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2024

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November 5, 2024

Abstract

Existing studies generally use "aggregate" temperature measures, such as mean temperature, degree-days, temperature bins, and piece-wise linear function within the growing season, to estimate the impact of global warming on crop yield. These temperature measures blend temperatures from different phenological stages of crop growth and thus implicitly assume that temperatures are additively substitutable within the growing season. However, this assumption contrasts with agronomic knowledge that crops are more sensitive to temperatures in certain phenological stages. Utilizing a unique site-level data on the detailed phenological stages of major crops in China, combined with crop production data and daily weather data, we develop an econometric model with stage-specific temperature measures. We then compare our estimates with models using traditional aggregate temperature measures, and find that adopting an aggregate temperature measure could overestimate the damage of global warming on crop yield up to two times that estimated using stage-specific temperature measures.

Keywords: Global warming, crop yield, temperature measure, crop phenological stages

JEL: Q54, Q51, Q15

1 Introduction

Agriculture is expected to be the most vulnerable sector under global warming (Adams 1989, Nelson et al. 2009, Dell et al. 2014). As such, many studies on the impact of global warming have focused on agriculture (e.g., Mendelsohn et al. 1994, Schlenker et al. 2005, Deschênes & Greenstone 2007, Schlenker & Roberts 2009, Burke & Emerick 2016, Cui 2020, Chen & Gong 2021, Wang et al. 2024). These studies generally utilize an "aggregate" temperature measures, such as mean temperature, degree-days, temperature bins, and piece-wise linear function within the growing season, which could blend temperatures from different stages of crop growth.[1] For example, Appendix Table A.1 shows 40 studies on the impact of global warming on agriculture published in mainstream journals that used aggregate temperature measures. An implicit assumption of these temperature measures is that temperatures are additively substitutable within the growing season of a crop. However, this assumption sharply contrasts with the agronomic knowledge that crops are more sensitive to temperature in certain phenological stages of growth (Porter & Gawith 1999, Jones et al. 2002, Fageria et al. 2006, Sánchez et al. 2014, Pessarakli 2021).

Adopting an aggregate temperature could lead to a biased estimate of the effect of temperature on crop yield given that the effect of temperature differs across stages *and* temperature fluctuates widely across stages in each year (see Figure A.1 for the fluctuations of daily temperature across growth stages for each year from 2000 to 2015 for a randomly selected county). An aggregate temperature measure, whether constructed linearly or nonlinearly, necessarily blends positive and negative temperature shocks from different stages. Therefore, the aggregate temperature shock

[1]For simplicity, we refer to temperature measures that blend temperatures from different stages of crop growth, whether through aggregation or averaging, as aggregate temperature measures.

could be smaller than the stage-specific temperature shock as the positive and negative shocks from different stages offset each other during aggregation. A regression model that utilizes the aggregate temperature measure thus tends to overestimate the impact by attributing the effect of large stage-specific temperature shocks to the effect of small aggregate temperature shocks.

This study proposes the use of stage-specific temperature measures. The key stages of major grain crops (e.g., rice, wheat, and corn) are sowing, tillering, elongation, flowering, milk ripening, and harvesting. Sowing is the first stage, involving planting of seeds in soil. Tillering is the formation of additional shoots from the base of the main stem. Elongation refers to rapid stem and leaf growth. Flowering indicates the formation of flowers. Milk ripening occurs when the kernels are in the "milk" stage. Harvesting is the final stage, involving the cutting or gathering of mature crops from the field. The duration of each key stage lasts for 5 to 10 days depending on the crop varieties (Fageria et al. 2006, Pessarakli 2021). Controlled environment studies have shown that the effects of temperature on crop yield considerably vary across phenological stages.[2]

Our empirical analysis combines a unique site-level data on the phenological stages of major crops in China with county-level crop production data and gridded daily weather data from 2001 to 2015 to investigate the importance of adopting stage-specific temperature measures. Specifically, based on crop progress data for the two most important grain crops in China (i.e., rice and wheat), we divide the growing season of each crop into 11 stages: six key stages and five non-key stages. As each key stage lasts for 5–10 days (Fageria et al. 2006, Pessarakli 2021), the baseline specification defines a key stage as 10 days around the median starting day of the stage; days between two key stages are defined as a non-key stage. The findings are robust to defining a key stage as 5 days around the median starting day of the stage. Figure 1 illustrates our

[2]See literature reviews from Porter & Gawith (1999), Sánchez et al. 2014 and Teng et al. 2022.

definition of the six key stages (sowing, tillering, elongation, flowering, milk ripening, and harvesting) and five non-key stages of rice growth in a randomly selected rice production county. For each of these stages we then construct temperature measures that are comparable to the frequently used aggregate temperature measures.

We estimate the effect of temperature in each stage with a panel model that regresses crop yield on temperature measures for all the 11 stages, controlling for the year- and county-fixed effects. The estimates confirm substantial differences in the effects of temperature across stages of crop growth. Specifically, we find that the effect of high temperature on rice yield is negative in seven stages and positive in the remaining four stages, leading to a significantly negative overall effect of temperature across the 11 stages. In addition, the marginal effects vary widely across stages and the positive and negative effects could alternate in successive stages. These findings are robust when different crops are examined; different stage-specific temperature measures (i.e., stage mean, non-linear functions of stage mean, stage degree-days, stage standardized deviations of temperature, and stage-specific temperature shocks) are adopted; different key stage are defined; the county-fixed effects are excluded; and other climatic factors are controlled (i.e., precipitation, wind speed, radiation, vegetation evaporation, and atmospheric pressure).

We then examine whether most of the effect of stage-specific temperatures can be captured with the usually used aggregate temperature measures. We estimate a model that regresses crop yield on a full set of stage-specific temperature measures and an aggregate temperature measure. The coefficients of the stage-specific temperature measures from this regression reflect the effect of stage-specific temperature that cannot be accounted for by the aggregate temperature measure. We find that controlling for the aggregate temperature measures (including growing season mean temperature and its square, a full set of temperature bins, degree-days and harmful degree-days) does not considerably alter the estimated effect of stage-specific temperature measures. This finding suggests that the stage-specific temperature measures have substantial variation independent of the aggregate temperature measures, which could be due to that a substantial portion of the positive and negative stage-specific temperature shocks is neutralized in the construction of an aggregate temperature measure.

Finally, we quantify the potential bias of adopting an aggregate temperature measure by comparing the impacts of global warming predicted with aggregate temperature measure and that based on the stage-specific temperature measures. We find that the impacts predicted with the aggregate temperature measures are considerably larger than those predicted with corresponding stage-specific temperature measures. This finding is robust when different aggregate and stage-specific temperature measures are adopted based on different global warming scenarios. The estimates suggest that adopting an aggregate temperature measure could overestimate the damage of global warming twofold. County-level estimates reveal that compared with stage-specific temperature measures, an aggregate temperature measure would overestimate the damage of warming in hot areas and underestimate the benefit of warming in cold areas.

This study contributes to the literature evaluating the impact of global warming on crop yield. Many controlled environment studies find that temperature effects vary over the life cycle of the plant (e.g., Seshu & Cady 1984, Porter & Gawith 1999, Wassmann et al. 2009, Sánchez et al. 2014, Teng et al. 2022), but existing econometric-based studies generally adopt aggregate temperature measures such as growing season mean, degree-days, temperature bins, and piece-wise linear functions when examining the impact of global warming on crop yield (e.g., Schlenker et al. 2007, Deschênes & Greenstone 2007, Moore & Lobell 2014, Ray et al. 2015, Burke & Emerick 2016, Chen & Gong 2021, Huang et al. 2024). This study illustrates that adopting an aggregate temperature measure tends to overestimate the damage of global warming on crop yield.

We are not the first to raise concerns about the aggregate temperature measures. For example, Schlenker & Roberts (2009) recognize that the time separability of temperature is a strong assumption for the growing season temperature measures. They address this concern by adopting different definitions of the growing season and allow the coefficients to vary across months.[3] Similarly, Welch et al. (2010) define three growth phases (vegetative, reproductive, and ripening) of rice, and allow the estimated coefficients of temperature to differ across three growth phases.[4] Jagnani et al. (2021) investigate how farmers adjust agricultural inputs in different stages of crop growth in response to temperature variation. However, none of these studies utilize detailed field data on the phenological stages of crops. To the best of our knowledge, we are the first to adopt a stage-specific temperature measure utilizing detailed field data on the phenological stages of crops to examine the impact of global warming on crop yield and to explicitly evaluate the potential bias of utilizing an aggregate temperature measure.

The rest of this study is organized as follows: Section 2 reviews the frequently used aggregate temperature measures and illustrates why adopting an aggregate temperature measure would overestimate the damage of global warming, Section 3 introduces the data and method of this study, Section 4 presents the empirical findings, and Section 5 concludes.

2 Conceptual Framework

Considering the production of a crop in year t according to a temperature-dependent Cobb-Douglas production function. For simplicity, we assume that temperature only affects the total factor productivity (TFP) of crop production, similar to Burke et al.

[3] Specifically, they provide three pieces of evidence to support the time separability assumption. First, they split the six-month growing season into three two-month intervals. Second, they jointly estimate the effect of temperature for each month of the growing season. Third, they test for whether the temperature response function is different in July than it is in other months.

[4] Felkner et al. (2009) also estimate the effect of temperature from three different stages on rice yield, but defining the three stages as planting, growing, and harvesting instead.

(2015); capital k_t, labor l_t, and output elasticity of capital α do not respond. Daily mean temperature in day d of the growing season is T_{dt}, the TFP is $f(T_{dt})$, and the yield of the crop is $y_t = f(T_{dt})k_t^{\alpha} l_t^{1-\alpha}$.

2.1 Aggregate temperature measures

Existing econometric-based studies generally adopt growing-season aggregate temperature measures (e.g., growing season mean temperature, degree-days, piece-wise linear function, and temperature bins), which can be summarized by

$$f(T_{dt}) = \widehat{f}\left(g\left(T_{dt}\right)\right),$$

where $g(\cdot)$ is a certain form of aggregation of temperature across the growing season, and $\widehat{f}(\cdot)$ can be a linear function or a high-order polynomial of the temperature measure.

Early studies (e.g., Mendelsohn et al. 1994) measure temperature by the growing season (or monthly, seasonal, and annually) mean

$$g\left(T_{dt}\right) = \frac{\sum_{d=1}^{D} T_{dt}}{D}, \tag{1}$$

where D is the number of days in the growing season (or month, season, and year). Later studies incorporate agronomic knowledge (Ritchie & Nesmith 1991) to measure temperature nonlinearly by growing season degree-days (e.g., Schlenker et al. 2006), which is typically defined as the sum of truncated degrees between two bounds. For example, when using bounds of 8°C and 32°C, the degree-days in each day can be calculated as:

$$d(T_{dt}) = \begin{cases} 0 & \text{if} \quad T_{dt} \leq 8 \\ T_{dt} - 8 & \text{if} \quad 8 < T_{dt} < 32 \\ 24 & \text{if} \quad T_{dt} \geq 32 \end{cases} \cdot$$

The growing season degree-days is then calculated as the sum of degree-days across all days in the growing season

$$g\left(T_{dt}\right) = \sum_{d=1}^{D} d\left(T_{dt}\right). \tag{2}$$

Degree-days above 34°C are sometimes included as a separate variable and speculated to be harmful.[5]

A more flexible temperature measure adopted in the literature is temperature bins, which use counts of days in various temperature bins to approximate a temperature distribution. For example, when three-degree temperature bins are adopted (e.g., Schlenker & Roberts 2009), and the measure for the bin of 6–9°C is the number of days in the growing season with temperature exposure falls into this interval. The resulting temperature measure is a set of variables capturing the effect of the number of days within each temperature interval.

$$g\left(T_{dt}\right) = \sum_{j=0,3,6,9,\cdots}^{33} \gamma_j x_j, \tag{3}$$

where x_j is the measure of bin j. Daily mean temperatures above 33°C occur less frequently and are usually lumped into the category of $j = 33$. Similarly, temperatures below freezing are lumped into the category of $j = 0$.

Similar to the degree-days, a parsimonious piece-wise linear function (or linear spline function) of temperature is adopted by some studies (e.g., Burke & Emerick 2016). This function assumes that yield increases linearly with temperature up to an endogenous threshold and then decreases linearly above the threshold.[6] As the piece-

[5] The degree-days and temperature bins can be more accurately calculated when using hourly temperatures or daily maximum and minimum temperatures based on a sinusoidal interpolation.

[6] The piece-wise linear function can be written as

$$g\left(T_{dt}\right) = \begin{cases} c_1 + b_1 T_t & \text{if} \quad T_t < T^* \\ c_2 + b_2 T_t & \text{if} \quad T_t \geq T^* \end{cases},$$

where T^* is the temperature threshold, T_t could be accumulated degree-days within the range of the segment of temperatures defined by the threshold, and c_1, b_1, c_2, and b_2 are constants. The threshold wise measure of temperature is a special form of the degree-days and temperature bins, this study does not specifically examine the piece-wise temperature measure.

Another group of studies measure temperature by the standardized deviations from the long-run local mean (e.g., Miller et al. 2021).

$$d(T_{dt}) = \frac{T_{dt} - \overline{T}_d}{SD_d}, \tag{4}$$

where $\overline{T}_d$ is the long-run local mean temperature of day d, and SD_d is the corresponding standard deviation. The daily standardized deviation is then used in constructing growing season aggregate temperature shocks, such as the number of days with a mean temperature 1-SD above the local mean:

$$g\,(T_{dt}) = \sum_{d} I(d(T_{dt}) \geq 1), \tag{5}$$

where $I(\cdot)$ is a dummy variable that equals one if $d(T_{dt}) \geq 1$.

2.2 Bias of using an aggregate temperature measure

By blending temperatures from different stages of crop growth, the aggregate temperature measures implicitly assume that temperatures are additively substitutable within the growing season. Specifically, the assumption is that a number of hot days in different stages of growth has the same effect on crop yield. This assumption is inconsistent with the fact that crops are more sensitive to temperatures in certain stages of growth. This concern is aggravated when temperature fluctuates substantially across days within a growing season. For example, we randomly select a rice-production county (Qidong County in Hunan province and plot daily standardized deviation of temperature during the growing season in Appendix Figure A.1. Considerable

is obtained by looping over all possible thresholds, estimating the least-squares segment slopes for each one, and selecting the threshold and segment slopes with the best fit.

fluctuations occur across days within a growing season. In Figure 2, we plot daily standardized deviation of temperature in 2004 and 2008 for the same county. Although these two years have nearly identical growing season mean temperatures (24.65 °C versus 24.68°C) and degree-days (2215 versus 2218), they have very different stage-specific temperatures.[7]

The aggregate temperature measures allow the positive and negative shocks from different stages of crop growth to offset each other and substantially reduce the temperature variation used for estimating the effect. Figure 3 shows that a growing season temperature measure could have much smaller temperature variation than a stage-specific temperature measure. Based on data from 1217 rice-producing counties, panel A presents the distribution of the deviation of stage mean temperature from the long-run average for stage 4 (i.e., flowering) in representative years; panel B presents the distribution of the deviation of stage mean temperature from the long-run average for each key stage in 2010; panel C presents the distribution of the deviation of the growing season mean temperature from the long-run average in representative years; and panel D presents the distribution of the total number of days in the growing season with positive and negative temperature shocks (defined as 1-SD above or below the long-run average) when calculated separately (dashed lines) or combined (solid line). We find that the stage-specific temperature variations are quite large over years (panel A) and across stages (panel B). However, the variations in growing season mean temperature are much smaller (panel C) because most of the positive and negative temperature shocks cancel each other out. Panel D further illustrates this by presenting the distribution of the total number of days with positive (dashed red line) and negative (dashed green line) temperature shocks during the growing season and the distribution of the sum of these two shocks (solid line).

Table 1 provides an intuitive illustration of the bias of using an aggregate tempera-

[7]The distribution of temperature bins for these two years are also similar, as presented in Appendix Figure A.3.

ture measure, using growing season mean temperature as an example. Assuming that the growing season of a crop can be classified into two stages: a key stage and a non-key stage. In each stage, the temperature shock (i.e., deviation from the local long-run average) could be positive ($b > 0$), none (0), or negative ($a < 0$).[8] For simplicity, we assume that a temperature shock in the non-key stage has no effect on crop yield and a positive (negative) temperature shock in the key stage reduces (increases) crop yield. The qualitative conclusion is the same if we adopt the more realistic assumption that temperature shocks in the non-key stage have a smaller effect (Hatfield & Prueger 2015).

Columns 1 and 2 present the nine combinations of potential temperature outcomes. Column 3 presents the temperature shocks used in identifying the effect when an aggregate temperature measure is adopted. The growing season mean temperature is used as an example. As a qualitative examination is performed, all conclusions based on growing season mean temperature naturally apply to other aggregate temperature measures discussed in subsection 2.1; in the following quantitative examinations, we examine the effect of each frequently used aggregate temperature measure. Column 4 presents the temperature shocks that should be used for estimating the effect because only the temperature from the key stage affects crop yield. Intuitively, the estimated effect based on the aggregate temperature measure should be biased when the temperature shocks in column 3 are different from those in column 4.

Column 5 shows that the estimated effects are unbiased only when the two stages experience the same temperature shock (rows 3, 5, and 7). Column 6 shows that the effects are overestimated when the absolute value in column 3 is smaller than that in column 4 (rows 1, 2, 8, and 9) and underestimated when the opposite occurs (rows 4 and 6). This is because when mistakenly attributing the effect of a large (small)

[8] Examining the effect of temperature shocks is relevant because studies that attempt to address endogeneity issues by including location-fixed effects in the regression model depend mainly on temperature shocks for identification (Deschênes & Greenstone 2007).

temperature shock to that of a small (larger) temperature shock, the marginal effect of temperature will be overestimated (underestimated).[9] As the chance of no temperature shock (rows 4 and 6) is very small (Figure A.1), Table 1 suggests that the effect of warming is most likely to be overestimated when an aggregate temperature measure is adopted. The intuition behind this is that aggregate temperature measures allow positive and negative shocks from different stages to offset each other and, incorrectly attribute the effect of large stage-specific temperature shocks to that of small aggregate temperature shocks. Notablt, this concern applies even to the most flexible aggregate temperature measure—temperature bins. For example, if a positive shock occurs in a key stage that increases the number of days belonging to a temperature bin and a negative temperature shock occurs in a non-key stage that reduces the number of days belonging to the same temperature bin, then the temperature bin calculated according to temperatures from these two stages will be neutralized.

2.3 Stage-specific temperature measures

We propose the following stage-specific temperature measure:

$$f(T_{dt}) = \sum_{s=1}^{S} \alpha_s \widetilde{f}\left(g\left(T_{dt}^{s}\right)\right) , \tag{6}$$

where the growing season of the crop is divided into S stages and all other variables are the same as defined before. As presented in Figure 1, we follow the agronomic tradition (Jones et al. 2002) to divide the growing season into six key stages (blue circles) and five non-key stages (small red circles). As each key stage lasts for 5–10 days (Fageria et al. 2006, Pessarakli 2021), our main analysis defines a key stage as 10 days around the median starting day of the stage; days between two key stages are defined as a non-key

[9] An implicit assumption here is that for rows 1 and 9, the directions of the shock are the same in columns 3 and 4. This assumption is supported by the fact that in a warmer (colder) year, most stages of growth are likely to be warmer (colder) than usual.

stage. The stage-specific temperature coefficient α_s captures the effect of temperature in stage s. The stage-specific temperature measure $g\left(T_{dt}^s\right)$ can be any of the temperature measures presented in subsection 2.1 but constructed according to only temperatures within the stage. The function $\widetilde{f}(\cdot)$ can be the first- or high-order polynomials of the stage-specific temperature measure. Therefore, the only difference between the stage-specific temperature measure and the aggregate temperature measure is that the stage-specific temperature does not blend temperatures from different stages.

3 Data and Empirical Strategy

3.1 Data

3.1.1 Crop yield

This study utilizes county-level crop yield data derived from the County-Level Agricultural Database managed by the Ministry of Agriculture and Rural Affairs of China.[10] The database contains an unbalanced panel of county-level input and output for each of the major crops in China starting since 1981. We have access to the data from 2001 to 2015 for rice and wheat, which are the two most important food crops in China. As different varieties of the same crop have very different growing seasons, we focus on counties producing the most widely cultivated variety of each crop: semilate rice and winter wheat.[11] Whenever there is no confusion, we simply refer to semilate rice as rice and winter wheat as wheat. We also exclude counties where the sown area of these crops is less than 1,000 hectares. As presented in Appendix Figure A.2, the final sample contains 1,217 counties producing rice and 1,080 counties producing wheat; there are 508 counties producing both of these two crops.

[10] http://www.zzys.moa.gov.cn/.

[11] In 2015, semilate rice accounted for 76% of the rice sown area in China, while winter wheat accounted for 94% of the wheat sown area. Some counties cultivated both early rice and semilate rice. To focus on semilate rice, we exclude all counties in which early rice was cultivated. This process excludes about one-fifth of the rice production counties, mainly from southeast China.

3.1.2 Crop progress

County-level crop progress data for each crop variety are derived from 778 agro-climatic monitoring sites managed by the National Meteorological Information Center of China.[12] These sites were established to monitor crop progress in major agricultural areas, and the locations of these sites were selected to represent different agricultural regions in China. Given that China has roughly 2,000 agricultural counties, each of the five agricultural counties share two monitoring sites. Each site collects detailed data on the starting date of each key stage of the major crop varieties cultivated near the site each year.[13] We have access to site-level median starting date of each key stage of each crop variety, calculated based on monitoring data from 1993 to 2013; unfortunately, we do not have access to the starting date of each single year.[14] We spatially interpolate the site-level progress data of each crop to all counties producing the crop using inverse-distance weighting with a radius of 200 km. Appendix Figure A.4 presents the distribution of the key stages of rice and wheat across the sample counties.

3.1.3 Weather

Daily temperature data are derived from the latest state-of-the-art global reanalysis dataset, the Enhanced Global Dataset for the Land Component of the Fifth Generation of European ReAnalysis (ERA5-Land).[15] The dataset spans from 1981 to the

[12]http://data.cma.cn/site.

[13]Parcels to be monitored are selected to ensure that the crops cultivated on these parcels accurately reflect regional cropping practices. The site's staff solely focuses on monitoring crop conditions, while the actual management of the parcels remains in the hands of ordinary farmers. The site's staff rely on on-site observations and agronomists' technical manual criteria to determine the starting date for each key stage of a crop.

[14]A potential concern stemming from this data limitation is that farmers may adjust the timing of production to adapt to climate change, and we may thus overestimate the impact of stage-specific temperature measures. However, given that this potential overestimation also applies to the growing season aggregate temperature measures, it does not undermine the main conclusion of the study, which is that adopting an aggregate temperature measure tends to overestimate the impact of climate change than stage-specific temperature measure.

[15]Details of ERA5-Land can be found in Muñoz-Sabater et al. (2021).

present and has a resolution of 9 km $\times$ 9 km. We use ArcGIS to construct county average daily mean temperature from 1981 to 2015 accordding to data from all grids within each county. The data before 2001 (the first year of our study sample) are only used to construct the long-run climatic normal. We then derive five other climatic measures (precipitation, wind speed, radiation, vegetation evaporation, and atmospheric pressure) as control variables from ERA5-Land. Appendix Table A.2 presents the summary statistics of key climatic variables.

3.1.4 Global warming prediction

The predicted daily temperatures used for forecasting the end-of-the-century impact of global warming on crop yield are also derived from ERA5-Land. Specifically, we use the daily temperatures predicted based on the medium (RCP 4.5) and high (RCP 8.5) global warming scenarios from the CanESM2 model.[16] We calculate county-level predicted changes in temperature on the basis of the predicted daily temperature difference between the 2011–2015 average and the 2096–2100 average. Figures 4 presents the predicted changes in stage-specific mean temperature for each of the 11 stages under scenarios RCP 4.5 and high RCP 8.5 in rice production counties. We find significant variation in the predicted warming across counties (as indicated by the box graph for each stage) and a larger temperature increase for each stage under RCP 8.5 than under RCP 4.5. The county-level increases in growing season mean temperature for each sample county are presented in Appendix Figure A.5.

[16]See more details from https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip5-daily-single-levels?tab=form.

3.2 Empirical Strategy

The effect of stage-specific temperature can be estimated by:

$$y_{ct} = \sum_{s=1}^{S} \alpha_s \widetilde{f}\left(g\left(T_{dct}^s\right)\right) + \delta_t + \delta_c + X_{ct}\gamma + \varepsilon_{ct}, \tag{7}$$

where y_{ct} is log yield of a crop cultivated in county c and year t, and $\sum_{s=1}^{S} \alpha_s \widetilde{f}\left(g\left(T_{dct}^s\right)\right)$ is a set of stage-specific temperature measures for each of the 11 stages. Each key stage is defined as the 10 days around the starting date of the stage in each county and the days between two connected key stages are defined as a non-key stage (Figure 1).[17] We show that the results are robust when each key stage as the 5 days around the starting date of the stage in panel A of Figure 6.

Model (7) includes the year fixed effects (δ_t) and county fixed effects (δ_c), and the effects are identified according to the plausibly exogenous county-specific inter-annual temperature fluctuations (Deschênes & Greenstone 2007). We show that the results are comparable when county fixed effectsare excluded. Vector X_{ct} includes a set of exogenous control variables: growing season total precipitation and its square, wind speed, radiation, vegetation evaporation, and atmospheric pressure.[18] The error term ε_{ct} is clustered at the county level to address the potential bias from serial correlation. In the estimation, we weight the model by the sown area of the crop in each county.

We examine the effect of stage-specific mean temperature, degree-days, standardized deviation of temperature, and positive and negative temperature shocks, which are calculated for each stage with Equations (1), (2) (4), and (5), respectively. We then examine the nonlinear effects of these stage-specific temperature measures by including their square terms in the regression. We do not examine the effects of stage-specific

[17] Specifically, a key stage is defined as five days before the starting date plus five days after the starting date.

[18] We do not control for capital and labor inputs in the regression model as they are likely to be endogenous. In addition, in a competitive equilibrium, the capital–labor ratios are fixed ($\frac{k_{ct}}{l_{ct}} = \frac{\alpha}{1-\alpha}$), so most of their effects could have been accounted for by the county-fixed effects.

temperature bins because the 11 stages divide the growing season into small sections with narrow temperature ranges. If we further divide each stage into, such as, 3°C bins, we would have to estimate the effect of more than 100 temperature coefficients. Owning to the narrow temperature range within each bin, most of the bins have insufficient variation for the estimation of a credible effect.

We compare the total effect of stage-specific temperature measures estimated with model (7), and the effect of the corresponding growing season temperature measures is estimated according to the following equation:

$$y_{ct} = \beta \widehat{f}\left(g\left(T_{dct}\right)\right) + \delta_t + \delta_c + X_{ct}\gamma + \varepsilon_{ct}, \tag{8}$$

where the only difference from model (7) is that the stage-specific temperature measure is replaced by the corresponding growing season temperature measure $\widehat{f}\left(g\left(T_{dct}\right)\right)$.

Futhermore, we verify that the stage temperature measures have substantial variation independent of growing season temperature measures:

$$y_{ct} = \sum_{s=1}^{S} \alpha_s' \widetilde{f}\left(g\left(T_{dct}^s\right)\right) + \beta' \widehat{f}\left(g\left(T_{dct}\right)\right) + \delta_t + \delta_c + X_{ct}\gamma + \varepsilon_{ct}, \tag{9}$$

where the only difference from model (7) is that it additionally controls for one of the growing season temperature measures $\widehat{f}\left(g\left(T_{dct}\right)\right)$. The coefficient α_s' identifies the effect of the stage-specific temperature measure that cannot be captured by the aggregate temperature measure. If the estimated coefficients of the stage-specific temperature measures (α_s' in model (9)) are similar to those from the model without controlling for the aggregate temperature measure (α_s in model (7)), we would conclude that stage-specific temperatures have substantial independent variation that cannot be captured by the aggregate temperature measure.[19] This finding suggests that growing season

[19]A potential concern of model (9) is the bad control problem as stage-specific temperature measures could be strongly correlated with the aggregate temperature measure. The bad control problem may lead to a substantial change in the coefficients of the stage-specific temperature

aggregate temperature measures may not fully capture the effect of stage-specific temperature on crop yield.

4 Results

For simplicity, this section only presents the estimates for rice, and the main estimates for wheat are presented in Appendix A.3. Estimates based on these two crops are comparable. We focus mainly on examining the effect of stage-specific or growing season mean temperature and degree-days, as they are the two most widely used temperature measures in the literature (Table A.1)

4.1 Effect of stage-specific temperature

Figure 5 presents the effect of stage-specific temperature on rice yield estimated with model (7). Each key stage is defined as the 10 days around the starting date of the stage, and the days between two connected key stages are defined as a non-key stage. The estimates in the figure are presented in chronological order of the 11 stages. The dependent variable (log rice yield) is multiplied by 100 so that the y-axis measures the percentage effect.

Panel A presents the effect of stage mean temperature. The estimates suggest that temperature has a statistically significant effect on rice yield in only five of the 11 stages, and the marginal effect differs across stages. The higher temperature in stages 2 and 8 increase rice yield, whereas the high temperatures in stages 7, 10, and 11 reduce rice yield. These estimates confirm the main argument of this study: crops are more sensitive to temperature in certain stages of growth. The negative marginal effect of temperature is larger than the positive marginal effect, suggesting an overall damage of

measures. Therefore, model (9) provides a strict examination of the independent effects of stage-specific temperature measures; the estimated coefficients of stage-specific temperature measures will be unchanged only when there are substantial independent variations.

warming on rice yield. Panel B adopts the temperature measure of stage degree-days constructed according to Equation 2 and shows a similar effect pattern. We postpone the discussion of the overall effect of stage temperature measures to subsection 4.2. We also consider the nonlinear effect of temperature within each stage.

Figure 6 presents various robustness checks. Panel A defines each key stage as 5 days instead of 10 days around the starting date of the stage and finds comparable estimates. Panel B adopts the temperature measure of total standardized deviations of temperature in each stage, constructed according to Equation 5 and finds a similar effect pattern, although the marginal effects are different because of differences in units.[20] Panels C and D respectively estimate the effect of total positive and total negative temperature shocks in each stage, defined as the number of days with temperature 1-SD above or below the long-run average. The estimates suggest the significantly different effects of positive and negative temperature shocks in different stages. Panels E and F examine the robustness to omitted variables by excluding the climatic control variables and county-fixed effects, respectively. The resulting estimates are comparable.

4.2 Independent effect of stage temperature measures

An intuitive way to illustrate the potential bias of adopting an aggregate temperature measure is to examine whether it can account for most of the effect of stage-specific temperatures. We do this by estimating model (9), which regresses rice yield on both stage-specific temperature measures and an aggregate temperature measure. The coefficient of the stage-specific temperature measure from this regression reflects the effect of stage temperatures that cannot be accounted for by the aggregate temperature

[20] The total standardized deviation is calculated by subtracting the long-run (1981–2015) average from the daily mean temperature, dividing by the standard deviation, and summing across all days in the stage. This temperature measure allows us to account for the accumulated effect of temperature within a stage and to relieve concerns of stage-specific time-invariant confounding factors by removing stage mean from the regression.

measure. If the estimated coefficient of the stage-specific temperature measure is similar to the model without controlling for the aggregate temperature measure, we would conclude that stage-specific temperatures have substantial independent variation (relevant for identifying the impact on rice yield) that cannot be captured by the aggregate temperature measure.

Figure 7 presents the estimated effect of stage mean temperature (panel A) and stage degree-days (panel B) conditional on the aggregate temperature measures (including growing season mean temperature and its square, a full set of temperature bins, and degree-days and harmful degree-days). Specifically, we estimate the effect of stage temperature measures based on four model settings. The first is the baseline estimation without controlling for any aggregate temperature measure, which is the same as that presented in Figure 5. The second is a version of model (9) that controls for growing season mean temperature and its square. The third is a version of model (9) that controls for a full set of temperature bins, setting the bin of 9–12°C as the reference group. The fourth is a version of model (9) that controls for degree-days and harmful degree-days. All these aggregate temperature measures are defined in subsection 2.1. The estimates presented in Figure 7 suggest that controlling for these aggregate temperature measures does not significantly affect the estimated effect of stage temperature measures.[21]

We cannot conclude from Figure 7 that the stage temperature measure has a larger or smaller effect than the aggregate temperature measure. The estimates only tell us that the stage temperature measure has substantial and independent variation (relevant for identifying the impact on rice yield) that cannot be captured by the

[21]The finding that controlling for aggregate temperature measures does not alter the estimated effect of stage-specific temperature measures is not because these aggregate temperature measures themselves have no significant effect on rice yield. Appendix Table A.3 shows that growing season mean temperature and degree-days have significant and nonlinear effects on crop yield. Appendix Figure A.6 similarly shows the significant nonlinear effects of growing season temperature bins. These estimates are consistent with what has been found in the literature (e.g., Schlenker & Roberts 2009, Huang et al. 2018, Chen & Gong 2021).

growing season temperature measures. This finding is intuitive when considering that a substantial portion of the positive and negative stage-specific temperature shocks has been neutralized when constructing an aggregate temperature measure, as illustrated in Figure 3. However, the estimates in Figure 7 indeed suggest the bias of using an aggregate temperature measure as it cannot fully capture the impact of stage-specific temperatures.

4.3 Bias of using an aggregated temperature measure

This subsection quantifies the bias of adopting an aggregate temperature measure by comparing the predicted impacts of global warming according to the estimated marginal effect of stage-specific temperature measures and the estimated marginal effect of the corresponding aggregate temperature measures. We compare across the impacts of global warming predicted according to stage mean temperature and its square, stage degree-days and harmful degree-days, growing season mean temperature and its square, growing season degree-days and harmful degree-days, and growing season temperature bins.

The marginal effects of growing season mean temperature, growing season degree-days, and growing season temperature bins are reported in Table A.3 and Figure A.6. These estimates are obtained by estimating versions of model (8) versions that use different growing season temperature measures as the key explanatory variables. The estimates suggestion that high growing season mean temperature first increases and then reduces rice yield (column 1 of Table A.3). The effect pattern is the same for growing season degree-days (column 1 of Table A.3), and we find that harmful degree-days reduce rice yield. Similarly, Figure A.6 shows that low and high temperature bins are harmful for rice yield when compared with the temperature bin of 9–12°C.

We present the predicted impact under a medium global warming scenario (RCP 4.5) and a high global warming scenario (RCP 8.5). The county-level predicted warming from the 2011–2015 average to the 2096–2100 average is presented in Appendix Figure A.5. For an average rice production county, the predicted increase in growing season mean temperature is 2.30°C under the medium scenario and 5.04°C under the high scenario. We examine the impact of a uniform warming scenario, which assumes that all counties experience a temperature increase of 5°C on all days, showing that the finding is not primarily driven by differences in predicted warming across counties and over days in a growing season.

Column 1 of Table 2 presents the predicted impact of stage mean temperature, which is calculated by summing up the predicted impacts across the 11 stages. The impact in each stage is calculated by multiplying the marginal effect of stage mean temperature with the county-level predicted warming in each stage. The resulting estimates suggest that global warming will reduce the county mean rice yield by 3.88%, 7.11%, and 6.37%, respectively, under scenarios RCP 4.5, RCP 8.5, and the scenario of 5°C uniform warming. Column 2 replicates column 1 but accounts for the potential nonlinear effect of stage mean temperature. We first estimate a version of model (7) that regresses rice yield on stage mean temperature and its square. The estimated stage-specific nonlinear effect is presented in Figure A.7. We then combine the estimated nonlinear effect with predicted warming in each stage to calculate the predicted impact of warming. As expected, since each stage has a narrow temperature range, accounting for the stage nonlinear effect that does not affect the predicted impact of warming substantially. Column 3 presents the predicted impact of stage degree-days and harmful degree-days. The predicted impacts are much larger under RCP 8.5 under the 5°C uniform warming scenario, although these two scenarios predict similar temperature increases (5.04 °C versus 5.00 °C). This is because RCP 8.5 predicts much more extreme warming in some counties and days and substantially increases the predicted damage of harmful degree-days.

Columns 4–6 present the predicted impact of global warming according to the estimated marginal effects of the aggregate temperature measures of growing season mean temperature and its square, growing season degree-days and harmful degree-days, and growing season temperature bins, respectively. The predicted damage of warming on rice yield based on the aggregate temperature measures are significantly larger than that based on the corresponding stage-specific temperature measures. Specifically, when columns 2 and 4 are compared (both examines the effects of temperature mean and its square), we find that the aggregate temperature measure predicts damage that is 1.28–1.74 times that predicted by the stage temperature measure under different warming scenarios. Similarly, by comparing columns 3 and 5 (both examines the effects of degree-days and harmful degree-days), we find that the aggregate temperature measure predicts damage that is 0.42–1.94 times as large. In addition, column 6 shows that the predicted impacts based on growing season temperature bins are significantly larger than that based on the stage mean temperature.

Figure 8 presents the county-level impact of global warming on rice yield predicted according to the stage mean temperature and its square (left panel) and growing season mean temperature and its square (right panel) under the global warming scenario RCP 4.5. The figure suggests that while warming reduces rice yield in a large share of rice production counties, it increases rice yield in a large number of cold counties in north China and the southwest uplands of China. A larger number of counties are expected to be damaged when measuring temperature by the growing season mean instead of the stage mean (927 versus 724 counties). In addition, the estimated county-level damages are generally larger when temperature is measured by the growing season mean. For example, 345 counties are expected to experience a yield loss of more than 10% when the growing season mean temperature is used, but the number of counties is only 28 when the stage mean temperature is used. All these observations are consistent with the finding that adopting an aggregate temperature measure overestimates the damage of global warming.

5 Concluding Remarks

Agriculture is expected to be the most vulnerable sector under global warming because temperature serves as a direct and critical input in crop production. Consequently, numerous important studies on the impact of global warming focus on agriculture. Considerable progress in the estimation of the impact of global warming on crop yield. While early studies measure temperature by annual or seasonal means, later studies propose measuring temperature by growing season mean, degree-days, temperature bins, piece-wise linear functions, and temperature shocks, after incorporating the fact that temperature affects crop yield mainly during the growing season and that the effect could be cumulative and nonlinear.

However, all these widely used temperature measures can be classified as aggregate temperature measures that blend temperatures from different stages of crop growth owing to the implicit assumption that temperatures are additively substitutable within the growing season. This assumption is inconsistent with agronomic knowledge, which suggests that crops are more sensitive to temperature in certain phenological stages. This study illustrates that as temperature fluctuates widely across growth stages, an aggregate temperature measure tends to overestimate the impact by attributing the effect of large stage-specific temperature shocks to the effect of small and neutralized growing season temperature shocks.

Based on county-level data on the phenological stages of rice and wheat in China, this study confirms that temperature shocks occurring in different stages of crop growth have quite different effects. By estimating a regression model that includes both the stage and aggregate temperature measures, we show that the stage-specific temperature measure has a substantial effect independent of the aggregate temperature measure. By comparing the predicted impact of global warming based on stage and aggregate temperature measures, we find that adopting an aggregate temperature measure could overestimate the impact of global warming twofold. These findings suggest the adoption of stage-specific temperature measures when information on crop stages is available.

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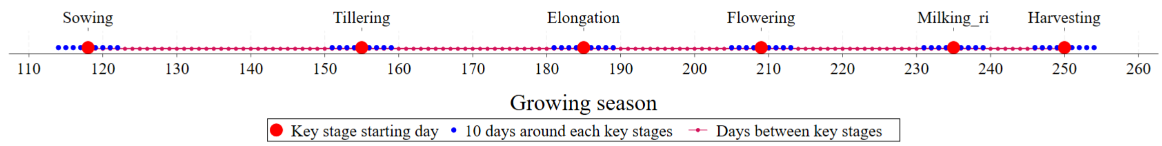

Figure 1: Stages of rice growth in a representative county

Note: This figure presents the stages of rice growth in a randomly selected rice production county (Dingyuan county in Anhui province). The large red circles represent the median starting date of each key stage documented in the county, and the small blue circles represent the 10 days belonging to each key stage. The date is coded as the number of days since the first day of the year.

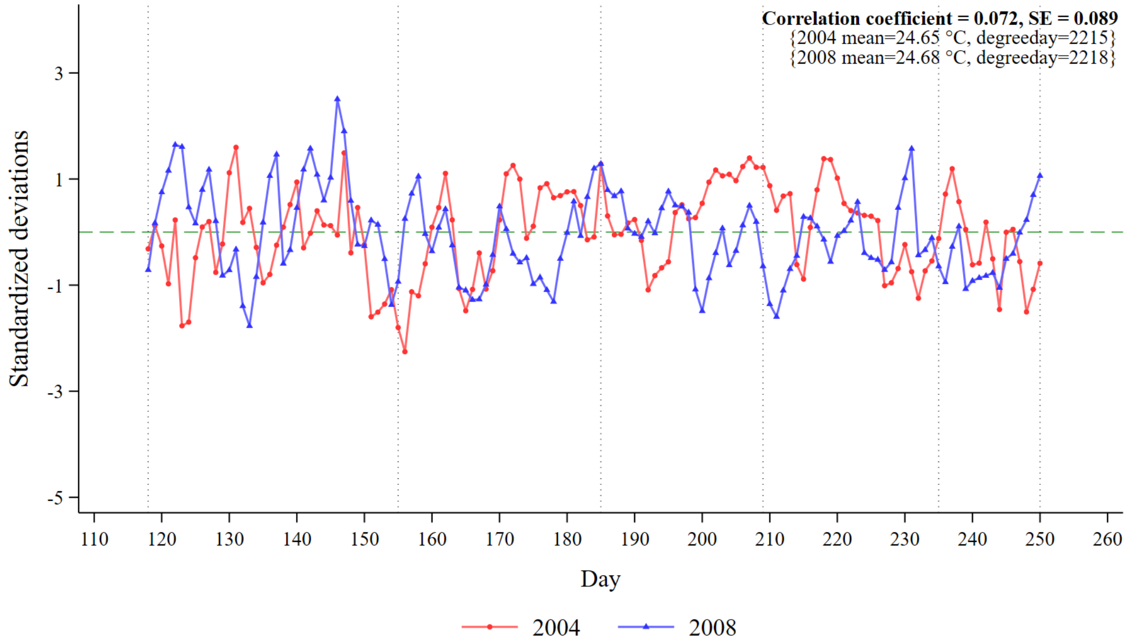

Figure 2: Daily temperature fluctuations in two years with nearly identical growing season mean temperature and degree-days

Note: This figure presents the daily standardized deviation of temperature for two years (2004 and 2008) with similar growing season mean temperatures (24.65°C and 24.68°C) and degree-days (2215 and 2218). The daily standardized deviation is calculated according to Equation (4). The data come from a randomly selected rice-production county (Qidong county in Hunan province). The date is coded as the number of days since the first day of the year. The dashed vertical lines mark the starting day of each key stage of rice in the county.

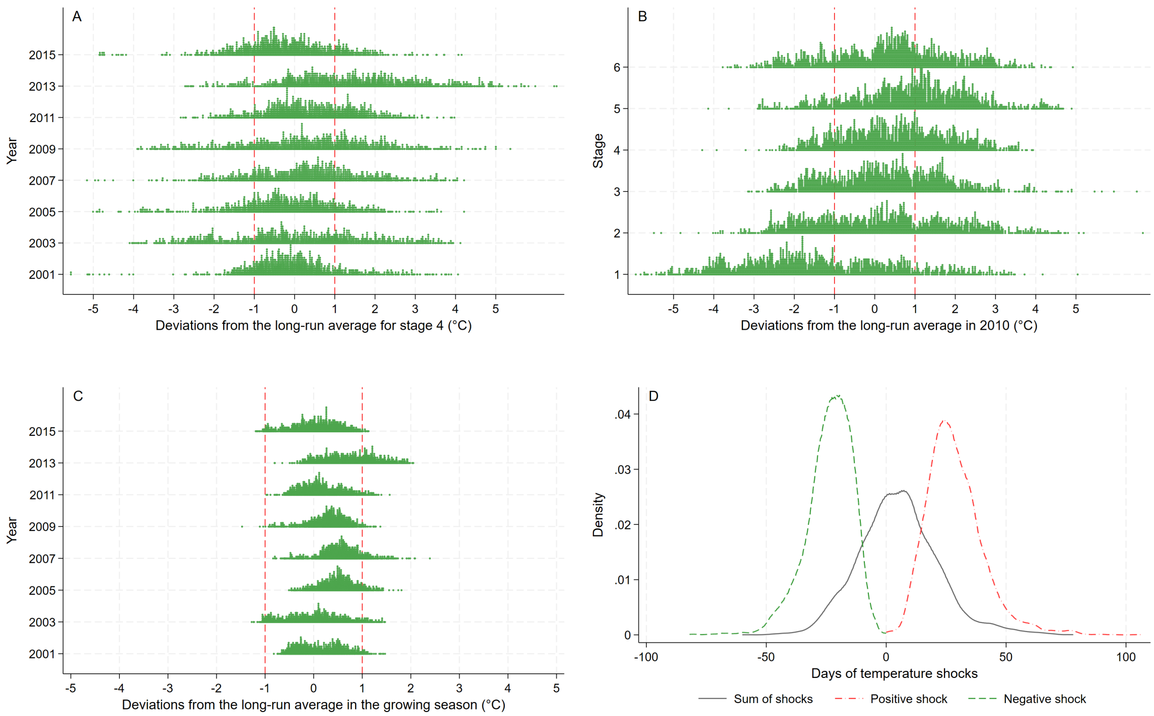

Figure 3: Stage and growing season temperature deviations

Note: Based on data from 1217 rice-producing counties, Panel A presents the distribution of the deviation of stage mean temperature from the long-run average for stage 4 (i.e., flowering) in representative years. Panel B presents the distribution of the deviation of stage mean temperature from the long-run average for each key stage in 2010. Panel C presents the distribution of the deviation of the growing season mean temperature from the long-run average in representative years. Panel D presents the distribution of the total number of days in the growing season with positive and negative temperature shocks (defined as 1-SD above or below the long-run average) when calculated separately (dashed lines) or combined (solid line).

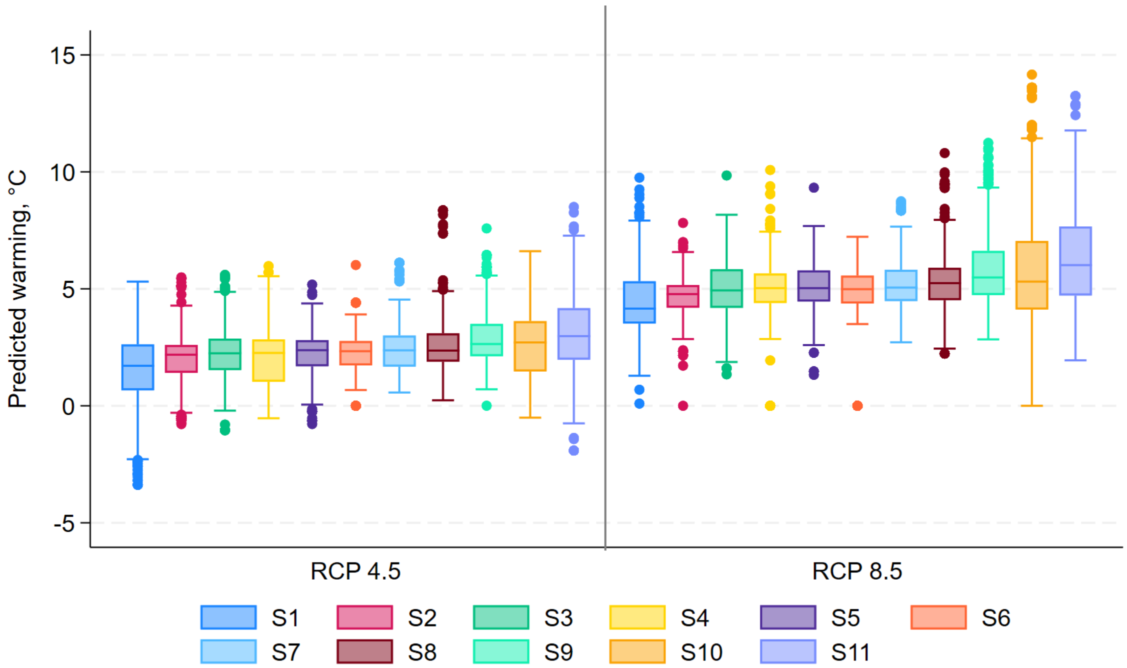

Figure 4: Predicted end-of-the-century increase in stage-specific mean temperature

Note: This figure presents the predicted increase in stage-specific mean temperature, calculated as the difference between the 2011–2015 average and the 2096–2100 average, under global warming scenarios RCP 4.5 and RCP 8.5 for 1217 rice production counties. For each stage, the box plot presents the mean, upper and lower quartile values, minimum and maximum data values, and outliers. The legend markers S1–S11 denote each stage of rice growth.

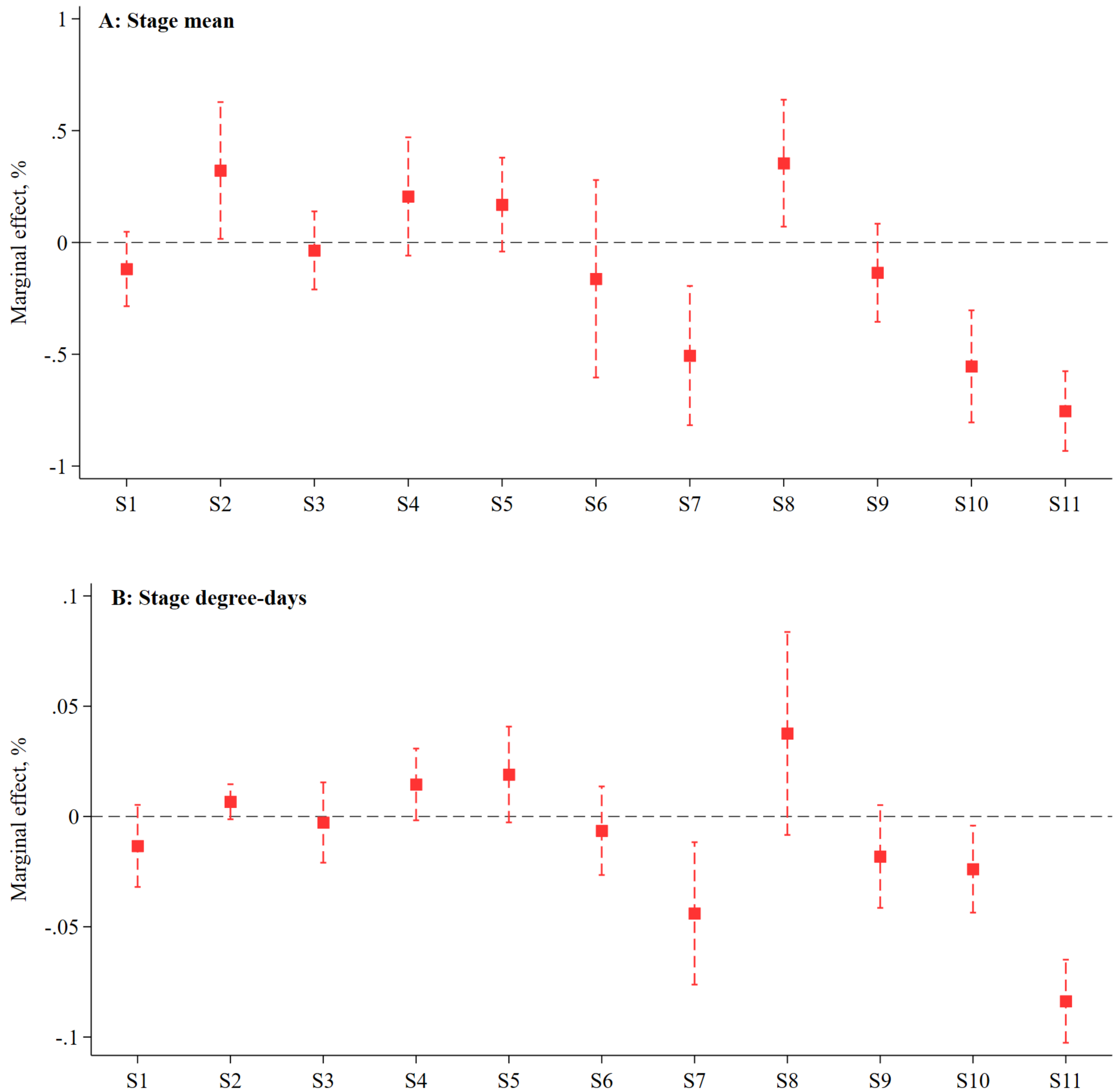

Figure 5: Effect of stage-specific temperature on rice yield

Note: This figure presents the estimated effect of stage-specific temperature on rice yield based on model (7). Panel A measures temperature by stage mean, and Panel B measures temperature by stage degree-days and stage harmful degree-days. The x-axis S1–S11 denote each stage of rice growth, in chronological order. The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

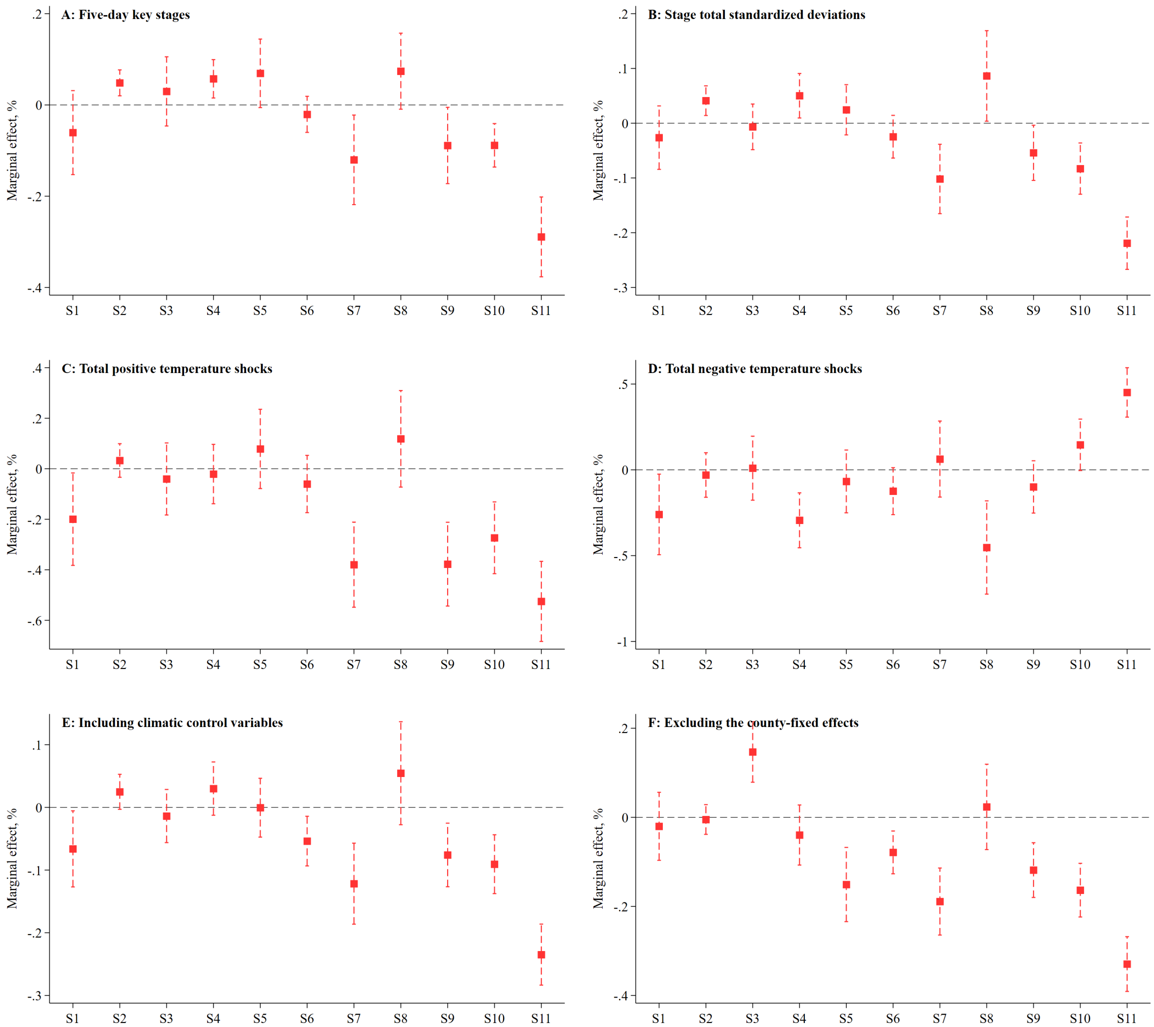

Figure 6: Robustness of the stage-specific temperature estimates

Note: This figure presents robustness checks for the estimates in Panel B of Figure 5. Panel A defines each key stage as 5 days around the starting date of the stage; Panel B measures temperature by the total standardized deviations (i.e., z-score) of daily temperature in each stage; Panels C and D, respectively, estimate the effect of stage total positive and total negative temperature shocks, defined as the number of days with temperature 1-SD above or below the long-run average; Panels E and F, respectively, exclude the climatic control variables and county-fixed effects. The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

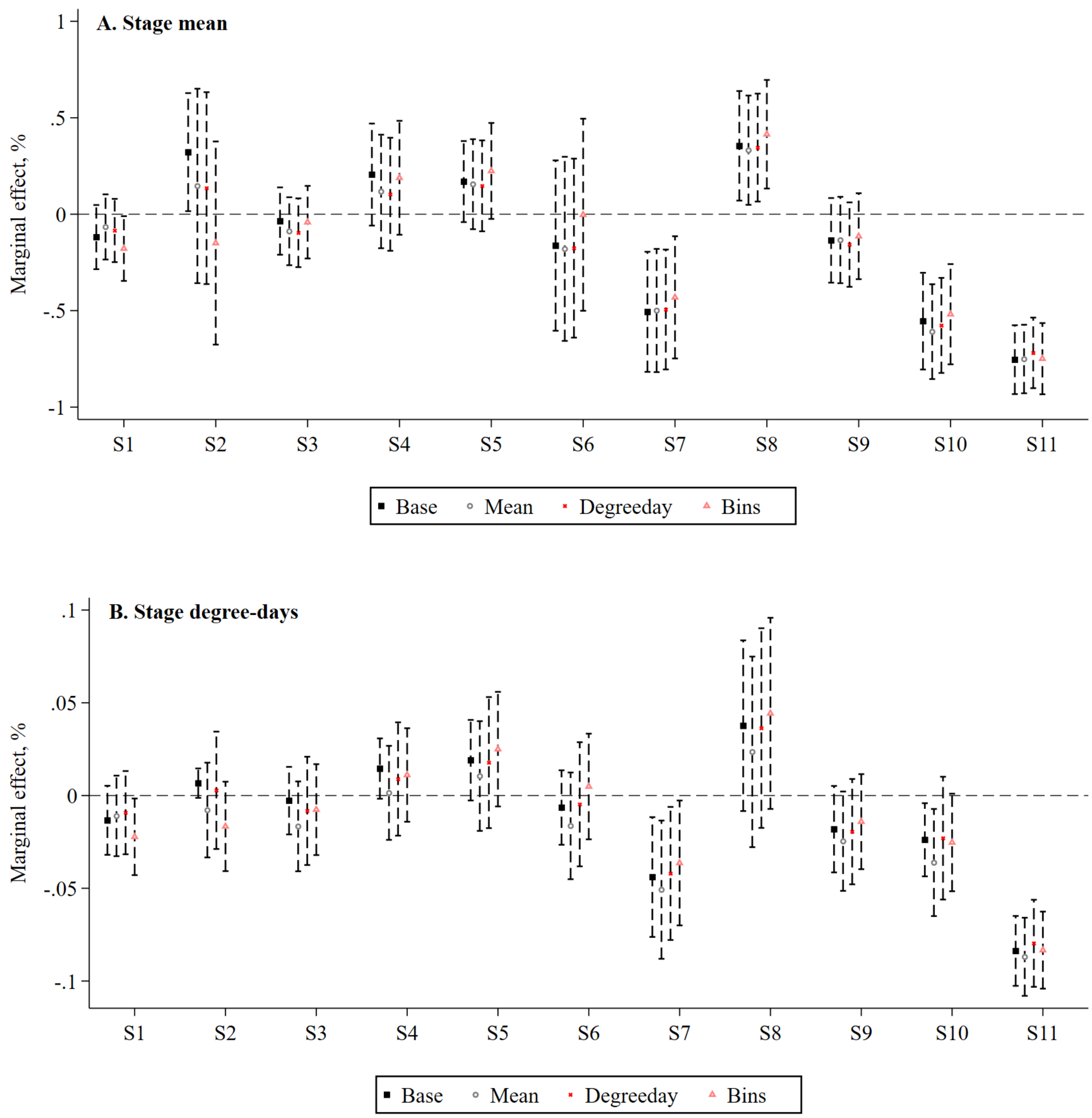

Figure 7: Effect of stage-specific temperature measures on rice yield conditional on aggregate temperature measures

Note: The figure presents the estimated effects of stage mean temperature (Panel A) and stage degree-days and harmful degree-days (Panel B) on rice yield based on a version of model 9 that does not control for the aggregate temperature measure (Base), controls for growing season mean temperature and it square (Mean), controls for growing season degree-days and harmful degree-days (Degreeday), or controls for growing season temperature bins (Bins). The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

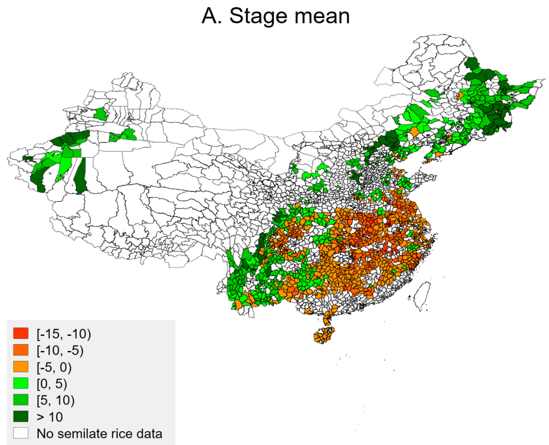

Figure 8: County-level impact of global warming on rice yield under scenario RCP 4.5 (%)

Note: This figure presents the county-level impact of global warming on rice yield predicted based on estimates of the stage mean temperature and its square (left panel) and growing season mean temperature and its square (right panel) under global warming scenario RCP 4.5. Specifically, the impact in each county is calculated by combining the marginal effect of temperature in each county with the county-level predicted warming from the 2011–2015 average to the 2096–2100 average.

Table 1: Potential bias of adopting an aggregate temperature measure

	(1)	(2)	(3)	(4)	(5)	(6)
	Stage temperature outcome		Temperature measure		Biased (X) or Unbiased (✓)	Over- (↑) or under-estimate (↓)
	Key	Non-Key	Aggregate	Stage		
1	a	b	$\frac{a+b}{2}$	a	X	↑
2	a	0	$\frac{a}{2}$	a	X	↑
3	a	a	a	a	✓	-
4	0	b	$\frac{b}{2}$	0	X	↓
5	0	0	0	0	✓	-
6	0	a	$\frac{a}{2}$	0	X	↓
7	b	b	b	b	✓	-
8	b	0	$\frac{b}{2}$	b	X	↑
9	b	a	$\frac{b+a}{2}$	b	X	↑

Notes: This table classifies the growing season of a crop into a key stage (column 1) and a non-key stage (column 2) of growth. Each stage is randomly subject to a negative (a), none (0), or positive (b) temperature shock, resulting in 9 combinations of shocks (rows 1–9). Column 3 presents the temperature shocks used when adopting an aggregate temperature measure, while column 4 presents the temperature shocks that should be used if only the key-stage temperature affects crop yield. Columns 5 and 6 present the bias and the direction of the bias when adopting an aggregate temperature measure.

Table 2: Predicted impact of global warming on rice yield (%)

Scenario	Predicted warming (°C)	(1)	(2)	(3)	(4)	(5)	(6)
		Stage			Growing season		
		Mean, linear	Mean, non-linear	Degree-days and harmful degree-days	Mean, non-linear	Degree-days and harmful degree-days	Temperature Bins
(1) RCP 4.5	2.30	-3.88	-3.50	-10.8	-7.98	-15.3	-6.69
		(.395)	(.387)	(1.02)	(.726)	(2.03)	(2.11)
(2) RCP 8.5	5.04	-7.11	-6.13	-35.3	-16.8	-70.4	-19.9
		(.796)	(.777)	(4.89)	(1.59)	(12.2)	(4.04)
(3) 5°C uniform	5.00	-6.37	-6.56	-7.69	-16.8	-22.6	-14.9
		(.780)	(.759)	(1.23)	(1.57)	(2.47)	(3.82)

Notes: This table presents the predicted impact of global warming on rice yield under three global warming scenarios: a medium scenario (RCP 4.5), a high scenario (RCP 8.5), and a scenario of uniform warming of 5°C. Column 1 presents the predicted impact of stage mean temperature, column 2 presents the predicted impact of stage mean temperature and its square, and column 3 presents the predicted impact of stage degree-days and harmful degree-days. Columns 4–6 present the predicted impact of growing season mean temperature and its square, growing season degree-days and harmful degree-days, and growing season temperature bins, respectively. See more details of the impact prediction from the main text. All estimates reported are the area-weighted average across the sample counties. Standard errors reported in parentheses are constructed using the Delta method.

A Appendix for Online Publication

A.1 Summary statistics

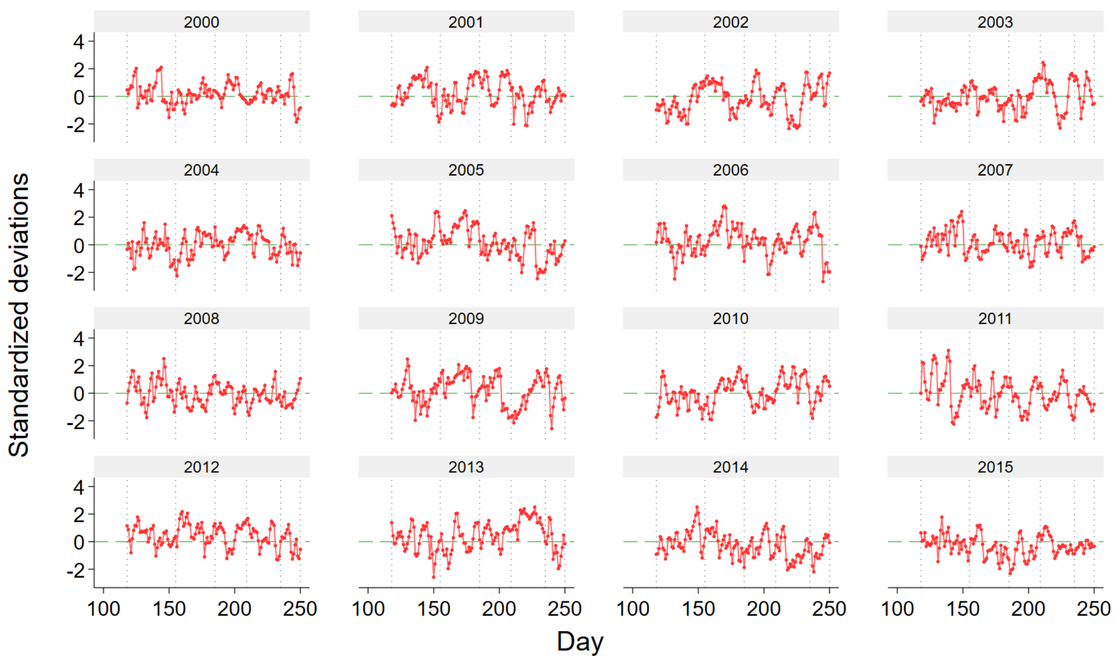

Figure A.1: Daily standardized deviation of temperature during the growing season

Note: This figure presents the daily standardized deviation of temperature in a randomly selected rice production county (Qidong county in Hunan province) for each year from 2000 to 2015. The daily standardized deviation is calculated according to Equation (4). The dashed vertical lines mark the starting day of each key stage of rice in the county.

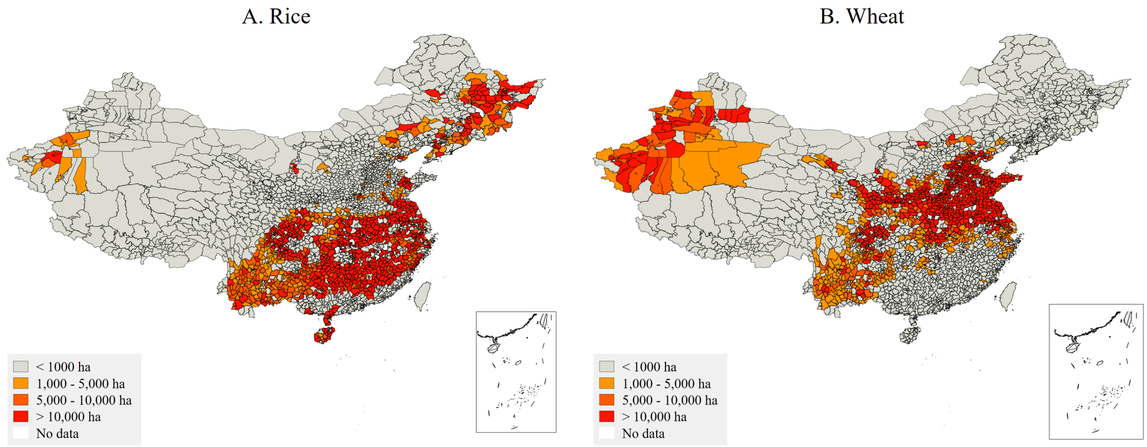

Figure A.2: Sample counties producing semilate rice (left) and winter wheat (right)

Note: This figure presents sample counties producing semilater rice (left) and winter wheat (right). The sample excludes counties producing early rice and spring wheat.

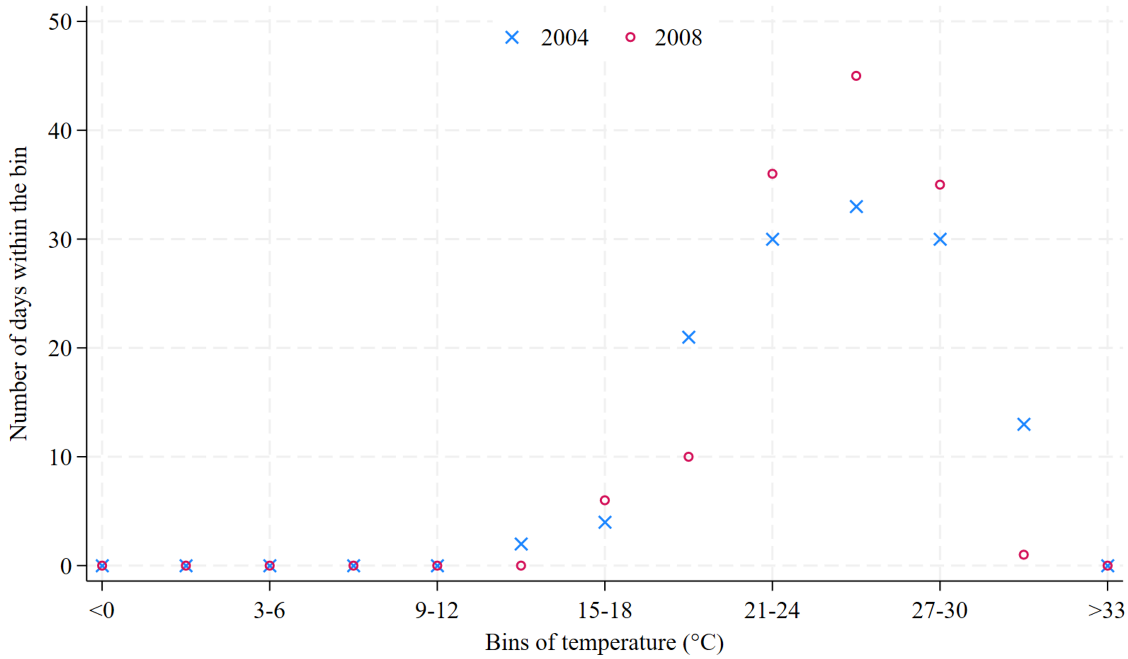

Figure A.3: Distribution of temperature bins for two years with nearly identical growing season mean temperature

Note: This figure presents the distribution of 3-degree temperature bins (calculated according to (3)) for two years (2004 and 2008) with similar growing season mean temperatures (24.65°C and 24.68°C). The data come from a randomly selected rice-production county (Qidong county in Hunan province).

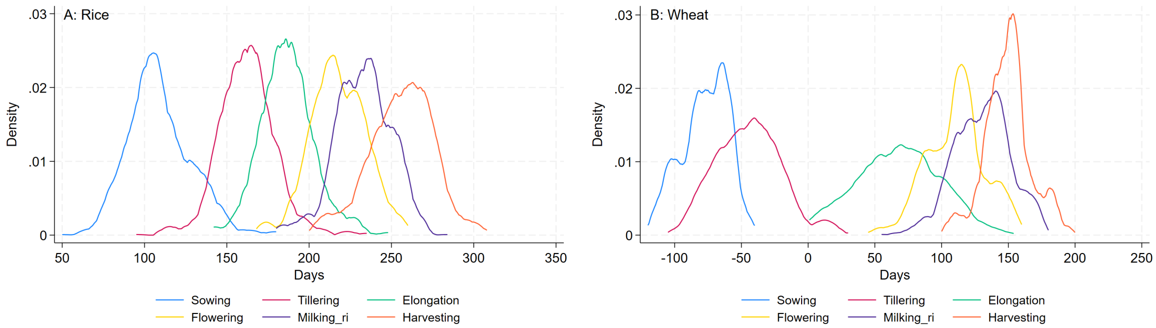

Figure A.4: Distribution of each key stages of rice and wheat across the sample counties

Note: This figure presents the distribution of the starting date of each of the six key stages for semilate rice (left) and winter wheat (right) across all sample counties cultivating each crop. The date of each stage is coded as the number of days since the first day of the year. The first two stages of winter wheat are coded by negative values as winter wheat was sown last year.

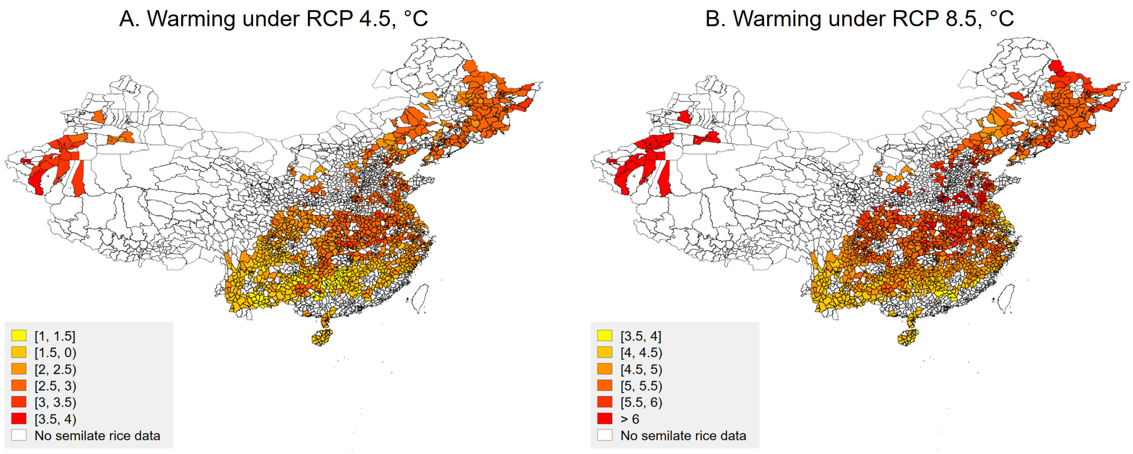

Figure A.5: Predicted end-of-the-century increase in growing season mean temperature

Note: This figure presents the predicted increase in county-level growing season mean temperature, calculated as the difference between the 2011–2015 average and the 2096–2100 average, under global warming scenarios RCP 4.5 and RCP 8.5 for 1217 rice production counties.

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

	Articles	Temperature Measures	Measured over
1	Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. "The Impact of Global Warming on Agriculture: a Ricardian Analysis." American Economic Review (1994): 753-771.	Temperature mean	Individual months
2	Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "Will US Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." American Economic Review 95.1 (2005): 395-406.	Temperature mean	Growing season
3	Negri, Donald H., Noel R. Gollehon, and Marcel P. Aillery. "The Effects of Climatic Variability on US Irrigation Adoption." Climatic Change 69.2 (2005): 299-323.	Degree-days	Growing season
4	Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "The Impact of Global Warming on US Agriculture: an Econometric Analysis of Optimal Growing Conditions." Review of Economics and Statistics 88.1 (2006): 113-125.	Degree-days	Growing season
5	Deschênes, Olivier, and Michael Greenstone. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." American Economic Review 97.1 (2007): 354-385.	Temperature mean, Degree-days	Growing season
6	Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "Water Availability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California." Climatic Change 81.1 (2007): 19-38.	Degree-days	Growing season

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

7	Schlenker, Wolfram, and Michael J. Roberts. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields Under Climate Change." Proceedings of the National Academy of Sciences 106.37 (2009): 15594-15598.	Temperature mean, Piece-wise function, Degree-days	The whole year
8	Piao, Shilong, et al. "The Impacts of Climate Change on Water Resources and Agriculture in China." Nature 467.7311 (2010): 43-51.	Temperature mean	The whole year
9	Lobell, David B., et al. "Nonlinear Heat Effects on African Maize As Evidenced by Historical Yield Trials." Nature Climate Change 1.1 (2011): 42-45.	Temperature mean, Degree-days, Piece-wise function	Growing season
10	O'Loughlin, John, et al. "Climate Variability and Conflict Risk in East Africa, 1990–2009." Proceedings of the National Academy of Sciences 109.45 (2012): 18344-18349.	Temperature standard deviations	Individual months
11	Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." American Economic Journal: Macroeconomics 4.3 (2012): 66-95.	Temperature mean	The whole year
12	Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. "What Do We Learn from the Weather? the New Climate-economy Literature." Journal of Economic Literature 52.3 (2014): 740-798.	Temperature mean, Temperature bins	The whole year
13	Moore, Frances C., and David B. Lobell. "Adaptation Potential of European Agriculture in Response to Climate Change." Nature Climate Change 4.7 (2014): 610-614.	Temperature mean, Temperature standard deviations	Growing season

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

14	Mueller, Valerie, Clark Gray, and Katrina Kosec. "Heat Stress Increases Long-term Human Migration in Rural Pakistan." Nature Climate Change 4.3 (2014): 182-185.	Temperature mean	Growing season
15	Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. "Global Non-linear Effect of Temperature on Economic Production." Nature 527.7577 (2015): 235-239.	Temperature mean, Restricted cubic splines	The whole year
16	Mukherjee, Monobina, and Kurt Schwabe. "Irrigated Agricultural Adaptation to Water and Climate Variability: the Economic Value of a Water Portfolio." American Journal of Agricultural Economics 97.3 (2015): 809-832.	Degree-days	Growing season
17	Ashraf, Quamrul, and Stelios Michalopoulos. "Climatic Fluctuations and the Diffusion of Agriculture." Review of Economics and Statistics 97.3 (2015): 589-609.	Temperature standard deviations	Growing season
18	Ray, Deepak K., et al. "Climate Variation Explains a Third of Global Crop Yield Variability." Nature Communications 6.1 (2015): 5989.	Temperature mean	Growing season
19	Tack, Jesse, Andrew Barkley, and Lawton Lanier Nalley. "Effect of Warming Temperatures on US Wheat Yields." Proceedings of the National Academy of Sciences 112.22 (2015): 6931-6936.	Degree-days, Temperature mean, Piece-wise Linear Function	Growing season
20	Lesk, Corey, Pedram Rowhani, and Navin Ramankutty. "Influence of Extreme Weather Disasters on Global Crop Production." Nature 529.7584 (2016): 84-87.	Temperature mean	Growing season

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

21	Burke, Marshall, and Kyle Emerick. "Adaptation to Climate Change: Evidence from US Agriculture." American Economic Journal: Economic Policy 8.3 (2016): 106-140.	Degree-days, Temperature mean, Piece-wise function	Growing season
22	Chen, Shuai, Xiaoguang Chen, and Jintao Xu. "Impacts of Climate Change on Agriculture: Evidence from China." Journal of Environmental Economics and Management 76 (2016): 105-124.	Temperature bins, Degree-days	Growing season
23	Cai, Ruohong, et al. "Climate Variability and International Migration: the Importance of the Agricultural Linkage." Journal of Environmental Economics and Management 79 (2016): 135-151.	Temperature mean	Growing season
24	Zhang, Peng, Junjie Zhang, and Minpeng Chen. "Economic Impacts of Climate Change on Agriculture: the Importance of Additional Climatic Variables Other Than Temperature and Precipitation." Journal of Environmental Economics and Management 83 (2017): 8-31.	Temperature bins	Growing season
25	Huang, Kaixing, et al. "The Potential Benefits of Agricultural Adaptation to Warming in China in the Long Run." Environment and Development Economics 23.2 (2018): 139-160.	Degree-days	Growing season
26	Sellers, Samuel, and Clark Gray. "Climate Shocks Constrain Human Fertility in Indonesia." World Development 117 (2019): 357-369.	Temperature mean	Individual months
27	Diffenbaugh, Noah S., and Marshall Burke. "Global Warming has Increased Global Economic Inequality." Proceedings of the National Academy of Sciences 116.20 (2019): 9808-9813.	Temperature mean	The whole year

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

28	Wang, Xuhui, et al. "Emergent Constraint on Crop Yield Response to Warmer Temperature from Field Experiments." Nature Sustainability 3.11 (2020): 908-916.	Temperature mean	Growing season, The whole year
29	Cui, Xiaomeng. "Beyond Yield Response: Weather Shocks and Crop Abandonment." Journal of the Association of Environmental and Resource Economists 7.5 (2020): 901-932.	Temperature bins, Degree-days	Growing season
30	Cui, Xiaomeng. "Climate Change and Adaptation in Agriculture: Evidence from US Cropping Patterns." Journal of Environmental Economics and Management 101 (2020): 102306.	Temperature mean, Temperature bins	Growing season
31	Huang, Kaixing, et al. "The Impact of Climate Change on the Labor Allocation: Empirical Evidence from China." Journal of Environmental Economics and Management 104 (2020): 102376.	Temperature bins, Degree-days	Growing season
32	Bozzola, Martina, and Melinda Smale. "The Welfare Effects of Crop Biodiversity As an Adaptation to Climate Shocks in Kenya." World Development 135 (2020): 105065.	Temperature mean	Growing season
33	Huang, Kaixing, and Nicholas Sim. "Adaptation May Reduce Climate Damage in Agriculture by Two Thirds." Journal of Agricultural Economics 72.1 (2021): 47-71.	Degree-days	Growing season
34	Chen, Shuai, and Binlei Gong. "Response and Adaptation of Agriculture to Climate Change: Evidence from China." Journal of Development Economics 148 (2021): 102557.	Degree-days, Temperature bins, Temperature Variation	Growing season

Table A.1: Temperature measures used in studies on the impact of global warming on agriculture

35	Kotz, Maximilian, et al. "Day-to-day Temperature Variability Reduces Economic Growth." Nature Climate Change 11.4 (2021): 319-325.	Temperature standard deviation, Degree-days	Individual months
36	Gatti, Nicolas, Kathy Baylis, and Benjamin Crost. "Can Irrigation Infrastructure Mitigate the Effect of Rainfall Shocks on Conflict? Evidence from Indonesia." American Journal of Agricultural Economics 103.1 (2021): 211-231.	Temperature mean, Temperature bins	Growing season
37	Ciccone, Antonio, and Adilzhan Ismailov. "Rainfall, Agricultural Output and Persistent Democratization." Economica 89.354 (2022): 229-257.	Temperature mean	The whole year
38	Huang, Kaixing, Jingyuan Guo, and Da Zhao. "Positive Rainfall Shocks, Overoptimism, and Agricultural Inefficiency in China." Journal of the Association of Environmental and Resource Economists (Just Accepted) (2023).	Temperature mean	Growing season
39	Wang, Di, et al. "Adaptation to Temperature Extremes in Chinese Agriculture, 1981 to 2010." Journal of Development Economics 166 (2024): 103196.	Degree-days, Piece-wise function	Growing season
40	Cui, Xiaomeng, and Zheng Zhong. "Climate Change, Cropland Adjustments, and Food Security: Evidence from China." Journal of Development Economics 167 (2024): 103245.	Temperature mean, Degree-days, Temperature bins	Growing season

Table A.2: Summary statistics of key variables

	(a1)	(a2)	(b1)	(b2)
	Rice		Wheat	
	Mean	SD	Mean	SD
Yield (ton/ha)	6.8	1.6	3.8	1.7
Mean temperature in:				
Stage 1	15.7	5.1	15.7	3.5
Stage 2	19.4	3.8	12.4	3.9
Stage 3	22.5	3.6	8.6	4.6
Stage 4	23.6	3.4	3.7	3.9
Stage 5	24.4	3.5	9.5	5.3
Stage 6	24.9	3.3	12.6	4.1
Stage 7	24.5	3.5	16.5	4.1
Stage 8	23.7	3.9	17.7	4.1
Stage 9	23.3	4.0	19.5	4.2
Stage 10	21.6	4.4	20.3	3.9
Stage 11	20.3	5.4	21.9	3.8
Growing season:				
Mean temperature	22.1	3.3	9.3	3.1
Degree-day	2047.6	435.8	524.2	159.5
Harmful degree-day	0.02	0.3	0.01	0.01
N	11,309		10,080	

Notes: This table presents summary statistics of key variables for rice and wheat, respectively. The units of all temperature measures are °C.

A.2 Rice appendix

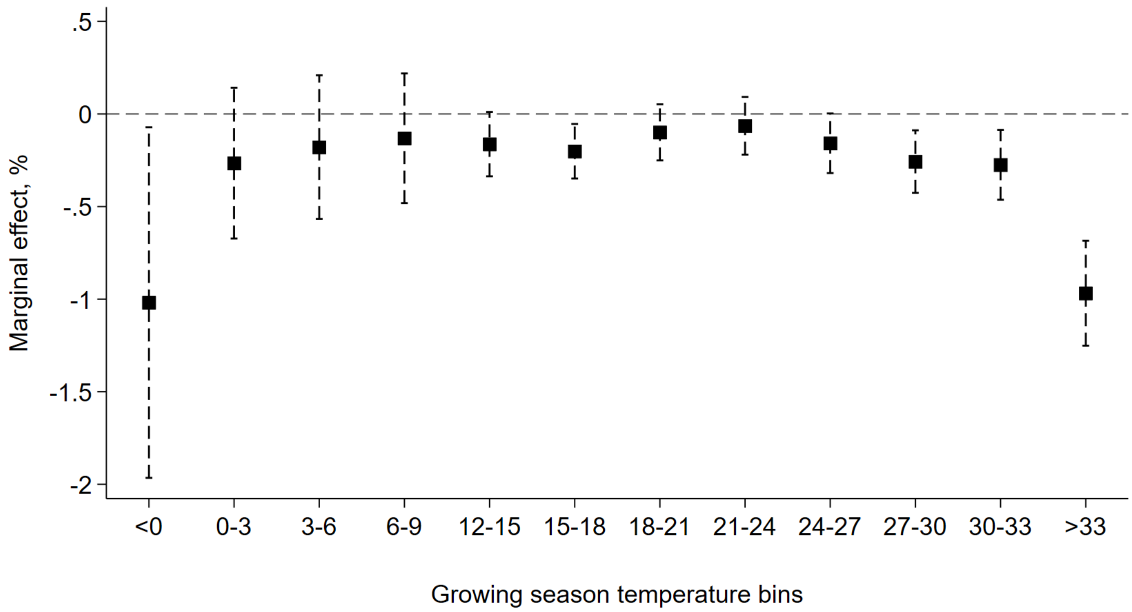

Figure A.6: Effect of growing season temperature bins on rice yield

Note: The figure presents the effect of growing season temperature bins estimated based on model (8). The 3°C temperature bins are constructed according to Equation (3), and the bin of 9–12°C is used as the baseline. The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

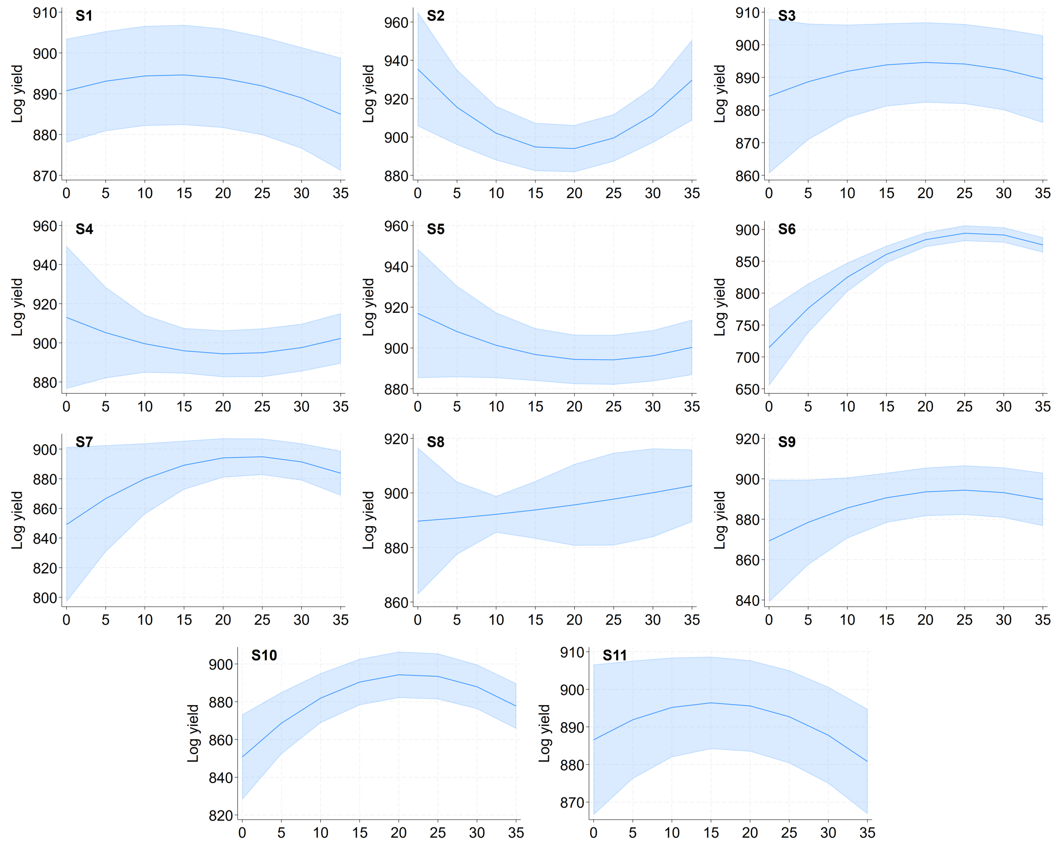

Figure A.7: Stage non-linear effect of temperature on rice yield (100 log)

Note: This figure is plotted based on estimates of a version of model (7) that includes both the stage mean temperature and its square for each stage. Each panel plots the nonlinear relationship between rice yield and temperature based on the quadratic temperature estimates. The shadow area represents the 95% confidence intervals calculated based on standard errors clustered at the county level.

Table A.3: Effect of aggregate temperature measures on rice yield (%)

	(1)	(2)
	Growing season	
	Mean temperature	Degree-days
Growing season mean temp (°C)	19.604***	
	[5.002]	
Growing season mean temp^2	-0.430***	
	[0.108]	
Growing season degree-day (100 day)		7.318***
		[2.247]
Growing season degree-day^2		-0.172***
		[0.053]
Growing season harmful degree-day (day)		-0.178***
		[0.066]
Five climatic control variables	Y	Y
County and year fixed effects	Y	Y
Observations	11,309	11,309
R-squared	0.660	0.660

Notes: The table presents the estimates of model (8) that measures temperature by growing season mean and its square (column 1) or growing season degree-days and harmful degree-days (column 2). The temperature measures are constructed according to Equations (1) and (2). Standard errors reported in square brackets are clustered at the county level. Significance levels are *** p<0.01, ** p<0.05, and * p<0.1.

A.3 Wheat appendix

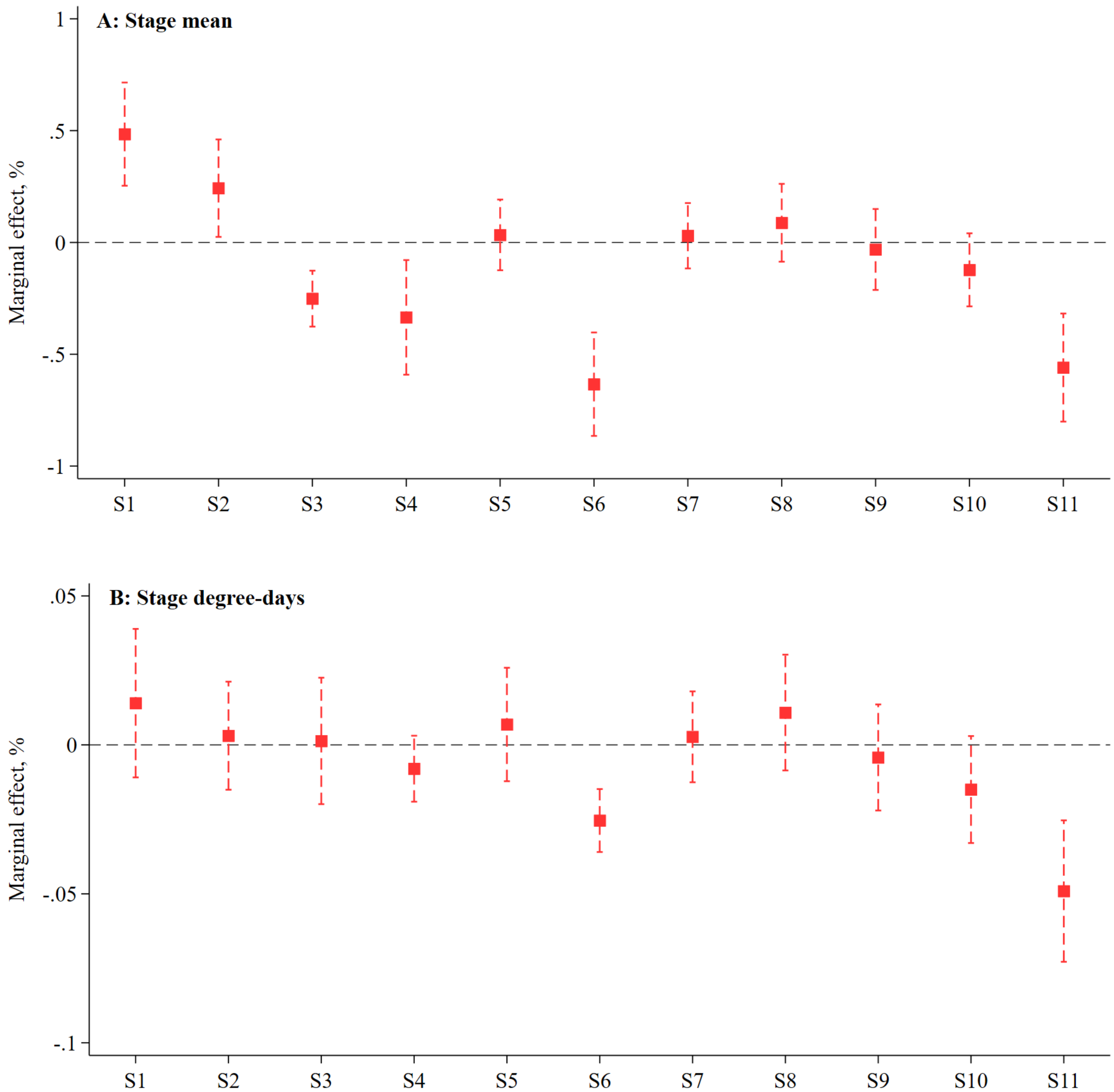

Figure A.8: Stage impact of temperature on wheat yield (%)

Note: This figure presents the estimates of model (7) for wheat. Panel A measures temperature by stage mean, while Panel B measures temperature by stage degree-days. The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

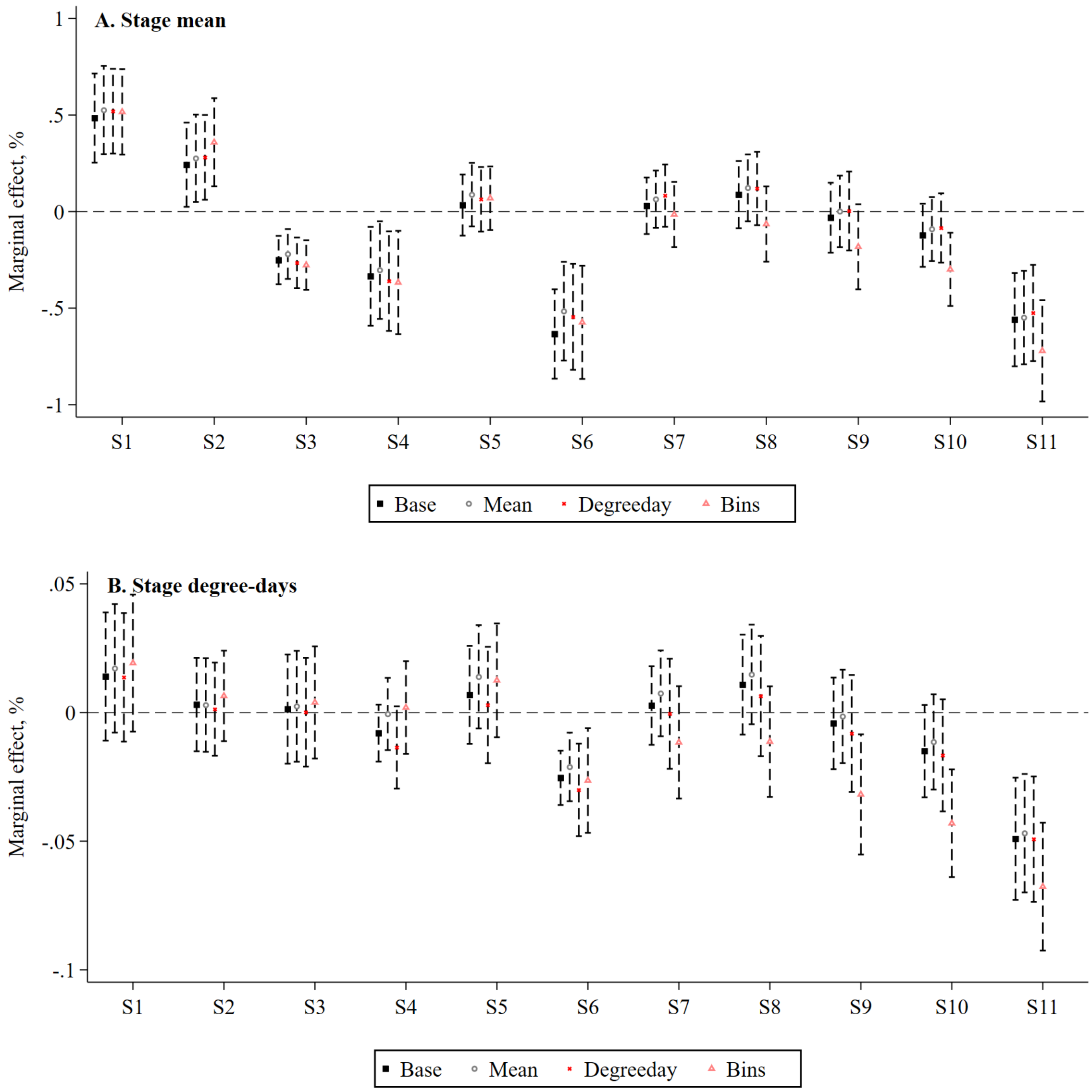

Figure A.9: Effect of stage temperature measures on wheat yield conditional on aggregate temperature measures

Note: The figure presents the estimated effects of stage mean temperature (Panel A) and stage degree-days (Panel B) on wheat yield based on a version of model 9 that does not control for the aggregate temperature measure (Base), controls for growing season mean temperature and it square (Mean), controls for growing season degree-days and harmful degree-days (Degreeday), or controls for growing season temperature bins (Bins). The capped spikes represent the 95% confidence intervals constructed based on standard errors clustered at the county level.

Table A.4: Predicted impact of global warming on wheat yield (%)

Scenario	Predicted warming (°C)	(1)	(2)	(3)	(4)	(5)	(6)
		Stage			Growing season		
		Mean, linear	Mean, non-linear	Degree-days and harmful degree-days	Mean, non-linear	Degree-days and harmful degree-days	Temperature Bins
(1) RCP 4.5	2.78	-3.15	-3.65	-3.22	-4.42	-7.40	-9.89
		(.330)	(.357)	(.540)	(.778)	(3.56)	(.746)
(2) RCP 8.5	4.96	-4.37	-5.03	-6.58	-8.22	-45.5	-23.1
		(.652)	(.695)	(1.13)	(1.40)	(36.7)	(3.72)
(3) 5°C uniform	5.00	-5.36	-6.20	-7.53	-7.52	-13.9	-11.7
		(.582)	(.624)	(1.11)	(1.39)	(5.35)	(1.76)

Notes: This table presents the predicted impact of global warming on wheat yield under three global warming scenarios: a medium scenario (RCP 4.5), a high scenario (RCP 8.5), and a scenario of uniform warming of 5 °C. Column 1 presents the predicted impact of stage mean temperature, column 2 presents the predicted impact of stage mean temperature and its square, and column 3 presents the predicted impact of stage degree-days and harmful degree-days. Columns 4–6 present the predicted impact of growing season mean temperature and its square, growing season degree-days and harmful degree-days, and growing season temperature bins, respectively. See more details of the impact prediction from the main text. All estimates reported are the area-weighted average across the sample counties. Standard errors reported in parentheses are constructed using the Delta method.