Journal of Development Economics 166 (2024) 103196

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular article

Adaptation to temperature extremes in Chinese agriculture, 1981 to 2010☆

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ARTICLE INFO

JEL classification:
Q54
Q56
O13
C23

Keywords:
Climate change
Adaptation
Irrigation
Chinese agriculture

ABSTRACT

Causal evidence for adaptation effects of specific agricultural instruments is scant but important for identifying potentially useful adaptive measures for climate change in the future. To address this gap, we leverage quasi-experimental variations in irrigation induced by a natural experiment for irrigation expansion started in 1996 and quantify the contribution of irrigation access to the overall adaptation effect. There are three primary findings. First, using a period-specific panel fixed effect model, the analysis shows a significant decline in the temperature-related yield loss in the post-1996 period compared to before, indicating a substantial overall adaptation effect. Second, estimation of marginal adaptation effects of inputs points to irrigation as the central input for adaptation among the inputs observed in the data. Third, using a difference-in-differences approach united with the panel methodology for identifying temperature effects, we show that the presence of the irrigation expansion experiment significantly mitigated the high temperature impacts on crop yields, with increased irrigation through the natural experiment accounting for about 40% of the overall adaptation effect.

1. Introduction

The agriculture sector is highly vulnerable to the impacts of climate change. Understanding how specific adaptation measures can moderate these impacts on agricultural production is crucial for identifying solutions to the risks posed by climate change and designing effective policies to facilitate adaptation to climate change. While considerable attention has been given to estimating overall adaptation effect (e.g., Mendelsohn et al., 1994; Burke and Emerick, 2016; Chen and Gong, 2021; Heutel et al., 2021), relatively fewer efforts have been made to comprehend how the use of particular adaptation measures can mitigate the effects of climate change in the agricultural sector.[2] For example, Chen and Gong (2021) demonstrate substantial overall adaptation effects on agricultural output using the long-difference

☆ We are grateful to Olivier Deschênes, Kelsey Jack and Kyle Meng for their continuous guidance and support on this project. We also appreciate comments from Tamma Carleton, Clement de Chaisemartin, Christopher Costello, Minpeng Chen, Tatyana Deryugina, Ignacio Esponda, Frances Moore, Ariel Ortiz-Bobea, Yazhen Gong, Fanbin Kong, Teng Li, Andrew Plantinga, Huangnan(James) Shen, Shuo Shi, Jeffery Shrader, Douglas Staigerwald, Dick Startz, and all the participants of Econometrics Reading Group and Environmental Economics Reading Group at UCSB, the OSWEET Seminar, and the 2nd Annual Conference of Chinese Association of Environmental and Resource Economists. Di Wang acknowledges that this paper is supported by the Scientific Fund of Chinese Universities, China (Grant No. 15053357). Peng Zhang acknowledges support from the National Natural Science Foundation of China (Grant No. 72203193) and Natural Science Foundation of Guangdong Province, China (Grant No. 2023B1515020065). Generous financial support was given to Shuai Chen by the Natural Science Foundation of Zhejiang Province, China (LR22G030003); National Natural Science Foundation of China (72273131; 72134006); Humanities and Social Sciences Program of the Ministry of Education (22JJD790075); National Key R and D Program of the Ministry of Science and Technology of China (2020YFA0608600); CGIAR Mitigate+: Research for Low Emissions Food Systems. Ning Zhang thanks the support of National Natural Science Foundation of China (Grant No. 72033005) and the National Social Science Foundation of China, Major Project (Grant No. 21ZDA065). We are responsible for all the errors.

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[2] Recent relevant studies have focused on the effects of specific measures to mitigate the impacts of climate change on health or violence, including Barreca et al. (2016), Mullins and White (2020) and Colmer and Doleac (2022). But evidence for adaptation effects of specific adaptive measures in the agricultural sector is quite limited.

https://doi.org/10.1016/j.jdeveco.2023.103196
Received 10 November 2021; Received in revised form 24 September 2023; Accepted 25 September 2023
Available online 30 September 2023

approach but do not estimate the adaptation effect of each potential channel.

To address this gap, we adopt a causal framework to identify the adaptation effect of a specific instrument using a panel fixed effect approach and quantify its contribution to the overall adaptation effect. Specifically, we causally identify the adaptation effect of irrigation by investigating whether increased access to irrigation through a nationwide project in China aimed at expanding irrigation can mitigate the high temperature effect on crop yields.

In 1996, the Central Rural Work Conference, organized by the central government, decided to provide subsidized loans annually to support irrigation expansion and explicitly stated the establishment of 300 piloting counties for irrigation construction (The State Council of China, 1996a). The irrigation expansion project was initiated as a complementary policy endeavor during a period when several concurrent agricultural support policies were formulated to attain a goal of achieving food self-sufficiency objective. In the same year, the Chinese government established a goal of achieving grain self-sufficiency, with the aim of fulfilling a minimum of 95% of domestic consumption for several crops such as rice, wheat, corn, coarse grains, soybeans, and potatoes through domestic production (The State Council of China, 1996b). Alongside other articulated agricultural modernization policies, the irrigation expansion project has enhanced the adoption of contemporary agricultural practices, potentially bolstering adaptive capacity (Hyde and Syed, 2014).

Utilizing thirty years of county-level agricultural production data (1981–2010) and fine-scale meteorological data, this paper presents the first large-scale causal evidence on a specific adaptation mechanism in the agriculture sector of the world's most populous country. In accordance with the grain self-sufficiency objective, which establishes self-sufficiency targets for specific crops, our analysis centers around the adaptive capacity of crop yields. Our primary attention is directed towards corn and soybeans, two pivotal grain crops on a national scale, collectively occupying over 20% of China's cropland. These crops hold significant importance as essential resources for producing edible oils and livestock feed. Within the grain category, our focus on studying the climate sensitivities of corn and soybeans as opposed to wheat and rice, is based on the consideration that corn and soybeans exhibit better geographical representativeness. Corn and soybeans are distributed throughout China, whereas wheat and rice are more regionally concentrated—wheat in the north and rice in the south.

The empirical analysis is divided into three parts. In the first part, we establish a period-specific panel fixed effect model that examines the change in the temperature-yield relationship around the year for the irrigation project implementation to estimate the overall adaptation effect. The analysis shows a significant decline in the temperature-related yield loss in the post-1996 period compared to before, indicating a substantial overall adaptation effect. We find the impacts of 100-day exposure to extreme high temperatures (measured by degree days above an endogenously-selected temperature threshold–28 °C for corn and 26 °C for soybean) on corn and soybean yields in 1996 to 2010 is 40% to 50% less than that in the period of 1981 to 1995. This results in a loss reduction by about 14.5% of the national corn production (16.2 million tons) and 7% of national soybean production (1.1 million tons) compared to the scenario in which the pre-1996 extreme temperature impacts on crop yields prevailed.

The second part of the analysis aims to uncover adaptive instruments by estimating the marginal adaptation effects of various agricultural inputs, including irrigation, fertilizer, machinery, and electricity. We estimate an augmented panel model with temperature-input interactions where inputs are interacted with all the temperature variables. Province-by-year fixed effects and county-specific time trends are controlled for so that the biases generated by factors confounding with adaptive inputs cannot occur through province-by-year differences or county-specific gradual changes that may affect crop yields. The results highlight irrigation as the only effective input for adaptation. Increasing irrigation coverage from 0% to 100% is associated with a significant reduction in temperature-related yield loss by 25 to 28 percentage points (13 to 15 percentage points) percentage points for corn (soybean), whereas the use of fertilizer, agricultural machinery, and electricity does not show statistically significant reductions in heat-related yield losses.

To lend credibility to the OLS estimation regarding adaptation effects of inputs in the second part, we identify the adaptation effect of irrigation using quasi-experimental variations induced by the irrigation expansion project. This consists of the third part of our empirical analysis. We first estimate the treatment effect of the project on access to irrigation using a Difference-in-Differences (DID) model, confirming a strong and causal relationship between the project and irrigation coverage. The irrigation project has led to approximately 7 percentage-point increase in irrigation coverage.

We then construct a two-way fixed effect model with interactions between temperatures and the project implementation to estimate the effect of access to irrigation via the irrigation expansion project on the temperature-yield relationship. The interaction model employs two sources of exogenous variations—the irrigation project treatment and temperature. Conceptually, it unites the difference-in-differences approach with the panel-fixed effects methodology that has been widely used to identify causal impacts of temperatures on a variety of outcomes including those within the agricultural sphere (Deschênes and Greenstone, 2007; Zhang et al., 2017). It compares within-county temperature effects before and after the irrigation expansion project was implemented. If no other adaptive inputs change at the same time as the project treatment changes, this will identify the causal effect of the irrigation project on the temperature-yield relationship. The analysis reveals that the presence of the irrigation project significantly mitigated the high temperature impacts on crop yields by approximately 4.5 percentage points, with project-induced irrigation expansion accounting for about 40% of the overall adaptation effect.

This paper contributes to an active literature on adaptation to climate change in two major aspects. Firstly, it contributes to the literature on estimating the overall adaptation effects that has been conducted with two approaches recently (Shrader, 2021). Following Dell et al. (2009), the first approach compares responses of outcome variables to high-frequency weather variation (e.g., year-to-year variation) with those to low-frequency weather variation (e.g., decade-to-decade variation or cross-sectional weather average).[3] The most recent development of the first approach compares panel estimates with long-difference estimates to quantify adaptation effects (Burke and Emerick, 2016; Chen and Gong, 2021). The second approach is comparing estimates derived from high-frequency variation in weather realization across subsamples with different characteristics (e.g., cooler versus hotter areas or earlier versus later period) (Barreca et al., 2016; Taraz, 2018; Heutel et al., 2021; Auffhammer, 2022). There have been attempts to quantify agricultural adaptation in the U.S. by examining evolution of agricultural sensitivities to extreme high temperatures over time but little evidence of decline in temperature sensitivity has been found (Schlenker and Roberts, 2009; Roberts and Schlenker, 2011; Bleakley and Hong, 2017; Ortiz-Bobea et al., 2018).[4]

[3] The idea is that high-frequency variation in weather identifies without-adaptation effects of climate change (direct effects) while low-frequency variation in weather identifies with-adaptation effects (a combination of direct effects and adaptation effects) (Shrader, 2021). Therefore, the difference between the two can be used to estimate adaptation effects. The recent literature using this approach includes Dell et al. (2009, 2012), Butler and Huybers (2013), Schlenker et al. (2013), Moore and Lobell (2014), Burke and Emerick (2016), Bento et al. (2020), and Chen and Gong (2021).

[4] Bleakley and Hong (2017) is an exception among the literature investigating temporal evolution of temperature impacts. It documents the temperature sensitivity of farm value in the US of the 20th century was significantly lower than that in the 19th century but does not show how the farm value had

We employed a period-specific panel fixed effect model which is an application of the second approach for overall adaptation effect estimation, to examine the temporal evolution of the temperature-yield relationship in the world's most populous country. The analysis provides evidence of a significant decline in extreme temperature impacts on yields that is larger than those found in the literature. The temporal progression of temperature effects implies that estimates pertaining to temperature impacts in preceding periods could inaccurately represent the effects in the future.

Unlike alternative empirical strategies that estimate overall adaptation effect by comparing responses to high- and low-frequency weather variation, particularly the long difference approach, our panel approach achieves causal identification of the adaptation effect of particular adaptive instruments. The identification strategy hinges on spatial variation in the temporal change of the temperature and adaptive instrument treatments assigned by a natural experiment while controlling for time-invariant unobservables correlated with the outcome through spatial fixed effects. This distinction is caused by the potential correlation between low-frequency weather variations and economic factors that influence the overall adaptive capacity. Chen and Gong (2021) find that long-difference estimates of agricultural inputs and total factor productivity (TFP) are less sensitive to high temperatures compared to panel estimates, which serves as a suggestive mechanism for the overall adaptation in agricultural production. However, they do not estimate the adaptation effect through each channel nor quantify the extent to which input and TFP adjustments contribute to the overall adaptation effect. Lack of knowledge on adaptation benefits of input adjustments prevents policy makers from identifying effective adaptation strategies.

Secondly, this paper contributes to the literature on specific adaptation strategies. An emerging literature has focused on farmers' adjustments of behaviors in response to temperature shocks or change of climatic normals including within-season variable input adjustments (Jagnani et al., 2020; Aragón et al., 2021), growing season adjustments (Cui and Xie, 2021), cropland reallocation (Costinot et al., 2016; Cui, 2020; Cui and Zhong, 2023), risk-buffering and financing behaviors (Cui and Tang, 2023) as well as energy use (Auffhammer, 2022). But these studies lack formal evaluations on the extent to which those adaptation measures moderate the extreme temperature impacts.[5] The main challenge for evaluating the effectiveness of adaption measures is the endogeneity of specific measures. This paper adds to the literature by identifying the *causal* adaptation effect of a specific instrument using its *quasi-experimental* variations and quantify its contribution to the overall adaptation effect.

In particular, our paper contributes to the literature on the role of irrigation in adapting to climate change. While Hornbeck and Keskin (2014) evaluate the effect of groundwater on drought sensitivity by exploiting local exogenous variation in access to new groundwater aquifer, to our best knowledge, our paper is the first to use a nationwide natural experiment in access to irrigation to address the endogeneity issue of irrigation. Other relevant studies estimate the heterogeneous temperature or precipitation impacts by the level of irrigation coverage and find that lower climate sensitivity for irrigated areas (Fishman, 2018; Tack et al., 2017; Zaveri and Lobell, 2019). But they cannot rule out confounding factors for irrigation without exogenous variations in irrigation.

The remainder of the paper is organized as follows. Section 2 outlines a conceptual framework explaining how the temperature effects depend on use of adaptive inputs. Section 3 introduces the background for the irrigation expansion project. Section 4 describes the data sources and reports the summary statistics. Section 5 presents the econometric strategies. Section 6 reports the results from fitting the models in Section 5. Section 7 concludes.

2. Conceptual framework

The conceptual framework illustrates the identification strategies for the overall adaptation effect and marginal adaptation effects of adaptive inputs (i.e., agricultural inputs) by introducing how the impacts of high temperatures on crop yields depend on adjustments of inputs. Suppose that the yield of a crop is a function of temperature T and a vector of adaptive inputs $\mathbf{x} = (x_1, \dots, x_n)$, which can be expressed in Eq. (1)

$$y = F(T, \mathbf{x}), \tag{1}$$

where y is the yield of a crop. High temperature shocks generate negative impacts on crop yields, i.e., $F_T = \frac{\partial F(T,\mathbf{x})}{\partial T} < 0$, but the negative high temperature impacts can be moderated by the adaptive inputs such that for an arbitrary input x_i, $F_{Tx_i} = \partial F^2/\partial T \partial x_i > 0$. So, the adaptation effect, which is the total change in the temperature-yield relationship F_T due to use of adaptive inputs can be expressed by total differentiating the high temperature effect F_T in Eq. (2):

$$dF_T = F_{Tx_1} dx_1 + \cdots + F_{Tx_n} dx_n. \tag{2}$$

We need to estimate the overall adaptation effect which is the change in the temperature-yield relationship as denoted by dF_T and identify the adaptation effect through using some specific adaptive instrument as denoted by $F_{Tx_i} dx_i$. To be cohesive with the exogenous change in irrigation due to the natural experiment, the overall adaptation effect can be identified by comparing the high temperature effect before the occurrence of the experiment with after. Based on Eq. (2), specific instruments take into effect in terms of mitigating high temperature impacts either through change in quantities of adaptive inputs or through changes in marginal adaptation effects which may be related to technology advancement. Because we only observe agricultural inputs rather than technology advancements in the data, this study can only estimate the adaptation effect through the mechanism of quantity changes in inputs. The assumption for the approach of comparing the high temperature effects between different policy regimes is that the marginal adaptation effect of each input remains stable. We use a model specification of province-by-year fixed effects and county-specific time trends to account for the temporal change in technology that may affect the marginal adaptation effects of inputs over time whereby we can disentangle the mechanism of changes in marginal adaptation effects from the mechanism of changes in inputs quantities to some degree.

Fig. 1 illustrates the empirical strategy of estimating the overall adaptation effect by depicting the evolution of temperature-yield relationship over time periods. This relationship is modeled as an inverted "U" shaped parabola because the literature has documented the nonlinear effects of temperature on crop yields (Schlenker and Roberts, 2009; Lobell et al., 2013). The steeper parabola denotes the temperature-yield relation in Period 1 and the flatter one denotes the relation in Period 2. In Period 1, an unanticipated increase of temperature from the yield-maximizing T_0 to T_1 generates yield loss measured by $AB = Y_0 - Y_1$. If farmers have more access to adaptive inputs in Period 2, the yield loss caused by the same temperature increase reduces to $AC = Y_0 - Y_2$. The adaptation benefit is $BC = Y_2 - Y_1$, which represents the reduction in temperature-related yield loss due to increased use of adaptive inputs. The evolutionary effects of high temperatures on crop yields can be estimated by a period-specific panel fixed effect model

evolved since the 20th century while others studying the same topic only focus on the temporal evolution of extreme temperature effects since the 20th century.

[5] Earlier relevant studies quantified how farmers adapt to their current climate by comparing choices of inputs and farming methods in one climate zone versus another (Kurukulasuriya and Mendelsohn, 2008c,a,b; Wang et al., 2010; Haigh et al., 2015; Huang et al., 2015) and factors that impact farmers' adaptation decisions (Bryan et al., 2009; Di Falco et al., 2011; Di Falco and Veronesi, 2013; Di Falco, 2014). The estimation in this thread of literature is mainly derived from cross-sectional variation in average weather, which is the major difference from the most recent emerging literature.

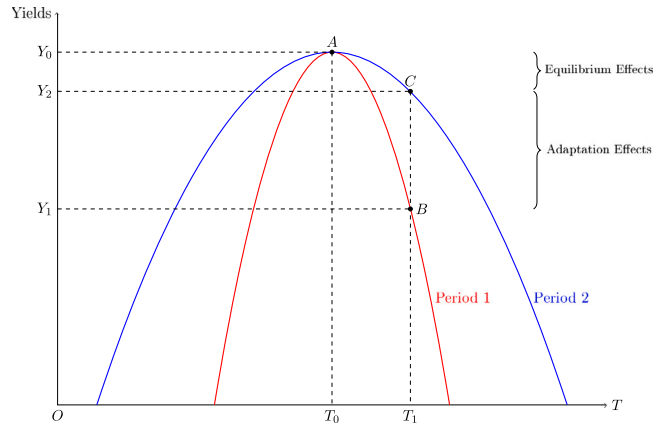

Fig. 1. Crop yields of two periods as a function of temperature.

following the empirical strategy by Barreca et al. (2016). The period-specific coefficients for the high temperature variable in the regression model estimate $\frac{|AB|}{|T_1-T_0|}$ and $\frac{|AC|}{|T_1-T_0|}$.

The goal of this paper is to identify the marginal adaptation benefits of adaptive inputs, i.e., $F_{Tx_i} > 0$ and to quantify their individual contributions to the overall adaptation effect. The identification relies on the assumption that no other factors that are relevant to the investigated adaptive input covary with the input. An agricultural policy that assigns some places with resources to promote use of the investigated input while leave other places unaffected can provide quasi-experimental variations in the adaptive input. An extensive assumption from above is that the project treatment is independent of temperature shocks that may induce use of other adaptive inputs. In presence of a natural experiment that changes access to a specific adaptive instrument, the goal can be accomplished by a difference-in-differences approach that disentangles variations of the investigated input from variations of confounding factors.

This study is focused on within-crop adaptation. The conceptual framework relies on a single-crop production function holding across time such that the production function changes only via changes in non-crop inputs. The channel of adaptation via crop switching is assumed away from this analytical framework. However, crop substitution as responses to high temperature shocks may be constrained by inconsistent growing seasons of crops for substitution and market distortions that weaken the incentives of crop production in areas that are most suited to the new economic environment. We will examine how crop mixture in terms of planted area respond to high temperature shocks within growing season in Section 5 to verify the assumption for framing.

3. Background of agricultural policies used for the identification strategy

Agricultural policies that stimulate investments on agricultural inputs can modify the temperature-yield relationship. Policy implementation marks the starting point of the change in high temperature effects on crop yields and provides quasi-experimental variations in relevant adaptive inputs for identifying adaptation effect via the relevant input. In 1996, the Chinese government set an objective for grain self-sufficiency, aiming to satisfy a minimum of 95% of domestic consumption of rice, wheat, corn, coarse grains, soybeans and potatoes through domestic production (The State Council of China, 1996b; Hyde and Syed, 2014). This state objective stems from the Chinese government's view that China's food security is best maintained by meeting its domestic food demand with domestically produced food. Instead of incentivizing crop substitution as response to environmental change, the self-sufficiency objective strengthens production of individual crops (Clapp, 2017). The self-sufficiency objective is supported by agricultural subsidies to improve uptake of modern agricultural practices, thereby providing farmers with an incentive to adopt capital-intensive inputs (OECD, 2013).[6] Other subsidies known as awards are paid directly to county governments in areas that have high grain production. These subsidies are aimed to encourage public investment in both infrastructure and research to support production (Gale, 2013).

Policies to promote expansion of concrete agricultural inputs come along with the objective change. In the same year of 1996, the Central Rural Work Conference held by the central government decided that the government would allocate subsidized loans annually to support irrigation expansion (The State Council of China, 1996a). It explicitly stated that in 1996, 300 pilot counties for irrigation construction would be established nationwide. Each key county was required to add an area of over 100,000 mu (about 6667 hectares) for irrigation. Practical and feasible development plans should be formulated for constructing the 300 key counties. The irrigation plans for key counties should include water delivery, on-field measures, and water use management. The choice of irrigation methods should be tailored to local conditions and scientifically reasonable, with efforts to expand irrigation coverage.

Fig. 2 depicts the time trends of irrigation coverage for the counties treated by the irrigation expansion project (treatment group) and counties that are not affected by the project (control group). Among counties which plant corn or soybean intensively, the treatment group and the control group show similar trends before 1996, the year of project implementation. But they diverge significantly after 2003, when the growth of irrigation coverage in the control group lagged behind that in treated counties. Fig. 2 illustrates the validity of the empirical strategy of using the quasi-experimental variation in irrigation to identify its marginal adaptation benefit.

4. Data sources and summary statistics

4.1. Data sources

Agricultural production data. We use an unbalanced county-level panel data on Chinese agriculture from 1981 to 2010. The data comes from the county-level database collected by the Department of Planting Management, the Ministry of Agriculture and Rural Affairs of China. The data was aggregated from surveys about farmers' agricultural production activities in local counties. Observations on the Xizang Autonomous Region (Tibet) and Qinghai Province are very limited as the two provinces are located on the Qinghai–Tibet Plateau with an average elevation of over 4000 m where agricultural activities are not intensive. The agricultural data set provides data on total outputs and planted area of four major grain crops—wheat, rice, corn, and soybeans as well as the total outputs and total planted area of the whole grain category. It also provides data on agricultural inputs that may moderate high temperature effects. These inputs include the effectively irrigated arable land, agricultural machinery power, aggregate labors (number of labors employed in the crop farming, forestry, husbandry, and fishery sector as a whole), fertilizer, and electricity in each county's rural area. However, we cannot observe agricultural inputs for each crop.

We choose to study corn and soybeans as the major subjects in this paper for two reasons. First, corn and soybean have better representativeness in terms of geographical distribution than wheat and rice.

[6] An example is the "One Exemption and Three" policy. "One Exemption" refers to the exemption of agricultural taxes. "Three Subsidies" refers to subsidies to farmers based on individual's total planted area to increase their income, subsidies for high-quality seed varieties and subsidies for the purchase of mechanized agricultural inputs. The adaptation effect of adopting heat-resilient seed varieties cannot be explicitly investigated because of data limitations. Hence, we use province-year fixed effects and county-specific quadratic time trends in the panel model to account for the changes in crop yields that may confound with the adaptation effects of investigated inputs such as irrigation.

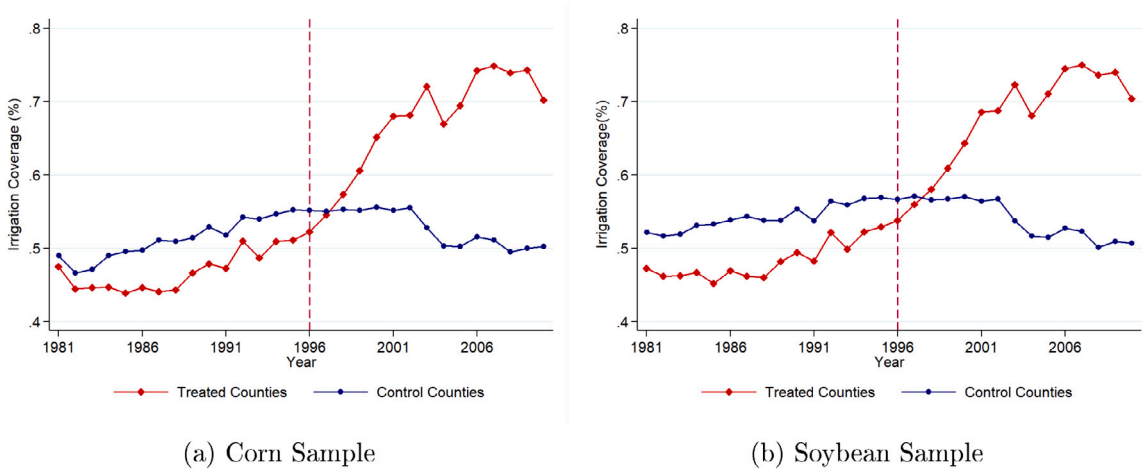

Fig. 2. The time trends of irrigation coverage: treated counties versus control counties.
Notes: Data is missing for counties that never planted corn or soybean from 1981 to 2010. Counties that did not plant corn during the period from 1981 to 2010 have been removed from the sample, leaving a total of 2301 counties that are referred to "corn sample". Similarly, "soybean sample", which follow the same criteria, are composed of 2194 counties. 295 out of the 300 treated counties as the pilots for irrigation expansion can be observed in our data (the rest 5 treated are state-owned farms which cannot be observed in the agricultural data). The irrigation coverage is the percentage of arable land that is effectively irrigated (effectively irrigated area over total arable land area).

Corn and soybean in China are distributed all over the country but other grain crops such as wheat and rice are regional crops—wheat is concentrated in northern China while rice is concentrated in the south. Second, the yields within the growing season for multiple-season crops like rice is hard to be measured accurately (Zhang et al., 2017). In China, the rice can be classified as single-season rice and multiple-season rice (including early rice and late rice) in terms of cropping system. But the data only provides aggregate output and planted area for the whole year without specifying the counterparts for each season. We are not able to measure yields of early rice and late rice accurately. Using the aggregate output for multiple seasons can only estimate an average of temperature sensitivities of all seasons. The temperature sensitivity of the aggregate rice output may be compromised by the temperature sensitivities of rice planted in different seasons with opposite signs. Studies on wheat and rice will be used as supporting evidence to show whether the temporal evolution of temperature-yield relationship in corn and soybeans can be extended to the overall cropping sector of agriculture.

Crop region division and growing season. Corn and soybeans are planted across China but they differ in variety and growing season by region because of spatially varying climatic conditions. Liu (1993) provides us with the division of the corn and soybean regions and corresponding growing seasons, as illustrated in Figure A.1 and A.2 in Appendix A.1, respectively. Corn and soybeans in China can be categorized by season (Chen et al., 2016). Spring corn and soybeans, typically planted in April and harvested in late September, are concentrated in the northeast, northwest inland areas, and southwest mountainous areas. Summer corn and soybeans are grown in June and have a slightly shorter growing season than spring corn does and are primarily produced in the Huang-Huai-Hai (HHH) Plain area. Autumn corn and soybeans are mainly planted in the mountainous areas of the south and southwest regions. A small amount of winter corn and soybeans are planted in the tropical areas of the south and southwest regions, accounting for less than 5% of national production (Zhang et al., 2017). Figure A.2 shows that the growing seasons of the two crops are concentrated around April to September (i.e., spring and summer) when the country is experiencing frequent heat shocks. This provides us more data variation for estimating the heat-related yield loss.

Weather. The weather data are from the National Meteorological Information Center of China, which is the official institute of weather data gathering and publishing. We collected station-day data for 824 stations across China from 1981 to 2010. To transform the weather data from the station level to the county level, we use the inverse distance weighting method, a standard method commonly used in the literature (Deschênes and Greenstone, 2007, 2011; Zhang et al., 2017). First, we choose a circle with a 200 km radius for each county's centroid. We then take the weighted average of the weather data for all the stations within the circle, where the weights are the inverse of the distance between each station and the county's centroid. Finally, we assign the weighted average to each county.[7]

4.2. Summary statistics

Weather and crop yields statistics. Table 1 summarizes the corn and soybean productivity and climate conditions within the growing season of each crop. The mean value of each variable is the national mean of county's average within each time period (1981–1995 and 1996–2010) weighted by county's planted area for each crop. To highlight changes over time, Table 1 reports summary statistics separately for the 1981–1995 and 1996–2010 periods. From the pre-1996 period to the post-1996 period, the average annual corn(soybean) yield increased from 4262 kg/ha (1361 kg/ha) to 5698 kg/ha (1819 kg/ha).

Climate conditions are described by two parts: regular climate variables including temperature and precipitation as well as additional climate variables including relative humidity, sunshine duration, wind speed, evaporation, and ground surface temperature. Evolution of these climate conditions in Table 1 suggests that the climate has become hotter, drier, less humid and exposed to less sunshine in the historical long run. Figure A.3 in Appendix A.1 depicts the spatial distributions of the temporal change in temperature for corn and soybean as well as the temporal change of the crop yields while Figure A.4 demonstrates the counterpart of precipitation. The spatial difference and changing climate provide large variation for reliably estimating the temperature-yield relationship.

[7] Auffhammer et al. (2014) suggest using a relatively continuous weather record for weather stations when averaging daily station-level data across space. This is to avoid the large pseudo-variation generated by missing station-level data, which is crucial for estimating standard errors because the weather variation should be small in the panel setting relative to the cross-sectional setting. This is a minor issue, as the proportion of missing values in all the observations is less than 0.01% for all the climate variables except evaporation (Zhang et al., 2017). The share of missing values for evaporation is about 25% and the stations with a large amount of missing observations for evaporation are all located in the Tibet–Qinghai Plateau, which is dropped from the analysis.

Table 1
Summary statistics.

	1981–1995				1996–2010			
	Mean	Min	Max	Std.Dev.	Mean	Min	Max	Std.Dev.
Corn								
Yields(kg/ha)	4,262.52	111.49	14,764.87	1,772.02	5,697.73	100.24	14,359.79	1,898.82
Temperature (°C)	20.33	6.01	29.65	3.41	20.80	6.18	30.57	3.39
Precipitation (cm)	45.29	0.27	294.01	16.56	43.62	0.31	280.23	17.53
Humidity (%)	73.29	24.88	94.83	8.08	70.41	27.00	93.51	9.29
Sunshine Hours	6.45	0.94	11.34	1.65	6.41	0.32	11.29	1.61
Wind Speed (m/s)	2.20	0.20	7.25	0.79	2.14	0.19	7.00	0.67
Evaporation (mm)	5.44	0.03	17.75	1.40	3.24	0.00	16.46	2.60
Ground Surface Temperature (°C)	23.11	0.20	34.89	3.67	23.80	0.83	36.15	3.39
Observations	29,083				31,917			
Soybean								
Yields(kg/ha)	1,361.23	66.82	7,101.01	569.40	1,818.71	103.64	7,748.96	629.56
Temperature (°C)	20.59	7.13	29.11	3.11	20.37	7.82	28.97	3.18
Precipitation (cm)	57.24	0.45	327.68	27.33	53.96	1.05	339.64	28.63
Humidity (%)	73.53	24.85	90.04	6.40	70.67	27.20	90.99	7.06
Sunshine Hours	6.66	2.37	11.20	1.24	6.77	0.33	10.94	1.51
Wind Speed (m/s)	2.41	0.34	6.27	0.67	2.29	0.33	6.93	0.60
Evaporation (mm)	5.63	0.13	17.53	0.94	3.63	0.00	16.36	2.59
Ground Surface Temperature (°C)	23.57	0.70	34.56	3.16	23.63	0.69	35.04	2.94
Observations	27,772				28,084			

Notes: The mean value of each variable is weighted by the corn or soybean planted area. Crop yields are quantified as the ratio of crop products to the planted area.

Area Planted to Corn and Soybeans. Figure A.5 in Appendix A.1 shows the trends of area planted to corn and soybean (Panel a) as well as the trends for the share of total area planted to corn and soybeans (Panel b). Corn plantation has been expanded substantially over time while soybeans have remained stable. In correspondence, the share of corn and soybean acreage accounting for the total planted acreage has increased about from 20% to 30%. Overall speaking, the two crops have been accounting for a substantial share of total planted area in the last three decades.

Statistics for Agricultural Inputs. Due to data availability, we mainly investigate four agricultural inputs—fertilizer, machinery, irrigation, and electricity, which potentially may moderate high temperature effects on crop yields.[8] The data set provides data of county-level total labor input for cropping, fishery, and forestry sectors, which is more than the real labor input used for crops. Hence, labor will not be regarded as a major input in the study but evidence on its effect on moderation of temperature sensitivity will be provided in Appendix C.1. Irrigation coverage is measured by the fraction of arable land that is effectively irrigated[9]; agricultural machinery is measured by agricultural machinery power used for each hectare of total planted area; fertilizer is measured by fertilizer inputs used for each hectare of total planted area; electricity is measured by electricity consumption per capita of rural population. The total planted area is the aggregate planted area for all crops. We cannot observe separate inputs for each crop in the data.

We are interested in changes in the four inputs over time, which may be potential drivers of the decline in the temperature sensitivity over the two periods. Figure A.6 in Appendix A.1 depicts the time trends of the four mainly investigated inputs.[10] Each observation in the trend plot is a county-level average of an adaptive input in a given year. There is a growing trend of utilizing more inputs in agricultural production over time, suggesting that later periods witnessed an increased use of inputs compared to earlier periods. Irrigation coverage has a ascending trend with oscillation. As shown in Fig. 2, the oscillation is driven by the sluggish growth of irrigation coverage of counties that were not treated by the irrigation expansion project.

Fig. 3 presents the spatial distribution of the counties that are treated by the national irrigation expansion project versus those that are not as well as the temporal change of the irrigation coverage for these two groups. The temporal change of irrigation coverage is calculated by the difference in county-specific mean of irrigation coverage between the pre-1996 period and the post-1996 period. It shows that treated counties are distributed throughout China and there are large temporal and spatial variations in irrigation coverage, which facilitates identifying the adaptation effect of irrigation. Most of the treated counties have experienced a substantial increase of irrigation coverage, which is consistent with the temporal pattern in Fig. 2.

5. Empirical strategy

This section describes the empirical models to estimate the relationship between crop yields and weather shocks over time periods and effects of agricultural inputs in terms of moderating the extreme temperature impacts.

5.1. The temporal evolution of temperature-yield relationship

We use a panel model with county and province-by-year fixed effects to estimate the temperature-yield relationship. All the weather variables are interacted with a dummy variable of period indicator to

[8] The four inputs may help farmers moderate extreme temperature effects in different ways based on agronomic theory. More details are provided in Appendix A.2.

[9] According to *Technical Terminology for Irrigation and Drainage* by Ministry of Water Resources of China (1993), effective irrigation area is defined as the area of arable land that is relatively flat, accompanied by water sources nearby, equipped with irrigation infrastructure and can be irrigated normally in the situation without extreme weather intervention.

[10] Another way to show the change in agricultural inputs over time is exhibiting the distribution of the temporal changes. Figure A.7 in Appendix A.1 depicts the distribution of the change between the pre-1996 and post-1996 periods for each adaption input. The change in an input variable over time is calculated by the difference between the 1981–1995 average and the 1996–2010 average. There are large variations in the change in each input across counties, allowing us to accurately estimate the effects of inputs in mitigating extreme heat impacts.

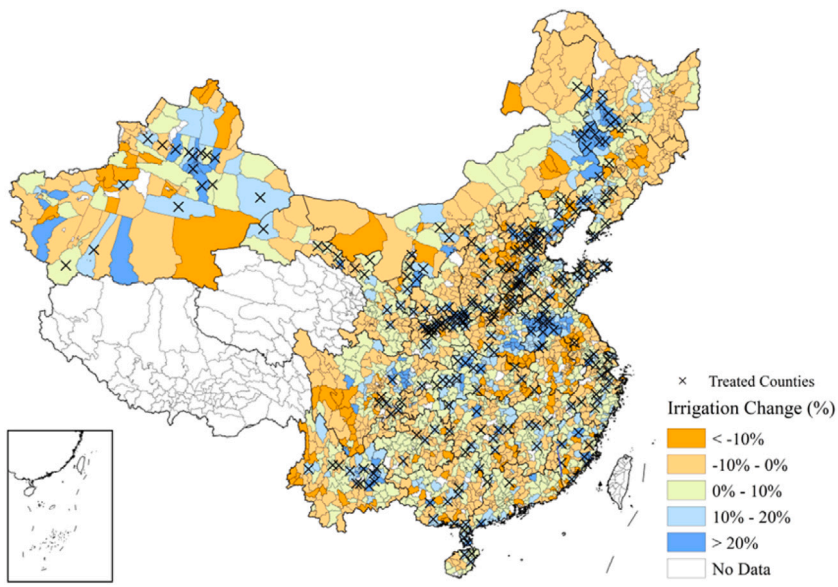

Fig. 3. Temporal change in irrigation coverage: Treatment versus control.
Notes: Data is missing for counties that never planted corn or soybean from 1981 to 2010. 295 out of the 300 treated counties as the pilots for irrigation expansion can be observed in our data (the rest 5 treated are state-owned farms which cannot be observed in the agricultural data) (The State Council of China, 1996a). The irrigation coverage is the percentage of arable land that is effectively irrigated (effectively irrigated area over total arable land area). The temporal change for each county is calculated as the difference in the county-level mean of irrigation-coverage between the pre-1996 period and post-1996 period.

capture the evolution of temperature-yield relationship due to adaptation. The baseline regression model we estimate is as follows:

$$\begin{aligned} y_{it} = & \sum_{d=1}^{D} \beta_{1,d} \cdot GDD_{it,l_0:l_1} \cdot \mathbf{1}\{period = d\} \\ & + \sum_{d=1}^{D} \beta_{2,d} \cdot GDD_{it,l_1:\infty} \cdot \mathbf{1}\{period = d\} \\ & + \sum_{d=1}^{D} \mathbf{w}_{it} \cdot \mathbf{1}\{period = d\} \cdot \boldsymbol{\beta}_{\mathbf{3},d} + \sum_{d=1}^{D} \mathbf{w}'_{it} \cdot \mathbf{w}_{it} \cdot \mathbf{1}\{period = d\} \cdot \boldsymbol{\beta}_{\mathbf{4},d} \\ & + \alpha_i + \eta_{pt} + \lambda_{i,1} t + \lambda_{i,2} t^2 + \epsilon_{it} \end{aligned} \tag{3}$$

where y_{it} is the log of annual crop yields in county i and year t. D denotes the number of periods. We use the year of 1996 to break the whole 30 years into two periods—pre-1996 period and post-1996 period. 1996 marks the start of a new policy regime where buffering grain production from volatility due to environmental change has been put at a higher priority than before and policies that stimulated investments in inputs came into practice. For example, 1996 witnessed an exogenous structural change in irrigation caused by the irrigation project implemented in 1996 which is about constructing 300 key counties for irrigation expansion and improving agricultural production whereby we are able to identify adaptation benefits via irrigation while controlling for relevant confounding factors.

GDD_{it} denotes growing degree days, which is classified by endogenously-selected thresholds into a low-level piece and a high-level piece. The vector $\mathbf{w}_{it}$ denotes extra climate variables other than temperature including precipitation, relative humidity, sunshine duration, wind speed, evaporation and ground surface temperature and their quadratic forms captured by the inner product of vector $\mathbf{w}_{it}$. Additional climate variables are controlled for because the full set of climate variables are correlated (Lawrence, 2005; Wooten, 2011) and omitting climate variables other than temperature and precipitation can overestimate the extreme temperature effects on crop yields (Zhang et al., 2017). The indicator variable $\mathbf{1}\{period = d\}$ specifies the time period denoted by d and this interacts with all climate variables.

The specification includes a full set of fixed effects. α_i denotes the county fixed effects that accounts for county-specific time-invariant determinants of crop yields such as soil quality; η_{pt} denotes province-by-year fixed effects to account for province-specific shocks that may affect crop yields (e.g., agricultural subsidies and price shocks).[11] By conditioning on county fixed effects and province-by-year fixed effects, the responses of crop yields to weather shocks are identified from county-specific deviations in weather about county averages after adjusting for common shocks to all counties within a province in a year.

The vector of controls also includes a quadratic time trend that is allowed to vary at the county-year level. The time trend along with province-by-year fixed effects can control for changes in crop yields over time at the local level that may confound with the effect of adaption through adjustments of inputs. One confounding factor is the gradual advancement in adaptation technology that can increase marginal adaptation effect of inputs over time such that extreme high temperature effects may not be moderated through input adjustments.

The variable of central interest is extreme high temperature. The literature has demonstrated strong nonlinearities in the relationship between temperature and agricultural outcomes (Schlenker and Roberts, 2009). Nonlinearities are captured by the concept of growing degree days (GDD), which measure the amount of time a crop is exposed to temperatures between a given lower and upper bound. Following Schlenker and Roberts (2009) and Burke and Emerick (2016), we use the within-day distribution of temperatures to calculate the percentage of each day that each county is exposed to temperatures between given lower and upper bounds, and then sum these daily exposures over a fixed growing season (e.g., April 10 to October 20 for corn in North region) to get a measure of annual growing degree days for those bounds.[12] The lower temperature piece $GDD_{it,l_0:l_1}$ is the

[11] Gale (2002) points out agricultural markets in China have been more regional than national due to each province's or region's resource endowments, local consumer tastes and agricultural growing conditions therefore prices of the same agricultural product in China have been various across regions.

[12] We use trigonometric sine curve to approximate the within-day distribution following Snyder (1985). In the following illustrative example, we assume instantaneous temperature within a day is identical. If $l_0 = 0$ and $l_1 = 30$, a set of daily average temperature of −1, 0, 5, 10, 29, 31 and 35 would generate $GDD_{it,l_0:l_1}$ equal to 0, 0, 5, 10, 29, 30 and 30 and $GDD_{it,l_1:\infty}$ equal to 0, 0,

sum of GDD between bounds l_0 and l_1 and the upper temperature piece $GDD_{it,l_1:\infty}$ has a lower bound l_1 and is unbounded at the upper end.

Similarly, we measure precipitation in a county as a piece-wise linear function with a kink at p_0. The variable $Prec_{it,p<p_0}$ ($Prec_{it,p>p_0}$) that is incorporated in the vector $\mathbf{w}_{it}$ is the difference between precipitation and p_0 interacted with an indicator variable for precipitation being below (above) the threshold p_0.[13]

We set $l_0 = 8$ because 8 °C is considered as the minimum temperature for crop growth (Chen et al., 2016) and allow the data to determine l_1 and p_0 by looping over all possible thresholds and selecting the model that best fits the data based on the Bayesian Information Criterion. This selection process is applied to both the full sample (nationwide) and each single region described in Figure A.1 of Appendix A.1. The selected thresholds for growing degree days and precipitation by region are reported in Table B.1 of Appendix B.1.[14] It shows no change in temperature thresholds over time periods and small fluctuations in precipitation threshold over time periods for both corn and soybeans. As a robustness analysis, we estimate the period-specific weather response function in Eq. (3) using the thresholds selected for the 15-year periods of 1981–1995 and 1996–2010. The results are presented in Table B.7 of Appendix B.3. The choice of period length, either 10 or 15 years as a period does not make a big difference to the selected thresholds for the nationwide sample nor for the regional samples. We also conduct robustness checks with multiple thresholds other than the initially selected ones to avoid threshold misspecificiation.

The key coefficients of the model in Eq. (3) is the β_2 in each period, which measures how crop yields are impacted by exposure to extreme heat in each time period. If effect of adaptation to extreme high temperatures is significant, we expect $\beta_{2,d=1} < \beta_{2,d=2} < 0$; in other words, the estimated marginal effect of a daily exposure to temperature above the threshold in the later period should be significantly lower than that in the earlier period. The value $(\beta_{2,d=1} - \beta_{2,d=2})/\beta_{2,d=1}$ provides the percentage of the direct impacts of extreme heat offset by adaptation.

As the robustness analysis, we examined whether temporal evolution of the temperature-yield relationship is robust to changes of model specifications. We change the standard error estimator, manipulated temperature thresholds and specifications of time periods, and remove outlier observations for yield growth. Moreover, we check whether the temporal evolution of the temperature-yield relationship in corn and soybeans is applied to other major grains including wheat and rice, which can be used to infer the adaptive capacity of the overall agriculture to climate change.

5.2. Estimating marginal adaptation effects of inputs

This part of empirical analysis aims to figure out inputs that may have muted the temperature-yield relationship overtime. We estimate an augmented panel model described in Eq. (4), where the interactions of temperature variables and the quantities of agricultural inputs are added to estimate the marginal adaptation effects of inputs, which is the parameter of $F_{T_{x_i}}$ in Eq. (2).

$$\begin{aligned} y_{it} =& \beta_1 \cdot GDD_{it,l_0:l_1} + \theta_1 \cdot GDD_{it,l_0:l_1} \cdot \mathbf{Inputs}_{it} \\ &+ \beta_2 \cdot GDD_{it,l_1:\infty} + \theta_2 \cdot GDD_{it,l_1:\infty} \cdot \mathbf{Inputs}_{it} \\ &+ \phi \cdot \mathbf{Inputs}_{it} + \mathbf{w}_{it} \cdot \boldsymbol{\beta_3} + \mathbf{w}'_{it} \cdot \mathbf{w}_{it}\boldsymbol{\beta_4} + \alpha_i + \eta_{pt} + \lambda_{i,1}t + \lambda_{i,2}t^2 + \epsilon_{it} \end{aligned} \quad (4)$$

where $\mathbf{Inputs}_{it}$ is a vector of inputs that including irrigation, machinery, fertilizer, and electricity. Eq. (4) is different from Eq. (3) in two ways. First, Eq. (4) includes the main effects for the inputs (denoted by $\mathbf{Inputs}_{it} \cdot \phi$) and their interactions with the temperature variables to estimate marginal adaptation effects of inputs, the extent to which the effect of an additional-day exposure to high temperatures is affected by marginal increase in inputs. We also interact irrigation with all precipitation variables considering that precipitation can affect the abundance of irrigating water. All other specifications are the same as Eq. (3). Second, Eq. (4) is estimated without specifying the period-specific effects. This specification aims to derive a uniform estimation of marginal adaptation effects of inputs over time periods, which echoes the assumption that marginal adaptation effects of inputs remain stable over time. The adaptation effect of each input is estimated by comparing the temperature sensitivity of yields in counties with a larger increase of input adoption to that in counties with a smaller increase or even decrease. Our hypothesis is that the coefficients for the interaction terms (θ_2) will be positive at the high temperature categories. A positive coefficient vector ($\theta_2 > 0$) would be interpreted as evidence that the diffusion of a particular input reduces a crop's vulnerability to temperature extremes.

The primary challenge to identification of the inputs' adaptation effects is the fact that the variation in inputs is not experimental, so the estimation of θ_2 coefficients is likely to be biased. The province-by-year fixed effects and county-specific quadratic time trends are controlled for so that the bias generated by confounding factors cannot occur through province-by-year differences (e.g., Province A expanded irrigation coverage this year relative to Province B as A encountered a growing season with abnormally high temperature) or county-specific gradual changes that may affect crop yields (e.g., adoption of new seed varieties that are more resilient to extreme heat). Moreover, we have three strategies to bolster the credibility of the OLS estimation of the marginal adaptation effects of inputs. First, we investigate the reactions of the four examined inputs to high-temperature shocks. If these inputs do not exhibit responsiveness to high-temperature shocks, it becomes less likely that their usage is correlated with unobserved adaptation measures induced by high temperature exposure.

Second, interactions between inputs and the low temperature category (i.e., $GDD_{l_0:l_1}$) serves as a placebo check because adaptive inputs should not directly protect crops from low temperatures. Third, we add a temperature-by-year trend to Eq. (4) as a robustness check following Barreca et al. (2016). The local temperature trend consists of the interaction between all the temperature variables and a linear year trend. This specification allows for the possibility that temperature sensitivity of crop yields changes over time for temperature-related factors that may be correlated with the investigated inputs. In addition to local temperature trend, we further control for factors that may affect use of adaptation inputs. Utilization of inputs for adaptation such as water, fertilizer, electricity, and machinery relies on local economic prosperity and infrastructure development. In light of this, interactions of temperature variables with local GDP and cargo quantities shipped by road (a proxy for infrastructure development) over time are added to Eq. (4) as a second check of robustness. The results for these two robustness checks are provided in Section 6.2.

5.3. Identifying adaptation effects of irrigation through exogenous variation

The major empirical challenge in identifying the marginal adaptation effect of inputs lies in the potential omitted variable bias. The investigated adaptive inputs, including irrigation, fertilizer, machinery, and electricity, could be correlated in either a positive or negative direction. For example, irrigation might be utilized in conjunction with other unobserved adaptive instruments as a response to high-temperature shocks, leading to co-variation with confounding adaptive instruments in the same direction. Conversely, investments in irrigation might also reduce investments in other adaptive instruments, given a

0, 0, 0, 1 and 5. This example is the same as the one in Burke and Emerick (2016).

[13] We use a simple example to illustrate the idea of piece-specific linear measurement of precipitation. Suppose a county with precipitation of 60 cm this year and the kink point is 48 cm, then $Prec_{it,p<p_0} = 0$ and $Prec_{it,p>p_0} = 12$.

[14] To check whether the thresholds are distinct for different time periods, we also allow thresholds to vary over time and conduct the threshold selection for each period separately The results are presented in Table B.7 of Appendix B.3.

tightening budget constraint, potentially compromising the moderating effect of irrigation on agricultural sensitivity to high temperatures. Due to the ambiguous effects of confounding factors on the adaptation effects of the four investigated inputs, the direction of the omitted variable bias is unknown a priori.

To address this issue and identify the adaptation effects through adjustments in agricultural inputs, we take advantage of quasi-experimental variations in adaptive inputs. Specifically, we leverage the irrigation expansion project that designated 300 counties as pilots to stimulate irrigation expansion with financial support since 1996. This allows us to isolate variation of irrigation from other confounding factors.

5.3.1. Documenting exogenous variation in irrigation

We first establish the causal relationship between the project and irrigation coverage using a difference-in-differences (DID) model that relies on the temporal and geographic variations in the project treatment. The baseline DID regression model is in Eq. (5).

$$\text{Irrigation}_{it} = \beta \cdot \text{Project}_{it} + \mathbf{W}_{it} \cdot \Pi + \alpha_i + \eta_{pt} + \lambda_{i,1} t + \lambda_{i,2} t^2 + \epsilon_{it} \tag{5}$$

where the outcome variable is the irrigation coverage of county i in year t, Project_{it} is the project implementation indicator which takes the value of one for treated counties after 1996, and $\mathbf{W}_{it}$ is a vector including all the climate variables which have the same specifications as those in Eq. (3). α_i's are the county fixed effects that control for time-invariant factors that affect irrigation coverage (e.g. a county's topographic character can affect the cost of irrigation investment). η_{pt}'s are the province-by-year fixed effects that control for provincial-level shocks that have generated spatial differences in irrigation coverage but confound with the irrigation expansion project and improving agricultural production (e.g. provincial-level policies that affect investments in irrigation). $\lambda_{i,1} t + \lambda_{i,2} t^2$ is county-specific time trend that controls for smooth changes in irrigation coverage. Standard errors are clustered at county level.

Identification of the causal effect β requires the regular parallel-trend assumption that time trends of irrigation coverage would have been similar between counties that are treated by the irrigation project and those that are not in absence of the project treatment. Although Fig. 2 demonstrates the parallel trends before irrigation project implementation, the parallel trend hypothesis will be tested by an event study that estimates year-wise changes in irrigation coverage before and after implementation of the irrigation project within a time window of at least 20 years (10 years before treatment and 10 years after) using the following equation.

$$\text{Irrigation}_{it} = \sum_{k=-10}^{10} \beta_k \cdot D_{i,t_0+k} + \mathbf{W}_{it} \cdot \Pi + \alpha_i + \eta_{pt} + \lambda_{i,1} t + \lambda_{i,2} t^2 + \epsilon_{it}$$

The dummy variables D_{i,t_0+k} jointly represent a time window of 10 years around the event of irrigation project implementation. In particular, t_0 denotes the year when county i was treated by the irrigation project. D_{i,t_0+k} is a series of dummies indicating whether $t - t_0 = k$ with $-10 \le k \le 10$. The omitted time category is $k = -1$, the parameters of interest β_k identify the treatment effects k years following its occurrence.

The exogeneity of the irrigation expansion project necessitates that the irrigation project does not cause changes in confounding adaptive inputs that cannot be observed. We will conduct two tests to ensure that the irrigation project affects temperature-yield relationship solely by increasing irrigation coverage. First, we will test whether the irrigation project has led to changes in other observed inputs including labor, fertilizer, machinery, and electricity using the DID specification in Eq. (5) (changing the outcome variable in Eq. (5) to other inputs). Second, we will assess whether the assignment of the project treatment is correlated with contemporaneous and past temperatures because adaptive inputs may respond to contemporaneous or previous temperature shocks.

5.3.2. Unraveling the moderating effect of exogenous access to inputs on yield sensitivity to high temperatures

We propose a causal framework to examine whether increasing access to irrigation expansion through the irrigation expansion project mitigates the impacts of extreme high temperatures on crop yields. To take advantage of the temporal and spatial variation in irrigation, a model incorporating the interaction between project implementation and temperatures is constructed. Conceptually, the interaction model employs a difference-in-differences (DID) design to estimate the effect of access to irrigation via the irrigation expansion project on the temperature-yield relationship. It compares within-county temperature effects before and after the irrigation expansion project was implemented. If no other adaptive inputs change at the same time as the treatment assignment changes, this will identify the causal effect of the irrigation project on the temperature-yield relationship. The interaction model is expressed in Eq. (6).

$$\begin{aligned} y_{it} =& GDD_{it,l_0:l_1} \cdot \beta_1 + GDD_{it,l_0:l_1} \cdot \text{Project}_{it} \cdot \gamma_1 + GDD_{it,l_1:\infty} \cdot \beta_2 \\ &+ GDD_{it,l_1:\infty} \cdot \text{Project}_{it} \cdot \gamma_2 \\ &+ \text{Project}_{it} \cdot \phi + \mathbf{w}_{it} \cdot \boldsymbol{\beta_3} + \mathbf{w}'_{it} \cdot \mathbf{w}_{it} \boldsymbol{\beta_4} + \alpha_i + \eta_{pt} + \lambda_{i,1} t + \lambda_{i,2} t^2 + \epsilon_{it} \end{aligned} \tag{6}$$

The outcome variable of interest in Eq. (6) is log yields of corn or soybean. Project_{it} is the treatment indicator for the irrigation expansion project which takes the value of one for treated counties after 1996. Climate variables, fixed effects and county-specific quadratic time trends have the same specifications as Eq. (3). In addition to time fixed effects controlling for differences in crop yields over time that are common to counties in a given province, our interaction model also allows for county-specific smooth changes in yields using county-specific quadratic time trends. The treatment effect muting the temperature-yield relationship is captured by the interaction between the project implementation and the high temperature variable. γ_2 is the coefficient of interest, which identifies how the high temperature effects on crop yields depend on access to irrigation through the project.

6. Results

This section presents the estimation results in Section 5. We first estimate the period-specific effects of random year-to-year variation in temperature on the yields of corn and soybeans. We then quantify roles of agricultural inputs in the temporal evolution of temperature sensitivity by estimating marginal adaptation effects of inputs and changes in penetration rates of inputs over periods. At last, we investigate how the increased access to irrigation due to the irrigation expansion project has mitigated the yield sensitivity to high temperatures. For the accessibility of the empirical results, the unit for the temperature hereafter is 100 degree days and the unit for precipitation is 100 centimeter(cm).

6.1. Temporal evolution of the temperature-yield relationship

6.1.1. Temperature-yield relationship for corn and soybeans

Table 2 presents the temporal evolution of temperature-yield relationships of corn and soybeans in Panel A and Panel B, respectively. In our analysis, we adopt a piece-wise linear approach, wherein crop yields are expected to increase linearly up to an endogenous threshold and then decrease linearly beyond that point. Columns 1–3 differ in the specification of fixed effects, as outlined in the table. On the other hand, Columns 4 and 5 vary from Columns 1–3 in terms of the estimation of standard errors. In Columns 1–3, we cluster the standard errors at the county level. In comparison, for Columns 4 and 5, we use spatial HAC robust standard errors, taking into account heteroskedasticity, county-specific serial correlation and cross-sectional spatial correlation of the error term. The results remain robust when using spatial HAC robust standard errors. The selected temperature threshold for corn and

Table 2
Temperature-yield relationship of corn and soybeans over time periods.

	(1) Log Yields	(2) Log Yields	(3) Log Yields	(4) Log Yields	(5) Log Yields
	A. Temperature-yield relationship of corn				
period=1981 × GDD below T	0.0449***	−0.0096	0.0086	−0.0096	0.0086
	(0.0065)	(0.0097)	(0.0083)	(0.0122)	(0.0116)
period = 1996 × GDD below T	0.0067	−0.0057	0.0045	−0.0057	0.0045
	(0.0069)	(0.0099)	(0.0089)	(0.0121)	(0.0110)
period = 1981 × GDD above T	−0.3753***	−0.2879***	−0.2295***	−0.2879***	−0.2295***
	(0.0279)	(0.0330)	(0.0292)	(0.0478)	(0.0431)
period = 1981 × GDD above T	−0.0405**	−0.0834***	−0.1147***	−0.0834**	−0.1147***
	(0.0203)	(0.0277)	(0.0272)	(0.0364)	(0.0382)
p-Value of $H_0 : \beta_{1981} = \beta_{1996}$ for GDD below T	0.0000	0.5667	0.5463	0.5538	0.5973
p-Value of $H_0 : \beta_{1981} = \beta_{1996}$ for GDD above T	0.0000	0.0000	0.0001	0.0000	0.0114
T Threshold	28 °C	28 °C	28 °C	28 °C	28 °C
P Threshold	51 cm	51 cm	51 cm	51 cm	51 cm
	B. Temperature-yield relationship of soybean				
period = 1981 × GDD below T	0.0108	0.0257	0.0427***	0.0257*	0.0427***
	(0.0088)	(0.0157)	(0.0107)	(0.0141)	(0.0108)
period = 1996 × GDD below T	0.0004	0.0210	0.0279**	0.0210	0.0279***
	(0.0091)	(0.0159)	(0.0117)	(0.0140)	(0.0100)
period = 1981 × GDD above T	−0.0310	−0.1621***	−0.1572***	−0.1621***	−0.1572***
	(0.0218)	(0.0292)	(0.0218)	(0.0273)	(0.0252)
period = 1996 × GDD above T	0.0619***	−0.0747**	−0.0828***	−0.0747***	−0.0828***
	(0.0193)	(0.0290)	(0.0204)	(0.0249)	(0.0225)
p-Value of $H_0 : \beta_{1981} = \beta_{1996}$ for GDD below T	0.0001	0.2037	0.0120	0.1408	0.0099
p-Value of $H_0 : \beta_{1981} = \beta_{1996}$ for GDD above T	0.0000	0.0001	0.0029	0.0000	0.0161
T Threshold	26 °C	26 °C	26 °C	26 °C	26 °C
P Threshold	44 cm	44 cm	44 cm	44 cm	44 cm
Observations	59,269	59,274	59,274	59,274	59,274
R squared	0.0708	0.0338	0.0210	0.0338	0.0210
County FE	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	No	Yes	Yes	Yes	Yes
County Quadratic Trend	No	No	Yes	No	Yes
Standard Error	Clustered	Clustered	Clustered	Spatial HAC	Spatial HAC
Distance	N/A	N/A	N/A	500 km	500 km
Years of Lag	N/A	N/A	N/A	5	5

Notes: The outcome variable and all the regressors are demeaned by removing various fixed effects and year trends before the regression models are fit into the data. Each column corresponds to a separate regression varying on specifications of fixed effects, county-specific quadratic trends, and standard error estimators. The dependent variable is log annual yields of corn or soybean. The regressions are weighted by annual hectares planted to the two crops. Only coefficients for temperatures are reported. Precipitation and additional climate variables are also controlled for and their results are reported in Appendix B.2. The selected temperature threshold for corn and soybeans is set at 28 °C and 26 °C, respectively, while the precipitation threshold is established at 51 cm for corn and 44 cm for soybean. The p values for testing the hypotheses of coefficient estimate distinction for temperature variables are provided at the bottom of the table. For simplicity, only the number of observations and the R squared for regressions on corn are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

soybeans is set at 28 °C and 26 °C, respectively, while the precipitation threshold is established at 51 cm for corn and 44 cm for soybean.

Regarding the exposure to growing degree days (GDD), results show that in the periods of 1981–1995 and 1996–2010, GDD values below the threshold of 28 °C for corn and 26 °C for soybean have minor and generally insignificant effects on yields. However, exposure to temperatures above these thresholds leads to significant declines in crop yields. As shown in Panel A, during the 1981–1995 period, corn yield losses due to an additional 100-day exposure to temperatures above 28 °C range from −37% to −23%, while the corresponding estimates in the period of 1996–2010 range from −11% to −4%, which are significantly lower than the yield loss estimations of 1981–1995. This is evident from the p values derived from an F test of the null hypothesis $\beta^{1981} = \beta^{1996}$. Columns 1 to 3 demonstrate that the temperature-yield relationship over the two periods remains robust to the province-by-year differences and county-specific gradual changes in unobserved determinants of corn yields. These factors indeed affect the extent of reduction in yield loss due to extreme temperatures. In summary, the findings indicate the critical impact of temperature on corn and soybean yields and provide valuable insights into the adaptive capacity of these crops under varying conditions. From Column 1 to 3, the relative adaptation effects are 90%, 71%, and 50%, respectively, indicating a decline as the model specifications become more restrictive.[15] The 11.5 percentage-point or 50% ((0.2295-0.1147)/0.2295) decline in the extreme temperature effects over time is therefore considered the most valid estimation of the overall adaptation effect.

Panel B of Table 2 displays the results for soybean. Similar to corn, increases in exposure to temperatures above 26 °C lead to significant declines in soybean yields. During the period of 1981–1995, yield losses due to additional 100-day exposures to temperatures above 26 °C range from −16% to −3%, while in the period of 1996–2010, the range is from −8% to 6%. These values are notably lower than the yield loss

[15] The relative adaptation effects for different model specifications are estimated through the uniform formula shown in the previous section: $(\beta_{2,d=1} - \beta_{2,d=2})/\beta_{2,d=1}$.

estimation of the pre-1996 period, as indicated by the row of p-values derived from an F-test of the null hypothesis. The decline in extreme temperature effects over time remains robust across various specifications, including fixed effects, time trends, and standard error estimator. In Column 3, we present the primary result of the temperature-yield relationship estimation using the main specification in Eq. (3). The 7.4 percentage-point decline or 47% ((0.1572-0.0828)/0.1572) decline in the extreme temperature effects represents the overall adaptation effects on soybean. The estimation of the temperature-yield relationship for both corn and soybeans controls for precipitation and additional climate variables, the results of which are presented in Appendix B.2.

Corn and soybeans have been accounting for a substantial share of total planted area in the last three decade, as demonstrated by the time trend of planted area of the two crops and the percentage of total farmland planted to the two crops shown in Figure A.5 This implies that the magnitude of the decline in the yield loss due to extreme high temperatures is substantial. The annual average corn yield in the post-1996 period is 5697.7 kg (see Table 1). Therefore, it saves about 655 kg (5697.7 × 11.5%) of corn per hectare if the effect of 100-day exposure to temperature above 28 °C is reduced from 23% to 11%. The annual planted area of corn in the post-1996 period is 24.8 million hectares on average. Therefore, the loss reduction of national aggregate corn production is about 16 million tons (0.655 ton/hectare × 24.8 million hectares) or 14.5% of the national corn production per year compared with the scenario in which the pre-1996 extreme temperature impacts prevailed (The annual average of national corn production after 1996 is about 112.03 million tons). The loss reduction of aggregate soybean production is about 1.1 million tons or 7% per year based on the same reasoning. A presumption for our back-of-envelop estimation of the loss reduction is that the planted areas of the two crops are not affected by temperature extremes, which will be verified by the following study on the effects of high temperature shocks on planted area specific to corn and soybeans.

To test whether 1996 serves as an appropriate breakpoint between two regimes for adaptation to climate change, we estimate the temporal evolution of the temperature-yield relationship using a 5-year or 10-year period as the period specification.[16] The results are reported in Fig. 4, which displays the point estimates and 95% confidence intervals of the extreme temperature impacts on crop yields in the first period (1981–1986 is the first period in the 5-year setting and 1981–1990 is the first period in the 10-year setting) and of the change in the extreme temperature impacts in later periods relative to the first period. Various temperature thresholds are also applied to the 5-year and 10-year period settings, the results for which are reported in Figure B.3 to Figure B.6 in Appendix B.5.

The significant difference between the initial period and later periods mainly happen for the periods after 1996. In the 5-year setting, the improvement of temperature sensitivity to extreme heat for the 1986–1990 period and 1991–1995 period is not statistically significant at 5% level, which implies that the adaptation effect mainly happened after 1996 and justifies 1996 as the break point for two regimes of the temperature-yield relationship.

A secondary result documents heterogeneous temperature-yield relationship by the crop regions defined in Figure A.1 (Liu, 1993). This approach allows us to investigate whether areas that are accustomed to temperature extremes have adapted better such that they have a more muted temperature-yield relationship. The estimation is conducted with a single regression in which the sample is restricted to the corresponding corn regions in Figure A.1. The results are reported in Table B.9 and Table B.10 of Appendix B.4. We find that northern regions generally suffer more from extreme temperatures than southern regions and the yield loss of the two crops due to temperature extremes in the southern regions has declined by a larger extent than that of the northern regions, which is consistent with the idea that hotter places adapt to temperature extremes better than cooler ones.

6.1.2. Robustness analyses

The standard error estimator is changed to a spatial HAC standard error estimator in the robustness check to account for heteroskedasticity, county-specific serial correlation and cross-sectional spatial correlation (Hsiang, 2010). The nonparametric estimation of the variance–covariance matrix for the error term allows for contemporaneous spatial correlations between counties whose centroids lie within d km of one another (Conley, 1999). Following Conley (2007), the weights in the matrix are uniform up to the cutoff distance d. Moreover, nonparametric estimates of county-specific serial correlation are estimated using linear weights that decrease to zero after a lag length of q years (Newwey and West, 1987). In our model, the cutoff distance d takes the value from 100 km to 400 km with an increment of 100 km and the length of years q is 3 years or 5 years. We find that the spatial HAC standard errors do not change the estimation of temperature-yield relationships for the two crops compared with clustering-robust standard errors. The results are reported in Figure B.1 in Appendix B.4.

Extreme values of yield change are dropped from the sample. According to Figure A.3, about 200 counties observed an extreme drop in crop yields by more than 30% or an extreme increase by more than 120% during last 30 years. Such a heavy-tailed (outlier-prone) distribution makes a predicted regression line tend to fit more closely outlying observations at the expense of the rest of data sample. We drop observations with a decline in yields of more than 30% or an increase of more than 120% and re-estimate the period-specific weather response function as specified by the panel fixed effect model in Eq. (3) introduced in Section 5.1. The results are reported in Table B.8 of Appendix B.3. We find that the decline in temperature-related yield loss still hold, suggesting that the decline in high temperature effect is not driven by outliers in yield change.

Various temperature thresholds are applied to check the sensitivity of estimation to variation in temperature thresholds. It is a concern that the selected temperature thresholds may be misspecified. Figure B.2 in Appendix B.4 reports the estimation of temperature-yield relationships of corn and soybeans using five consecutive temperature thresholds including the initially selected thresholds in Table 2.[17] The significance of the yield loss decline is robust to variation in temperature thresholds.

The model specification is changed from a period-specific panel model to a more flexible panel model that allows all the climate variables to interact with polynomials of calendar years such that the impact of extreme temperature can change smoothly and flexibly over time (Roberts and Schlenker, 2011). The polynomial takes linear, quadratic and cubic form in this study. Figure B.7 and Figure B.8 in Appendix B.5 display the coefficients for the high temperature impacts over time. The linear and quadratic form of year trend exhibit a steadily rising tolerance of crop yields to extreme temperatures. In the linear(quadratic) model, the effect of 100-day exposure to temperatures above 28 °C on corn yields increases from −23% (−27%) to −9% (−13%), consistent with the results provided by the period-specific panel model. We have a similar evolutionary pattern for soybean. The model of cubic time trend depicts a more complex evolutionary path but exhibits an improving trend of heat tolerance.

[16] An alternative way of checking the robustness of the results to the ending years of the time periods is running panel regressions over rolling time periods such as 1950 to 1965 compared with 1966 to 1980, 1966 to 1980 compared with 1981 to 1995, 1981 to 1995 compared with 1996 to 2010, and so on. However, we only collected 30 years of data from 1981 to 2010. Hence, using rolling time periods is not feasible.

[17] We fix the precipitation thresholds at the initially selected values in Table 2, as we find that changing the precipitation thresholds does not change the estimation results and the results are available upon request.

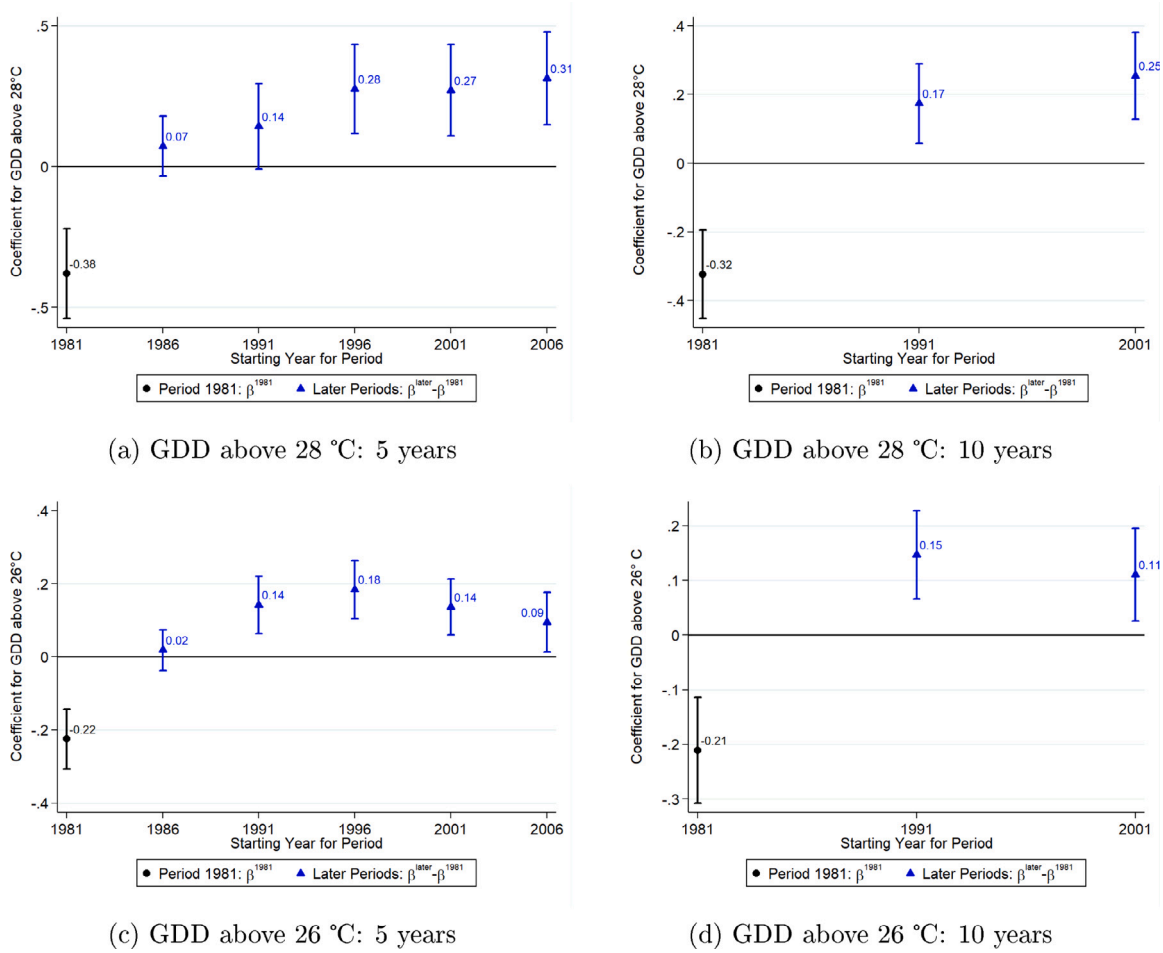

Fig. 4. Sensitivity of Results to Starting Year and Length of Time Period–Using 5 years or 10 years as a Period.
Notes: Fig. 4 presents the evolution of extreme temperature effect on crop yields estimated with model in Eq. (3) using 5 years or 10 years as a period. The regressions are weighted by annual planted area for each crop and the standard errors are clustered at the county level. In each panel, we report the point estimates and the corresponding confidence intervals at the 95% significance levels for the effects of 100-day exposure to temperature above the threshold in the first period (period 1981–1985 or period 1981–1990 denoted by the circle symbol) and the difference in the effects between the following periods and the first period (denoted by the triangle symbol). The initial year for each period is specified below the horizontal axis.

6.1.3. More discussions

How informative is the decline of temperature sensitivity of corn and soybeans about the adaptive capacity of overall agriculture? It is likely that temperature sensitivity of the overall agriculture may not be changed because farmers who experienced high temperature shocks during the growing season or long-run increase in temperature normal may switch to crops which are less sensitive to high temperatures making it appear that corn and soybeans in the remaining cropped areas are less sensitive while the overall sensitivity of agriculture might not have changed. We examine the applicability of temporal pattern of corn and soybeans to the overall agriculture from two perspectives. First, we check if there exists crop switching in response to temperature shocks or long-run change in temperature normal by estimating temperature sensitivities of corn and soybean cropland and how the substitutability between corn or soybean and other grain crops is affected by high temperatures. We established both a panel model to estimate the effects of short-run high temperature shocks (Deschênes and Greenstone, 2007; Aragón et al., 2021) and a long-difference model to estimate the effects of long-run temperature change (Burke and Emerick, 2016). Table B.11 and Table B.12 in Appendix B.6 report the results for the impacts of high temperature shocks and long-term increase in temperature normal on cropland adjustments. We find that exposure to short-run high temperature shocks or long-term extreme heat does not cause shrinkage of corn and soybean plantation nor causes switching away from corn and soybeans to other crops. The decline in the temperature sensitivity of corn and soybeans is not caused by crop selection.

Second, we investigate the temporal evolution of temperature-yield relationships for wheat, rice and the overall grain category. Table B.13 in Appendix B.7 reports the temporal evolution of temperature sensitivity of wheat, rice, and overall grain yields. Rice is categorized into single-season rice which is planted in dryland of northern China and multiple-season rice which is planted in paddy field of southern China. We find that point estimates of temperature sensitivities for wheat, single-season rice, and the overall grain decline over time periods and the decline for the wheat yields and the overall grain is statistically significant. This suggests that the decline of temperature sensitivity is prevalent for grain crops rather than only exists for corn and soybeans. As the single-season rice is only planted in a few counties of northern China, the sample size for the single-season rice is not large enough to generate an inferential estimate of temperature sensitivity. The point estimates for the multiple-season rice are much smaller than those for the single-season rice because the temperature sensitivity of the former is moderated by the paddy field just like the function of irrigation.

6.2. Mechanisms: Estimating adaptation effects of agricultural inputs

The analysis in Section 6.1 showed a large decline in the temperature sensitivity of crop yields. The question that arises is why the temperature sensitivity declines over time periods. We address this

Table 3
Interaction effects of inputs with high temperatures.

	(1) Log Yields	(2) Log Yields	(3) Log Yields	(4) Log Yields	(5) Log Yields
	A. Interaction effects for corn				
GDD above T	−0.2976***	−0.1471***	−0.1637***	−0.1512***	−0.2704***
	(0.0393)	(0.0259)	(0.0315)	(0.0255)	(0.0397)
GDD above T × Irrigation (%)	0.2522***				0.2815***
	(0.0452)				(0.0498)
GDD above T × Machinery (kW/Ha)		0.0013			−0.0045
		(0.0023)			(0.0029)
GDD above T × Fertilizer (Ton/Ha)			0.0833		−0.1304
			(0.0815)		(0.0958)
GDD above T × Electricity (kWh per capita)				0.0236	0.0173
				(0.0328)	(0.0227)
T Threshold	28 °C	28 °C	28 °C	28 °C	28 °C
P Threshold	51 cm	51 cm	51 cm	51 cm	51 cm
Inputs Included	Irrigation	Machinery	Fertilizer	Electricity	All Combined
	B. Interaction effects for soybeans				
GDD above T	−0.1937***	−0.1275***	−0.1265***	−0.1140***	−0.2113***
	(0.0391)	(0.0231)	(0.0230)	(0.0235)	(0.0425)
GDD above T × Irrigation (%)	0.1384***				0.1507***
	(0.0495)				(0.0527)
GDD above T × Machinery (kW/Ha)		0.0006			−0.0004
		(0.0005)			(0.0036)
GDD above T × Fertilizer (Ton/Ha)			0.0026		0.0063
			(0.0023)		(0.0252)
GDD above T × Electricity (kWh per capita)				−0.0159	−0.0190
				(0.0230)	(0.0257)
T Threshold	26 °C	26 °C	26 °C	26 °C	26 °C
P Threshold	44 cm	44 cm	44 cm	44 cm	44 cm
Inputs Included	Irrigation	Machinery	Fertilizer	Electricity	All Combined
Observations	59,255	59,229	59,229	59,169	59,136
R squared	0.8663	0.8686	0.8686	0.8419	0.8702

Notes: The dependent variables are log annual yields of corn or soybean for all the regressions. Each column corresponds to a separate regression varying on the number of inputs that are investigated. Precipitation and additional climate variables including relative humidity, sunshine duration, wind speed, evaporation, and ground temperatures are controlled for in all the regressions. The standard errors are clustered at county level and the regressions are weighted by annual corn planted area. All the regressions take into account county fixed effects, province-year fixed effects, and county-specific quadratic time trends. For simplicity, only the number of observations and R squared for regressions on corn are reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

question in two steps. The first step estimates the marginal adaptation effects of agricultural inputs, which is the parameter of $\partial^2 F/\partial T \partial x$ in the conceptual framework of Section 3. It also helps us determine which inputs contribute to the decline in temperature sensitivity of crop yields. The marginal adaptation effects are estimated by the interactions of extreme high temperatures with quantities of inputs in Eq. (4).

We now describe the estimation results of Eq. (4), the augmented model to quantify how agricultural inputs moderate the impacts of extreme temperatures on crop yields. The data allows us to examine four inputs. Table 3 reports the direct effects of exposure to extreme temperatures on the two crops and the interaction effects between the extreme temperature variables and input variables.[18] Each interaction effect captures how the extreme temperature impacts on yields have been moderated by marginal increase in the corresponding input, i.e., the marginal adaptation effect of each input. We consider the specification in which each input enters individually (Columns 1–4 in Table 3) as well as the one in which all the inputs enter the same specification (Columns 5 in Table 3).

Columns 1 in Table 3 show that the diffusion of irrigation is associated with a sizable and significant decrease in crop yield loss due to extreme temperatures. In Table 3, an expansion of irrigation coverage from 0% to 100% in a county is associated with a reduction in the impact of 100-day exposure to extreme temperatures on corn (soybean) yields by 25 to 28 (13 to 15) percentage points on average. On the contrary, none of the other three inputs generate significant reduction in the extreme temperature impacts on crop yields.

Endogeneity of the agricultural inputs may lead to biased estimation of the adaptation effects of inputs. There are three pieces of evidence that lend credibility to the OLS estimation of adaptation effects of inputs. First, we examine the responses of agricultural inputs to high temperature shocks. Table C.2 in Appendix C.1 demonstrates that input adjustment is not significantly associated with high temperature shocks, which suggests that the investigated inputs are less likely to co-vary with unobserved adaptation strategies that may confound the effects of the investigated inputs.

Second, as a placebo test, we show that none of the inputs moderates the yield sensitivity to low temperatures, suggesting that adoption of these adaptation strategies is not coincident with factors that determine the overall crop yields. The results are provided in Table C.3 in Appendix C.1. Third, we add a temperature-by-year trend and interactions of temperature with factors that may affect farmers' decision

[18] Labor is also an important input but the dataset only provides observations of the aggregate labor input for cropping, forestry, husbandry, fishery and agricultural manufacturing, which cannot be an accurate measure of the labor input for each crop. We provide the results for the interaction model incorporating aggregate labor input and compare the adaptation effect of labor with the counterparts of other inputs in Table C.1. We do not find either statistically or economically significant adaptation effect of labor.

making on input utilization to Eq. (4) to account for confounding factors that co-vary with the inputs following Barreca et al. (2016).[19] Table C.4 in Appendix C.1 presents the results of this robustness analysis.[20] Comparison of Table C.4 with Table 3 suggests that controlling for potential confounding factors through the above specifications does not significantly change the estimates of the adaptation effects of inputs. The robustness analysis thus supports the key finding that irrigation is the central adaptation input among the four examined ones.

Based on the estimated marginal adaptation effects of the four inputs, it becomes evident that irrigation plays a crucial role in driving the decline of extreme temperature effects. Therefore, the next step in understanding the reduction in temperature sensitivity involves calculating the degree to which irrigation has expanded across the country and quantifying its contribution to the decline in temperature sensitivity. As Figure A.7 in Appendix A.1 demonstrates significant variations in the extent of irrigation expansion, the role of irrigation in moderating yield sensitivity to extreme high temperatures is contingent upon the extent of irrigation coverage growth. Consequently, our investigation focuses on the heterogeneous evolution of temperature sensitivity in relation to the extent of irrigation expansion.

We estimate a triple-interaction panel model in Equation (C.2) of Appendix C.2 which allows period-specific temperature effects to vary across categories indicating the extent to which irrigation expanded. The 25th, 50th, and 75th percentile of the difference in irrigation coverage between pre-1996 period and post-1996 period are −0.022, 0.029, and 0.095, respectively, whereby we can classify the whole sample into four categories with different extent of irrigation change over time periods.[21] Figure C.1 reports the results for the heterogeneous irrigation effects. Notably, our findings show that a decrease in temperature sensitivity is primarily observed in counties with irrigation expansion, implying that irrigation plays a significant role in mitigating the impact of extreme temperatures on crops.

Next, we proceed to assess the contribution of irrigation expansion to the overall adaptation effects, specifically the proportion of the decline in temperature sensitivity that can be attributed to irrigation expansion. As indicated in Table 3, increasing irrigation coverage from 0% to 100% is associated with a substantial 25–28 percentage-point reduction in extreme temperature effects on corn yields. For counties experiencing irrigation expansion (i.e., above the median in irrigation coverage growth), the average change in irrigation coverage is 0.14. Consequently, this leads to a reduction of heat-related yield losses by 3.50–3.92 percentage points (ranging from 0.25×0.14 to 0.28×0.14), accounting for 29% to 34% of the overall adaptation effect, which corresponds to an 11.47 percentage-point decline in yield losses due to high temperatures. Similarly, in soybean-growing counties with irrigation expansion, the irrigation coverage increased by 13.3 percentage points between the pre-1996 and post-1996 periods, explaining about 25% to 27% of the 7 percentage-point decline in soybean yield loss.

6.3. Identifying the adaptation effect of irrigation using exogenous variations

Although variations in inputs over time have exogenous characteristics and the estimation is robust to specifications with confounding factors, the evidence on adaptation effects of inputs is only suggestive rather than causal. We present a causal framework that leverages quasi-experimental variations in irrigation to investigate whether the expansion of irrigation coverage through an irrigation project mitigates the effects of extreme high temperatures on crop yields. We first investigate the treatment effect of irrigation project on irrigation coverage using temporal and spatial variation of the treatment. This approach aims to demonstrate the quasi-experimental nature of the irrigation variation within the project. We then estimate a two-way fixed effect model that incorporates an interaction between extreme high temperatures and the project implementation designated by the project. This analysis aims to explore the extent to which the irrigation project mitigates the effects of high temperatures.

6.3.1. Quasi-experimental variation in irrigation coverage

We employ a DID model to validate the quasi-experimental nature of the variation in irrigation coverage. In order to demonstrate the validity of the difference-in-differences (DID) approach concerning parallel pre-treatment trends, we perform an event study analyzing the irrigation project's impact on irrigation coverage over time. The results are shown in Fig. 5. Panels (a) and (b) show the trends of project treatment effects on irrigation coverage for counties that have planted corn and soybeans intensively (counties that never planted corn or soybean are excluded from the sample). None of the pre-treatment indicators show any statistical significance suggesting that the treated and control counties have similar time trends at least 10 years before implementation of the project. Meanwhile, the coefficients become significant and increase gradually after 1996. The event study verifies that the irrigation project has caused substantial variations in irrigation across places over time.

Table 4 reports the average treatment effect of the irrigation project on irrigation coverage over years using the difference-in-differences approach. Columns 1 and 3 report the results for specifications controlling for county-specific fixed effects and province-year fixed effects. For both corn and soybean counties, irrigation coverage has significantly increased by about 16 percentage points. Columns 2 and 4 show the results for specifications adding county-specific time trends which absorb unobserved factors that lead to smooth change in irrigation. Although the treatment effect decreases due to the county-specific time trends, the irrigation coverage has significantly increased by about 7 percentage points. The average treatment effect is significant over specifications implying that the relationship between the irrigation project and irrigation access is strong.

Irrigation may be substituted by other inputs in counties in absence of irrigation expansion. We check whether inputs other than irrigation are more responsive to high temperatures in counties with irrigation expansion to a lower extent. We classify counties in terms of irrigation expansion. First, we estimate the heterogeneous responsiveness of inputs other than irrigation to high temperatures by the treatment status for corn and soybean counties. The results are reported in Table C.6 of Appendix C.3, which shows that there is no significant difference in the responsiveness of inputs to high temperature shocks between counties that are treated by the irrigation project and those that are not. Second, we estimate the heterogeneous responsiveness of inputs other than irrigation to high temperatures by the extent of irrigation expansion for corn and soybean counties. The results are reported in Table C.7 of Appendix C.3, which shows that there is no significant difference in the responsiveness of inputs to high temperature shocks between counties with irrigation expansion to a higher extent and those otherwise.

[19] Our new data source–*the Statistical Yearbook of Chinese Cities(1984 to 2010)* allows us to control for prefecture-level GDP and tons of cargo that is transported by road as a proxy for local infrastructure development, both of which are positively correlated with input utilization. But the Statistical Yearbook of Chinese Cities only provides data in the prefecture level which consists of several counties. It is reasonably to assume that counties in a more prosperous prefecture are highly likely to have a higher level of GDP than otherwise. County-level data sources such as *the Public Finance Statistical Materials of Prefectures, Cities and Counties* and *the Social and Economic Yearbook of Counties and Cities* can only provide county-level GDP since mid-1990s and lack of proxy variables for infrastructure development.

[20] Table C.5 presents the results of the same type of robustness analysis for the interaction effects between inputs and low temperature variables in Appendix C.1.

[21] We classify all the counties into four categories based on the distribution of irrigation variation: strictly below the 25th percentile, above the 25th percentile but strictly below the median, above the median but strictly below the 75th percentile, and above the 75th percentile. More details are referred to Appendix C.2.

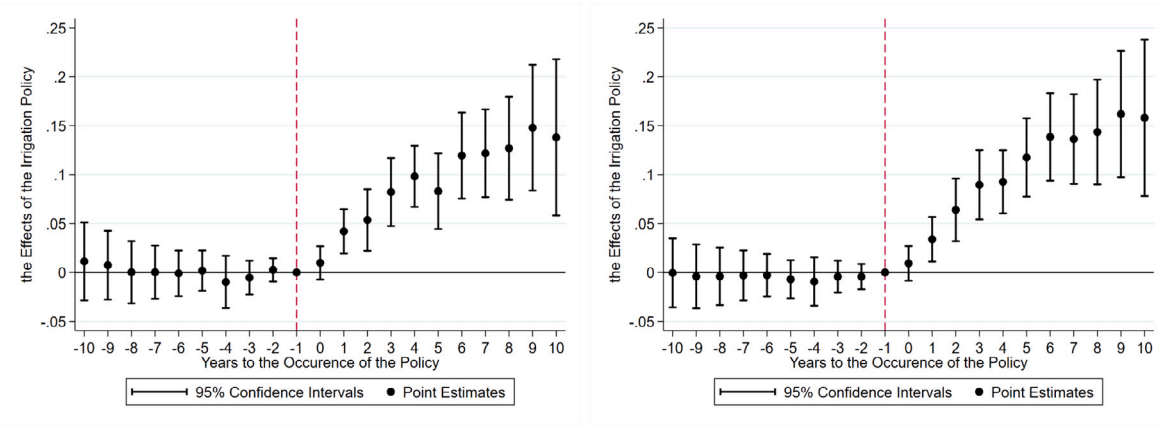

Fig. 5. Event study: the treatment effects of the irrigation expansion project over time.
Notes: Data is missing for counties that never planted corn or soybean from 1981 to 2010. Counties that did not plant corn during the period from 1981 to 2010 have been removed from the sample, leaving a total of 2301 counties that are referred to "corn sample". Similarly, "soybean sample", which follow the same criteria, are composed of 2194 counties. 295 out of the 300 treated counties as the pilots for irrigation expansion can be observed in our data (the rest 5 treated are state-owned farms which cannot be observed in the agricultural data). Both of the two event studies take into account county fixed effects, province-year fixed effects, and county-specific quadratic trends and employ the county-level clustering robust standard errors. The point estimates and the corresponding 95% confidence intervals are depicted in the figure.

Table 4
Treatment effect of the national irrigation project on irrigation coverage.

	(1) Irrigation Coverage	(2) Irrigation Coverage	(3) Irrigation Coverage	(4) Irrigation Coverage
Irrigation Project	0.1662***	0.0715***	0.1623***	0.0787***
	(0.0078)	(0.0114)	(0.0075)	(0.0104)
GDD below T	−0.0001	0.0005	−0.0061**	0.0005
	(0.0033)	(0.0030)	(0.0030)	(0.0025)
GDD above T	−0.0002	0.0084	0.0046	−0.0012
	(0.0097)	(0.0079)	(0.0069)	(0.0051)
	Corn	Corn	Soybean	Soybean
Observations	56,072	56,072	53,684	53,684
R squared	0.9227	0.9431	0.9247	0.9519
County Quadratic Trends	No	Yes	No	Yes
T Threshold	28 °C	28 °C	26 °C	26 °C
P Threshold	51 cm	51 cm	44 cm	44 cm

Notes: Columns (1) and (2) report the results for corn counties and Columns (3) and (4) do the same for soybean counties. Each column corresponds to a separate regression varying on specifications of county-specific quadratic trends. The dependent variables are irrigation coverage (the ratio of effectively irrigated area over total arable area). Irrigation Project denotes the project implementation indicator which takes the value of one for treated counties after 1996. Precipitation and additional climate variables including relative humidity, sunshine duration, wind speed, evaporation, and ground temperatures are controlled for in all the regressions. The regressor "Irrigation Project" is defined as the product of the project indicator and the indicator for the year 1996 when the project was implemented. The county fixed effects and province-year fixed effects are controlled for in all the regressions. The standard errors are clustered at county level and the regressions are weighted by annual planted area of each crop. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In order to identify the interaction effects between the irrigation project and high temperatures, we require the additional assumption that the project treatment and the temperature treatment are independent of one another, conditional on the controls such that the irrigation project would not induce use of other temperature-related adaptation instruments. Because we are relying on random weather shocks within a county-year, it is not plausible that temperature variation is related to assignment of the irrigation project treatments. But we test more directly for independence between the irrigation project and temperature by regressing project indicator showing whether a county was treated by the irrigation project in a given year on all the climate variables and find no significant relationships. The results are shown in Table C.8 of Appendix C.3. We further test whether previous climatic normals which may induce investment of stock adaptation can predict assignment of project treatments. If so, the project treatment may be correlated with stock adaptation other than irrigation, which may confound the adaptation effect of irrigation. Table C.9 in Appendix C.3 shows that previous temperature normals are not predictive of the treatment assignment.

6.3.2. The impact of irrigation expansion project in mitigating high temperature effects

In this part of analysis, we examine how the high temperature impacts on yields depend on the treatment assigned by the irrigation project. The findings are presented in Table 5. Columns 1 and 3 reports the results for specifications that control for county and province-year fixed effects but for corn sample and soybean sample, respectively. The analysis reveals that the irrigation project led to about 8-percentage-point reduction in the temperature sensitivity of yields. The overall adaptation effect estimated using the same fixed effect specification which is presented in Column 2 of Table 2 indicates a substantial 20 percentage-point decline in temperature sensitivity for corn. It is noteworthy that the irrigation expansion caused by the project treatment

Table 5
The Impact of irrigation expansion project in mitigating high temperature effects.

	(1) Log Yields	(2) Log Yields	(3) Log Yields	(4) Log Yields
Irrigation Project	−0.0401	−0.0161	−0.0592	0.0159
	(0.0946)	(0.0962)	(0.1008)	(0.1391)
GDD above T	−0.1279***	−0.1447***	−0.1097***	−0.1101***
	(0.0250)	(0.0237)	(0.0285)	(0.0215)
GDD above T × Irrigation Project	0.0790***	0.0452*	0.0779***	0.0472*
	(0.0289)	(0.0235)	(0.0264)	(0.0286)
	Corn	Corn	Soybean	Soybean
Observations	59,269	59,269	51,057	51,057
R squared	0.7948	0.8677	0.7246	0.8195
County Quadratic Trends	No	Yes	No	Yes
T Threshold	28 °C	28 °C	26 °C	26 °C
P Threshold	51 cm	51 cm	44 cm	44 cm

Notes: Columns (1) and (2) report the results for corn counties and Columns (3) and (4) do the same for soybean counties. Each column corresponds to a separate regression varying on specifications of county-specific quadratic trends. For all the regressions, the dependent variables are log crop yields for all the regressions. Irrigation Project denotes the project implementation indicator which takes the value of one for treated counties after 1996. Precipitation, interactions of precipitations with the project indicator, and additional climate variables including relative humidity, sunshine duration, wind speed, evaporation, and ground temperatures are controlled for. All the regressions take into account county fixed effects and province-year fixed effects. The standard errors are clustered at county level and the regressions are weighted by annual planted area of each crop. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

accounted for approximately 38.6% (0.079/(0.2879 - 0.0834)) of the overall adaptation effect observed in the corn sector.

Another model specification used for estimating the irrigation project effect in moderating temperature sensitivity involves adding county-specific year trends to the specifications in Columns 1 and 3. This addition helps to control for county-specific factors that lead to smooth changes in crop yields. The results, shown in Columns 2 and 4, reveal that the impact of extreme high temperatures on yields is reduced by 4.5 percentage points due to the irrigation project. Additionally, the overall adaptation effect indicates an 11-percentage-point decline in high temperature impacts on corn yields, as demonstrated in Column 3 of Table 2. Consequently, the irrigation project contributed to 40.0% (0.0459/(0.2295 - 0.1147)) of the overall adaptation effect. Similar results are observed for soybean.

Notably, the difference-in-differences (DID) estimation indicates a larger contribution of irrigation to the overall adaptation effect compared to ordinary least squares (OLS) estimation. This discrepancy may be due to the fact that investment in irrigation could potentially redirect funding away from other adaptive measures when the budget is fixed, thereby influencing the overall adaptation effect. However, the Chinese government's provision of extra financial aid for irrigation construction during the implementation of the irrigation project ensured that investments in irrigation did not compromise investments in other adaptive instruments.

Irrigation is also an important adaptive instrument for other crops. We investigate how the high temperature effects on yields of wheat, rice and the overall grain category depend on changes in irrigation coverage. We employ two specifications for measuring irrigation's impact. In the first approach, we interact irrigation coverage with all temperature and precipitation variables. To address endogeneity concerns regarding irrigation coverage, we substitute it with the irrigation project indicator in the first specification. The results for the two specifications are reported in Panel A and Panel B of Table C.10 in Appendix C.4, respectively and demonstrate consistency. We find that an increase in irrigation coverage is associated with a significant reduction in yield losses due to high temperature exposure, except for multiple-season rice, which benefits from being grown in paddy fields that can mitigate the effects of high temperature shocks, much like irrigation does.

However, there exists a caveat concerning the enduring effectiveness of irrigation in mitigating heat-related yield losses. Hornbeck and Keskin (2014) posit that irrigation might constitute a mal-adaptation. Their study reveals that the access to groundwater has led to an increase in agricultural land values. In the initial two decades (1950 to 1974) of utilizing groundwater from the Ogallala aquifer, the cultivation area for irrigated crops (which are water-intensive) substantially expanded, resulting in a diminished impact of drought. As land utilization gradually shifted towards water-intensive crops, the vulnerability to drought amplified during the period from 1976 to 1993. Our study, constrained by data limitations, prevents us from delving as extensively into the adaptive benefits of irrigation as Hornbeck and Keskin (2014) have done. Furthermore, the long-term adaptation effect of irrigation could potentially be compromised if climate change results in water shortages or if farmers respond to the expansion of irrigation by planting more water-intensive and lucrative crops. Therefore, the long-term adaptation effect of irrigation remains a subject for future research.

7. Conclusion

The goal of this paper is to understand how specific adaptation measures mitigate agricultural impacts of exposure to high temperatures and how implementation of these specific measures contributes to the overall adaptation effect. To achieve this, we leverage quasi-experimental variations in irrigation induced by a natural experiment for irrigation expansion started in 1996 and quantify the contribution of irrigation access to the overall adaptation effect. There are three primary findings. First, using a period-specific panel fixed effect model, the analysis shows a significant decline in the temperature-related yield loss in the post-1996 period compared to before, indicating an overall adaptation effect. Second, estimation of marginal adaptation effects of inputs points to irrigation as the central input for adaptation among the inputs observed in the data. Third, using the difference-in-differences approach, we show that the presence of the irrigation expansion experiment significantly mitigated the high temperature impacts on crop yields, with increased irrigation through the natural experiment accounting for about 40% of the overall adaptation effect. Our results indicate that improving irrigation access may be a useful instrument for mitigating yield loss from a warming climate.

Our findings carry significant implications for forecasting the effects of climate change and formulating policies for investment in adaptation. First, the temporal progression of temperature effects suggests that estimates concerning temperature impacts in previous periods may inaccurately portray future effects. If extreme temperature effects on agricultural outcomes declined over time, estimates of temperature sensitivity in the earlier periods may overestimate climate-change impacts in the future. Second, there exist significant prospects for mitigating the adverse effects of climate change on agriculture by harnessing

established technologies. Moreover, there are substantial opportunities to apply existing technologies across various sectors to minimize the impacts of climate change, necessitating urgent research efforts. Also of great importance is the exploration of novel technologies that hold value in an altered climate. Embracing both forms of adaptation shows immense potential, but it is essential to acknowledge that they demand resources that might otherwise be allocated to different priorities and their long-term effectiveness needs investigation.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103196.

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