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Response and adaptation of agriculture to climate change: Evidence from China☆,☆☆

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ABSTRACT

This article aims to identify the mechanism of how climate change affects agriculture through various channels and the mechanism of longer-run adaptation. Using a county-panel dataset spanning the past 35 years, we evaluate the impact of global warming on agricultural total factor productivity (TFP) as well as the impacts on agricultural inputs and outputs in China. Results show that, in the short run, extreme heat has negative effects on China's agricultural TFP and input utilization, which results in a more negative effect on agricultural output measured by yield. However, longer-run adaptation has offset 37.9% of the short-run effects of extreme heat exposure on TFP, while climate adaptation mitigates agricultural output loss to a greater extent due to more flexible adjustment in labor, fertilizer, and machines in the long run. Despite the detected climate adaptation, projections of impacts under future climate change scenarios still imply a substantial loss in China's agriculture.

1. Introduction

Mitigation and adaptation are two important tools for reducing the risks of climate change. In terms of mitigation, many international climate negotiations and agreements have been made to reduce and curb global greenhouse gas (GHG) emissions.[1] Accordingly, many countries have enacted mitigation policies to improve energy efficiency (e.g., energy conservation laws in major emitters) or to encourage the greater use of renewable energy (e.g., carbon tax and renewable portfolio standards), since emission intensity reduction is the major pathway for mitigation. In terms of adaptation, however, strategic principles, rather than operational policies, have been established to reduce vulnerability to climate change, given that the mechanism of potential adaptation to climate change is sector-specific and not clearly identified. Agriculture, in particular, is one of the most vulnerable sectors to rising temperatures and is directly affected by climate change. Therefore, more clearly understanding the mechanisms of how climate change affects agriculture and the extent of longer-run adaptation offsets could help to design better

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[1] United Nations Framework Convention on Climate Change (UNFCCC) and Kyoto Protocol are established as the framework of international pacts on dealing with climate change. Since 1995, 24 meetings have been held by UNFCCC to implement Kyoto Protocol. Among them, milestone progress includes Kyoto Protocol in 1997, Bali Roadmap in 2007, Durban Platform in 2011, and Paris Agreement in 2015. UNFCCC contains an important principle for international efforts to mitigate climate change – the Principle of Common but Differentiated Responsibility (the CDR principle) between developed counties and developing countries (Liu and Lo, 2020). See https://unfccc.int/in details.

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agricultural and climate policies.

Earlier studies in this area typically exploit cross-sectional variation (i.e., using only one observation per spatial unit) in average temperature and precipitation to examine their relationship with agricultural outcomes across locations. The cross-sectional specification has typically used cross-sectional variation to compare outcomes across different climatic areas (e.g., Mendelsohn et al., 1994; Liu et al., 2004; Schlenker et al., 2006; Wang et al., 2009). As the cross-sectional approach is prone to endogeneity issues such as omitted variable bias, newer studies typically use panel-regression approach (i.e., multiple observations for one spatial unit) to examine outcomes for a given area under different climatic conditions (e.g., Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011; Dell et al., 2012; Chen et al., 2016; Zhang et al., 2017) and many have found significant effect of global warming on agriculture.

Burke and Emerick (2016) develop a long differences approach and use the difference between panel estimates and long differences estimates to quantify agricultural adaptation. In terms of the economic outcomes of agricultural adaptation, existing research has focused on the perspectives of either land value (Mendelsohn et al., 1994) or crop yields (Schlenker and Roberts, 2009). In recent years, many studies (e.g., Wheeler and Von Braun, 2013; Pittelkow et al., 2015; Burke and Emerick, 2016) have aimed to evaluate the effect of climate change on agricultural productivity, where productivity refers to yield (i.e., land productivity). However, land productivity is not the only measure of agricultural productivity. Ruttan (2002) summarizes that comparative research on agricultural productivity has directed at the measurement of single/partial factor productivity (such as labor productivity or land productivity) in the past and on total factor productivity (TFP) in recent years. Single factor productivity, such as land productivity, only considers one input and is easy to calculate when agricultural output and land area are available. Total factor productivity, on the other hand, takes all inputs into consideration and therefore better measures technological progress and technical efficiency in the agriculture sector (Gong, 2020a).

In recent years, agricultural input portfolios in different places have become more diversified, which enlarges the gap between land productivity and TFP. Therefore, it is necessary to study the effect of climate change on TFP in addition to its impact on yield, which is relatively understudied in literature. Moreover, studying the response of TFP on climate change helps to identify the mechanism of how climate change eventually affects yield. With a few exceptions (e.g., Aragón et al., 2020), most existing researches (Schlenker and Roberts, 2009; Burke and Emerick, 2016) estimate the overall impact of climate change on yield rather than broken down change in yield into change in TFP and changes in other inputs based on productivity analysis. Understanding how climate change affects yield though its impact on TFP and input utilization helps to better analyze adaptation behaviors in the past and shed light on future adaptation in agricultural production.

With a few exceptions (Welch et al., 2010; Lobell et al., 2011; Chen et al., 2016; Zhang et al., 2017), most economic analyses examining the effects of climate change on agriculture have focused more on developed countries (see a detailed review in Dell et al. (2014)). However, the development of agriculture may be more important in developing countries since it is a vital and unique instrument for achieving poverty reduction and sustainable development (Thirtle et al., 2003; Mondiale, 2008; Zhang et al., 2020). Considering that three-quarters of poor populations make a living from agriculture, it is not only important but necessary to investigate the response of agriculture on climate change in developing countries. Moreover, such an impact is likely to be negative in most areas, and is harder to adapt to or prevent in developing countries due to a lack of funding and technology. Therefore, the impacts of climate change on agricultural production in developing countries are worth studying, which will help to better move climate and industrial policies forward.

This article aims to evaluate the responses and adaptations of agricultural TFPs to climate change in China, which is the largest global emitters and largest developing country boasting the largest agricultural economy and population. China's mitigation policy aims at reducing GHG emissions intensity, through industrial structure adjustment, energy consumption structure optimization, energy efficiency improvement, carbon sequestration capacity enhancement, and pilot carbon trading, among others. By 2017, carbon intensity in China had dropped by about 46% compared with 2005. In terms of adaptation policies, apart from *China's National Climate Change Programme*, we have been unable to find policies at the national level specifically targeting agricultural adaptation to climate change. However, some other policies, such as the "One Exemption and Three Subsidies" policy,[2] are not only designed to ensure food security and increase farmers' income, but also improve agricultural adaptation to climate change. This is because they not only encourage innovation and adoption of heat-resistant and drought-resistant species that can reduce productivity loss, but also motivate more investments in agriculture. Understanding how these policies mitigate agricultural losses in the context of global warming through two channels including productivity and input utilization, is of great significance for developing more effective adaptation policies. Hence, this article also aims to identify the mechanism by which climate change affects yield through its impact on TFP and input utilization, as well as the mechanism of adaptation behaviors of Chinese farmers. The data used for this study comes from two sources. On the one hand, a county-year panel data for 2495 counties consisting of specific agricultural inputs and outputs over the period of 1981–2015 is used to construct four agricultural TFP measures under various specifications to rule out the effect of labor, fertilizer and machinery on yield. On the other hand, comprehensive daily weather records from 820 weather stations are merged to these 2495 counties using the inverse distance weighting method (IDW), which makes it possible to further investigate how inputs and TFPs are affected by climate change.

We combine the strength of existing literature to investigate the nonlinear relationship between agricultural TFPs and variation in temperature and other weather variables. This article follows two representative approaches introduced by Schlenker and Roberts (2009) in panel regressions: 1) a simple piecewise linear function of temperature and construct the variables of growing degree days (GDDs) below and above a selected threshold and 2) more specific temperature bins that calculate the accumulation of heat for each 3–6 °C temperature interval. The simultaneous variations in additional weather variables, such as rainfall, sunshine duration, humidity, and wind force are also taken into account (Zhang et al., 2017). Panel estimates suggest that piecewise linear function yields results similar to those estimated using more complicated functional forms. An increase in exposure to temperatures above 33 °C results in sharp declines in agricultural TFPs. We use the same methods to evaluate the impact of climate change on yield (measured by unit land output value) and find it to be more negative than the impact on agricultural TFP, as we expected, since extreme hot weather may also lower input utilization in the short run. Applying the same approach, we find evidence that labor and fertilizer usage is indeed significantly reduced with an increase in exposure to high temperature.

To investigate whether longer-term adjustment to climate change has significantly exceeded shorter-run adjustment, we follow Burke and Emerick (2016) to compare the panel estimates with the long differences estimates. Long-run adaptations appear to have mitigated 37.9% (95% confidence interval [CI], 5.3%–54.8%) of the short-run impacts of extreme heat exposure on China's agricultural TFPs. In terms of yield, 46.8% (95% CI, 30.2%–58.0%) of the short-run effect is offset in the long run, which is larger than the offset in TFP, implying the existence of adaptation in input usage. Comparing the panel estimates with the long differences estimates of inputs, we find that adaptation indeed occurred in all three inputs. The negative impact of climate change in labor and

[2] direct subsidies, subsidies for improved varieties and subsidies for the purchase of agricultural machinery.

fertilizer is smaller, and a positive effect on machinery is found in the long run, indicating that farmers use more machines to replace labor when the weather gets hotter. This finding provides new evidence for the induced innovation theory proposed by Hayami and Ruttan (1971).

Our findings remained remarkably robust when alternative methods to merge climate and agriculture data, alternative temperature bins, alternative productivity measures, and alternative estimation strategies are adopted. Using the estimated coefficients, together with different future climate change scenarios, we further projected the effect of future warming on China's agriculture. China's agricultural TFP is projected to decline by 2–6% by 2050 and by 4–12% by 2070 under the global climate models HadGEM2-ES and NorESM1-M. The decline in agricultural yield is projected to be nearly twice as large as the reduction in agricultural TFP in the future. Although climate adaptation is occurring, future global warming is still expected to make a significant negative effect on China's agricultural production. This effect is likely to increase in the long term, relative to the midterm. This means that the earlier the mitigation actions are taken, the better the policy effects will be.

This article contributes to the existing literature in three major aspects. First, both yield and total factor productivity are adopted to estimate the impact of climate change on agriculture, where the latter is a better measure of agriculture productivity, but understudied in climate change literature. Second, to our best knowledge, this is the first article that identifies not only the mechanism by which climate change affects yield through its impact on TFP and input utilization, but also the mechanism of the adaptation behaviors. Third, we provide some of the earliest empirical evidence of nonlinear temperature effects and significant adaptation behaviors on agriculture in China based on a long study period of 35 years and a specific spatial pattern at the county level.

The remainder of this article is organized as follows. Section 2 investigates the mechanism and proposes hypotheses. Section 3 introduces the econometric model and Section 4 describes the data. Empirical results are presented and analyzed in Section 5. Section 6 builds a projection of future impacts and Section 7 concludes the article.

2. Mechanism

This section introduces the mechanism of agricultural response and adaptation to climate change. For illustration purposes, consider a Cobb-Douglas production function of agriculture in the form:

$$y = f(\boldsymbol{X};\boldsymbol{\beta}) + tfp = \boldsymbol{X\beta} + tfp \tag{1}$$

where y represents yield (i.e., agricultural output per hectare) in logarithm; $f(\boldsymbol{X};\boldsymbol{\beta})$ measures the input-output relationship of the agricultural production process; $\boldsymbol{X} = c(l, f, m)$ vectors agricultural inputs per hectare, including labor (l), fertilizer (f) and machinery (m), all in logarithm; $\boldsymbol{\beta} = c(\beta_1, \beta_2, \beta_3)$ vectors the coefficients of inputs; and tfp accounts for agricultural total factor productivity in logarithm.

Many scholars (e.g., Mendelsohn et al., 1994; Schlenker et al., 2006; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011; Burke and Emerick, 2016) have studied the overall impact of climate change on land productivity. This article argues that total factor productivity is a better measure of productivity since it considers all the inputs in addition to land. Eq. (1) helps establish the relationship between the total factor productivity that we focus on in this article and the land productivity (yield) widely adopted in literature. According to the production function in Eq. (1), climate change may affect yield through two channels: its impact on the utilization of various inputs (i.e., $\boldsymbol{X}$) and its impact on total factor productivity (i.e., tfp).

Let's assume that farmers choose an optimal input portfolio and suitable technology at year t based on previous weather conditions. On the one hand, extreme heat may lead to lower agricultural outputs, even if input utilization remains unchanged, since hot weather can affect normal growth of the crops and lower production efficiency from other pathways.[3] This can result in a negative response of TFP on climate change ($\Delta tfp^{sr} < 0$), which leads to the first hypothesis:

Hypothesis 1. *Climate change has a negative impact on TFP in the short run.*

On the other hand, when suffering from extreme heat, farmers may reduce outdoor farming activities and therefore lead to lower labor inputs ($\Delta l^{sr} < 0$), which may consequently reduce the application of fertilizer ($\Delta f^{sr} < 0$) in the short run. Meanwhile, farmers may have a limited ability to change capital stock, for example, to buy new machines to replace labor force in the short run ($\Delta m^{sr} \approx 0$). As a result, the input portfolio is no longer optimal and leads to a negative impact on agricultural yield due to climate change ($\beta_1 \Delta l^{sr} + \beta_2 \Delta f^{sr} + \beta_3 \Delta m^{sr} < 0$). Accordingly, this article proposes a second hypothesis:

Hypothesis 2. *Climate change has negative impacts on labor and fertilizer utilization but no significant impact on capital stock (machinery) in the short run.*

Moreover, considering the first two hypotheses and the production function in Eq. (1), the impact of climate change on yield is more negative than its impact on TFP, as $\Delta y^{sr} = \beta_1 \Delta l^{sr} + \beta_2 \Delta f^{sr} + \beta_3 \Delta m^{sr} + \Delta tfp^{sr} < \Delta tfp^{sr} < 0$, which leads to the third hypothesis:

Hypothesis 3. *Climate change has a more negative impact on yield than on TFP in the short run.*

Besides its response to climate change, this article also aims to analyze the adaptation of agriculture to climate change in the long run. Once again, the mechanism of agricultural adaptation can be illustrated using the production function. On the one hand, in the context of global warming, farmers may adopt heat-resistant types of crops, and research institutes may invent new varieties that can better adapt to hot weather, which could reduce the negative impact of climate change on agricultural TFP ($\Delta tfp^{sr} < \Delta tfp^{lr} < 0$). Accordingly, this article proposes the fourth hypothesis:

Hypothesis 4. *Climate change has a less negative impact on TFP in the long run than in the short run, which implies adaptation in TFP.*

On the other hand, farmers may find more ways to fight against hot weather when it occurs more frequently in the long run, such as new medicines to prevent heatstroke and working more at dawn and dusk, rather than in the heat of the day. These adaptations can reduce the negative impact of climate change on labor supply ($\Delta l^{sr} < \Delta l^{lr} < 0$) and thus reduce the negative impact on fertilization application ($\Delta f^{sr} < \Delta f^{lr} < 0$). Moreover, farmers may invest more in machinery to overcome labor shortage in the long run ($\Delta m^{lr} > \Delta m^{sr} \approx 0$). As a result, the fifth hypothesis is:

Hypothesis 5. *Climate change has fewer negative impacts on labor and fertilizer utilization and a positive impact on capital stock (machinery) in the long run, which implies adaptation in all three inputs.*

Considering both the fourth and fifth hypotheses, and the production function in Eq. (1), this article derives $\Delta y^{lr} - \Delta y^{sr} = \beta_1(\Delta l^{lr} - \Delta l^{sr}) + \beta_2(\Delta f^{lr} - \Delta f^{sr}) + \beta_3(\Delta m^{lr} - \Delta m^{sr}) + (\Delta tfp^{lr} - \Delta tfp^{sr}) > 0$, which implies less of a negative impact of climate change on yield in the long run than in the short run, as is stated in the sixth hypothesis:

Hypothesis 6. *Climate change has a less negative impact on yield in the long run than in the short run, which implies adaptation in yield.*

Finally, the adaptation in yield is greater than the adaptation in TFP ($\Delta y^{lr} - \Delta y^{sr} > \Delta tfp^{lr} - \Delta tfp^{sr}$), since farmers can also adjust their input portfolio to adapt to climate change. Therefore, this article proposes a

[3] For example, Gong et al. (2020) point out climate change has accelerated the evolution and spread of pathogens, which can reduced agricultural TFP during the epidemic period.

seventh hypothesis:

Hypothesis 7. *The adaptation in yield is greater than the adaptation in TFP.*

Aside from these seven hypotheses, whether the response to climate change on yield is greater or lesser than the response on TFP in the long run is unknown ($\Delta y^{lr} - \Delta tfp^{lr} = \beta_1 \Delta l^{lr} + \beta_2 \Delta f^{lr} + \beta_3 \Delta m^{lr}$, where Δl^{lr} and Δf^{lr} are negative, and Δm^{lr} is positive). If the adaptations in all three inputs are quite small, Δl^{lr} and Δf^{lr} will be more negative and Δm^{lr} will be less positive, meaning that climate change will have a more negative impact on yield than on TFP in the long run, similar to the situation in the short run. However, if the adaptations in all three inputs are quite large, climate change will have a less negative impact on yield than on TFP in the long run.

To summarize, this article predicts that, in the short run, climate change 1) has negative impacts on labor and fertilizer utilization, but no significant impact on capital stock (machinery), and 2) has a negative impact on TFP and a more negative impact on yield. In the long run, we expect adaptations to exist in all three inputs, and the adaptation in yield is greater than the adaptation in TFP. Fig. 1 summarizes the mechanism and hypotheses constructed in this section.

3. Model

This section first introduces a stochastic frontier analysis that models the agricultural production process and estimates agricultural TFPs. We then employ the panel approach introduced by Schlenker and Roberts (2009) to estimate the short-run impacts of global warming on agriculture (including input utilization, TFP, and yield), as well as the long differences approach developed by Burke and Emerick (2016) to estimate the long-run impacts. Finally, the difference between the panel estimates and the long differences estimates can derive climate adaptations during our study period.

3.1. Agricultural TFP estimates

The stochastic frontier model, proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), is a popular approach to estimate TFP (e.g., Campbell and Hand, 1998; Sherlund et al., 2002; Bos et al., 2010; Jin et al., 2010; Kilby, 2015; Gong, 2018b). Consider a Cobb-Douglas (C-D) stochastic frontier model in the form:

$$y_{it} = \alpha + \beta_1 l_{it} + \beta_2 f_{it} + \beta_3 m_{it} + \lambda_t - u_{it} + v_{it} \tag{2a}$$

where y_{it} represents yield in county i at time t, while l_{it}, f_{it}, and m_{it} separately account for labor, machinery, and fertilizer input per hectare, all in logarithm. Total factor productivity can be derived by $tfp_{it} = \exp(\alpha + \lambda_t - u_{it})$, where α is the intercept, λ_t measures year fixed effects, and u_{it} accounts for technical inefficiency. This article follows Battese and Coelli (1992) and Gong and Sickles (2020) to employ the most widely used "Error Components Frontier" that models the inefficiency $u_{it} = \exp(-\eta(t-T))u_i$, where u_i is an i.i.d. non-negative truncation of the $N(\lambda, \sigma^2)$ distribution. v_{it} is a normally distributed disturbance.

This article employs several approaches to check the robustness of the production function and TFP estimates. First, this article uses the method in Sheng et al. (2019a) to relax the constant returns to scale assumption of the production function. Second, this article follows Gong (2020b) to use a conventional production function to derive TFPs and compare the results with the ones estimated by the stochastic frontier model. Third, this article also adopts a Transcendental Logarithmic (T-L) specification (Christensen et al., 1973; Wang et al., 2016; Gong, 2018a) rather than the Cobb-Douglas specification. A Transcendental Logarithmic stochastic frontier model has the following form:

$$\begin{aligned} y_{it} = {} & \alpha + \beta_1 l_{it} + \beta_2 f_{it} + \beta_3 m_{it} + \beta_4 l_{it}^2 + \beta_5 f_{it}^2 + \beta_6 m_{it}^2 + \beta_7 l_{it} f_{it} + \beta_8 l_{it} m_{it} \\ & + \beta_9 f_{it} m_{it} + \lambda_t - u_{it} + v_{it} \end{aligned} \tag{2b}$$

3.2. Panel estimates

The panel approach typically uses panel data to investigate the agricultural outcome response to short-run variation in weather. Past literature (e.g. Schlenker and Roberts, 2009; Chen et al. (2016)) uses the concept of growing degree days (GDD hereafter) to capture the nonlinear relationship between agricultural outcomes and variation in temperature. GDD measures the amount of time exposure to temperatures between a given lower and upper bound. Standard practice calculates the percentage of each day that a country's temperature is between the given bounds, and then sums over daily exposures to arrive at an annual GDD. For each day, the within-day distribution of temperatures is constructed using daily maximum and minimum temperatures and fitted by a sine curve (Baskerville and Emin (1969); Allen (1976); hereafter the sine curve approach).

The predetermined definition of temperature bounds for GDD generates two panel estimates—the temperature bins approach and the piecewise linear approach—as illustrated by the following two equations:

$$z_{it} = \sum_m \beta^m Tbin_{it}^m + \boldsymbol{W_{it}\gamma} + c_i + \lambda_t + \varepsilon_{it}, \tag{3}$$

$$z_{it} = \beta_1^{FE} GDD_{it}^{l_0:l_1} + \beta_2^{FE} GDD_{it}^{l_1:l_\infty} + \boldsymbol{W_{it}\gamma} + c_i + \lambda_t + \varepsilon_{it}. \tag{4}$$

Equation (3) demonstrates the temperature bins approach, z_{it} refers to variables of interest, which can be agricultural TFP, yield, or input utilization. $Tbin_{it}^m$ denotes the heat accumulation in county i and year t when temperature is in the mth temperature bound during the whole year using the sine curve approach. In the baseline, this article constructs temperature factors using temperature bounds for each 3 °C interval. Specifically, we divided daily temperatures, calculated in °C, into fourteen

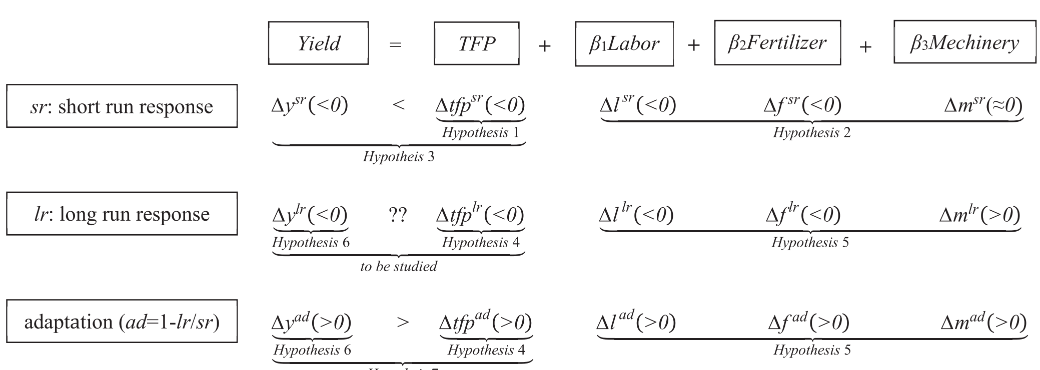


Fig. 1. Mechanism and hypotheses constructed in this paper. *Notes*: This figure demonstrates the mechanisms and hypotheses 1–7 in this article; see text in details.

temperature bins, each of which was 3 °C wide. We defined $Tbin_{it}^{1}$ = heat accumulation when temperature was in the range of [0 °C, 3 °C), $Tbin_{it}^{2}$ = heat accumulation when temperature was in the range of [3 °C, 6 °C), and so on. Finally, $Tbin_{it}^{13}$ equals heat accumulation when the temperature was over 36 °C. As robustness checks, we also construct $Tbin_{it}^{m}$ by each 4 °C, 5 °C, and 6 °C temperature interval, respectively.

To isolate the impacts of temperature on agricultural outcomes, linear and quadratic terms of the daily averages of rainfall, sunshine duration, relative humidity, and wind force are controlled as covariates and represented by $\boldsymbol{W}_{it}$ (Zhang et al., 2017). County fixed effects (c_i) were included to account for unobserved time-invariant characteristics that was specific to county i, such as soil quality and geographic features. Year fixed effects (λ_t) were also included to control for any factors that affect all counties similarly in a given year. β^m are the coefficients of interest. The main purpose in Eq. (3) is to test whether $\beta^m = 0$, namely to test the null hypothesis that the mth temperature bin has no impact on agricultural outcomes.

The piecewise linear approach demonstrated in Equation (4) can be considered a special case of the temperature bin approach in Equation (3), when daily temperatures are only divided into two intervals, below and above the temperature threshold l_1. The heat accumulation in county i and year t when temperature is in either [l_0°C, l_1°C) or above l_1 during the whole year are again calculated using the sine curve approach, denoted by $GDD_{it}^{l_0:l_1}$ and $GDD_{it}^{l_1:l_\infty}$. Following Schlenker and Roberts, 2009, we loop all possible temperature thresholds and choose the best-fitting one for specific agricultural outcomes. In such specification, the nonlinear effect of temperature on agricultural is reflected by the distinction between β_1 and β_2.

3.3. Long differences approach

The long differences approach is typically employed to estimate how agricultural outcomes respond to long-run changes in climate. The long-run change is constructed by the difference between two different points in time for a given region. Using agricultural yield as an example of the variable of interest (z), consider two periods, denoted "a" and "b", where the long run difference is calculated by $\Delta\overline{z_i} = \overline{z_{ia}} - \overline{z_{ib}}$. To avoid inaccurate calculation using a single year, existing literature suggests the use of averages by multi-year periods. If each period spans "n" years, the average agricultural yield "z" in period "a" is given by $\overline{z_{ia}} = \left(\sum_{t\in a} z_{it}\right)/n$, while the average agricultural yield "z" in period "b" is given by $\overline{z_{ib}} = \left(\sum_{t\in b} z_{it}\right)/n$. After performing the same transformation for all variables in Equation (4), the time-invariant factors drop out, and the resulting long-run difference equation is:

$$\Delta\overline{z_i} = \beta_1^{LD}\Delta\overline{GDD_i^{l_0:l_1}} + \beta_2^{LD}\Delta\overline{GDD_i^{l_1:l_\infty}} + \Delta\overline{\boldsymbol{W}_i}\boldsymbol{\gamma} + \Delta\overline{\varepsilon_{it}} \tag{5}$$

In long differences estimation, we follow Burke and Emerick (2016) to use the piecewise linear approach for three reasons. First, past literature on both the U.S. and Chinese agricultural response to climate change suggests that a simple piecewise linear function yields results similar to the ones estimated by the temperature bins approach, where the latter approach has much more complicated function forms (Schlenker and Roberts, 2009; Chen et al., 2016; Zhang et al., 2017). Second, as demonstrated in Equation (5), the long differences estimation is based on cross-sectional data with a much smaller sample size (compared with panel data), which may not have enough degrees of freedom when the temperature bins approach is adopted. Third, the temperature bins approach delivers estimations of much more coefficients, which makes the evaluation of adaptation more complicated.

To eliminate any concerns of time-varying unobservable factors that possibly correlate with both climate and agricultural outcomes in Equation (5), Burke and Emerick (2016) establish a two-period panel of long differences, which divides the dataset into two subsamples, one for the first half of the period and the other for the second half of the period. For each subsample, this approach adopts the long differences method in Equation (5). In this way, we eventually obtain a separate two-period Equation (5). We then append and estimate the following two-period long differences panel model:

$$\Delta\overline{z_{it}} = \beta_1^{LD}\Delta\overline{GDD_{it}^{l_0:l_1}} + \beta_2^{LD}\Delta\overline{GDD_{it}^{l_1:l_\infty}} + \Delta\overline{\boldsymbol{W}_{it}}\boldsymbol{\gamma} + c_i + \lambda_t + \Delta\overline{\varepsilon_{it}} \tag{6}$$

where t refers to the first and second period. Although this two-period panel approach of long differences eliminates the concern of time-varying unobservable factors, it requires panel data with a longer period. With this concern, Burke and Emerick (2016) treat long differences method as the benchmark approach and panel long differences as a robustness check when analyzing 40 years of U.S. agricultural data. Since our Chinese agricultural panel data covers 35 years, this article also adopts long differences as the benchmark approach and uses panel long differences to confirm its robustness.

3.4. Long-run adaptation and offset

The basic idea to quantify past climate adaptation is to compare the short-run impacts delivered from the panel estimates with the long-run impacts delivered from the long differences estimates. Climate adaptation is observed if the short-run effect is offset in the long run. Since we illustrate that a piecewise linear approach is preferred in long differences estimate to predict the long-run impact, this article also treats the piecewise linear approach in Eq. (4) as the main model to evaluate the short-run effect of climate change on agricultural TFP, yield, and input utilization. On the other hand, the temperature bins approaches with various temperature intervals are estimated as robustness checks of short-run impacts.

Given the long differences estimates and panel estimates above, Burke and Emerick (2016) suggest that the value $1 - \beta_2^{LD}/\beta_2^{FE}$ can be interpreted as the overall negative short-run effect that is compensated in the long run, which is our estimation of adaptation to extreme heat. In addition to the point estimate given by $1 - \beta_2^{LD}/\beta_2^{FE}$, the distribution of bootstrapped adaptation estimates make it possible to test, for each time period, the null hypothesis of "zero adaptation" to extreme heat, i.e., $1 - \beta_2^{LD}/\beta_2^{FE} = 0$.

4. Data and descriptive statistics

4.1. Agriculture

An unbalanced county-level panel for 2495 counties from 1981 to 2015 in mainland China with a total of 71,047 observations is collected from the County-level Agricultural Database by the Ministry of Agriculture and Rural Affairs of China.[4] This dataset includes agricultural output, land, labor, fertilizer, and machinery in each county on a yearly basis. Since we aim to identify how climate change affects yield through various channels, this article follows the literature (e.g., Wang et al. (2016)) in inputs and outputs selection for agriculture in China. The output variable is the agricultural yield, which is the deflated gross value of agricultural output per hectare. There are three major types of inputs: labor (agriculture labor force per hectare), fertilizer (the gross weight of nitrogen, phosphate, potash, and complex fertilizers per hectare), and machinery (kilowatts of total power per hectare). When the assumption of constant returns to scale is relaxed, this article follows Sheng et al. (2019a) to add land into the production function.

[4] http://zzys.agri.gov.cn/nongqingxm.aspx.

4.2. Weather

This article collects the weather data from the China Meteorological Data Service Center (CMDC) affiliated with the National Meteorological Information Center of China.[5] The CMDC records weather information for 820 weather stations in China on a daily basis,[6] including minimum, maximum, and average temperatures, precipitation, relative humidity, wind speed, as well as sunshine duration. This article matches the weather data for those 2495 counties included in our agricultural dataset using the inverse-distance weighting (IDW) method, which is widely used in existing studies to impute either weather or pollution data (Currie and Neidell, 2005; Deschênes and Greenstone, 2007; Schlenker and Walker, 2015). For each of the 2495 counties, this method calculates the weighted average of all weather stations within a certain radius of the centroid of that county, where inverse distance square is the weight. This article chooses 100 km (km) as the threshold radius and the results are robust to different radii.

4.3. Summary statistics

Table 1 summarizes county-level agriculture and weather variables in China during the period of 1981–2015. In one hectare of arable land, on average, China uses 4.36 workforce, 0.49 tons of fertilizer, and 7.23 kW of machine power to generate agricultural products worth 11.26 thousand RMB at a 1980's constant price. In terms of weather conditions, on average, the minimum and maximum temperature of a day is 7.3 and 17.8 °C, daily precipitation is 2.4 mm, solar duration is 5.9 h per day, humidity is 66.7%, and wind force is 2.2 m per second.

Moreover, as shown in Fig. 2, two distinct characteristics of climate change in China over the past three decades are rising temperature and decreasing sunshine duration. On the one hand, temperatures in China are rising much faster than the global average,[7] as shown in Panel (A) of Fig. 2, where China's average temperature has increased more than 1.1 °C during the period 1981–2015. On the other hand, as shown in Panel (C) of Fig. 2, the difference in average temperatures in northern and southern China is vast. Therefore, we find both significant time-series and cross-sectional variation in temperature, which makes China a good country for studying the impact of climate change.

5. Empirical results

5.1. TFP results

This article first uses the unbalanced county-level panel for 2495 counties to estimate the agricultural production function and derive TFP for the period of 1981–2015 in mainland China. Table 2 reports the estimation results of the agricultural production function. The first column presents the results of the Cobb-Douglas stochastic frontier model with constant returns to scale (CD-SFA-w/CRS, hereafter), which is the baseline model. The second to the fourth column reports the results of three other models to check the robustness of the baseline model, including the Translog stochastic frontier model with constant returns to scale (TL-SFA-w/CRS, hereafter), the Cobb-Douglas stochastic frontier model without constant returns to scale (CD-SFA-w/oCRS, hereafter), and TFP based on the Cobb-Douglas conventional production function with constant returns to scale (CD-CPF-w/CRS, hereafter).

The four production models derive different TFP estimates. Our baseline TFP derived from the CD-SFA-w/CRS model shows that agricultural productivity achieved a remarkable increase in the early 1980s followed by a significant decline at the end of the 1980s. TFP then achieved dramatic improvement in the 1990s but has gradually lost momentum since the beginning of the 21st century. This trend is consistent with findings in the literature (e.g., Lin, 1992; Pratt et al., 2008; Dekle; Vandenbroucke, 2010; Wang et al., 2013; Sheng et al., 2019b). Moreover, the other three TFP measures all confirm the robustness of the TFP trend over time.

Finally, Fig. 3 compares changes in temperature and changes in agricultural TFP over the period of 1981–2015. The northwest regions of China experiencing a faster temperature rise are also the areas with lower agricultural productivity growth, whereas the southeast regions with a slower temperature rise achieved faster growth in agricultural TFP. Therefore, climate change may have a negative impact on agricultural TFP in China.

5.2. Panel results

In order to use the piecewise linear approach in Eq. (4), the lower temperature bound l_0 and the endogenous threshold l_1 must be predetermined. Agricultural and meteorological literature (e.g., Baskerville and Emin, 1969; Roltsch et al., 1999; Dai et al., 2014) generally classifies GDD into three sections: negative accumulated temperature (GDD below 0 °C), invalid accumulated temperature (GDD between 0 and 10 °C), and active accumulated temperature (GDD above 10 °C), as illustrated in Figure A2 in the appendix.[8] Since GDD above 10 °C is beneficial to the agricultural sector, we choose 10 °C as the lower temperature bound l_0. It is worth noting that all our subsequent findings still hold when we choose 0 °C as an alternative lower temperature bound. To determine the threshold l_1, we loop all possible thresholds, ranging from 25 to 40 °C (see Table A1 in the appendix), where 33 °C appears to be the best-fitting one. We thereby choose 33 °C as our baseline threshold, while 32 °C and 34 °C are used in robustness checks.[9] In addition to the definition of l_0 and l_1, agricultural TFP is determined by any season of the year, instead of specific growing seasons, so we aggregate daily exposures to construct GDDs during the whole year.

The results from our piecewise linear approach are reported in Table 3. In the piecewise linear approach, the nonlinear effect of temperature on agricultural outcomes is captured by two GDD variables, i.e., GDD below threshold (GDD between 10 °C and 33 °C) and GDD above threshold (GDD above 33 °C). In Table 3, Column (1) only includes GDDs, whereas county fixed effects, year fixed effects, additional weather controls, and agricultural land weight are gradually added into the regression in Columns (2)–(5). All estimation results consistently show a nonlinear relationship between temperature and agricultural TFP. Exposure to GDD below threshold slightly promotes agricultural TFP, but GDD above threshold leads to a sharp decrease in agricultural TFP. We prefer the estimated coefficients of Column (5) because it has the most complete controls in model specification, in which agricultural TFP is expected to decrease linearly by 2.6% with an additional one-day cumulative exposure to temperatures above 33 °C during the whole year.

The nonlinear relationship between temperature and agricultural TFP is further enhanced by the traditional temperature bins approach. In Fig. 4, we depict the estimates of Equation (3) using an array of GDDs with every 3 °C temperature bin. Results also show a clearly nonlinear, inverse U-shaped effect of temperature on agricultural TFP, and the turning point again occurs around 33 °C. This article also uses alternative temperature bins (every 4 °C, every 5 °C, and every 6 °C temperature bin, respectively) in the temperature bins approach and finds that the turning

[5] The data can be obtained at http://data.cma.cn/.

[6] See the location of these 820 weather stations in Figure A1 in appendix.

[7] Global average temperature has increased by 0.85 °C during the past 130 years (IPCC AR5).

[8] Also see two summary linkage: http://ipm.ucanr.edu/WEATHER/ddeval.html and https://hort.extension.wisc.edu/articles/degree-day-calculation/.

[9] For other agricultural outcomes in our further analyses, such as machinery, fertilizer, labor, and land output, the temperature threshold varies slightly from 32 to 34 °C, and the long difference and panel estimates deliver very similar temperature thresholds. We summarize the thresholds for all agricultural outcomes used in this article in Table A2.

Table 1
Summary statistics.

Variable	Unit/Definition	Mean	SD	Min	Max	N
Output						
Yield	Land output value (10,000 RMB/Ha)	1.126	0.825	0.061	6.465	67,951
Input						
Labor	# of workforce/Ha	4.361	2.531	0.319	14.253	67,951
Fertilizer	Ton/Ha	0.489	0.337	0.017	2.387	67,951
Machinery	Kilowatt/Ha	7.229	5.597	0.496	38.391	67,522
Weather variables						
*T*ave	Daily average temperature (°C)	11.975	12.026	−44.6	38.9	10,488,766
*T*max	Daily maximum temperature (°C)	17.823	11.818	−39.1	54.3	10,488,837
*T*min	Daily minimum temperature (°C)	7.328	12.646	−50.6	33.1	10,488,922
Precipitation	Daily average (mm)	2.359	9.027	0	3205	10,486,566
Solar duration	Daily total (hours)	5.918	4.098	0	16.4	10,462,522
Humidity	Daily average (%)	66.671	19.107	0	100	10,488,501
Wind force	Daily average (m/s)	2.213	1.628	0	40	10,477,816

Notes: Summary statistics for agricultural output and inputs are based on 2495 unbalanced county panel over the period 1981–2015, while weather variables are based on 820 weather stations with daily records. Summary statistics for exposure days by temperature intervals see Figure A2 in appendix. Yield is in 10,000 RMB at 1980's constant price.

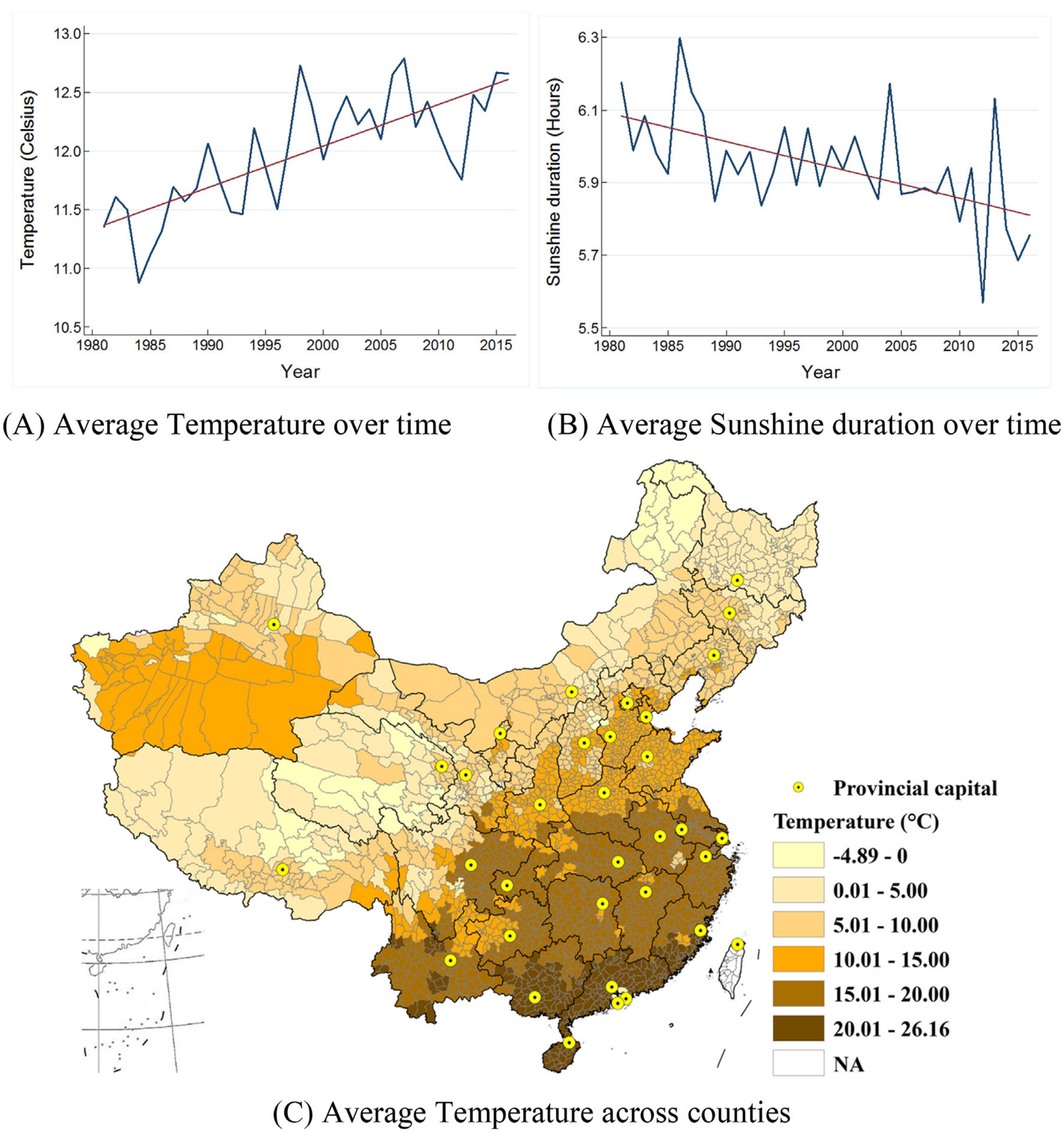


Fig. 2. Climate change and variation in China (1981–2015). Notes: This figure presents the time trend of average temperature (Panel A) and sunshine duration (Panel B) for China, as well as the cross-county average temperature (Panel C) during the sample period (1981–2015).

Table 2
Estimation results of the production function.

Dependent variable	Agricultural yield			
	(1)	(2)	(3)	(4)
	CD-SFA-w/ CRS	TL-SFA-w/ CRS	CD-SFA-w/ oCRS	CD-CPF-w/ CRS
Labor	0.3079***	0.2433***	0.1881***	0.2651***
	(0.0147)	(0.0318)	(0.0081)	(0.0047)
Fertilizer	0.1810***	0.2690***	0.1512***	0.1769***
	(0.0147)	(0.0171)	(0.0068)	(0.0036)
Machine	0.2713***	0.1477***	0.1355***	0.2007***
	(0.0152)	(0.0214)	(0.0077)	(0.0037)
Labor × Labor	–	0.0625	–	–
	–	(0.0546)	–	–
Labor × Fertilizer	–	−0.0053	–	–
	–	(0.0872)	–	–
Labor × Machine	–	−0.0336	–	–
	–	(0.0428)	–	–
Fertilizer × Fertilizer	–	0.0160***	–	–
	–	(0.0057)	–	–
Fertilizer × Machine	–	−0.0340	–	–
	–	(0.0598)	–	–
Machine × Machine	–	0.0425	–	–
	–	(0.0513)	–	–
Land	–	–	−0.4353***	–
	–	–	(0.0048)	–
Year FE	Yes	Yes	Yes	Yes
AIC	5.679×10^4	6.321×10^4	5.772×10^4	–
R-squared	–	–	–	0.8586

Notes: $N = 67{,}951$. The dependent variable is agricultural yield that measures the land output value (10,000 RMB/Ha) for all columns (1)–(4). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

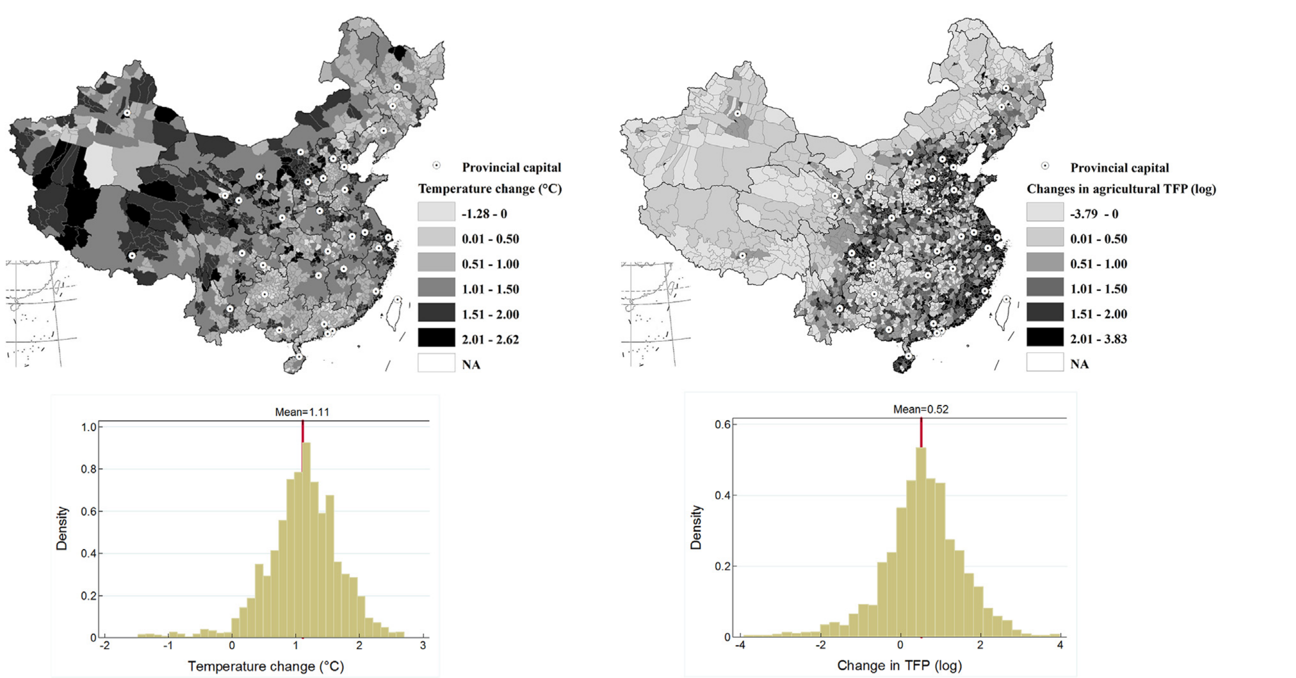
point is robust around 33 °C, as shown in Figure A3. Together with the estimates from the temperature bins approach, we also illustrate the estimates of the piecewise linear approach in Fig. 4, which jointly show that the two estimates deliver a very similar pattern and threshold.

Table 4 reports the panel estimates using alternative agricultural TFPs, together with land output value, namely yield. In addition to our baseline in Column (1) - TFP based on the CD-SFA-w/CRS model, we alternatively use TFP based on the TL-SFA-w/CRS model in Column (2), TFP based on the CD-SFA-w/oCRS model in Columns (3), and TFP based on the CD-CPF-w/CRS model in Columns (4). Results show that our baseline findings from panel estimates are stable under different TFP measurements and support Hypothesis 1.

On the other hand, Column (5) of Table 4 shows that extreme heating also significantly reduces agricultural yield in the short run. More specifically, yield is expected to decrease by 4.4% with an additional one-day cumulative exposure to temperatures above 33 °C during the year. Therefore, relative to such impacts on agricultural TFP, extreme heating has a nearly 71% larger negative impact on yield, which confirms Hypothesis 3.

5.3. Long term estimates

The estimation results from our long differences approach are reported in Table 5, which predicts the long-run impact of climate change on agricultural TFPs and yield. Suggested by Burke and Emerick (2016), we choose the 5-year difference as our baseline and report the estimation results in Table 5. During our study period of 1981–2015, the 5-year difference is given by the difference between the averages of the earliest 5-year period 1981–1985 (i.e., $\overline{z_{i,1981-1985}} = (\sum_{t=1981}^{1985} z_{it})/5$) and the averages of the latest 5-year period 2011–2015 (i.e., $\overline{z_{i,2011-2015}} = (\sum_{t=2011}^{2015} z_{it})/5$). The long differences approach is then estimated after calculating the difference between the two-period averages of all variables in Equation (4) (i.e., both agricultural outcomes and weather variables). Similar to Table 4, we alternatively use three other TFP estimates in Columns (2) to (4), in addition to the benchmark TFP estimate in Column (1). Similar to panel estimates, the long differences approach also reveals an inverse U-shaped nonlinearity as temperature exceeds the turning point, and the results are robust using various TFP estimates. In Column (1) in particular, the estimation indicates that exposure to one extra day of temperature above 33 °C during the whole year decreases



(A) Change in temperature (°C) (B) Change in Log(TFP)

Fig. 3. Change in temperature (°C) and Log(TFP) over the period 1981–2015. *Notes*: This figure presents the changes in average temperature (Panel A) and agricultural TFP measured by CD-SFA-w/CRS (Panel B) for China in each county during the sample period (1981-2015). Variable shading of each map corresponds to the histogram beneath the plot.

Table 3
Panel estimates of the impacts of temperature on China's agricultural TFP.

Dependent variable:	Log(Agricultural TFP)				
	(1)	(2)	(3)	(4)	(5)
GDD below threshold	0.0055***	0.0188***	0.0042***	0.0040***	0.0035***
	(0.0004)	(0.0006)	(0.0007)	(0.0007)	(0.0008)
GDD above threshold	−0.0275**	−0.0201***	−0.0128**	−0.0136**	−0.0256***
	(0.0130)	(0.0062)	(0.0064)	(0.0069)	(0.0085)
Precipitation	–	–	–	0.0210***	0.0147***
	–	–	–	(0.0044)	(0.0053)
Precipitation2	–	–	–	−0.0006***	−0.0005**
	–	–	–	(0.0002)	(0.0002)
Sunshine duration	–	–	–	−0.0032	0.0225
	–	–	–	(0.0247)	(0.0348)
Sunshine duration2	–	–	–	−0.0017	−0.0034
	–	–	–	(0.0022)	(0.0032)
Humidity	–	–	–	0.0356***	0.0347***
	–	–	–	(0.0083)	(0.0106)
Humidity2	–	–	–	−0.0003***	−0.0003***
	–	–	–	(0.0001)	(0.0001)
Wind force	–	–	–	0.0033	0.0327
	–	–	–	(0.0263)	(0.0366)
Wind force2	–	–	–	−0.0047	−0.0074
	–	–	–	(0.0050)	(0.0072)
R-squared	0.0331	0.5331	0.6300	0.6314	0.6171
County *FE*	No	Yes	Yes	Yes	Yes
Year *FE*	No	No	Yes	Yes	Yes
Weight	No	No	No	No	Yes

Notes: $N = 67,951$. The dependent variable is log agricultural TFP derived from the baseline model (CD-SFA-w/CRS) for all columns (1)–(5). Specifications are estimated using an annual panel with different fixed effects and weather variables shown at the bottom. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

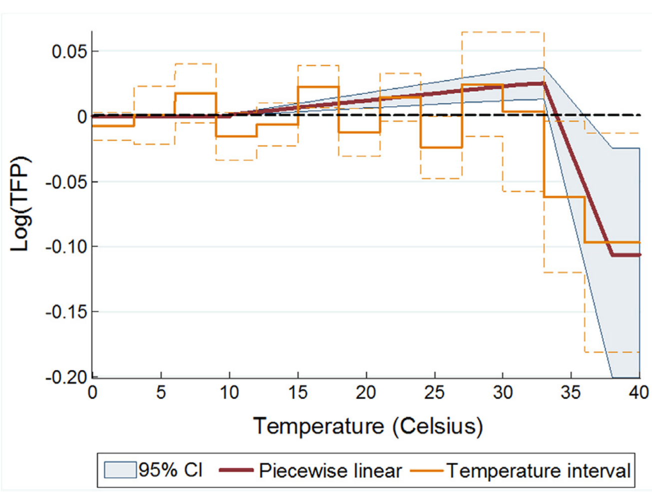


Fig. 4. Estimates with fine temperature bins and piecewise linear function. Notes: This graph displays changes in log agricultural TFP measured by CD-SFA-w/CRS model if a county is exposed for one day to a particular 3 °C temperature interval (red line) where we sum the fraction of a day temperatures fall within each interval. The 95% confidence bands, after adjusting for spatial correlation and clustering at county level, are added by dash line (yellow). The black line and shaded area reflect the estimates and 95% CIs derived from piecewise linear approach, in which the log agricultural TFP changes under an additional day of exposure to a given °C temperature relative to a day spend at 0 °C. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

China's agricultural TFP by nearly 1.6% percent in the long run. Column (5) of Table 5 reports the long-run impact of extreme heating on agricultural yield, which implies that a 2.3% reduction in yield is expected in the long run, with an additional one-day cumulative exposure to temperatures above 33 °C during the year.

Since our study period spans 35 years, we are also able to construct 10-year and 15-year difference estimations as robustness checks. These results reported in Columns (2) and (3) of Table A3 in the appendix suggest that the estimates from the long differences approach are stable under different period-average definitions. In addition, a potential concern about the long differences approach is that the estimation is based only on cross-sectional variation after data transformation. To eliminate any concerns of time-varying unobservable factors that possibly correlate with both climate and agricultural outcomes, we adopt the two-period long differences panel model in Eq. (6) and report the estimation results in Column (4) of Table A3. The main estimated coefficient and significance for GDD above threshold are also highly consistent with our baseline.

5.4. *Adaptations*

Since the long differences estimates account for farmers' adaptation to longer-run changes in climate during our study period, the difference between short-run responses given by panel estimates and the longer-run estimates given by long differences estimates reflect recent climate adaptation in the past three decades. Table 6 reports panel estimates in Panel A, longer-run estimates in Panel B, and adaptations in Panel C. Columns (1) and (2) of Table 6 reflect the response of yield and TFP, respectively. The results in Panel C show that longer-run adaptation has offset 46.8% and 37.9% of the short-run effects of extreme heat on China's agriculture yield and agricultural TFP, respectively.

It is worth noting that we only have weather records for 820 weather stations in China and hence match the weather data for those 2495 counties using the IDW method, where 100 km is selected as the threshold radius. In other words, the weather condition of a county is estimated by taking the weighted average of all weather stations within 100 km radius of the centroid of that county. To check the sensitivity of our estimations under different threshold radius, this article runs the regression only for counties in which there is one or more weather stations. Moreover, we also run regressions using 50 km, 150 km, and 200 km as the threshold radius, respectively. Table A4 in appendix compares the results of these robustness checks with our baseline model using 100

Table 4
Panel estimates of the impacts of temperature on either China's agricultural TFPs and land output values.

Dependent variable:	Log(Agricultural TFP)				Log(Yield)
	(1) CD-SFA-w/CRS	(2) TL-SFA-w/CRS	(3) CD-SFA-w/oCRS	(4) CD-CPF-w/CRS	(5)
GDD below threshold	0.0035***	0.0026***	0.0033***	0.0026***	0.0003
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)
GDD above threshold	−0.0256***	−0.0212**	−0.0263***	−0.0294***	−0.0438***
	(0.0085)	(0.0088)	(0.0084)	(0.0084)	(0.0095)
R-squared	0.6171	0.6072	0.6280	0.7038	0.8118
County *FE*	Yes	Yes	Yes	Yes	Yes
Year *FE*	Yes	Yes	Yes	Yes	Yes
Additional weather	Yes	Yes	Yes	Yes	Yes
Weight	Yes	Yes	Yes	Yes	Yes

Notes: $N = 67{,}951$. The dependent variable is log agricultural TFP for all columns (1)–(4) with different TFP measurements, and log Yield for column (5). Specifications are estimated using an annual panel with county fixed effects and year fixed effects. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5
Long difference estimates of the impacts of temperature on either China's agricultural TFPs and land output values.

Dependent variable:	Log(Agricultural TFP)				Log(Yield)
	(1) CD-SFA-w/CRS	(2) TL-SFA-w/CRS	(3) CD-SFA-w/oCRS	(4) CD-CPF-w/CRS	(5)
GDD below threshold	0.0016***	0.0013***	0.0015***	0.0016***	0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
GDD above threshold	−0.0159***	−0.0160***	−0.0163***	−0.0175***	−0.0233***
	(0.0043)	(0.0043)	(0.0042)	(0.0042)	(0.0045)
Additional weather	Yes	Yes	Yes	Yes	Yes
Weight	Yes	Yes	Yes	Yes	Yes

Notes: $N = 1649$. The dependent variable is log agricultural TFP for all columns (1)–(4) with different TFP measurements, and log Yield for column (5). Specifications are estimated using long difference with 5-year lengths of differencing period. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6
Adaption and mechanisms.

Dependent variable:	Output	Productivity	Input		
	Log(Yield)	Log(Agricultural TFP)	Log(Labor)	Log(Fertilizer)	Log(Machinery)
	(1)	(2)	(3)	(4)	(5)
Panel A: Panel estimates [$N = 67{,}951$]					
GDD above threshold (β_2^{FE})	−0.0438***	−0.0256***	−0.0276***	−0.0491***	0.0069
	(0.0095)	(0.0085)	(0.0077)	(0.0091)	(0.0079)
Panel B: Long difference estimates [$N = 1649$]					
GDD above threshold (β_2^{LD})	−0.0233***	−0.0159***	−0.0115***	−0.0175***	0.0084**
	(0.0045)	(0.0043)	(0.0031)	(0.0039)	(0.0035)
Panel C: Adaptations (%)					
(1-$\beta_2^{LD}/\beta_2^{FE}$) × 100%	46.80***	37.89***	58.33***	64.36***	–
Bootstrap percentiles [5%, 95%]	[30.20, 58.04]	[5.29, 54.75]	[42.03, 69.39]	[56.24, 70.03]	–

Notes: The dependent variable is log land output value for column (1), log agricultural TFP derived from the baseline model (CD-SFA-w/CRS) for column (2), and log form of unit land inputs, i.e. labor, fertilizer, and machinery, for columns (3)–(5); see text for details. Panel A are estimated using panel estimation and the specifications are strictly in line with Table 4, while Panel B are estimated using long difference with 5-year lengths of differencing period and the specifications are strictly in line with Table 5. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. GDD below threshold is controlled but not reported. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

km as the threshold radius, and the results are very robust.

In addition to point estimates, we further quantify the uncertainty of climate adaptation by bootstrap procedure[10]. We follow three steps of bootstrap procedure: 1) we randomly pick 2000 counties from our dataset with replacement to construct a subsample at a time and construct 1000 such subsamples; and then 2) deliver both the panel estimates and long differences estimates for each subsample; finally, 3) we recalculate the percentage of $1 - \beta_2^{LD}/\beta_2^{FE}$ for each subsample and report the distribution of bootstrapped adaptation estimates at 5%, 25%, 50%, 75% and 95%, respectively.

In Fig. 5, we illustrate bootstrapped adaptation estimates for both agricultural TFP and yield. Using the full sample of 1981–2015, the median estimates show that 37.9% of the negative short-run impacts on TFP and 46.9% of the negative short-run impacts on yield are offset in the longer run during our study period, which is consistent with our point estimates in Table 6 and are both statistically significant. Moreover, Fig. 5 also reports adaptation in different periods. The extent of climate adaptation has gradually amplified in the most recent period. In terms of agricultural TFP, climate adaptation appears to be around 9.0% (95% CI, 1.3%–13.0%) during 1981–1990 but reaches nearly 36.3% (95% CI,

[10] The accurate point and bootstrap estimates for climate adaptation are reported in Table A5 and Table A6 in appendix.

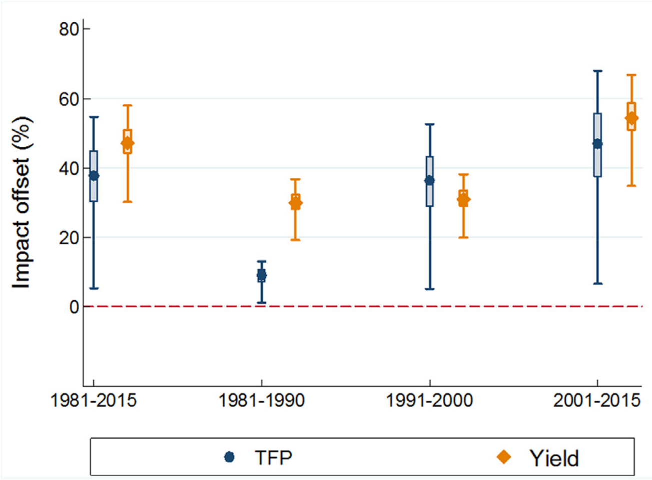


Fig. 5. Percentage of short-run impacts offset by adaptation. Notes: This figure shows the percentage of the short-run effects of extreme heat on either agricultural TFP measured by CD-SFA-w/CRS model or yield that are mitigated in the longer run. Each box plot corresponds to a particular time period as labeled, and represent 1000 bootstrap estimates of 1-$\beta_2^{LD}/\beta_2^{FE}$ for that time period. The scatter in each distribution is the median, the grey box represents the interquartile range, and the cap-line represent the fifth to ninety-fifth percentile.

5.1%–52.7%) during 1991–2000 and further increases to 46.9% (95% CI, 6.6%–68.0%) during the most recent period of 2001–2015. In terms of yield, climate adaptation offsets 29.9% (95% CI, 19.1%–36.8%) of short-run impacts during 1981–1990, improving to 31.1% (95% CI, 19.9%–38.2%) during 1991–2000 and 54.3% (95% CI, 34.8%–66.8%) during the most recent period of 2001–2015. In line with our theoretical hypothesis, climate adaptation for agricultural output shows a larger offset than agricultural TFP.

5.5. Mechanisms and alternate explanations

Table 6 not only reports significant adaptation in agricultural yield and TFP but also shows that the impact of climate change on yield is more negative than on TFP in both the short and long run. The difference between the response of yield and TFP is due to the impact of climate change on input utilization. Columns (3) to (5) of Table 6 report the impact of climate change on labor, fertilizer and machinery, respectively. As predicted in Section 2, extreme heat has a significant negative impact on labor[11] and fertilizer, but no significant impact on machinery in the short run. In the long run, however, labor and fertilizer usage is gradually recovered, and the usage of machinery is increasingly replacing labor in hot weather. The estimation result in Table 6 supports all seven hypotheses in Fig. 1. To summarize, the impact on yield is the combination of the impact on input usage and the impact on TFP. In the short run, extreme heat has a negative impact on labor, fertilizer, and TFP, leading to a more negative impact on yield in the short run. In the long run, both the adaptations in input utilization and TFP are witnessed, and therefore lead to a larger adaptation in yield.

6. Projections of impacts under future climate change

Finally, this article employs the estimated coefficients of GDD below and above threshold in our baseline model to project the impact of future global warming on agricultural TFP in China. Projections of future climate factors were collected from WorldClim-Global Climate Data,[12] which generates climate predictions according to the constantly updated global climate models under four representative greenhouse gas (GHG) concentration pathways (RCPs) for the medium term (2050, average for 2041–2060) as well as the long term (2070, average for 2061–2080): RCP2.6, RCP4.5, RCP6.0, and RCP8.5. On the one hand, the RCP2.6 (the most optimistic pathway) and RCP8.5 (the most pessimistic pathway) are adopted in this article for projection, since these two pathways cover the whole range of the projected GHG emissions changes in the future. On the other hand, this article follows Warszawski et al. (2014) to choose climate data derived from the global climate models HadGEM2-ES and NorESM1-M, which represent two different projections for future global temperature changes. Considering different projections for future GHG emissions and future global temperature, we eventually narrowed the field to four scenarios for the medium term and four scenarios for the long term.

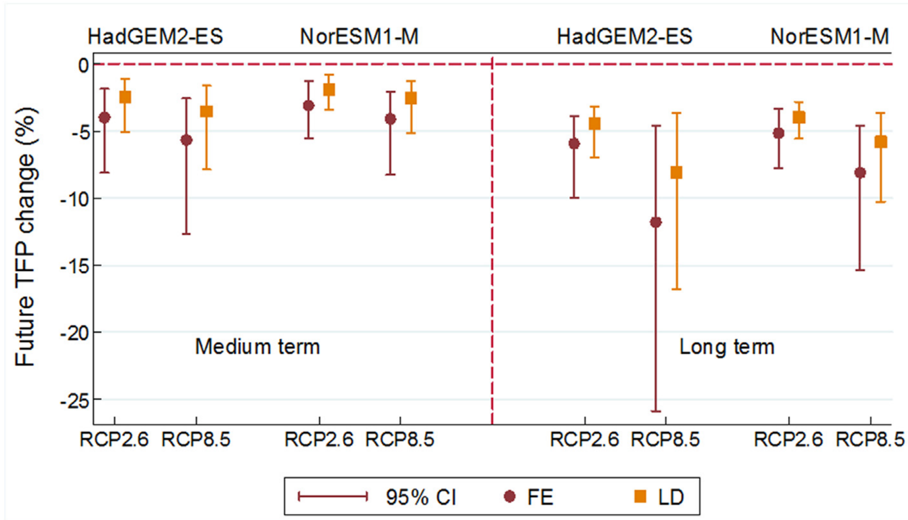
This article calculates the projected changes in GDDs across regions, which are the differences between the GDDs derived from the constructed daily $T_{\min}$ and $T_{\max}$ data for the 21st century and the average temperature bins during the sample period (1981–2015). The coefficient estimates of the GDD below and above threshold allow us to predict county-specific changes in agricultural TFP and yield to estimate the effects of future warming on agricultural TFP and yield.

Fig. 6 (A) presents the effects of future warming on agricultural TFP under different scenarios. In general, we find that future global warming will significantly lower China's agricultural TFP, and predictions based on panel estimates tend to overestimate the reductions. Specifically, in the left panel of Fig. 6 (A), under the HadGEM2-ES model, average agricultural TFP in the medium term by 2041–2060 is projected to reduce by 2.5–3.9% under RCP2.6 and by 3.5–5.7% under RCP8.5. Under the NorESM1-M model, corresponding declines in TFP are smaller, by 1.9–3.1% under RCP2.6 and by 2.5–4.1% under RCP8.5. In the right panel of Fig. 6 (A), the declines in agricultural TFP in the long term are projected to be considerably greater than those in the medium term. China's agricultural TFP is projected to decrease by 4.4–11.8% by 2061–2080 under the HadGEM2-ES model and by 3.9–8.1% under the NorESM1-M model. In the medium term (2041–2060), on average across different GHG concentration trajectories under different climate models, China's agricultural TFP is projected to decrease by 4.2% based on panel estimates and by 2.6% based on long differences estimates, which means that climate adaptation offsets 38.1% of the TFP reductions in the midterm. However, in the long term (2061–2080), China's agricultural TFP is projected to decrease by 7.8% based on panel estimates and by 5.6% based on long differences estimates, where the climate adaptation offset shrinks to 28.2% of the TFP reductions in the long run.

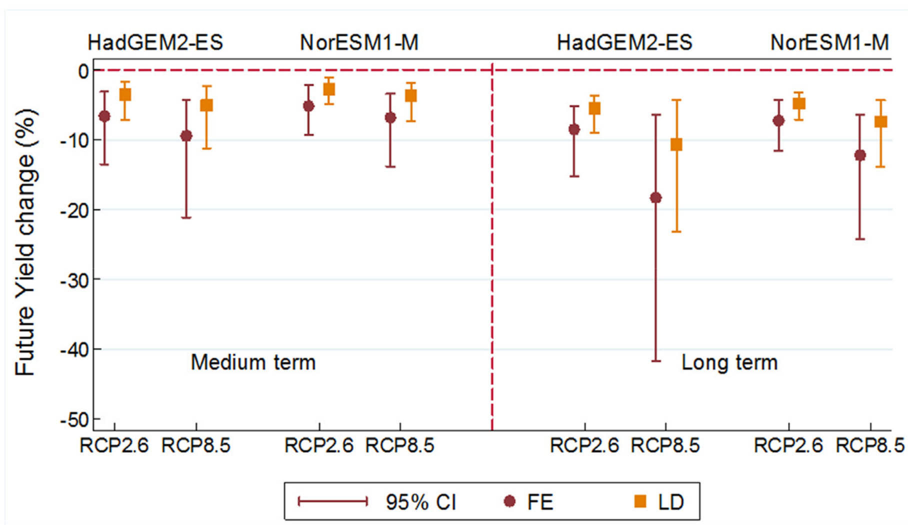
Similarly, Fig. 6 (B) presents the effects of future warming on agricultural output. All findings from predictions in Fig. 6 (B) are in line with Fig. 6 (A). The most remarkable difference between panel (A) and panel (B) is that the projected reductions in agricultural output are nearly twice as large as the decline in agricultural TFP, as shown by the different scale of values on the vertical axis, which is also consistent with expectations because our previous estimates show a more negative climate impact on yield, relative to TFP, due to the negative impact of climate change on inputs. Again, the climate adaptation offset on yield reduction will decrease in the long run.

[11] In our dataset, we only have the number of agricultural workforce rather than working hours. Therefore, input adjustment on the labor margin cannot be fully captured. Existing studies (Crocker and Horst, 1981; Dell et al., 2014; Graff Zivin; Neidell, 2014; Zhang et al., 2018; Fishman et al., 2019; Kjellstrom et al., 2019; Acevedo et al., 2020) find that extreme heat will decrease labor intensity, reduce working hours (especially outdoor activities), and even threaten occupational health. Accordingly, we believe that extreme hot weather is not likely to increase the average working hours of the farmers. As a result, we estimate the effect of climate change on labor employment in agriculture, which is likely to be the lower bound of the impact on labor input. In other words, the actual impact of climate change on labor input can be more negative, and our conclusion still holds.

[12] Future climate data are available on line at http://www.worldclim.org/.This article follows Chen and Chen (2018) to construct future climate projections.



(A) Agricultural TFP change



(B) Yield change

Fig. 6. Projected impacts of future warming on TFP and Yield. Notes: Panels (A) and (B) show predicted percentage changes in China's agricultural TFP measured by CD-SFA-w/CRS model and yield under either HadGEM2-ES model or NorESM1-M model, based on long differences (square) or panel estimates (circle) of historical sensitivities to climate. The scatter in each climate model represents the median and the cap-line represents the fifth to ninety-fifth percentile.

In summary, although climate adaptation is occurring, future global warming is still projected to make a sizeable negative impact on China's agricultural productivity, since more than half of the short-run effects still exist. In particular, two points evaluated from the future projections are worth additional attention. First, compared to the medium term, the nonlinear relationship between temperature and agricultural outcomes revealed by our estimates directly lead to a faster reduction in TFP and yield in the long term. Second, climate adaptation decreases in the long term, relative to the medium term, which suggests limited adaptations in the agricultural sector without new policy interventions.

7. Discussion and conclusion

Most existing literature quantifies the impact of climate change on economic outcomes based on estimates of short-run response, which fails to consider the adaptation behavior that may mitigate the short-run response in the longer run. Some recent studies have captured this long-run adjustment to a changing climate by estimating and comparing both short-run and long-run responses. However, understanding the mechanism of the response and adaptation is a more important input to public policy. Take agriculture as an example, identifying the mechanism of how climate change affects yield through its impact on TFP and input utilization, as well as the mechanism of how farmers adapt to these impacts, can provide more useful information to fight against climate change.

Using county-year panel data for 2495 counties over the period of 1981–2015, this article finds that extreme hot weather has a negative impact on agricultural TFP and a more negative impact on yield in the short run, since TFP and yield are expected to decrease linearly by 2.6% and 4.4%, with an additional one-day cumulative exposure to temperatures above 33 °C during the whole year, respectively. The difference between the impact on TFP and yield is due to the negative effect of extreme hot weather on labor and fertilizer usage.

Significant adaptation of TFP and all three inputs are found, which leads to a larger adaptation in yield. Long-run adaptations appear to have mitigated 37.9% (95% CI, 5.3%–54.8%) of the short-run effects in TFP. Moreover, Chinese farmers mitigate the reduction in labor and fertilizer due to extreme hot weather and employ more machines to replace the shortage of labor. All these adaptation behaviors in TFP and inputs have jointly and significantly offset the short-run effects in yield by 46.8% (95% CI, 30.2%–58.0%). The existence of the long-run offset suggests a potential overestimation of the negative climate change impacts based on panel estimates in previous literature (Chen et al., 2016; Zhang et al., 2017). According to our analysis, future climate adaptations in agriculture are thereby emerging from two pathways: adaptation in agricultural TFP and adaptations in agricultural input portfolio. Therefore, the government should enact more policies to induce technical change and improve agricultural productivity. At the same time, policy instruments, such as subsidy of machinery purchase and agricultural insurance policy, are essential to motivate agricultural investments.

Although climate adaptation is happening, future global warming is still likely to make a sizeable negative impact on China's agricultural productivity, considering that more than half of the short-run effects still exist. Moreover, the restated nonlinearity in this article, based on a longer dataset, is a reminder that the hazards of climate change will disproportionately exacerbate in the long run, while the adaptation will decrease in the long run. This means that the earlier the mitigation actions are taken, the better the policy effects will be. Besides the policies to fight against climate change, the government must make relevant policies to reduce welfare loss in the context of a seemingly inevitable agricultural reduction.

There are a few limitations to this article that are worth emphasizing. First, input adjustment on the labor margin cannot be fully captured due to the lack of data on working hours, and our estimation is likely to be the lower bound of the impact of climate change on labor input. That implies the negative impact of climate change on labor input can be even greater than we predicted. Second, we do not further decompose the impact mechanism on agriculture into the impact on cropping pattern changes and the impact on each farm commodities since we don't have complete commodity-county-level data for the sample period. Future research is warranted to better understand the mechanism at commodity level.

CRediT authorship contribution statement

Shuai Chen: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Visualization. **Binlei Gong:** Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing.

Appendix A. Figures and Tables

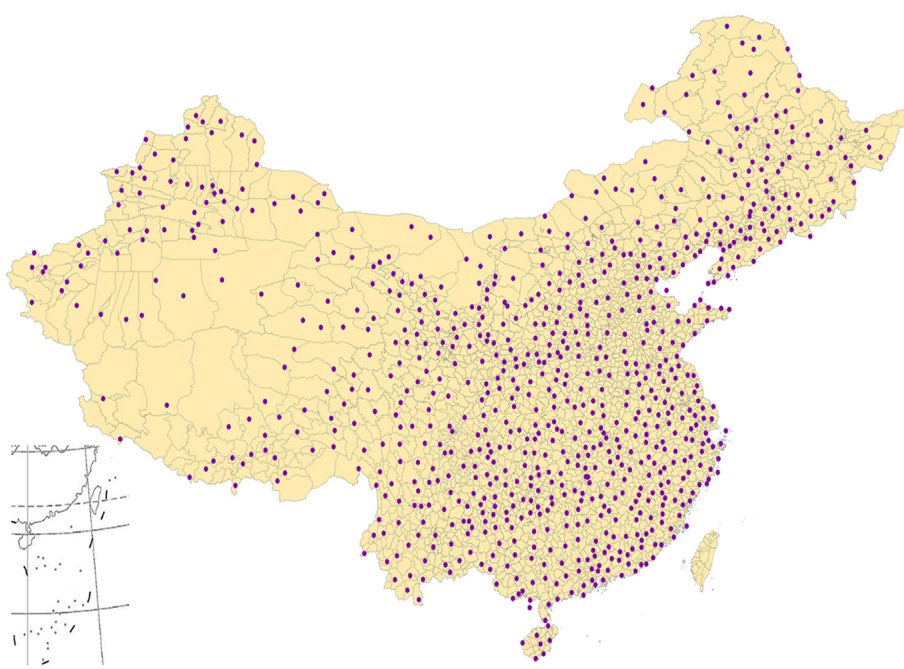


Fig. A1. Location of weather stations in China. *Notes*: The scatters display the location of 820 weather stations in China. The inverse-distance weighting (IDW) method is employed to impute weather data for each county. For each county, the IDW algorithm calculates the weighted average of all weather stations within a certain radius of the centroid of that county, where inverse distance square is the weight..

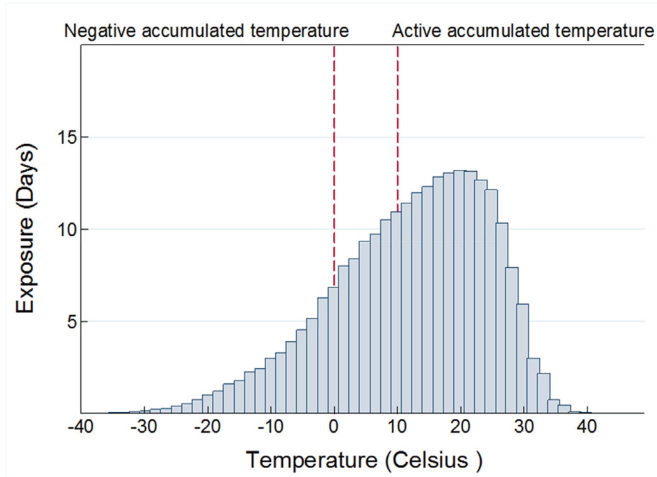


Fig. A2. Growing degree days in China (1981–2015). *Notes*: This figure presents the distribution of time (measured by days) for each 1-celsius temperature interval during the whole year in China.

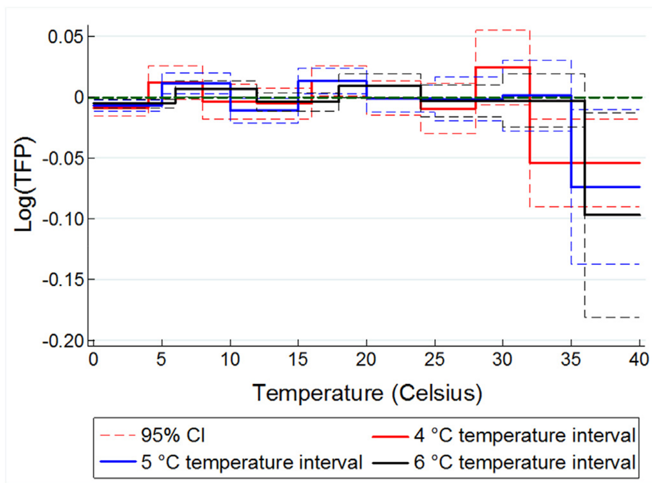


Fig. A3. Estimation with alternative temperature bins. *Notes*: This graph displays changes in log agricultural TFP measured by CD-SFA-w/CRS model if a county is exposed for one day to a particular 4 °C temperature interval (red line), a particular 5 °C temperature interval (blue line), or a particular 6 °C temperature interval (blue line), where we sum the fraction of a day temperatures fall within each interval. The 95% confidence bands, after adjusting for spatial correlation and clustering at county level, are added by dash line. The black line and shaded area depict the estimates and 95% CIs derived from piecewise linear approach, in which log agricultural TFP changes under an additional day of exposure to a given °C temperature relative to a day spend at 0 °C. .

Table A1
Temperature thresholds

Dependent variable:	Log(CD-SFA-w/CRS)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Threshold (°C)	25	26	27	28	29	30	31	32
GDD below threshold	0.0033***	0.0032***	0.0033***	0.0035***	0.0035***	0.0035***	0.0036***	0.0036***
	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
GDD above threshold	0.0015	0.0013	0.0004	−0.0012	−0.0029	−0.0055	−0.0101**	−0.0164***
	(0.0020)	(0.0022)	(0.0025)	(0.0029)	(0.0034)	(0.0040)	(0.0049)	(0.0063)
R-squared	0.6168	0.6168	0.6169	0.6169	0.6169	0.6170	0.6170	0.6170
Threshold (°C)	33	34	35	36	37	38	39	40
GDD below threshold	0.0035***	0.0034***	0.0033***	0.0032***	0.0031***	0.0030***	0.0029***	0.0028***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
GDD above threshold	−0.0256***	−0.0392***	−0.0613***	−0.0997***	−0.1606***	−0.2584***	−0.4171**	−0.7614**
	(0.0085)	(0.0120)	(0.0182)	(0.0293)	(0.0495)	(0.0878)	(0.1623)	(0.3104)
R-squared	0.6171	0.6171	0.6170	0.6170	0.6170	0.6169	0.6169	0.6168

Notes: $N = 67{,}951$. The dependent variable is log agricultural TFP measured by CD-SFA-w/CRS for all columns (1)–(8). Specifications are estimated using an annual panel with both county and year fixed effects. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A2
Summary for temperature thresholds

Variables	Log(Agricultural TFP)				Output	Input		
	CD-SFA-w/CRS	TL-SFA-w/CRS	CD-SFA-w/oCRS	C-D (CPF)	Yield	Fertilizer	Machinery	Labor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Threshold (°C)	33–34	32–33	32–33	31–32	32–34	32–33	32–34	33–34

Notes: This table summarizes all possible temperature thresholds for agricultural outcomes involved in this article, using piecewise linear approach.

Table A3
Long difference estimates of the impacts of temperature on China's agricultural TFP

Dependent variable:	Log(Agricultural TFP)			
	(1) 5-year dif	(2) 10-year dif	(3) 15-year dif	(4) Panel-dif
GDD below threshold	0.0016***	0.0017***	0.0021***	0.0007***
	(0.0004)	(0.0005)	(0.0005)	(0.0002)
GDD above threshold	−0.0159***	−0.0142**	−0.0173**	−0.0148***
	(0.0043)	(0.0064)	(0.0083)	(0.0026)
Additional weather	Yes	Yes	Yes	Yes
Weight	Yes	Yes	Yes	Yes
County *FE*	No	No	No	Yes
Observations	1649	2015	2096	3298
$1\text{-}\beta_2^{LD}/\beta_2^{FE}$	0.3789	0.4453	0.3242	0.4219

Notes: The dependent variable in all regressions is the difference in the log of smoothed agricultural TFP measured by CD-SFA-w/CRS model. Specifications are estimated with long differences using different lengths of differencing period for columns (1)–(3). The panel of difference in column (4) is a two period panel with 15-year differences, i.e., 1981–1995 and 2000–2015. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4
Robustness checks for weather data

Dependent variable:	Log(Yield)	Log(Agricultural TFP)	Log(Labor)	Log(Fertilizer)	Log(Machinery)
	(1)	(2)	(3)	(4)	(5)
Panel A: IDW radius = 100 km (Baseline)					
Panel Esimtimates [N = 67,951]					
GDD above threshold (β_2^{FE})	−0.0438***	−0.0256***	−0.0276***	−0.0491***	0.0069
	(0.0095)	(0.0085)	(0.0077)	(0.0091)	(0.0079)
Long-dif Estimates [N = 1649]					
GDD above threshold (β_2^{LD})	−0.0233***	−0.0159***	−0.0115***	−0.0175***	0.0084**
	(0.0045)	(0.0043)	(0.0031)	(0.0039)	(0.0035)
Adaptations					
$(1\text{-}\beta_2^{LD}/\beta_2^{FE}) \times 100\%$	46.80	37.89	58.33	64.36	–
Panel B: 812 counties with weather stations					
Panel Esimtimates [N = 30,598]					
GDD above threshold (β_2^{FE})	−0.0527***	−0.0286**	−0.0414***	−0.0580***	0.0098
	(0.0149)	(0.0134)	(0.0120)	(0.0132)	(0.0133)
Long-dif Estimates [N = 739]					
GDD above threshold (β_2^{LD})	−0.0297***	−0.0243***	−0.0089**	−0.0196***	0.0115**
	(0.0070)	(0.0068)	(0.0045)	(0.0056)	(0.0054)
Adaptations					
$(1\text{-}\beta_2^{LD}/\beta_2^{FE}) \times 100\%$	43.64	15.04	78.50	66.21	–
Panel C: IDW radius = 50 km					
Panel Esimtimates [N = 67,046]					
GDD above threshold (β_2^{FE})	−0.0421***	−0.0243***	−0.0270***	−0.0490***	0.0069
	(0.0095)	(0.0085)	(0.0077)	(0.0092)	(0.0080)
Long-dif Estimates [N = 1633]					
GDD above threshold (β_2^{LD})	−0.0232***	−0.0158***	−0.0114***	−0.0174***	0.0083**
	(0.0045)	(0.0042)	(0.0031)	(0.0039)	(0.0035)
Adaptations					
$(1\text{-}\beta_2^{LD}/\beta_2^{FE}) \times 100\%$	44.89	34.98	57.78	64.49	–
Panel D: IDW radius = 150 km					
Panel Esimtimates [N = 67,951]					
GDD above threshold (β_2^{FE})	−0.0488***	−0.0255***	−0.0393***	−0.0662***	0.0083
	(0.0103)	(0.0093)	(0.0084)	(0.0094)	(0.0087)
Long-dif Estimates [N = 1649]					
GDD above threshold (β_2^{LD})	−0.0299***	−0.0188***	−0.0191***	−0.0237***	0.0122**
	(0.0060)	(0.0057)	(0.0043)	(0.0048)	(0.0051)
Adaptations					
$(1\text{-}\beta_2^{LD}/\beta_2^{FE}) \times 100\%$	38.73	26.27	51.40	64.20	–

(*continued on next column*)

Table A4 (*continued*)

Dependent variable:	Log(Yield)	Log(Agricultural TFP)	Log(Labor)	Log(Fertilizer)	Log(Machinery)
	(1)	(2)	(3)	(4)	(5)
Panel E: IDW radius = 200 km					
Panel Esimtimates [$N = 67{,}951$]					
GDD above threshold (β_2^{FE})	−0.0492***	−0.0277***	−0.0419***	−0.0689***	0.0071
	(0.0105)	(0.0090)	(0.0085)	(0.0096)	(0.0089)
Long-dif Estimates [$N = 1649$]					
GDD above threshold (β_2^{LD})	−0.0313***	−0.0163***	−0.0203***	−0.0246***	0.0125**
	(0.0064)	(0.0052)	(0.0047)	(0.0051)	(0.0055)
Adaptations					
(1-$\beta_2^{LD}/\beta_2^{FE}$) × 100%	36.38	41.16	51.55	64.30	–

Notes: The specification of panel and long difference regressions are strictly in line with Tables 4 and 5 in main text. GDD below threshold is controlled but not reported. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A5
Long difference estimates of the impacts of temperature on either China's agricultural TFP and land output values

Dependent variable:	Log(Agricultural TFP)				Log(Yield)
	(1) CD-SFA-w/CRS	(2) TL-SFA-w/CRS	(3) CD-SFA-w/oCRS	(4) CD-CPF-w/CRS	(5)
Panel A: 1981–2015					
GDD above threshold	−0.0159***	−0.0160***	−0.0163***	−0.0144***	−0.0233***
	(0.0043)	(0.0043)	(0.0042)	(0.0043)	(0.0045)
1-$\beta_2^{LD}/\beta_2^{FE}$	0.3789	0.2453	0.3802	0.2871	0.4680
Panel B: 1981–1990					
GDD above threshold	−0.0233***	−0.0131**	−0.0218***	−0.0204**	−0.0307**
	(0.0064)	(0.0063)	(0.0062)	(0.0079)	(0.0135)
1-$\beta_2^{LD}/\beta_2^{FE}$	0.0898	0.3821	0.1711	2.0099	0.2991
Panel C: 1991–2000					
GDD above threshold	−0.0163***	−0.0131***	−0.0168***	−0.0102**	−0.0302***
	(0.0042)	(0.0041)	(0.0042)	(0.0042)	(0.0068)
1-$\beta_2^{LD}/\beta_2^{FE}$	0.3633	0.3821	0.3612	0.4950	0.3105
Panel D: 2001–2015					
GDD above threshold	−0.0136**	−0.0122**	−0.0137**	−0.0143**	−0.0200***
	(0.0058)	(0.0059)	(0.0058)	(0.0061)	(0.0044)
1-$\beta_2^{LD}/\beta_2^{FE}$	0.4688	0.4245	0.4791	0.2921	0.5434

Notes: $N = 1649$. The dependent variables are log agricultural TFP for all columns (1)–(4) with different TFP measurements and log Yield for column (5). Specifications are estimated using long difference with 5-year lengths of differencing period. For brevity, GDD below threshold and additional weather controls is not reported here. Additional weather variables include second-order polynomials in accumulative precipitation, sunshine duration, average relative humidity, as well as wind speed. Regressions are weighted by 1981–2015 county-average farm area. Standard errors listed in parentheses are adjusted for spatial correlation and are clustered at county level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A6
Bootstrap estimates of 1-$\beta_2^{LD}/\beta_2^{FE}$ for short-run impacts offset by adaptation

Period	Bootstrap percentiles: (1-$\beta_2^{LD}/\beta_2^{FE}$) × 100%				
	50%	25%	75%	5%	95%
(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Agricultural TFP (CD-SFA-w/CRS)					
1981–2015	37.76	30.21	44.94	5.29	54.75
1981–1990	8.98	7.18	10.69	1.26	13.02
1991–2000	36.33	29.06	43.23	5.09	52.68
2001–2015	46.88	37.50	55.79	6.56	67.98
Panel B: Output (Yield)					
1981–2015	47.19	44.36	50.96	30.20	58.04
1981–1990	29.91	28.12	32.30	19.14	36.79
1991–2000	31.05	29.19	33.53	19.87	38.19
2001–2015	54.34	51.08	58.69	34.78	66.84
Panel C: Inputs					
1981–2015 (Labor/Ha)	59.54	53.61	63.56	42.03	69.39
1981–2015 (Fertilizer/Ha)	65.18	67.51	62.59	56.24	70.03

Notes: This table reports the 1000 bootstrap estimates of (1-$\beta_2^{LD}/\beta_2^{FE}$) × 100% for agricultural TFP (Panel A) and Yield (Panel B) during a particular time period defined by column (1). The 50%, 25%, 75%, 5%, and 95% percentile of the bootstrap estimates are listed in column (2)–(6), respectively. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2020.102557.

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