeans and fertilizer use (tonnes ha^{-1}) in the period 2001-2009 in China



(a) Corn production areas



(b) Soybean production areas

Fig 2. Five-year (2005-2009) average planted acres of corn and soybean in China

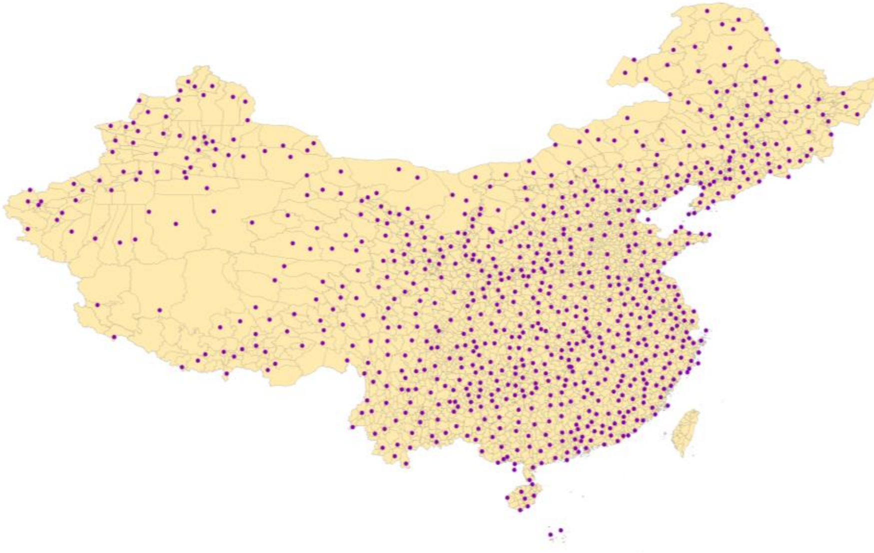
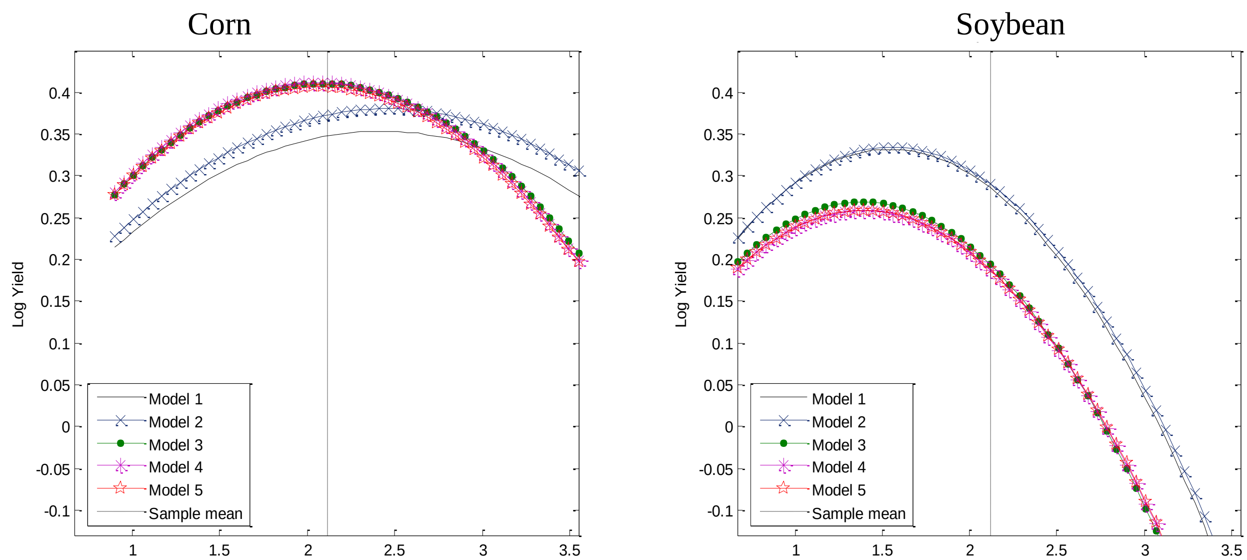
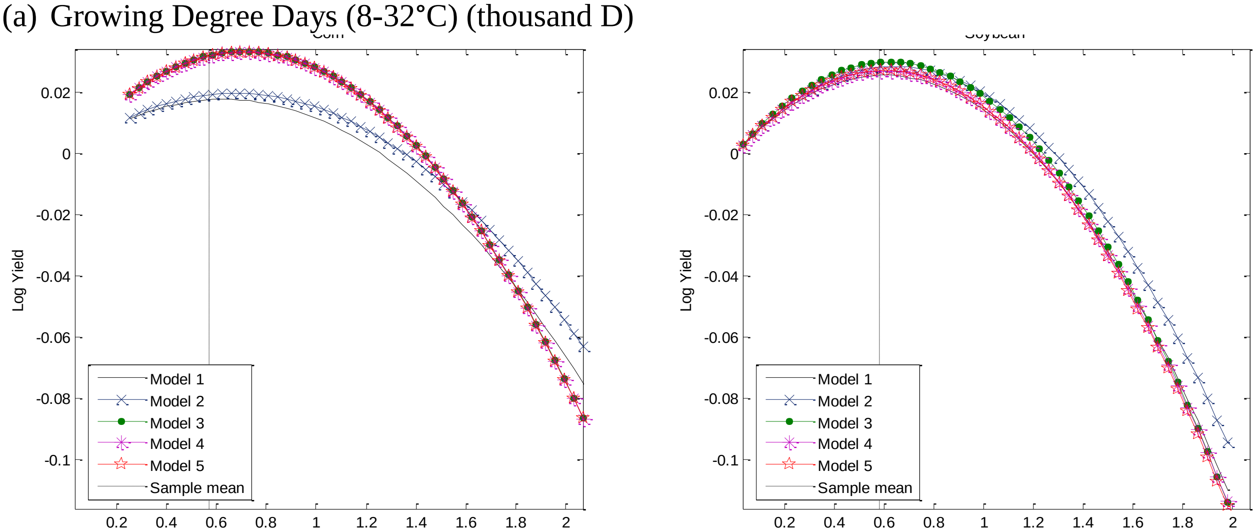


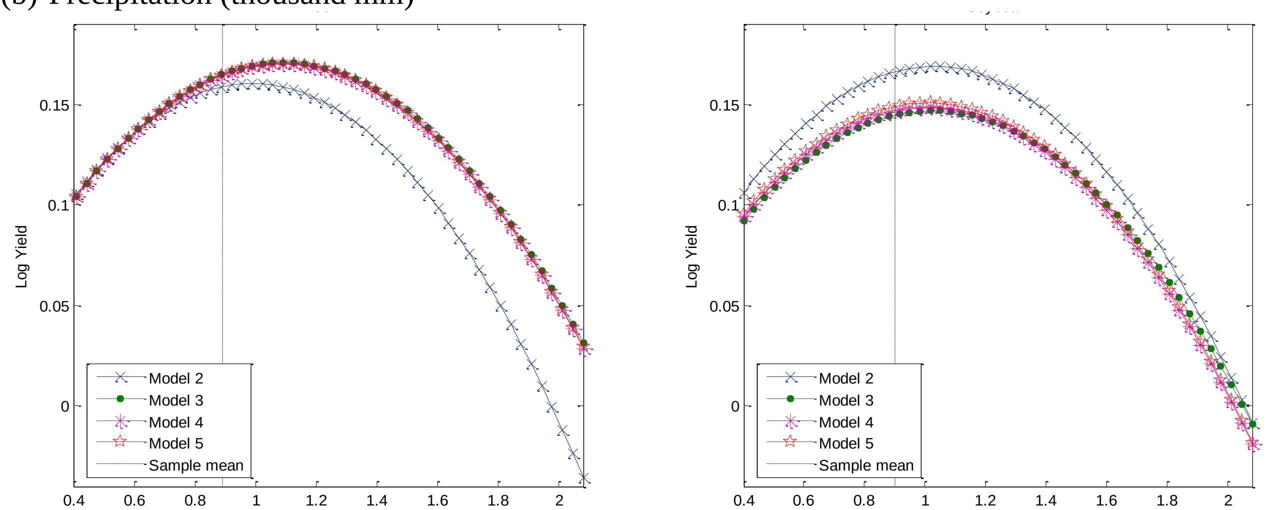
Fig 3. Weather stations in China



(a) Growing Degree Days (8-32°C) (thousand D)



(b) Precipitation (thousand mm)



(c) Radiation (1000 hours)

Fig 4. Comparison in coefficient estimates of climate variables between models (1)-(5)

Notes: Model 1 uses GDD, precipitation, a time trend and their quadratic forms as explanatory variables; Model 2 adds solar radiation; Model 3 includes LUC variables; Model 4 adds economic variables; and Model 5 incorporates irrigation variable.

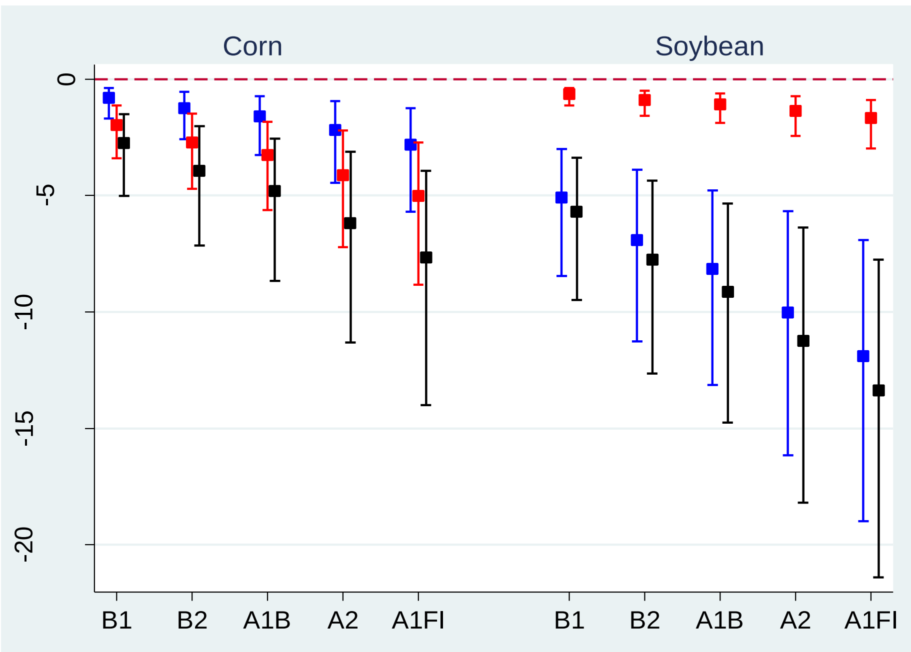


Fig 5. Predicted impacts of changes in temperature on crop yields under the Hadley III climate model (GDD calculated using daily minimum and maximum temperatures)
Notes: Graph displays predicted percentage changes in crop yields due to higher temperatures under five emissions scenarios in the long term (2070–2099). 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 for temperatures between 8-32°C; the red denotes the impact of GDD for temperatures greater than 34°C; and the black shows the total temperature impacts.

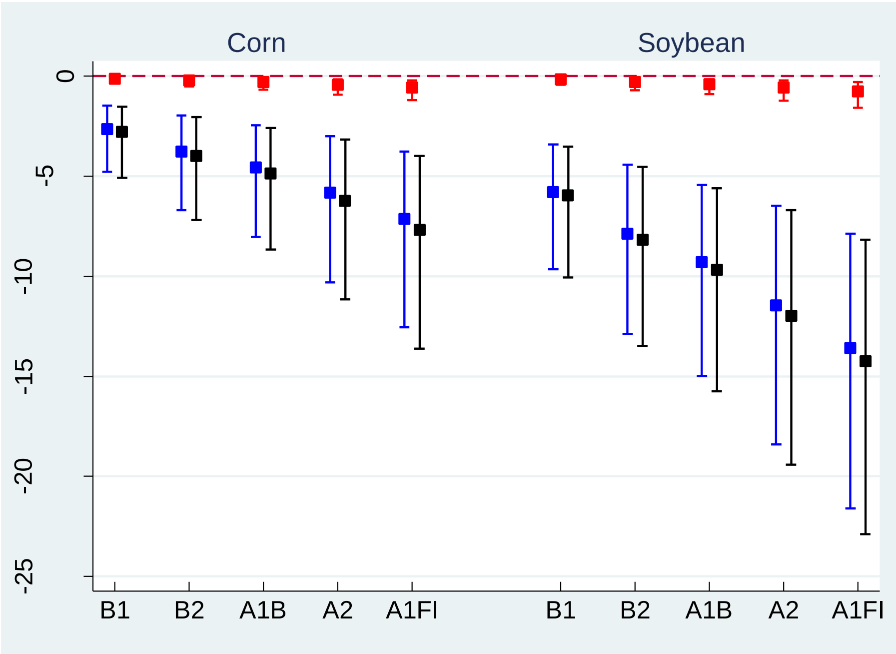


Fig 6. Predicted impacts of changes in temperature on crop yields under the Hadley III climate model (GDD calculated using daily mean temperature)
Notes: Graph displays predicted percentage changes in crop yields due to higher temperatures under five emissions scenarios in the long term (2070–2099). 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 corresponds to the impact of different temperature intervals on crop yields. The blue represents the impact of GDD for temperatures between 8-32°C; the red denotes the impact of GDD for temperatures greater than 34°C; and the black shows the total temperature impacts.

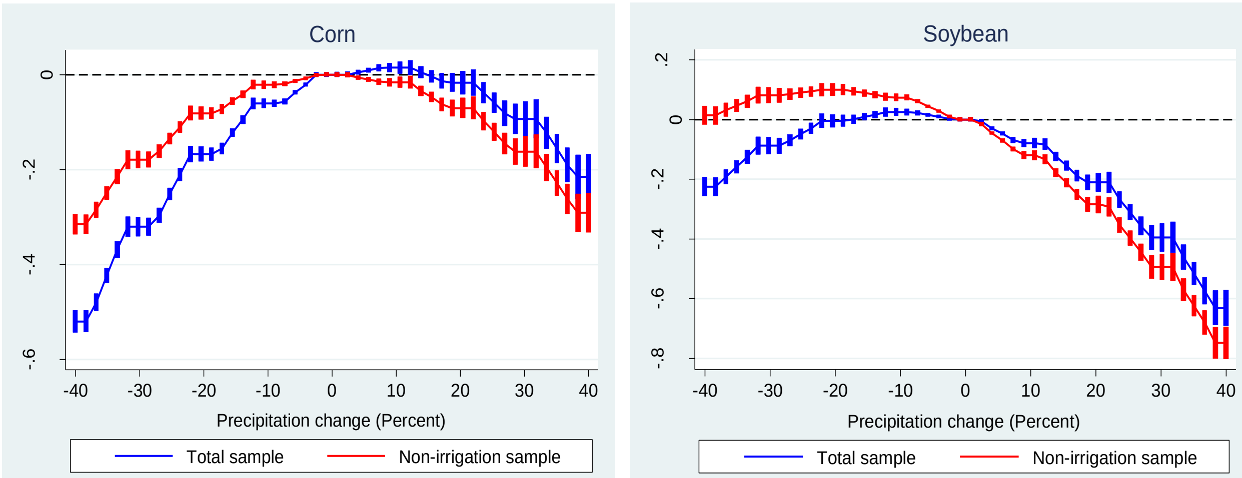


Fig 7. Predicted impacts of change in precipitation on crop yields

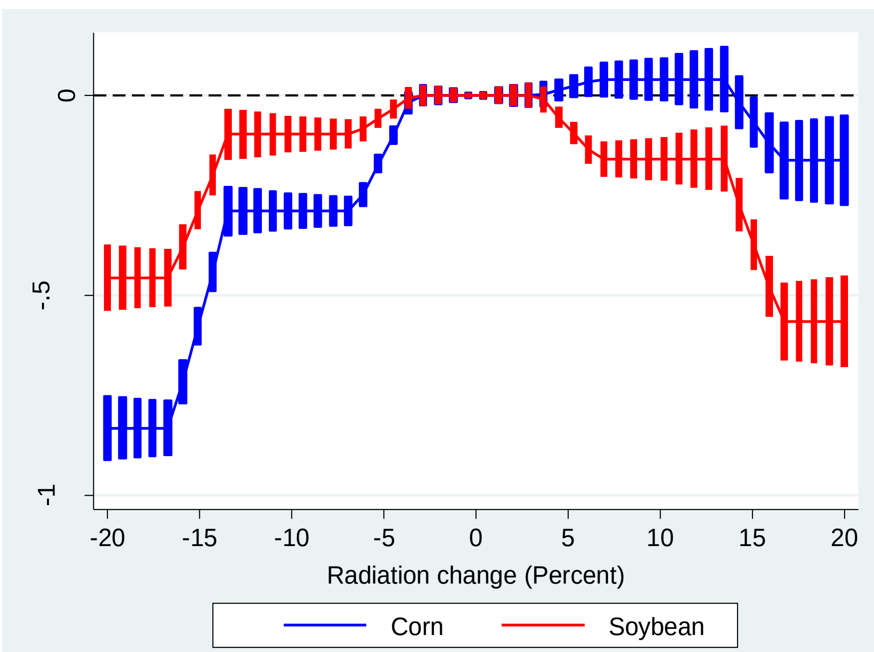


Fig 8. Predicted impacts of change in radiation on crop yields

References:

Food and Agricultural Organizations of the United Nations. 2012. FAOSTAT-Agriculture. Available online at: http://www.fao.org/corp/statistics/en/

Allan, R.P., and B.J. Soden. 2008. "Atmospheric Warming and the Amplification of Precipitation Extremes." *Science* 321(5895):1481-1484.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*: Dordrecht, Boston: Kluwer Academic Publishers.

Auffhammer, M., and R.T. Carson. 2008. "Forecasting the path of China's CO2 emissions using province-level information." *Journal of Environmental Economics and Management* 55(3):229-247.

Auffhammer, M., V. Ramanathan, and J.R. Vincent. 2006. "Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India." *Proceedings of the National Academy of Sciences* 103(52):19668-19672.

Aunan, K., T.K. Berntsen, and H.M. Seip. 2000. "Surface Ozone in China and Its Possible Impact on Agricultural Crop Yields." *Ambio* 29(6):294-301.

Baskerville, C.L., and p. Emin. 1969. "Rapid Estimations of Heat Accumulation from Maximum and Minimum Temperatures." *Ecology* 50:514-517.

Braulke, M. 1982. "A Note on the Nerlove Model of Agricultural Supply Response." *International Economic Review* 23(1):241-244.

Chavas, J.-P., and M.T. Holt. 1990. "Acreage Decisions Under Risk: The Case of Corn and Soybeans." *American Journal of Agricultural Economics* 72(3):529-538.

Christensen, J.H., and O.B. Christensen. 2003. "Climate modelling: Severe summertime flooding in Europe." *Nature* 421(6925):805-806.

Cole, M.A., R.J.R. Elliott, T. Okubo, and Y. Zhou. 2013. "The carbon dioxide emissions of firms: A spatial analysis." *Journal of Environmental Economics and Management* 65(2):290-309.

Daughtry, C.S.T., K.P. Gallo, and M.E. Bauer. 1983. "Spectral Estimates of Solar Radiation Intercepted by Corn Canopies1." *Agron. J.* 75(3):527-531.

Deschênes, O., and M. Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *The American Economic Review* 97(1):354-385.

Diffenbaugh, N.S., J.S. Pal, R.J. Trapp, and F. Giorgi. 2005. "Fine-scale processes regulate the response of extreme events to global climate change." *Proceedings of the National Academy of Sciences of the United States of America* 102(44):15774-15778.

Elhorst, J.P. (2010) Spatial Panel Data Models, ed. Manfred M. Fischer, and A. Getis. Handbook of Applied Spatial Analysis, Springer, pp. 377-407.

Erda, L., X. Wei, J. Hui, X. Yinlong, L. Yue, B. Liping, and X. Liyong. 2005. "Climate change impacts on crop yield and quality with CO2 fertilization in China." *Philosophical Transactions of the Royal Society B: Biological Sciences* 360(1463):2149-2154.

FAOSTAT (2013) FAOSTAT-Agriculture. Available at: http://www.fao.org/corp/statistics.

Howden, S.M., J.-F. Soussana, F.N. Tubiello, N. Chhetri, M. Dunlop, and H. Meinke. 2007. "Adapting agriculture to climate change." *Proceedings of the National Academy of Sciences* 104(50):19691-19696.

Huang, J., C. Pray, and S. Rozelle. 2002. "Enhancing the crops to feed the poor." *Nature* 418(6898):678-684.

Iglesias, A., and C. Rosenzweig. "Effects of Climate Change on Global Food Production under Special Report on Emissions Scenarios (SRES) Emissions and Socioeconomic Scenarios: Data from a Crop

Modeling Study." Palisades, NY: Socioeconomic Data and Applications Center (SEDAC), Columbia University.
IPCC. "Climate Change 2007: Synthesis Report ". Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Pachauri, R.K. and Reisinger, A. (Eds.).
---. "Climate: Observations, Projections and Impacts." Available online at: http://www.metoffice.gov.uk/climate-change/policy-relevant/obs-projections-impacts.
---. "The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change." S. Solomon et al., Eds. Cambridge University Press, Cambridge.
Kelejian, H.H., and I.R. Prucha. 1999. "A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model." *International Economic Review* 40(2):509-533.
Liu, H., X. Li, G. Fischer, and L. Sun. 2004. "Study on the Impacts of Climate Change on China's Agriculture." *Climatic Change* 65(1-2):125-148.
Lobell, D.B., and G.P. Asner. 2003. "Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields." *Science* 299(5609):1032.
Lobell, D.B., W. Schlenker, and J. Costa-Roberts. 2011. "Climate Trends and Global Crop Production Since 1980." *Science* 333(6042):616-620.
McCarl, B.A., X. Villavicencio, and X. Wu. 2008. "Climate Change and Future Analysis: Is Stationarity Dying?" *American Journal of Agricultural Economics* 90(5):1241-1247.
Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *The American Economic Review* 84(4):753-771.
Muchow, R.C., T.R. Sinclair, and J.M. Bennett. 1990. "Temperature and Solar Radiation Effects on Potential Maize Yield across Locations." *Agron. J.* 82(2):338-343.
Nerlove, M. 1956. "Estimates of the Elasticities of Supply of Selected Agricultural Commodities." *Journal of Farm Economics* 38(2):496-509.
Piao, S., P. Ciais, Y. Huang, Z. Shen, S. Peng, J. Li, L. Zhou, H. Liu, Y. Ma, Y. Ding, P. Friedlingstein, C. Liu, K. Tan, Y. Yu, T. Zhang, and J. Fang. 2010. "The impacts of climate change on water resources and agriculture in China." *Nature* 467(7311):43-51.
Ritchie, J.T., and D.S. NeSmith (1991) Temperature and Crop Development, ed. J. Hanks, and J.T. Richie. *Modeling Plant and Soil Systems. Agronomy 31*. Madison, WI, American Society of Agronoy.
Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2006. "The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions." *Review of Economics and Statistics* 88(1):113-125.
Schlenker, W., and M.J. Roberts. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change." *Proceedings of the National Academy of Sciences* 106(37):15594-15598.
Stone, B. 1988. "Developments in Agricultural Technology." *The China Quarterly* (116):767-822.
Szeicz, G. 1974. "Solar Radiation for Plant Growth." *Applied Ecology* 11(2):617-636.
UN. "Millennium Development Goals indicators: Carbon dioxide emissions (CO2), thousand tonnes of CO2 (collected by CDIAC) Human-produced, direct emissions of carbon dioxide only. Excludes other greenhouse gases; land-use, land-use-change and forestry (LULUCF); and natural background flows of CO2 ". United Nations Statistics Division.
Wang, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle, and L. Zhang. 2009. "The impact of climate change on China's agriculture." *Agricultural Economics* 40(3):323-337.
Weber, C.L., G.P. Peters, D. Guan, and K. Hubacek. 2008. "The contribution of Chinese exports to climate change." *Energy Policy* 36(9):3572-3577.

Welch, J.R., J.R. Vincent, M. Auffhammer, P.F. Moya, A. Dobermann, and D. Dawe. 2010. "Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures." *Proceedings of the National Academy of Sciences*.

Yunfeng, Y., and Y. Laike. 2010. "China's foreign trade and climate change: A case study of CO2 emissions." *Energy Policy* 38(1):350-356.

Zalom, F.G., P.B. Goodell, L.T. Wilson, W.W. Barnett, and W.J. Bentley (1983) Degree-Days: The Calculation and Use of Heat Units in Pest Management. Cooperative Extension, Univerity of California, Berkeley. Available online at: https://beaumont.tamu.edu/eLibrary/Publications/Ted_Wilson/LTW31.pdf.

Chinese Cropping System. 2005. Available online at: http://www.cropwatch.com.cn/en/product_zs.aspx

United Nations Statistics Division, Millennium Development Goals indicators: Carbon dioxide emissions (CO_2), thousand tonnes of CO_2 (collected by CDIAC) Human-produced, direct emissions of carbon dioxide only. Excludes other greenhouse gases; land-use, land-use-change and forestry (LULUCF); and natural background flows of CO_2 (See also: Carbon cycle)