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SUBMITTED ARTICLE

# Impact of extreme temperatures on production of different rice types: A county-level analysis for China

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**Abstract**

The response of China's rice yield to climate change is crucial for ensuring food security for China and the globe. However, previous studies have focused on the impact of climate change on a specific rice type or rice as a whole. For the first time, this study combines a new set of the early, middle, and late rice production data and daily weather data at the county level to comprehensively estimate the heterogeneous yield response to extreme temperatures in China. Along with the projections of future temperature and precipitation, we also forecast the potential yield losses when exposed to higher future warming trends. The results show that holding current growing regions and calendars fixed, the yield of popular middle and late rice types will drop by $5.7\% \pm 1.5\%$ and $11\% \pm 4.5\%$ under the most extreme scenario compared to no climate change scenarios by the end of this century (2070–2090 average). These results imply that recent structural changes in favor of producing these popular types of rice may satisfy the demand for high-quality rice but may also increase the risks of climate change to the food supply in China. Therefore, more efforts should be concentrated on incorporating this type of heterogeneity in climatic impacts into national and regional plans for the agricultural adaptation.

**KEYWORDS**
adaptation, climate change, food security, heterogeneity, rice types

**JEL CLASSIFICATION**
Q18, Q54

The impact of climate change on agriculture has been widely studied from different angles, such as crop yield (Burke & Emerick, 2016; Fisher et al., 2012; Lobell et al., 2011; Ray et al., 2015; Schlenker & Roberts, 2009; Tack et al., 2015; Welch et al., 2010), crop acreage (Costinot et al., 2016; Cui, 2020; Miao et al., 2016), and food price and trade (Baldos & Hertel, 2015; Hasegawa et al., 2018; Nelson et al., 2014; Xie, Huang, et al., 2018a; Xie, Xiong, et al., 2018b). Regarding the impact of climate change on crop yield, previous studies mainly focused on assessing the impact of climate change on specific crop varieties or a crop as a whole. More recently, some scholars have noticed that climate change has different effects on the same crop grown in different growing seasons, such as double-cropped wheat and barley (Gammans et al., 2017; Liu et al., 2018), double-cropped rice (Kawasaki, 2018), and triple-cropped rice (Chen & Tian, 2016).

The same crop with different growing seasons has different quality traits. Three types of rice are mainly grown in China: early rice, middle rice, and late rice. Early rice is typically planted in the Southern, from February to July. Middle rice is mainly grown in the Northeast and along the Yangtze River, from March to October. Late rice is primarily planted in the Southern, from June to November. Due to abundant sunshine and more suitable temperatures during the growing season, the middle rice and late rice are more nutritious and have better taste than early rice (Jin et al., 2021). Price can also serve as a critical indicator of crop quality (Dalhaus et al., 2020). According to the survey of PD-NDRC (Price Department of the National Development and Reform Commission (PD-NDRC), 2019), the price of middle rice was 1% higher than that of late rice, and late rice was 10% higher than that of early rice in 2018. Traditionally, late and middle rice is mainly directly consumed, while early rice is mainly used in the food processing industry (e.g., rice noodles) and livestock feed due to low quality (Jin et al., 2021). Thus, middle rice and late rice are superior to early rice in eating and cooking qualities.

In recent years, the harvested area and production of middle rice have increased gradually in China. Between 2000 and 2018, the proportion of middle rice planting area relative to total rice planting area increased from 52% to 67%, and the proportion of middle rice production relative to total rice production increased from 58% to 72% (National Bureau of Statistics of China (NBSC), 2018). Historical data also show that middle rice has become the primary source of China's rice supply. Although the proportion of early and late rice planting area relative to total rice planting area decreased gradually, these two types are essential to China's food security. The Chinese government is also hesitant about implementing policies that can increase or decrease the planting area of early and late rice. For example, the government issued a series of supporting policies in 2020 to encourage farmers to increase early and late rice production to ensure food security during COVID-19 (Ministry of Agriculture and Rural Affairs of the People's Republic of China (MARA), 2020).

According to the climate predictions estimated by the Coupled Model Intercomparison Project Phase 5 (CMIP5), by the end of this century (2070–2090 average), the exposure of early, middle, and late rice to hot days with temperatures above 30°C during growing seasons will increase by 26, 32, and 38 days, respectively. This further highlights the importance of understanding the heterogeneous impacts of extreme temperatures on early, middle, and late rice. Although some studies have shown adverse impacts of high temperatures on rice in China, they focused on middle rice or rice as a single crop (Chen et al., 2016a; Chen & Chen, 2018; Zhang et al., 2017). Due to the different heat resistance of each rice type and varying climate change shocks in different regions and seasons in the future, there is a high degree of uncertainty about the potential impacts of future climate change on rice in different growing seasons in China.

In this study, we comprehensively estimate the heterogeneous yield response to extreme temperatures for early, middle, and late rice and analyze whether the new structure of rice cropping systems is likely to increase the potential risk of yield loss when exposed to higher future warming trends. This article contributes in four major respects to the existing literature by examining the weather effects on crop yields, including data, construction of temperature variables, model specifications, and key findings. First, we use county-level data, the most precise spatial scale data available, to assess the impacts of climate change on rice yields in different growing seasons. Second, we estimate the non-linear relationship between temperature and yield using multiple temperature specifications, considering the effects of both minimum and maximum temperatures. We find that yields increase with temperature up to 32°C for early rice, 29°C for middle rice, and 34°C for late rice, but decrease sharply with higher temperatures. These results show that extreme temperatures play a vital yet heterogeneous role in determining rice yield. Third, we use multiple model specifications to estimate the relationships between rice yields and weather variables, which is a more comprehensive modeling approach than the single specification used in earlier work. Fourth, we predict the impact of climate change on yield for early, middle, and late rice in the future. We find important results from these predictions, that is, that middle and late rice, which are popular among China's consumers, are the most adversely affected. In the context of a recent expansion of middle rice production and meanwhile encouraging farmers to increase early and late rice production, the policy implications are particularly important. We need to incorporate this type-heterogeneity in climatic impacts into national and regional plans for the agricultural adaptation.

## LITERATURE REVIEW

Extensive work has analyzed the impact of climate change on crops (Burke & Emerick, 2016; Chen et al., 2016a, 2016b; Kawasaki, 2018; Schlenker & Roberts, 2009; Welch et al., 2010; Zhang et al., 2017). For example, Schlenker and Roberts (2009) found that when the temperature rises above a crop's upper-temperature threshold, it is very harmful to crop yield in a non-linear manner (i.e., the slope of the decline above the optimum is significantly steeper than the incline below it). Cui (2020) found that about 10%–35% of changes in the observed US corn and soybean planting area can be explained by climate change over the past 30 years. Kawasaki (2018) evaluated the feasibility of double cropping as an adaptation strategy. Xie, Huang, et al. (2018a) and Xie, Xiong, et al. (2018b) also found that climate change will affect food prices and trade. However, these studies have focused on yields of specific crop variety or crop as a whole, while our contribution focuses on type-heterogeneity in yield response to extreme temperatures and potential yield loss risk.

Some existing studies have assessed the links between climate change and rice yield in China; however, they lack geographic or crop varietal detail. For example, Chen and Tian (2016) investigated the response of early, middle, and late rice to weather variations in China; however, they used provincial-level yield data. Because of the large size of China's provinces and the non-uniform spatial distribution of rice production within a province, it is easy to get measurement error when using provincial data to construct province-level climate variables by computing average weather variables using weather stations located in that province. Thus, the estimated impacts of weather on yield could deviate from the actual effects of weather. This study uses county-level data, the most precise spatial scale available, to reduce measurement error and capture the heterogeneity in rice yields within a province.

Chen and Tian (2016) found that rising daily minimum temperature ($T_{\min}$) would increase early and late rice yields. However, they ignored that maximum temperature ($T_{\max}$) is also vital in determining rice yield. Although Chen et al. (2016a) examined the impacts of maximum temperature by growth stage on rice yield, that study only focused on middle rice. Neither of these studies modeled multiple temperature specifications. As well as considering early and late rice, we estimate the non-linear relationship between temperature and yield by using multiple temperature specifications, considering the effects of both minimum and maximum temperatures, such as degree-day variables and temperature bins (Burke & Emerick, 2016; Schlenker & Roberts, 2009; Zhang et al., 2017).

The econometric model is one of the most commonly used methods to predict the potential changes in crop yield in the future. For example, Zhang et al. (2017) predicted crop yield change due to climate change using point estimation and climate prediction from five climate models with three forcing scenarios. In comparison, Chen and Chen (2018) used estimated coefficients of temperature variables and climate data based on two climate models under RCP2.6 and RCP8.5 to evaluate future climate impacts on single-season rice yield. Our study considers whole China's rice with different growing seasons and climate predictions from five climate models associated with four representative concentration pathways. Considering the importance of China as a rice producer, there is incomplete knowledge of the potential impact of future climate change on the heterogeneous supply of rice. We contribute to filling that gap.

# CHINA'S RICE CROPPING STRUCTURE

In China, sowing and harvesting dates can be used to divide rice into double early rice (referred to as "early rice" for short), middle and single late rice (referred to as "middle rice" for short), and double late rice (referred to as "late rice" for short). As shown in Figure A1, early rice grows primarily in the southern part of the country. Middle rice is primarily produced in the Northeast provinces and several provinces along the Yangtze River. Late rice is planted after early crops are harvested, and its spatial distribution is very similar to that of early rice. However, the three types of rice differ substantially by their planting date. Tables A1–A3 present the growing seasons for early, middle, and late rice across regions. Early rice is typically planted from February to March and harvested in July. Middle rice is planted from March to May and harvested in October. For late rice, rice seedlings are generally raised in a small field in June, transplanted to the paddy field after early rice is harvested, and harvested in November.

Yield, sown areas, and production of rice with different growing seasons in China have changed over the past 40 years (Figure 1). The yield of middle rice has increased gradually in the last four decades, while the increase in the yield of the other two rice types was slowing down. Not only has the yield of middle rice increased relative to early rice and late rice, but the gap has been increasing rapidly, such that middle rice yield (7559 kg/ha) was about 27% higher

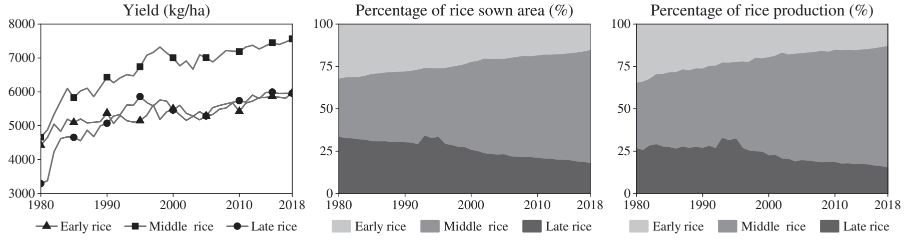


**FIGURE 1** Yield and percentage of sown area, production for rice with different growing seasons in China, 1980–2018

than the yield of early rice (5967 kg/ha) and late rice (5958 kg/ha) in 2018. In addition, the proportion of the sown areas of early rice and late rice relative to the total sown area of rice has been gradually decreasing, while the proportion of middle rice has increased continuously during the last 40 years. The rate of increase in the middle rice area is larger than the rate of decrease of early rice and late rice. As a whole, middle rice production has increased continuously and accounted for about 72% of China's rice production in 2018.

# MATERIALS AND METHODS

## Empirical model

We use various specifications of temperature $f(T_{\mathrm{it}})$ to estimate the non-linear relationship between temperature and yield of the early, middle, and late rice. The general form of the empirical model is given as follows:

$$\ln Y_{it} = \alpha_0 + \beta f(T_{it}) + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it}, \tag{1}$$

where $Y_{it}$ denotes the annual rice yield for county $i$ in year $t$, which we take as the natural log in the model; $T_{it}$ represents different specifications of temperature; $\mathrm{Pre}_{it}$ includes the cumulative precipitation during the growing season and its quadratic term; $h_{\mathrm{p}}(t)$ represents province-specific quadratic time trends to capture unobserved effects of macroeconomic factors and technological improvements; and $\mu_i$ controls for county-specific unobservables; $\varepsilon_{it}$ represents the error term.

Schlenker and Roberts (2009) emphasized the non-linear relationship between crop yields and temperature and the role of extreme temperatures on crop yields. Therefore, constructing temperature variables that capture exposure to extreme temperatures is essential for estimating the relationship between weather and yield. The variable of degree days is the sum of heat that the rice receives over the growing season, which considers both the strength and duration of the temperature and can better capture the nonlinearities in the relationship between temperature and crop growth. Following Schlenker and Roberts' (2009) approach, we used a fitted sine curve between daily minimum temperature and daily maximum temperature to approximate the distribution of temperatures within each day. Then we get daily degree days by using the within-day distribution of temperatures to calculate the fraction of each day in each county exposed to the temperature above a given upper threshold. We construct growing-degree days

(GDD) and harmful-degree days (HDD) as $T_{it}$ indices to capture the nonlinearities in the relationship between temperature and crop growth. GDD is defined as the amount of time over its growing season that a crop is exposed to a temperature that benefits crop growth, that is, between the lower and upper thresholds. HDD represents the degree days above a given upper threshold that are harmful to crop growth. Assuming that crop growth increases logarithmically in accumulated growing degree days (GDD) and decreases logarithmically in accumulated harmful degree days (HDD), we use a piecewise linear function including GDD and HDD. The model is built as follows:

$$\ln Y_{it} = \alpha_0 + \beta_1 \mathrm{GDD}_{it} + \beta_2 \mathrm{HDD}_{it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{2}$$

We consider all piecewise linear relationships by setting the lower temperature bound at 10°C and varying the upper temperature bound from 28 to 35°C and selecting the temperature threshold with the lowest sum of squared residuals. According to the results shown in Tables A4–A6, the upper-temperature thresholds selected for early, middle, and late rice were 32, 29, and 34°C, respectively.

To show the flexible effects of exposure to each temperature interval on crop yield, we break the degree-days variables into subcategories of 5°C intervals, create temperature bins from 10°C, and define <10°C as the reference group. A step function model is built as follows:

$$\ln Y_{it} = \alpha_0 + \sum_m \beta_m \mathrm{TemBin}_{m,it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{3}$$

Additionally, to consider the temperature variable construction methods commonly used in other pieces of literature, we construct other model specifications, including a model with the average temperature during the growing season $T_{\mathrm{avg}}$ and its quadratic term (Equation 4), and the average daily difference between day and night temperature, DIF (daily DIF $= T_{\mathrm{max,daily}} - T_{\mathrm{min,daily}}$) (Equation 5). The models are as follows:

$$\ln Y_{it} = \alpha_0 + \beta_1 T_{\mathrm{avg},it} + \beta_2 T^2_{\mathrm{avg},it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{4}$$

$$\ln Y_{it} = \alpha_0 + \beta_1 \mathrm{DIF}_{it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{5}$$

To explore the partial mitigation effect of precipitation on extreme high temperatures, we also consider the non-linear interactions between temperature and precipitation. Based on Equation (2), we add the interaction between HDD and precipitation. Then, the interaction between $T_{\mathrm{avg}}$ and precipitation is added to Equation (4). The models become:

$$\ln Y_{it} = \alpha_0 + \beta_1 \mathrm{GDD}_{it} + \beta_2 \mathrm{HDD}_{it} + \beta_3 \mathrm{HDD}_{it} * \mathrm{Pre}_{it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{6}$$

$$\ln Y_{it} = \alpha_0 + \beta_1 T_{\mathrm{avg},it} + \beta_2 T^2_{\mathrm{avg},it} + \beta_3 T_{\mathrm{avg},it} * \mathrm{Pre}_{it} + \gamma g(\mathrm{Pre}_{it}) + h_{\mathrm{p}}(t) + \mu_i + \varepsilon_{it} \tag{7}$$

In order to make tables much easier to read, the degree-days and precipitation variables are divided by 1000 to scale up the magnitude of coefficients, which does not affect the significance of coefficients. The standard errors are two-way clustered within counties and within province-years, which allows for serial correlation within each county and spatial correlation across each province-year. Furthermore, all regressions are weighted by average rice-specific area for the period 2009–2016 to correct for heteroskedasticity associated with each county.

## Data source and summary statistics

### Data source

#### *Rice-specific production*

The county-level annual rice production and sown acres of early, middle, and late rice were obtained from the Chinese Academy of Agricultural Sciences for the period 2009–2016. Among the rice production area, in order to construct a panel data set, a total of 1391 counties are used as samples, of which 545, 1204, and 470 counties planted early, middle, and late rice, respectively. According to the spatial distribution of rice-specific production area (shown in Figure A1), only 2.5% of the counties planted both early and middle rice, 2% of the counties planted middle and late rice, 8% of the counties planted early and late rice, and 23% of the counties planted early, middle and late rice. However, the three types of rice differ substantially by their planting date, which validates the weather variables we constructed for regressions, even if a county is a double-cropper or multiple-cropper.

#### *Growing season*

The growing seasons of the early, middle, and late rice in different regions were obtained from the National Meteorological Information Center of China, which includes the growth season information for early, middle and late rice at different agro-climatic monitoring sites within a province. We take the earliest sowing time and the latest harvest time of all stations within a province as the growing season of crops at the province level. The growing seasons for early, middle, and late rice across provinces are shown in Tables A1–A3.

#### *Weather*

The historical weather data are the station-day level data for 699 stations across China, from the National Meteorological Information Center of China, including daily minimum temperature ($T_{\min}$), daily maximum temperature ($T_{\max}$), and daily precipitation. Figure A2 presents the spatial distribution of weather stations. Since our early, middle, and late rice data are at the county level, we need to construct county-level weather variables for the regression analysis. To transform weather data from station-level to county-level, we use the Inverse-Distance Weighting method with a circle with a 200 km radius for each county's centroid, which is a method commonly used in the literature based on the same source of weather data (Chen & Gong, 2021; Cui & Xie, 2021; Zhang et al., 2017). First, we dropped the stations with an elevation greater than 3000 m in our study because they may not provide valid meteorological data for agricultural activities if the station elevation is too high. Second, we set a circle with a 200 km radius for each county's centroid. We then computed the weighted average weather variables using weather information from weather stations located in the circle and the inverse of the distance between each station and the county's centroid as the weights function. Finally, we took the weighted averages as county-level weather variables. After computing the daily $T_{\max}$ and daily $T_{\min}$ for each county, following the approach of Schlenker and Roberts (2009), we used a fitted sine curve between daily $T_{\min}$ and daily $T_{\max}$ to approximate the distribution of temperatures within each day and then estimated the length of time rice is exposed to each 1°C-interval in each day.

### *Climate prediction*

Since there are large uncertainties among the climate models used to predict climate change, we used climate predictions from five Global Climate Models (GCMs) in the CMIP5, including GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M, which cover the highest and lowest global mean temperature change (ΔGMT) and relative precipitation changes of almost all GCM models (25+) (Warszawski et al., 2014). Each model is associated with four RCPs: RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. We obtained projected end-of-the-century (2070–2090) daily minimum temperature, daily maximum temperature, and daily precipitation at each grid point. The values of climate data of each grid located in one county were averaged to transform the climate-change prediction data from the grid level to the county level.

## Summary statistics

As Table 1 shows, the rice yield in the sample varied substantially between early, middle, and late rice. Due to the different growing seasons, the weather variables of the early, middle, and late rice are also different. When given the same upper-temperature threshold (30°C), late rice experienced the most harmful accumulated degree days, which is probably because the growing season of late rice covers the hottest months of the year; and the planting areas of late rice are more concentrated than that of middle rice. From the spatial distribution of the mean and standard deviation of daily maximum temperature ($T_{\max}$) and minimum temperature ($T_{\min}$) during the growing season from 2009 to 2016 (shown in Figures A3 and A4), the areas with the average daily $T_{\max}$ above 30°C for middle and late rice are mainly concentrated in South China. The average daily $T_{\min}$ in Central and South China range from 16 to 24°C, which is suitable for all three types of rice. The average daily $T_{\max}$ and $T_{\min}$ variability (standard deviation [SD]) of early, middle, and late rice significantly differ across counties during the sample period. Although the data set we used covers 8 years, Tables A7 and A8, which show the summary statistics over eight time windows, also show that there still existed considerable variations in rice yields and weather conditions over time.

Figure 2 shows the distribution of historical temperature exposures during the growing seasons over 2009–2016 and depicts the mean shift in predicted temperature exposures for the five GCMs under RCP8.5 by the end of the century. Exposure days are defined as the amount of time the plants are exposed to each 1°C interval over the growing season (i.e., summed daily exposures calculated by using the within-day distribution of temperatures). Each box is plotted by the exposure days during the growing season across all counties and years. For early rice counties, the historical exposure temperatures during the growing season were mainly concentrated in the range 24–27°C (the exposure days were more than 10 days); for middle rice, it was 20–28°C; and for late rice, it was 24–29°C. However, under RCP8.5, by the end of this century (2070–2090 average), the exposure days on which temperatures are above 30°C, especially above 39°C, will become more frequent relative to 2009–2016.

More alarming is that the number of exposure days when the temperature exceeds 30°C will increase by more than 30 days in nearly 39% of early rice counties, 56% of middle rice counties, and 75% of late rice counties (shown in Figure A5). These projections suggest that rice will experience more extremely hot days, which may cause massive damage to rice yield. These facts further highlight the importance of understanding the heterogeneous yield response to extreme temperatures and the potential yield loss risk for early, middle, and late rice.

TABLE 1 Summary statistics of rice production and weather data during the years 2009–2016

| | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|
| Early rice (observations = 4360) | | | | |
| Yield (kg/ha) | 5848 | 906 | 2168 | 12,450 |
| Average temperature (°C) | 23.73 | 1.27 | 18.31 | 27.99 |
| Growing degree days (10–30°C) (1000D) | 1.91 | 0.24 | 1.32 | 2.55 |
| Growing degree days (10–32°C) (1000D) | 1.94 | 0.25 | 1.32 | 2.61 |
| Harmful degree days (30°C+) (1000D) | 0.05 | 0.02 | 0 | 0.13 |
| Harmful degree days (32°C+) (1000D) | 0.02 | 0.01 | 0 | 0.06 |
| Cumulative precipitation (1000 mm) | 0.90 | 0.23 | 0.21 | 1.48 |
| Middle rice (observations = 9632) | | | | |
| Yield (kg/ha) | 7099 | 1446 | 1000 | 13,703 |
| Average temperature (°C) | 23.04 | 2.86 | 13.68 | 28.71 |
| Growing degree days (10–29°C) (1000D) | 2.26 | 0.42 | 0.87 | 3.22 |
| Growing degree days (10–30°C) (1000D) | 2.29 | 0.43 | 0.87 | 3.26 |
| Harmful degree days (29°C+) (1000D) | 0.07 | 0.06 | 0 | 0.23 |
| Harmful degree days (30°C+) (1000D) | 0.05 | 0.04 | 0 | 0.17 |
| Cumulative precipitation (1000 mm) | 0.80 | 0.24 | 0.01 | 1.59 |
| Late rice (observations = 3760) | | | | |
| Yield (kg/ha) | 6049 | 1025 | 2383 | 13,583 |
| Average temperature (°C) | 25.70 | 1.09 | 21.85 | 28.23 |
| Growing degree days (10–30°C) (1000D) | 2.28 | 0.23 | 1.80 | 3.03 |
| Growing degree days (10–34°C) (1000D) | 2.35 | 0.25 | 1.81 | 3.14 |
| Harmful degree days (30°C+) (1000D) | 0.08 | 0.03 | 0 | 0.17 |
| Harmful degree days (34°C+) (1000D) | 0.01 | 0.01 | 0 | 0.04 |
| Cumulative precipitation (1000 mm) | 0.74 | 0.20 | 0.35 | 1.57 |

# EMPIRICAL RESULTS

## Main results

### Measuring non-linear effects of temperature using degree days variables

Table 2 reports the regression results for Equation (2) using degree days variables. The upper-temperature threshold of each type of rice is in the bottom row of the table, and the thresholds close to the selected upper-temperature threshold also show a similar relationship, as shown in Tables A4–A6.

The results show a non-linear relationship between temperature and rice yield, where rice yield increases linearly up to the upper temperature and decreases linearly above the upper temperature for early, middle, and late rice. For example, for early rice, a 1D increase of GDD during the growing season corresponds to an increase in yield by 0.02%, which is significant at the 1% level; a 1D increase in HDD is associated with a 0.1% significant decrease in yield. HDD

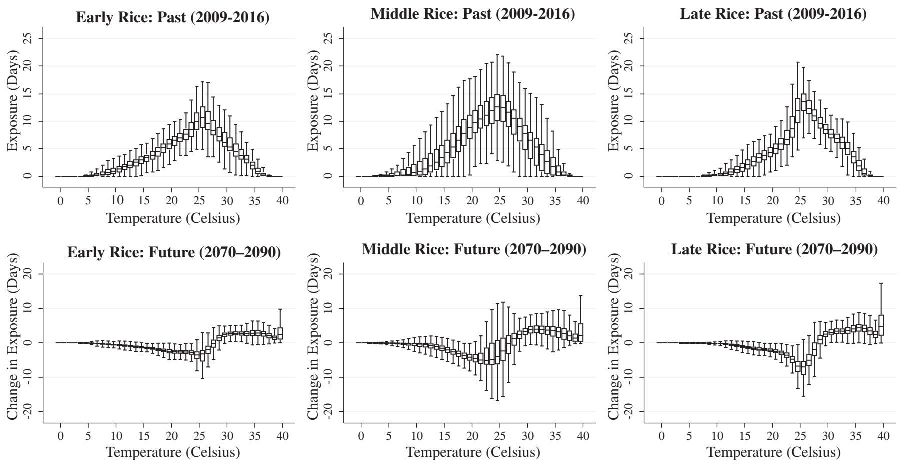


FIGURE 2 The distribution of historical temperature exposure and predicted temperature exposure changes during the growing season for early, middle, and late rice between 2009–2016 and 2070–2090. The temperature exposures are estimated using a fitted sine curve between daily minimum temperature and daily maximum temperature to approximate the distribution of temperatures within each day, as discussed in the Data Source. The first row shows historical temperature exposures in each 1°C interval. The second row displays the mean of the future predicted temperature exposure changes for the five GCMs under RCP8.5 (2070–2090 in comparison with the 2009–2016 baseline). The first interval includes the time during which temperatures fall below 0°C, and the last interval includes the time during which temperatures are above 39°C. Whiskers represent the range between minimum and maximum time across all counties and years, the outline of the box indicates the 25%–75% range, and the solid bold line in the box is the median

has significant adverse effects also for middle and late rice. Exposure to each additional degree-day of heat above 29°C results in a decrease in middle rice yield of 0.03% and a 0.1% decline in late rice yield for every 1D increase above 34°C. Notably, GDD is significant only for early rice, which is intuitive because the heat deficit is more likely a constraining factor for early rice, which is planted earlier (during a colder time of year). As shown in Table 1, given the same upper-temperature threshold (30°C), the accumulated GDD absorbed by early rice was nearly 370D less than middle and late rice.

Table 2 also reports the *t*-statistic estimated by using the block bootstrap method. First, we resample the residuals for the whole year at a time, then consider the combinations of 8 years ($8^8$ combinations), sample with replacement, and perform 400 replications. The results show that the *t*-statistics become smaller (the standard errors increase) than the two-way county and province-by-year clustering. The reason for this may be the differences between individuals, that is, damages could be a lot less or a lot worse than estimated. We tend to believe that the standard errors estimated using block bootstrap are more conservative for this study.

In order to directly compare weather effects across the different rice types, we pool all three into a single model with county fixed effects and provincial quadratic time trends and estimate interacted weather variables. We set the upper temperature bound at 30°C for all three types of rice, which helps us compare the effect on yield of exposure to each additional degree day of heat above the same temperature threshold. Table 3 reports the pooled regression results. In the pooled model for all rice types (column (1)), GDD had a significant positive effect on rice yield, and HDD showed a significant adverse effect. When accounting for different rice types (column (2)), early rice is the most positively affected by GDD and the most negatively affected by HDD.

TABLE 2 Regression results: Piecewise linear model

| | Early rice | | | Middle rice | | | Late rice | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) Coefficient | (2) Two-way cluster *t*-Statistics | (3) Block bootstrap *t*-Statistics | (1) Coefficient | (2) Two-way cluster *t*-Statistics | (3) Block bootstrap *t*-Statistics | (1) Coefficient | (2) Two-way cluster *t*-Statistics | (3) Block bootstrap *t*-Statistics |
| Growing degree days (1000D) | 0.182 | (4.12)*** | (1.77)* | 0.030 | (0.68) | (0.44) | 0.007 | (0.14) | (0.07) |
| Harmful degree days (1000D) | −1.027 | (−2.26)** | (−1.23) | −0.262 | (−3.07)*** | (−1.75)* | −0.983 | (−2.66)*** | (−1.07) |
| Precipitation (1000 mm) | 0.042 | (0.43) | (0.37) | 0.133 | (0.73) | (1.00) | −0.075 | (−1.27) | (−0.93) |
| Precipitation squared | −0.049 | (−0.96) | (−0.72) | −0.053 | (−0.63) | (−0.91) | 0.041 | (1.19) | (0.83) |
| Constant | 8.31 | (119.90)*** | (45.80)*** | 8.734 | (64.30)*** | (60.05)*** | 8.707 | (67.52)*** | (36.02)*** |
| Observations | 4360 | | | 9632 | | | 3760 | | |
| Adjusted $R^2$ | 0.792 | | | 0.817 | | | 0.816 | | |
| $R^2$ | 0.820 | | | 0.841 | | | 0.840 | | |
| RMSE | 0.068 | | | 0.095 | | | 0.075 | | |
| Temperature threshold | 32°C | | | 29°C | | | 34°C | | |

*Note*: All regressions include county fixed effects and provincial quadratic time trends and are weighted by the average planted area. Robust *t*-statistics are reported in parentheses. For each type of rice, column (2) reports the *t*-statistic clustered at counties and province-by-year pairs, column (3) reports the *t*-statistic estimated using block bootstrap. The $R^2$ and RMSE of the baseline (no weather variables) model for early rice are 0.811 and 0.070, middle rice are 0.829 and 0.099, late rice are 0.836 and 0.076, respectively.

Abbreviation: RMSE, root-mean-squared prediction error.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE 3** Regression results: Piecewise linear model with pooled regression

| | (1) All rice types | (2) Add interaction with rice type |
|---|---|---|
| Growing degree days (1000D) (10–30°C) | 0.199*** (8.95) | |
| Harmful degree days (1000D) (30°C+) | −0.540*** (−4.93) | |
| Growing degree days (1000D) (10–30°C) with rice type | | |
| Early rice | | 0.324*** (9.16) |
| Middle rice | | 0.043 (1.20) |
| Late rice | | 0.013 (0.39) |
| Harmful degree days (1000D) (30°C+) with rice type | | |
| Early rice | | −1.759*** (−4.73) |
| Middle rice | | −0.224* (−1.78) |
| Late rice | | −0.124 (−1.10) |
| Constant | 8.382*** (132.44) | 8.669*** (100.15) |
| Observations | 17,760 | 17,760 |
| Adjusted $R^2$ | 0.853 | 0.853 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Furthermore, the effect magnitude is significantly higher than the pooled mean (the lincom test of the type coefficients are presented in Table A9). Due to different growing seasons, the provincial time trend in the pooled model cannot reflect the respective production trends of early, middle, and late rice. Therefore, the estimated coefficients are slightly different from those in Table 2, but we still find similar conclusions: there is still a non-linear relationship between temperature and yield for early, middle, and late rice, and the early rice is the most vulnerable among all rice types under the same increase in HDD.

## Measuring non-linear effects of temperature using temperature bins variables

Figure 3 displays point estimates and the 95% confidence intervals for Equation (3) using temperature bins for each 5°C. Temperatures above 30°C are harmful to all three types of rice. The point estimates suggest that replacing a full day at 25–30°C with a full day above 30°C will decrease early rice yield by around 1.2%, middle rice yield by 0.96%, and late rice yield by 3.3%, holding all else constant. In addition, the first bin for middle rice is negative and statistically significant, and there is a significant upward jump in the marginal exposure effect between the 10 and 15°C bin and the 15 and 20°C bin. Carter et al. (2018) has pointed out that exposures to adjacent temperatures are systematically correlated in the interpolated data for the times spent at adjacent temperatures across the season, so this partially constructed multicollinearity typically results in volatile relationships between temperature exposure and yield, and it is unclear whether such nonlinearities reflect actual underlying effects or are simply caused by multicollinearity in the exposure data. Therefore, in this study, the step function model is only used to show the flexible effects of exposure to each temperature bin on crop yield.

## Exploring precipitation

Figure A6 plots the marginal effect of precipitation in various regression models. To better evaluate the effect of precipitation, firstly, we construct a baseline model with only precipitation and its quadratic term and other fixed effects. Second, we analyze precipitation results in the piecewise linear model (shown in Table 2). Third, we use lagged precipitation and its quadratic as proxy variables for irrigation in the piecewise linear model because the previous year's rainfall will affect irrigation water availability in the current period. The estimates suggest that the effect of precipitation exhibits a slight U-shaped relationship on rice, and the estimated patterns of precipitation effects are consistent across specifications. However, they are not statistically significant. Precipitation has no significant impact on yield for the three types of rice, probably because of the need for heavy irrigation during the rice planting process. These findings are similar to Chen and Tian (2016) and Carter et al. (2017), who found no significant relationship between precipitation and rice yield.

## Alternative weather variables measures

We also use average daily temperature during the growing season and its quadratic term to explore the non-linear relationship between temperature and rice yield. In column (3) of Tables A10–A12, the results show an inverted U-shaped relationship between yields and average daily temperature for rice, although the coefficients are not statistically significant. The inflection points of average temperature for early, middle, and late rice were 23, 19, and 24°C, respectively. Since the average daily temperature during the growing season can dilute the exposure to extreme high temperatures, the estimated temperature thresholds are lower than those of the piecewise linear models with degree days variables.

In agronomic theory, as long as the nighttime temperature is not lower than the minimum temperature threshold of rice growth, and the daytime temperature is not higher than the upper-temperature threshold, a larger temperature difference between day and night is more favorable for rice. Therefore, in column (5) of Tables A10–A12, only the average daily difference between day and night temperature (DIF) and precipitation are included in the regression. The estimates suggest that the DIF negatively affects rice yields, but this is not significant for early and late rice. The reason may be that during our sample period, rice had been damaged by prolonged exposure to high temperatures during the day. This also shows the great importance of studying the effects of extreme high temperatures on early, middle, and late rice.

It is also possible that precipitation and high temperatures have interaction effects. For example, precipitation can cool crops and mitigate damages from extreme high temperatures, but this may be less effective if exposure to high temperatures increases. Therefore, in Tables A10–A12, we interact the HDD with precipitation in column (2), and we also interact the average temperature with precipitation in column (4). However, only the interaction between average temperature and precipitation for early rice is significant at the 1% level. Given that the interaction is significantly positive and the effect of average temperature is statistically insignificant, this suggests that a 1°C increase in average temperature is associated with a 2.1% increase in yield at the average level of precipitation (900 mm), and the effect will be more positive as precipitation increases. This result may also be related to the earlier planting time of early rice, the colder environment during that time, and the lower amount of irrigation water storage after winter. Although the interaction between HDD and precipitation is not statistically significant for early, middle or late rice, the significance of HDD decreases after adding the interaction term. These results show that precipitation can slightly mitigate the harm from exposure to high temperatures, but the effect is not obvious. Since the variance of the model will increase with the addition of irrelevant variables, the significance of the parameters will decrease. At the same time, there may be multicollinearity, and the parameter estimation will be disturbed. Therefore, after adding interaction terms, the significance of HDD is lower, and the coefficient may even change.

An out-of-sample model prediction is a good approach for variable selection (Schlenker & Roberts, 2009). In this study, we leave out 1 year of data at a time, estimate the model with the remaining years and predict the year left out, do this for all years, and built up a complete sample of out-of-sample predictions. We do this for all regression model specifications and a baseline model with county fixed effects and quadratic province-level trends but without weather variables. The root-mean-squared prediction error (RMSE) reported in Table A13 shows that the "best" model for early and middle rice is the one with "Average Difference between Day and Night Temperature," while for the late rice is the one with "Quadratic Average Temperature and Interaction between Temperature and Precipitation." However, for all types of rice, compared to the baseline model, the reduction in RMSE of the "best" model is slight less than 3%. These results also suggest that even for the "best" model, the variance explained by weather variables only shows partial effects, and there are still many uncertainties of potential climate impacts. Besides, we also used another approach by calculating several commonly used in-sample criteria ($R^2$, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC)) and found that they behave very similar across different models (shown in the last three rows at the bottom of Tables A10–A12).

Using the $R^2$ and RMSE (in-sample) of the model with county fixed effects and quadratic province-level trends but without weather variables as a baseline (reported in the note under Table 2), the corresponding numbers of all regression model specifications indicate that the variances explained by weather variables show only partial effects. However, our point estimates suggest fairly substantial damages from the warming climate. Considering that degree-day variables better characterize the differential effects of heat accumulated over the growing season, especially the effects of extreme temperatures. That piecewise linear function results are robust under multiple robustness checks (shown in Tables A14–A16), we decided to use the piecewise linear function results as our preferred specification.

## Robustness check

Six types of sensitivity checks are applied to ensure the robustness of the climate effects on rice yield. In specification (1), we add economic variables to the baseline model. Due to the limited availability of data on inputs, the ratio between input and output price was added as a proxy for directly using the number of inputs according to the input–output optimization theory. We choose labor and fertilizer as the primary inputs for rice production. We use lagged rice prices in the preceding year as a proxy for the expected rice price in the current year. The provincial rice prices, wage, and fertilizer prices are obtained from the data compilation of China Agricultural Product Cost and Revenue. In specification (2), we use lagged precipitation and its square as proxy variables for irrigation to consider adaptation strategy to climate change. In specification (3), we winsorize data (i.e., replace values outside the 99th percentile with the 99th percentile) and replicate the regression analysis. In specification (4), we replace the fixed-effect model with spatial errors model (SEM), allowing error terms to be spatially correlated across the county. We use Conley standard errors in the specification (5) (Conley, 1999; Hsiang, 2010) to account for spatial correlation. In specification (6), we cluster the standard errors at the prefecture-level to allow the counties within each prefecture to have spatially and temporally correlated standard errors.

As shown in Tables A14–A16, the estimated patterns of non-linear effects are consistent across specifications, and the results are still robust. The HDD have detrimental effects that are statistically significant.

# PROJECTIONS: IMPACTS UNDER FUTURE CLIMATE CHANGE

The robustness check analysis in the previous sub-section shows that the regression coefficients in the piecewise linear model can be used for further analysis. This section projects the relative changes in rice yields due to climate changes by combining our regression coefficients in Table 2 with five global climate change models under four RCP scenarios. We choose the future years from 2070 to 2090, defined as the relatively long term, to predict the impacts of climate change on the three types of rice. Here we keep the growth season and sown area unchanged, which possibly overestimate the projection results. First, for each pair of RCP-GCM, we calculate the differences in weather variables between the historical (average for 2009–2016) and future years for each county. We then evaluate the possible yield changes by using regression coefficients and changes in weather variables. We take the average predicted impacts of 2070–2090 as the long-term shock for each county. Finally, for the three types of rice, the yield changes at the county level are aggregated to the national scale, using the average sown rice areas in 2009–2016 as the weight. Specifically, for the average predicted impacts of all GCMs, we first average the weather variables across the five GCMs and then multiplying that by the regression coefficients of Table 2. The national-level predicted results with only significant variables and full weather variables are shown in Table A17, there is little difference between the two cases.

The projected changes in extremely hot days can profoundly impact rice yields in the future, the extent of which depends on climate change models and RCP scenarios. Figure 4 displays the national-level predicted impacts using only significant weather variables. For early rice, it is notable that the climate predictions simulated by several climate models are beneficial to yield

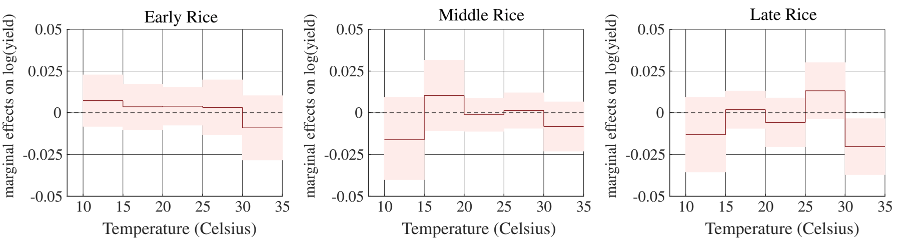


**FIGURE 3** Non-linear relationship between temperature and rice yield

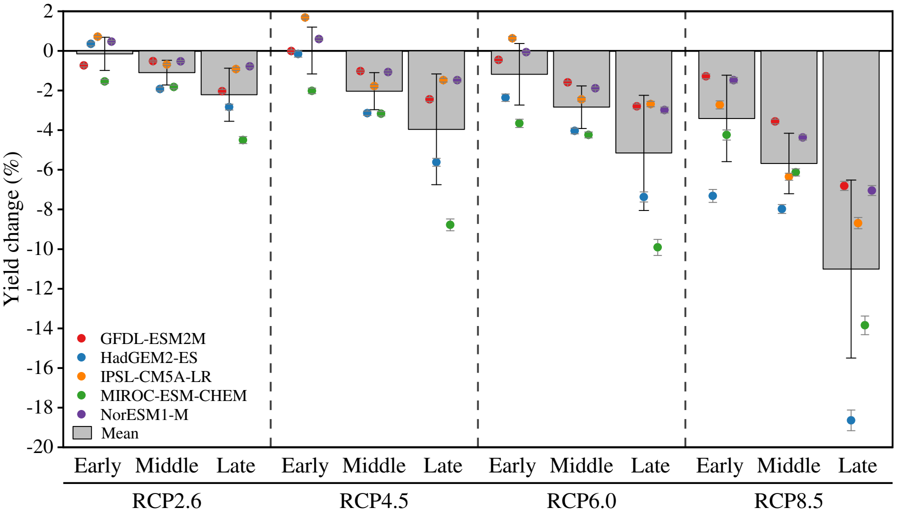


**FIGURE 4** Impacts of temperature changes on rice yield during 2070–2090. The different colored circles are the national average predicted impacts calculated by weighted county planted area for each GCM. The gray shaded bars are the average predicted impacts, which are calculated by first averaging the weather variables across the five GCMs, and then multiplying that by the regression coefficients. The error bars of circles represent 95% CI across counties, and whiskers of gray bars represent 95% CI across climate models. CI, confidence interval; GCM, global climate model; RCP, representative concentration pathway

under RCP2.6, RCP4.5, and RCP6.0. As discussed above, the heat deficit is more likely a constraining factor for early rice because it is planted during a colder time of year; therefore, early rice may benefit from warming. However, under RCP8.5-the most extreme scenario, the increase in temperature simulated by all climate models will reduce national early rice by an average of 3.4% ± 2.2%. For middle and late rice, exposure to extreme high temperatures due to climate warming will increase significantly in most counties, as we discussed in the Summary Statistics section. Specifically, the national average reduction in middle rice is 1.1% ± 0.6% under RCP2.6, increasing to 5.7% ± 1.5% under RCP8.5. The corresponding reductions in late rice yield are larger, by 2.2% ± 1.4% under RCP2.6 and by 11% ± 4.5% under RCP8.5. The substantial overlap in the CIs for projected yield losses across the three rice types through RCP6.0 in Figure 4 seems to indicate a smaller heterogeneity in the forecasted yield changes. However, the large CI/uncertainty in our analysis comes from different GCMs' projections of temperature and precipitation. The apparent difference in the average yield losses across the three rice types indicates that significant heterogeneity still exists among most GCMs' projections.

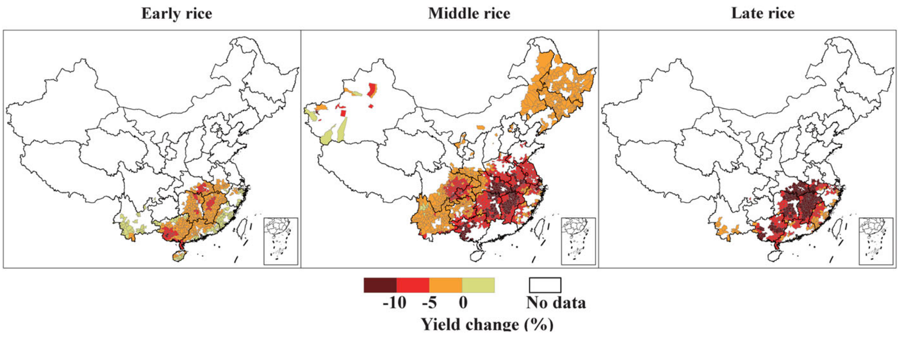


**FIGURE 5** Distribution of impacts from temperature changes by county (percent yield change) under RCP8.5 during 2070–2090. The early rice, middle rice, and late rice (left, middle, and right panel, respectively) impacts are shown. The impacts are the average predicted impacts under RCP8.5, which are calculated by first averaging the weather variables across the five GCMs, and then multiplying that by the regression coefficients. RCP, representative concentration pathway

Spatially, the predicted impacts are highly heterogeneous. Figure 5 shows the distribution of predicted impacts of temperature changes by county on the yields of early rice, middle rice, and late rice under RCP8.5. We find that aggregating the impacts at the national level masks the inter-regional differences. At the county level, the potential losses of middle and late rice are severe and widely distributed, especially in the main production provinces. Under RCP8.5, predicted late rice yield losses for Anhui (10% $\pm$ 0.4%) and Guangxi (8.5% $\pm$ 0.2%) are similar to the national average, while those for Jiangxi (13.9% $\pm$ 0.3%), Hubei (12.7% $\pm$ 0.2%), and Hunan (11.8 $\pm$ 0.3) are greater than the national average. For middle rice, the main production areas, accounting for 52% of the national middle rice production, will experience much more serious yield loss than the national average. These include Hubei (9.1 $\pm$ 0.3%), Jiangxi (8.5 $\pm$ 0.2%), Anhui (8.3 $\pm$ 0.1%), Henan (7.6 $\pm$ 0.1%), Guangxi (7.5 $\pm$ 0.3%), Hunan (6.8 $\pm$ 0.2%), Jiangsu (6.4 $\pm$ 0.1%), Chongqing (6.1 $\pm$ 0.3%). However, the predicted negative impact on early rice is small, while Yunnan and Fujian will benefit slightly from the increased temperature.

# CONCLUSIONS AND POLICY IMPLICATIONS

With the increasing demand for high-quality rice, the rice planting structure in China has gradually focused on middle and late rice. However, by the end of this century (2070–2090 average), it is likely that rice in China—especially the middle and late rice which consumers prefer—will be exposed to more extremely hot days, on which temperatures are above 30°C. Based on this background information, we comprehensively estimate the heterogeneous yield response to extreme temperatures for early, middle, and late rice in China and explore how the adjustment of rice production to accommodate consumer preferences will affect the ability of China's rice sector to adapt to future climate change. We use multiple temperature specifications, considering the effects of both minimum and maximum temperatures, to estimate the non-linear relationship between temperature and yield, and we use multiple model specifications to obtain robust results. We also predict the potential risk of yield loss when exposed to higher future warming trends by using various climate models and scenarios for considering uncertainty. To our knowledge, this study is the first empirical county-level study to estimate the heterogeneous yield response to extreme temperatures and the potential risk of yield loss when exposed to higher future warming trends for early, middle, and late rice in China.

Overall, our results robustly show that climate change has significant effects on rice yield, with substantial differences among early, middle, and late rice. We find that yields increase with temperature up to 32°C for early rice, 29°C for middle rice, and 34°C for late rice, but decrease sharply with higher temperatures. By the end of this century (2070–2090 average), the middle and late rice will bear the most adverse impacts because of more extreme hot days. Under RCP8.5, early rice will suffer yield losses of 3.4% ± 2.2%, middle rice 5.7% ± 1.5%, and late rice 11% ± 4.5% at the national level. Although middle rice and late rice are not the most vulnerable among all rice types under the same increase in HDD, their production will face more risks in the future because they will be exposed to higher future warming trends over the current growing regions and fixed crop calendar. Our method also highlights the disproportionate effects of climate change in different regions for different rice types.

The predicted climate impacts on rice yield run contrary to the increasing preference of consumers for middle and late rice. With rising income, it is also challenging to substitute from middle and late rice types that experience severe losses from climate change toward early rice that experiences modest impacts to buffer the heterogeneous impacts of climate change on different types of rice. The main reason is that the substitution elasticity of late and middle rice with early rice is fairly low. Due to the differences in rice quality, late and middle rice are mainly directly consumed, while early rice is mainly used in the food processing industry (e.g., rice noodles) and livestock feed. Even with more price increase of late and middle rice under changing climate, speculated by the severe losses and high own price elasticity of late and middle rice, it is difficult to substitute the consumption of late and middle rice with cheap early to adapt to climate change. Of course, due to the high substitution elasticity between late and middle rice, the climate impacts can be offset partly by diverting consumption of late rice to middle rice even after considering the highest price increase of late rice.

With mild impacts on early rice compared with middle and late rice, if the consumption of middle and late rice can be substituted with early rice, it would be possible to expand the planting area for early rice and reduce the planting area for middle and late rice to adapt to climate change. However, due to low substitution of low and high-quality rice, it is expected that more land will be allocated to middle and late rice in response to the higher price increase. Moreover, it is recognized that there is a high substitution elasticity between middle and late rice. Thus, it is suggested to move more planting area from late rice to the middle rice to cope with climate change considering that middle rice will experience less yield loss than late rice under changing climate in the future.

Therefore, it is more meaningful to understand the impact of climate change on rice in different growing seasons than that of aggregated rice production in China. The key policy implication is that, in the context of a recent expansion of middle rice, we need to incorporate this type-heterogeneity in yield response to extreme temperatures and potential risk of yield loss into national and regional plans for agricultural adaptation. For example, early rice should be given priority in the research of seed heat resistance in breeding programs, and middle and late rice should be given priority in the regional distribution of rice production, and make these estimates part of the cost–benefit analysis for different growing seasons of rice.

## ACKNOWLEDGMENT

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## APPENDIX A: Figures and Tables

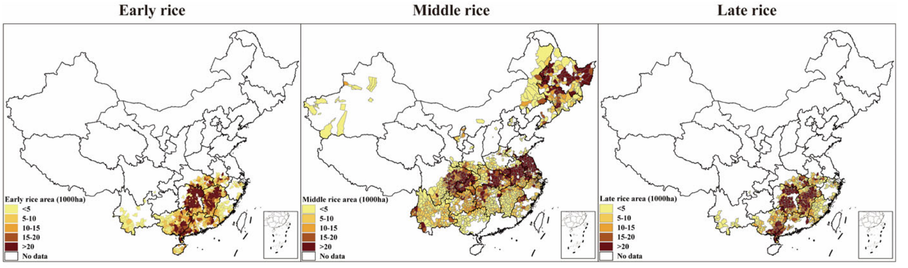


**FIGURE A1** Spatial distribution of average planted areas of early, middle, and late rice in China from 2009 to 2016

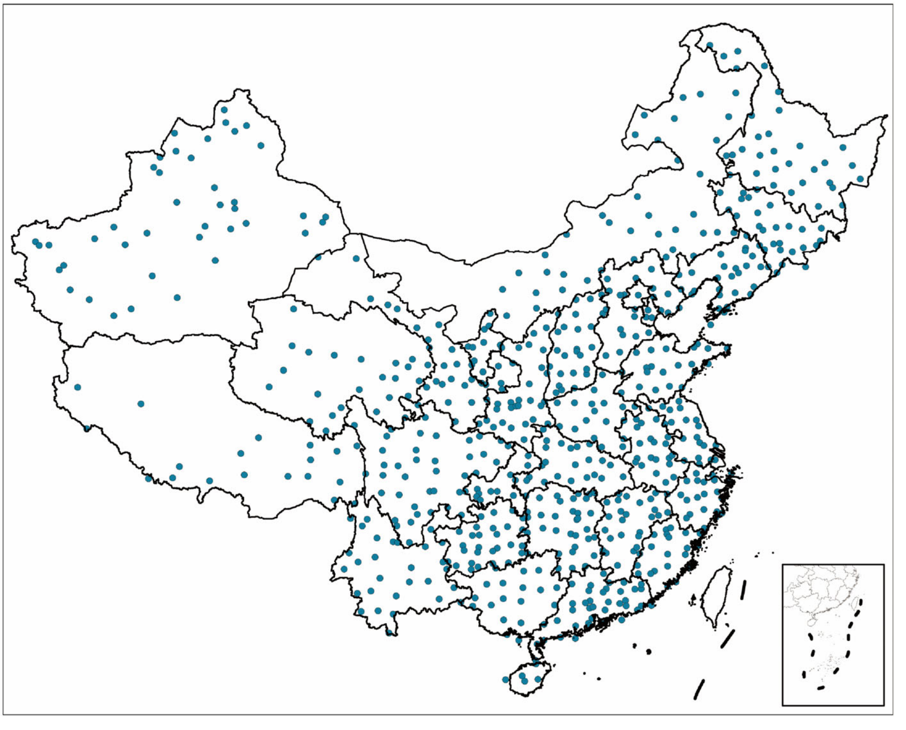

**FIGURE A2** Spatial distribution of weather stations in China

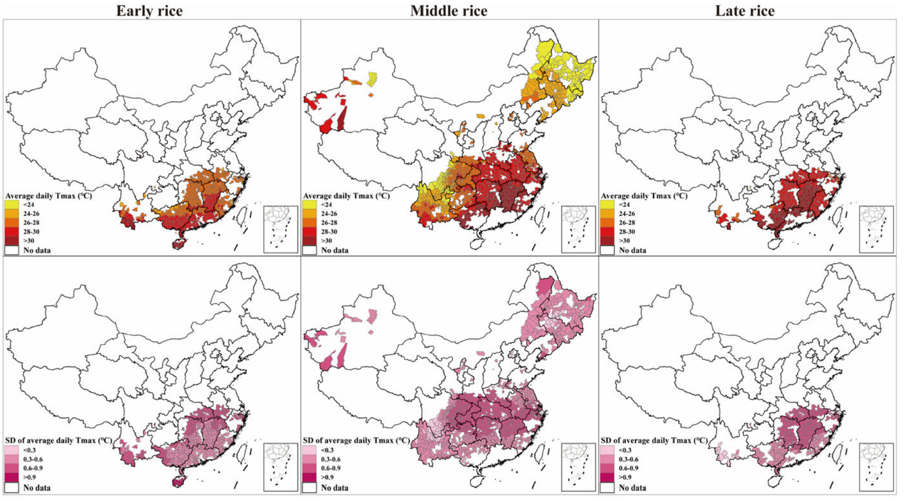


**FIGURE A3** Spatial distribution of mean and standard deviation of daily maximum temperature during growing season for early, middle, and late rice in China from 2009 to 2016. SD, standard deviation

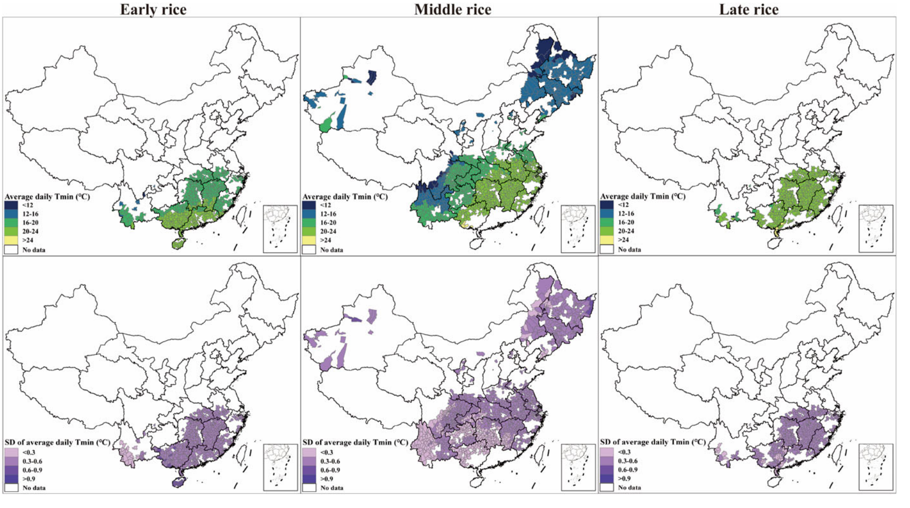


**FIGURE A4** Spatial distribution of mean and standard deviation of daily minimum temperature during growing season for early, middle, and late rice in China from 2009 to 2016. SD, standard deviation

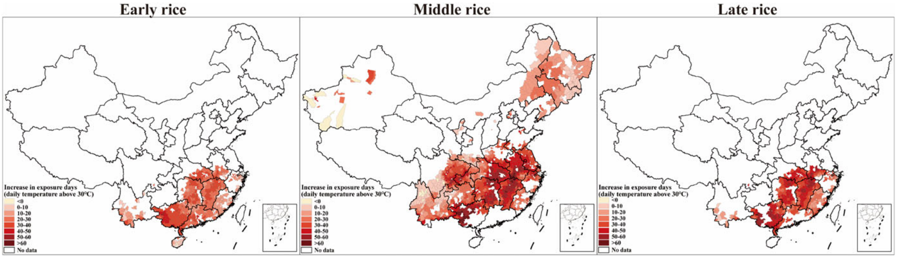


**FIGURE A5** Spatial distribution of average predicted increase in exposures days when temperature is above 30°C during the growing season for the five GCMs under RCP8.5 (2070–2090 in comparison with 2009–2016 baseline). GCM, global climate model; RCP, representative concentration pathway

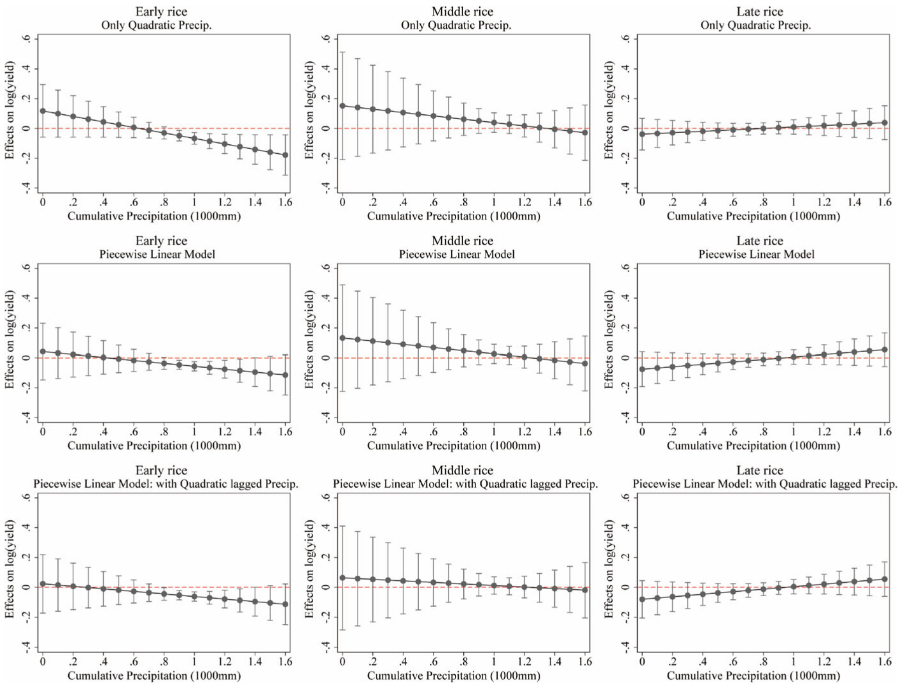


**FIGURE A6** The marginal effect of precipitation in various regression models

**TABLE A1** The growing season for early rice across regions

| Province | Early rice |
|---|---|
| Hainan | 2/20–6/30 |
| Guangdong, Guangxi, Sichuan, Yunnan | 3/01–7/31 |
| Fujian | 3/11–7/31 |
| Anhui, Hubei, Hunan, Jiangxi, Zhejiang | 3/21–7/31 |

**TABLE A2** The growing season for middle rice across regions

| Province | Middle rice |
|---|---|
| Yunnan | 3/01–10/10 |
| Sichuan | 3/10–10/10 |
| Chongqing | 3/10–9/30 |
| Guizhou, Hubei | 4/01–9/30 |
| Henan, Shaanxi | 4/10–9/20 |
| Anhui, Gansu, Guangxi, Shanxi, Xinjiang | 4/21–10/10 |
| Hebei, Heilongjiang, Hunan, Inner Mongolia, Jilin, Liaoning, Ningxia | 4/21–9/30 |
| Beijing, Fujian, Tianjin | 5/01–10/10 |
| Fujian, Jiangsu | 5/01–10/31 |
| Shandong | 5/10–10/20 |
| Zhejiang | 5/10–11/10 |
| Jiangxi | 5/20–10/10 |
| Shanghai | 5/20–10/30 |

**TABLE A3** The growing season for late rice across regions

| Province | Late rice |
|---|---|
| Sichuan, Yunnan | 6/01–10/31 |
| Anhui, Jiangxi | 6/10–10/31 |
| Hainan, Hunan | 6/10–11/10 |
| Hubei | 6/20–10/31 |
| Fujian, Zhejiang | 6/20–11/20 |
| Guangdong, Guangxi | 7/01–11/20 |

**TABLE A4** The regression results of piecewise linear model at various upper-temperature thresholds for early rice

| Temperature threshold | (1) 28°C | (2) 29°C | (3) 30°C | (4) 31°C | (5) 32°C | (6) 33°C | (7) 34°C | (8) 35°C |
|---|---|---|---|---|---|---|---|---|
| GDD below threshold (1000D) | 0.192*** (4.33) | 0.186*** (4.25) | 0.183*** (4.18) | 0.182*** (4.14) | 0.182*** (4.12) | 0.178*** (4.03) | 0.167*** (3.76) | 0.151*** (3.40) |
| GDD above threshold (1000D) | −0.225 (−1.55) | −0.307* (−1.73) | −0.433* (−1.91) | −0.649** (−2.10) | −1.027** (−2.26) | −1.663** (−2.25) | −2.653* (−1.99) | −4.244 (−1.63) |
| Precipitation (1000 mm) | 0.052 (0.58) | 0.053 (0.58) | 0.053 (0.57) | 0.049 (0.52) | 0.042 (0.43) | 0.036 (0.36) | 0.041 (0.41) | 0.057 (0.57) |
| Precipitation squared | −0.058 (−1.21) | −0.057 (−1.19) | −0.056 (−1.15) | −0.053 (−1.07) | −0.049 (−0.96) | −0.046 (−0.87) | −0.048 (−0.90) | −0.056 (−1.07) |
| Constant | 8.309*** (121.46) | 8.311*** (121.04) | 8.312*** (120.61) | 8.311*** (120.17) | 8.310*** (119.90) | 8.315*** (119.49) | 8.329*** (118.52) | 8.348*** (117.40) |
| Observations | 4360 | 4360 | 4360 | 4360 | 4360 | 4360 | 4360 | 4360 |
| $R^2$ | 0.820 | 0.819 | 0.819 | 0.820 | 0.820 | 0.820 | 0.819 | 0.819 |
| Residual sum of squares | 17.528 | 17.531 | 17.531 | 17.526 | 17.518 | 17.523 | 17.551 | 17.585 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.

Abbreviation: GDD, growing-degree days.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE A5 The regression results of piecewise linear model at various upper temperature thresholds for middle rice

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Temperature threshold** | **28°C** | **29°C** | **30°C** | **31°C** | **32°C** | **33°C** | **34°C** | **35°C** |
| GDD below threshold (1000D) | 0.033 (0.71) | 0.030 (0.68) | 0.025 (0.59) | 0.018 (0.43) | 0.009 (0.23) | 0.001 (0.02) | −0.008 (−0.22) | −0.017 (−0.50) |
| GDD above threshold (1000D) | −0.207*** (−3.08) | −0.262*** (−3.07) | −0.333*** (−2.97) | −0.421*** (−2.75) | −0.541** (−2.47) | −0.722** (−2.17) | −1.005* (−1.88) | −1.450 (−1.56) |
| Precipitation (1000 mm) | 0.130 (0.72) | 0.133 (0.73) | 0.135 (0.74) | 0.137 (0.74) | 0.138 (0.75) | 0.138 (0.75) | 0.139 (0.75) | 0.140 (0.76) |
| Precipitation squared | −0.052 (−0.62) | −0.053 (−0.63) | −0.054 (−0.64) | −0.055 (−0.65) | −0.055 (−0.65) | −0.055 (−0.65) | −0.055 (−0.65) | −0.055 (−0.65) |
| Constant | 8.732*** (61.86) | 8.734*** (64.30) | 8.741*** (67.33) | 8.753*** (70.94) | 8.769*** (75.07) | 8.785*** (79.21) | 8.801*** (82.82) | 8.819*** (85.65) |
| Observations | 9632 | 9632 | 9632 | 9632 | 9632 | 9632 | 9632 | 9632 |
| $R^2$ | 0.841 | 0.841 | 0.841 | 0.841 | 0.841 | 0.841 | 0.841 | 0.841 |
| Residual sum of squares | 76.372 | 76.365 | 76.366 | 76.379 | 76.398 | 76.418 | 76.441 | 76.470 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.

Abbreviation: GDD, growing-degree days.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A6** The regression results of piecewise linear model at various upper temperature thresholds for late rice

| Temperature threshold | (1) 28°C | (2) 29°C | (3) 30°C | (4) 31°C | (5) 32°C | (6) 33°C | (7) 34°C | (8) 35°C |
|---|---|---|---|---|---|---|---|---|
| GDD below threshold (1000D) | −0.034 (−0.54) | −0.022 (−0.35) | −0.011 (−0.18) | −0.002 (−0.04) | 0.005 (0.09) | 0.008 (0.17) | 0.007 (0.14) | −0.003 (−0.06) |
| GDD above threshold (1000D) | −0.079 (−1.28) | −0.109 (−1.43) | −0.158 (−1.62) | −0.236* (−1.84) | −0.372** (−2.18) | −0.602** (−2.55) | −0.983*** (−2.66) | −1.548** (−2.31) |
| Precipitation (1000 mm) | −0.068 (−1.10) | −0.067 (−1.07) | −0.066 (−1.07) | −0.066 (−1.08) | −0.068 (−1.13) | −0.071 (−1.19) | −0.075 (−1.27) | −0.078 (−1.32) |
| Precipitation squared | 0.034 (0.97) | 0.033 (0.95) | 0.033 (0.94) | 0.033 (0.97) | 0.035 (1.02) | 0.038 (1.10) | 0.041 (1.19) | 0.042 (1.25) |
| Constant | 8.805*** (53.33) | 8.777*** (53.98) | 8.751*** (54.68) | 8.731*** (56.31) | 8.714*** (59.60) | 8.704*** (64.06) | 8.707*** (67.52) | 8.727*** (68.53) |
| Observations | 3760 | 3760 | 3760 | 3760 | 3760 | 3760 | 3760 | 3760 |
| $R^2$ | 0.840 | 0.840 | 0.840 | 0.840 | 0.840 | 0.840 | 0.840 | 0.840 |
| Residual sum of squares | 18.273 | 18.270 | 18.266 | 18.260 | 18.252 | 18.243 | 18.237 | 18.240 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.

Abbreviation: GDD, growing-degree days.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A7** Summary statistics of rice production and weather data over windows (2009–2012)

| | 2009 | | 2010 | | 2011 | | 2012 | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| *Early rice (observations = 545)* | | | | | | | | |
| Yield (kg/ha) | 5781 | 838 | 5597 | 876 | 5744 | 868 | 5824 | 909 |
| Average temperature (°C) | 23.66 | 1.04 | 23.03 | 1.40 | 23.33 | 1.03 | 24.06 | 1.13 |
| Growing degree days (10–32°C) (1000D) | 1.93 | 0.21 | 1.85 | 0.27 | 1.89 | 0.2 | 1.99 | 0.23 |
| Harmful degree days (32°C+) (1000D) | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 |
| Cumulative precipitation (1000 mm) | 0.82 | 0.17 | 1 | 0.24 | 0.69 | 0.14 | 0.92 | 0.19 |
| *Middle rice (observations = 1204)* | | | | | | | | |
| Yield (kg/ha) | 7052 | 1388 | 7155 | 1410 | 7031 | 1577 | 7143 | 1475 |
| Average temperature (°C) | 23.11 | 3.08 | 22.91 | 2.73 | 22.78 | 2.94 | 23.00 | 2.82 |
| Growing degree days (10–29°C) (1000D) | 2.28 | 0.45 | 2.24 | 0.39 | 2.22 | 0.42 | 2.26 | 0.42 |
| Harmful degree days (29°C+) (1000D) | 0.08 | 0.06 | 0.08 | 0.05 | 0.08 | 0.06 | 0.07 | 0.05 |
| Cumulative precipitation (1000 mm) | 0.71 | 0.17 | 0.84 | 0.23 | 0.69 | 0.2 | 0.8 | 0.2 |
| *Late rice (observations = 470)* | | | | | | | | |
| Yield (kg/ha) | 5988 | 1023 | 6013 | 1029 | 6017 | 1135 | 6076 | 1058 |
| Average temperature (°C) | 26.19 | 1.07 | 25.52 | 0.92 | 25.51 | 1.05 | 25.42 | 1.02 |
| Growing degree days (10–34°C) (1000D) | 2.43 | 0.23 | 2.33 | 0.22 | 2.33 | 0.26 | 2.31 | 0.23 |
| Harmful degree days (34°C+) (1000D) | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0 | 0 | 0 |
| Cumulative precipitation (1000 mm) | 0.61 | 0.21 | 0.78 | 0.15 | 0.67 | 0.15 | 0.71 | 0.15 |

Abbreviation: SD, standard deviation.

**TABLE A8** Summary statistics of rice production and weather data over windows (2013–2016)

| | 2013 | | 2014 | | 2015 | | 2016 | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| *Early rice (observations = 545)* | | | | | | | | |
| Yield (kg/ha) | 5929 | 933 | 5978 | 922 | 5980 | 893 | 5947 | 941 |
| Average temperature (°C) | 24.06 | 1.11 | 23.93 | 1.26 | 23.86 | 1.46 | 23.90 | 1.30 |
| Growing degree days (10–32°C) (1000D) | 1.98 | 0.24 | 1.97 | 0.25 | 1.96 | 0.28 | 1.96 | 0.26 |
| Harmful degree days (32°C+) (1000D) | 0.02 | 0.01 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 |
| Cumulative precipitation (1000 mm) | 0.86 | 0.22 | 0.95 | 0.21 | 0.92 | 0.2 | 1.06 | 0.23 |
| *Middle rice (observations = 1204)* | | | | | | | | |
| Yield (kg/ha) | 7030 | 1473 | 7067 | 1393 | 7172 | 1415 | 7144 | 1425 |
| Average temperature (°C) | 23.56 | 2.97 | 22.84 | 2.74 | 22.82 | 2.61 | 23.29 | 2.86 |
| Growing degree days (10–29°C) (1000D) | 2.32 | 0.42 | 2.25 | 0.41 | 2.25 | 0.41 | 2.3 | 0.42 |
| Harmful degree days (29°C+) (1000D) | 0.1 | 0.07 | 0.06 | 0.04 | 0.05 | 0.03 | 0.08 | 0.05 |
| Cumulative precipitation (1000 mm) | 0.77 | 0.2 | 0.85 | 0.26 | 0.87 | 0.29 | 0.9 | 0.27 |
| *Late rice (observations = 470)* | | | | | | | | |
| Yield (kg/ha) | 5966 | 1001 | 6098 | 975 | 6140 | 979 | 6091 | 983 |
| Average temperature (°C) | 25.99 | 0.84 | 25.62 | 1.27 | 25.28 | 1.15 | 26.05 | 1.00 |
| Growing degree days (10–34°C) (1000D) | 2.39 | 0.21 | 2.34 | 0.27 | 2.3 | 0.26 | 2.4 | 0.26 |
| Harmful degree days (34°C+) (1000D) | 0.01 | 0.01 | 0 | 0 | 0 | 0 | 0.01 | 0 |
| Cumulative precipitation (1000 mm) | 0.64 | 0.22 | 0.78 | 0.19 | 0.86 | 0.21 | 0.87 | 0.11 |

Abbreviation: SD, standard deviation.

**TABLE A9** Lincom test of the rice-type coefficients

| Lincom test: (1) *b*[HDD * early rice] + _*b*[HDD * middle rice] = 0 | | | | | |
|---|---|---|---|---|---|
| **Ln(yield)** | **Coefficient** | **Standard error** | ***t*** | ***p* > \|*t*\|** | **95% confidence interval** |
| (1) | −1.98 | 0.38 | −5.21 | 0 | −2.73 to −1.23 |

Abbreviation: HDD, harmful-degree days.

**TABLE A10** Multiple model specifications for early rice

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Growing degree days (10–32°C) (1000D) | 0.182*** (4.12) | 0.184*** (3.99) | | | |
| Harmful degree days (32°C+) (1000D) | −1.027** (−2.26) | −1.444 (−1.45) | | | |
| Interaction between HDD and precipitation | | 0.501 (0.56) | | | |
| Average temperature (°C) | | | 0.127* (1.71) | 0.072 (0.97) | |
| Average temperature squared | | | −0.002 (−1.57) | −0.002 (−1.08) | |
| Interaction between average temperature and precipitation | | | | 0.023*** (2.88) | |
| Difference between day and night temperature (°C) | | | | | −0.002 (−0.24) |
| Precipitation (1000 mm) | 0.042 (0.43) | 0.027 (0.23) | 0.120 (1.47) | −0.465** (−2.01) | 0.110 (1.20) |
| Precipitation squared | −0.049 (−0.96) | −0.046 (−0.84) | −0.084* (−1.88) | −0.066 (−1.46) | −0.090* (−1.85) |
| Constant | 8.310*** (119.90) | 8.316*** (123.60) | 6.901*** (7.62) | 7.820*** (8.69) | 8.619*** (100.54) |
| Observations | 4360 | 4360 | 4360 | 4360 | 4360 |
| $R^2$ | 0.820 | 0.820 | 0.819 | 0.820 | 0.817 |
| AIC | −11,627 | −11,625 | −11,607 | −11,624 | −11,560 |
| BIC | −11,455 | −11,447 | −11,435 | −11,445 | −11,394 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.
Abbreviation: AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; HDD, harmful-degree days.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A11** Multiple model specifications for middle rice

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Growing degree days (10–29°C) (1000D) | 0.030 (0.68) | 0.024 (0.53) | | | |
| Harmful degree days (29°C+) (1000D) | −0.262*** (−3.07) | −0.054 (−0.23) | | | |
| Interaction between HDD and precipitation | | −0.244 (−0.99) | | | |
| Average temperature (°C) | | | 0.034 (0.44) | 0.032 (0.41) | |
| Average temperature squared | | | −0.001 (−0.56) | −0.001 (−0.56) | |
| Interaction between average temperature and precipitation | | | | 0.003 (0.38) | |
| Difference between day and night temperature (°C) | | | | | −0.025** (−2.59) |
| Precipitation (1000 mm) | 0.133 (0.73) | 0.137 (0.74) | 0.141 (0.74) | 0.091 (0.41) | 0.042 (0.27) |
| Precipitation squared | −0.053 (−0.63) | −0.044 (−0.54) | −0.056 (−0.66) | −0.066 (−0.73) | −0.025 (−0.32) |
| Constant | 8.734*** (64.30) | 8.739*** (64.61) | 8.486*** (9.68) | 8.520*** (9.55) | 9.061*** (105.55) |
| Observations | 9632 | 9632 | 9632 | 9632 | 9632 |
| $R^2$ | 0.841 | 0.841 | 0.841 | 0.841 | 0.842 |
| AIC | −19,148 | −19,150 | −19,131 | −19,129 | −19,181 |
| BIC | −18,754 | −18,748 | −18,736 | −18,728 | −18,794 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.

Abbreviation: AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; HDD, harmful-degree days.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A12** Multiple model specifications for late rice

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Growing degree days (10–34°C) (1000D) | 0.007 (0.14) | 0.008 (0.16) | | | |
| Harmful degree days (34°C+) (1000D) | −0.983*** (−2.66) | −2.830* (−1.85) | | | |
| Interaction between HDD and precipitation | | 2.975 (1.28) | | | |
| Average temperature (°C) | | | 0.171 (1.07) | 0.231 (1.43) | |
| Average temperature squared | | | −0.004 (−1.14) | −0.005 (−1.45) | |
| Interaction between average temperature and precipitation | | | | −0.014 (−1.04) | |
| Difference between day and night temperature (°C) | | | | | −0.004 (−0.45) |
| Precipitation (1000 mm) | −0.075 (−1.27) | −0.143 (−1.56) | −0.083 (−1.32) | 0.274 (0.80) | −0.054 (−0.80) |
| Precipitation squared | 0.041 (1.19) | 0.070 (1.62) | 0.039 (1.09) | 0.035 (1.00) | 0.029 (0.85) |
| Constant | 8.707*** (67.52) | 8.732*** (63.84) | 6.665*** (3.28) | 5.791*** (2.77) | 8.733*** (96.00) |
| Observations | 3760 | 3760 | 3760 | 3760 | 3760 |
| $R^2$ | 0.840 | 0.840 | 0.840 | 0.840 | 0.839 |
| AIC | −9316 | −9318 | −9312 | −9312 | −9305 |
| BIC | −9160 | −9156 | −9156 | −9150 | −9155 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust $t$-statistics are reported in parentheses.

Abbreviation: AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; HDD, harmful-degree days.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A13** RMSE statistics for out-of-sample prediction

| | Early rice | | Middle rice | | Late rice | |
|---|---|---|---|---|---|---|
| **Model** | $R^2$ | **RMSE** | $R^2$ | **RMSE** | $R^2$ | **RMSE** |
| Degree days | 0.820 | 0.1674 | 0.841 | 0.2296 | 0.840 | 0.1920 |
| Degree days and interaction between HDD and precipitation | 0.820 | 0.1676 | 0.841 | 0.2295 | 0.840 | 0.1920 |
| Temperature bins | 0.820 | 0.1677 | 0.842 | 0.2331 | 0.840 | 0.1855 |
| Replace degree days with quadratic average temperature | 0.819 | 0.1596 | 0.841 | 0.2297 | 0.840 | 0.1866 |
| Replace degree days with quadratic average temperature and interaction between temperature and precipitation | 0.820 | 0.1567 | 0.841 | 0.2299 | 0.840 | 0.1854 |
| Replace degree days with average difference between day and night temperature | 0.817 | 0.1538 | 0.842 | 0.2252 | 0.839 | 0.1894 |
| No weather (baseline) | 0.811 | 0.1545 | 0.829 | 0.2284 | 0.836 | 0.1902 |

*Note*: $R^2$ for in-sample reports the percentage of variation in log rice yields explained by the model. RMSE for out-of-sample prediction is estimated by leaving 1 year out. All models, including the baseline, have county fixed effects and quadratic province-level trends.
Abbreviations: HDD, harmful-degree days; RMSE, root-mean-squared prediction error.

**TABLE A14** Robustness check for early rice

| | Baseline | (1) Add price | (2) Lagged precipitation | (3) Winsorize | (4) Spatial errors model | (5) Spatial cluster | (6) City cluster |
|---|---|---|---|---|---|---|---|
| Growing degree days (10–32°C) (1000D) | 0.182*** (4.12) | 0.140*** (2.96) | 0.178*** (4.08) | 0.185*** (4.27) | 0.180*** (7.12) | 0.191*** (5.30) | 0.182*** (4.89) |
| Harmful degree days (32°C+) (1000D) | −1.027** (−2.26) | −0.754* (−1.98) | −1.020** (−2.25) | −0.966** (−2.29) | −0.956*** (−3.21) | −1.004*** (−2.76) | −1.027** (−2.61) |
| Precipitation (1000 m) | 0.042 (0.43) | 0.013 (0.13) | 0.023 (0.23) | 0.013 (0.14) | 0.027 (0.43) | 0.043 (0.56) | 0.042 (0.54) |
| Precipitation squared | −0.049 (−0.96) | −0.032 (−0.61) | −0.043 (−0.82) | −0.031 (−0.63) | −0.040 (−1.16) | −0.049 (−1.18) | −0.049 (−1.21) |
| Price ratio: rice/labor | | 3.637*** (2.79) | | | | | |
| Price ratio: rice/fertilizer | | −0.099 (−0.77) | | | | | |
| Lagged precipitation (1000 mm) | | | −0.016 (−0.28) | | | | |
| Lagged precipitation squared | | | 0.001 (0.03) | | | | |
| Spatial: lambda | | | | | 0.268*** (8.48) | | |
| Variance: sigma$^2$_e | | | | | 0.004*** (9.67) | | |
| Constant | 8.310*** (119.90) | 8.104*** (83.89) | 8.342*** (106.24) | 8.315*** (123.91) | | 8.444*** (112.12) | 8.310*** (127.56) |
| Observations | 4360 | 4360 | 4360 | 4360 | 4360 | 4360 | 4360 |
| Adjusted $R^2$ | 0.792 | 0.792 | 0.792 | 0.792 | 0.792 | 0.792 | 0.792 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust $t$-statistics are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**TABLE A15** Robustness check for middle rice

| | Baseline | (1) Add price | (2) Lagged precipitation | (3) Winsorize | (4) Spatial errors model | (5) Spatial cluster | (6) City cluster |
|---|---|---|---|---|---|---|---|
| Growing degree days (10–29°C) (1000D) | 0.030 (0.68) | 0.047 (1.16) | 0.022 (0.48) | 0.014 (0.35) | 0.022 (0.79) | 0.029 (1.00) | 0.030 (1.14) |
| Harmful degree days (29°C+) (1000D) | −0.262*** (−3.07) | −0.272*** (−3.07) | −0.257*** (−3.05) | −0.238*** (−2.95) | −0.258*** (−5.02) | −0.260*** (−4.49) | −0.262*** (−5.83) |
| Precipitation (1000 m) | 0.133 (0.73) | 0.154 (0.86) | 0.063 (0.36) | 0.043 (0.27) | 0.176** (1.97) | 0.133 (1.39) | 0.133 (1.11) |
| Precipitation squared | −0.053 (−0.63) | −0.064 (−0.78) | −0.026 (−0.31) | −0.003 (−0.04) | −0.083* (−1.70) | −0.053 (−1.12) | −0.053 (−0.91) |
| Price ratio: rice/labor | | −0.904 (−0.60) | | | | | |
| Price ratio: rice/ fertilizer | | 0.324** (2.28) | | | | | |
| Lagged precipitation (1000 mm) | | | −0.220* (−1.81) | | | | |
| Lagged precipitation squared | | | 0.089 (1.33) | | | | |
| Spatial: lambda | | | | | 0.35*** (13.68) | | |
| Variance: sigma$^2$_e | | | | | 0.007*** (14.34) | | |
| Constant | 8.734*** (64.30) | 8.603*** (62.91) | 8.902*** (61.82) | 8.806*** (71.60) | | 8.763*** (95.65) | 8.734*** (126.47) |
| Observations | 9632 | 9632 | 9632 | 9632 | 9632 | 9632 | 9632 |
| Adjusted $R^2$ | 0.817 | 0.817 | 0.817 | 0.817 | 0.817 | 0.817 | 0.817 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**TABLE A16** Robustness check for late rice

| | Baseline | (1) Add price | (2) Lagged precipitation | (3) Winsorize | (4) Spatial errors model | (5) Spatial cluster | (6) City cluster |
|---|---|---|---|---|---|---|---|
| Growing degree days (10–34°C) (1000D) | 0.007 (0.14) | −0.006 (−0.12) | 0.006 (0.12) | 0.014 (0.29) | 0.006 (0.16) | 0.011 (0.30) | 0.007 (0.18) |
| Harmful degree days (34°C+) (1000D) | −0.983*** (−2.66) | −0.902** (−2.36) | −0.985*** (−2.73) | −1.023*** (−2.76) | −0.930*** (−3.00) | −0.982*** (−2.77) | −0.983*** (−2.71) |
| Precipitation (1000 m) | −0.075 (−1.27) | −0.074 (−1.22) | −0.081 (−1.27) | −0.090 (−1.35) | −0.078 (−1.60) | −0.078 (−1.44) | −0.075 (−1.28) |
| Precipitation squared | 0.041 (1.19) | 0.039 (1.15) | 0.042 (1.18) | 0.053 (1.36) | 0.042 (1.45) | 0.045 (1.36) | 0.041 (1.05) |
| Price ratio: rice/labor | | 0.352 (0.40) | | | | | |
| Price ratio: rice/fertilizer | | −0.044 (−0.60) | | | | | |
| Lagged precipitation (1000 mm) | | | 0.023 (0.53) | | | | |
| Lagged precipitation squared | | | −0.023 (−0.85) | | | | |
| Spatial: lambda | | | | | 0.163*** (4.01) | | |
| Variance: sigma$^2$_e | | | | | 0.005*** (9.76) | | |
| Constant | 8.707*** (67.52) | 8.724*** (50.91) | 8.711*** (61.03) | 8.694*** (66.42) | | 8.983*** (91.90) | 8.707*** (91.93) |
| Observations | 3760 | 3760 | 3760 | 3760 | 3760 | 3760 | 3760 |
| Adjusted $R^2$ | 0.816 | 0.816 | 0.816 | 0.816 | 0.816 | 0.816 | 0.816 |

*Note*: All regressions include county fixed effects and provincial quadratic time trends, and are weighted by the average planted area. Standard errors are two-way clustered at counties and province-by-year pairs. Robust *t*-statistics are reported in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**TABLE A17** Predicted yield change (%)

| | | Early rice | | Middle rice | | Late rice | |
|---|---|---|---|---|---|---|---|
| RCP | GCM | Only significant weather variables | Full weather variables | Only significant weather variables | Full weather variables | Only significant weather variables | Full weather variables |
| RCP2.6 | GFDL-ESM2M | −0.74 | −0.74 | −0.52 | −0.47 | −2.03 | −1.96 |
| | HadGEM2-ES | 0.36 | 0.36 | −1.93 | −1.4 | −2.84 | −2.67 |
| | IPSL-CM5A-LR | 0.71 | 0.71 | −0.69 | −0.28 | −0.92 | −0.8 |
| | MIROC-ESM-CHEM | −1.54 | −1.54 | −1.82 | −1.3 | −4.5 | −4.34 |
| | NorESM1-M | 0.47 | 0.47 | −0.53 | −0.21 | −0.78 | −0.7 |
| | Mean | −0.15 | −0.15 | −1.1 | −0.73 | −2.21 | −2.09 |
| RCP4.5 | GFDL-ESM2M | −0.01 | −0.01 | −1.02 | −0.68 | −2.45 | −2.34 |
| | HadGEM2-ES | −0.16 | −0.16 | −3.14 | −2.18 | −5.62 | −5.35 |
| | IPSL-CM5A-LR | 1.68 | 1.68 | −1.77 | −0.89 | −1.47 | −1.27 |
| | MIROC-ESM-CHEM | −2.02 | −2.02 | −3.17 | −2.24 | −8.78 | −8.5 |
| | NorESM1-M | 0.6 | 0.6 | −1.06 | −0.44 | −1.48 | −1.34 |
| | Mean | 0.02 | 0.02 | −2.03 | −1.29 | −3.96 | −3.76 |
| RCP6.0 | GFDL-ESM2M | −0.46 | −0.46 | −1.58 | −1.11 | −2.8 | −2.66 |
| | HadGEM2-ES | −2.36 | −2.36 | −4.04 | −3.02 | −7.37 | −7.08 |
| | IPSL-CM5A-LR | 0.64 | 0.63 | −2.45 | −1.47 | −2.68 | −2.43 |
| | MIROC-ESM-CHEM | −3.65 | −3.66 | −4.24 | −3.13 | −9.91 | −9.61 |
| | NorESM1-M | −0.07 | −0.07 | −1.88 | −1.1 | −2.98 | −2.78 |
| | Mean | −1.18 | −1.18 | −2.84 | −1.96 | −5.15 | −4.91 |
| RCP8.5 | GFDL-ESM2M | −1.28 | −1.28 | −3.56 | −2.68 | −6.81 | −6.55 |
| | HadGEM2-ES | −7.32 | −7.32 | −7.98 | −6.32 | −18.64 | −18.18 |
| | IPSL-CM5A-LR | −2.72 | −2.73 | −6.35 | −4.61 | −8.69 | −8.26 |
| | MIROC-ESM-CHEM | −4.24 | −4.24 | −6.13 | −4.48 | −13.85 | −13.44 |
| | NorESM1-M | −1.48 | −1.48 | −4.37 | −3.1 | −7.05 | −6.73 |
| | Mean | −3.41 | −3.41 | −5.68 | −4.24 | −11.01 | −10.63 |

Abbreviations: GCM, global climate models; RCP, representative concentration pathway.