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Abstract

We analyzed a county-level data set of rice yield and daily weather outcomes in China to examine the effects of high temperatures and extreme temperature events on rice yield. We found that (i) rice yield responded negatively to high temperatures (>29°C) and extreme temperature events, including cold and heat waves; (ii) rice yield exhibited highly nonlinear responses to temperature changes: rice yield increased with temperature up to 29°C and peaked with 1,550-1,800 growing degree-days; and (iii) holding current growing seasons and regions constant, average rice yield in China is projected to decrease by 11-50 percent by 2070 under future warming. These results imply that both warming and extreme temperature events pose major challenges for Chinese rice farmers, and that the effectiveness of adaptations will depend on how well they reduce the negative temperature impacts on rice yield on very hot and cold days.

Key Words: rice yield, temperature, global warming, China

JEL Codes: Q10, Q54

Contents

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Xiaoguang Chen and Shuai Chen*

1. Introduction

With growing scientific evidence demonstrating that the earth is becoming warmer, agricultural vulnerability to rising temperature has been extensively studied (see a detailed review in Dell et al. 2014). Several studies discovered that corn, soybeans, wheat and cotton yields declined sharply when temperatures were above certain thresholds (Schlenker and Roberts 2009; Lobell et al. 2011; Zhang et al. 2017; Chen et al. 2016b). For instance, corn and soybean yields were found to increase with temperature up to 29°C-30°C, and higher temperatures above these levels can cause severe damage to crop yields (Schlenker and Roberts 2009; Chen et al. 2016b).

However, existing studies have inconsistent findings regarding how rice yield responds to temperature changes. For instance, based on observed data compiled from farmer-managed fields in tropical/subtropical Asia and on experimental data collected in Southeast Asia, respectively, Welch et al. (2010) and Peng et al. (2004) showed that rice yields in these regions responded *negatively* to higher daily minimum temperatures ($T_{\min}$). In contrast, rice yield in China was found to exhibit a *positive* response to elevated $T_{\min}$ (Chen and Tian 2016, Chen et al. 2016a). As regards the effects of higher daily maximum temperatures ($T_{\max}$) on rice yield, empirical findings are also mixed. Peng et al. (2004) found an insignificant correlation between rice yield in Southeast Asia and $T_{\max}$; Welch et al. (2010) found a positive correlation between rice yield in tropical/subtropical Asia and $T_{\max}$; and rice yield in China was found to respond negatively to higher $T_{\max}$ (Chen et al. 2016a). Several studies have used the same/similar data sets to analyze the effects of changes in $T_{\min}$ and $T_{\max}$ on rice yields in China, but still obtained mixed results (Tao et al. 2008, Zhang et al. 2010).

The purpose of this article is to reconcile these seemingly contradictory results by accounting for nonlinearity. Specifically, we analyzed the effects of temperature changes

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on single-season rice yield in China. We focused on single-season rice for two reasons. First, China is the world's largest rice producer and single-season rice production is widely distributed across China's agricultural heartland (Figure 1). Second, due to increased labor costs, many Chinese farmers have reduced the production of double-cropped and multiple-cropped rice and increased single-season rice production. Figure S1 in the appendix shows that the total planted acres of early rice and late rice in China declined by 38% and 37%, respectively, during the period 1990-2010, while the total planted acres of single-season rice increased by 30% over the same period.

In contrast to the above-mentioned studies using $T_{\max}$ and $T_{\min}$ as temperature variables, we used two alternative approaches to construct temperature variables. We first followed the standard agronomic literature and constructed temperature variables using *growing degree-days* (*GDD*). To account for the potential nonlinear relationship between rice yield and temperature, the regression model included the linear and quadratic terms of *GDD*. We then constructed temperature variables using temperature bins that measure accumulation of heat for each 3°C temperature interval (Schlenker and Roberts 2009). To capture the effects on yield of extreme temperature events, we included cold and heat waves as additional temperature variables. To account for the simultaneous variations in weather variables, the regression model also included rainfall and sunshine duration as additional weather variables. Moreover, the regression model incorporated county and year fixed effects to minimize the potential estimation biases originating from omitted variables. The data set used for this analysis is a county-level panel consisting of annual rice yield and daily weather observations in China over the period 2000-2009.

We found that rice yield exhibited negative responses to high temperatures and extreme temperature events and that the relationships between rice yield and weather variables were highly nonlinear. Rice yield increased with temperature up to 29°C and peaked with 1,550-1,800 growing degree-days. Temperatures above 29°C and extreme temperature events, including cold and heat waves during rice growing seasons, were very harmful for rice growth. These findings remained remarkably robust to variations in rice varieties and estimation strategies. Holding current rice growing seasons and regions fixed, county-average rice yield in China is projected to decline by 10-42% by 2050 and by 11-50% by 2070 under future warming.

2. Empirical Model

2.1. GDD as Temperature Variables

We first followed the standard agronomic literature and defined temperature variables using *GDD*:

$$\log Y_{r,t} = \beta_1 GDD_{r,t} + \beta_2 Coldwave_{r,t} + \beta_3 Heatwave_{r,t} + \beta_4 Weather_{r,t} + c_r + \theta_t + \varepsilon_{r,t} \quad (1)$$

where $\log Y_{r,t}$ represents the natural logarithm of average rice yield in county *r* and year *t*. $GDD_{r,t}$ denotes computed *GDD* for county *r* in year *t* during rice growing seasons. We introduced cold and heat waves as two additional temperature variables to examine the effects of extreme temperature events on rice yield, which are denoted by $Coldwave_{r,t}$ and $Heatwave_{r,t}$, respectively. Here, we defined a cold wave as a period of at least three consecutive days during which the daily T_{min} is below 0°C, and defined a heat wave as a period of at least three consecutive days during which the daily T_{max} is greater than 30°C. Linear and quadratic terms of the sums of rainfall and sunshine duration during rice growing seasons were also included and represented by $Weather_{r,t}$. County fixed effects (c_r) were incorporated to account for unobserved regional heterogeneity that was specific to county *r*, such as soil quality. Year fixed effects (θ_t) were also included to account for the unobserved factors that were the same for all counties in a given year, such as global CO_2 concentrations. $\varepsilon_{r,t}$ are the error terms, which were allowed to be both spatially and temporally correlated. In the baseline analysis presented below, we first adopted a spatial contiguity matrix that assigns 1 to neighboring counties sharing common boundaries and 0 to other counties. We also considered a distance weights matrix as a robustness check. The distance weights matrix assigned positive weights to the six adjacent counties relative to county *r* and 0 to other counties. The positive weights in this distance weights matrix were computed using the inverses of the geographical distances between the centroids of counties.

In the agronomic literature, the appropriate lower and upper temperature thresholds for rice growth are still the subject of debate. Normally, 20°C and 30°C can be considered as the critically low and high temperatures for rice, although they vary by rice type, duration of exposure to critical temperatures, and growth stage of the rice plant (Yoshida et al. 1981). In a recent study, Chen et al. (2016a) found that, given an average of daily T_{min} of 16°C during rice growing seasons, single-season rice yield in China benefited from elevated T_{min}. Thus, we set the lower and upper temperature thresholds at

16°C and 30°C, respectively, and estimated $GDD_{16,30}$. A squared form of $GDD_{16,30}$ was also included to account for the nonlinear relationship between temperature and rice yield. We also constructed an additional temperature variable GDD_{30+} to represent the heat accumulation when temperatures were above 30°C during rice growing seasons, which can cause irreversible damage to rice yield (Yoshida et al. 1981). Therefore, the variable $GDD_{r,t}$ in Equation (1) includes the linear and quadratic terms of $GDD_{16,30}$ and a linear term of GDD_{30+}. The main hypothesis was to test whether $\beta_1 = \beta_2 = \beta_3 = 0$, namely, to test the null hypothesis that temperature had no effect on rice yield.

2.2. Temperature Bins as Temperature Variables

Following Schlenker and Roberts (2009), we then used temperature bins as temperature variables and computed GDD for each 3°C temperature interval:

$$\log Y_{r,t} = \sum_{m} \alpha^{m} GDD_{r,t}^{m} + \beta_2 Coldwave_{r,t} + \beta_3 Heatwave_{r,t} + \beta_4 Weather_{r,t} + c_r + \theta_t + \varepsilon_{r,t} \quad (2)$$

where $GDD_{r,t}^{m}$ denotes heat accumulation in county *r* and year *t* when temperature falls into the *m*th temperature bin during rice growing seasons. We divided daily temperatures during rice growing seasons, measured in °C, into thirteen bins, each of which was 3°C wide. We defined $GDD_{r,t}^{1}$= heat accumulation when temperature fell into the range of [0°C, 3°C), $GDD_{r,t}^{2}$= heat accumulation when temperature fell into the range of [3°C, 6°C), and so on. Finally, $GDD_{r,t}^{13}$= heat accumulation when temperature was above 36°C. The implicit assumption made here is that the temperature effect on rice yield is consistent within each bin, which is reasonable given the small size of each temperature bin. Other variables were defined in the same way as in Equation (1).

3. Data

Data used for this analysis were assembled from several sources. We obtained county-level single-season rice yield for the period 2000-2009 from the National Bureau of Statistics of China. In the sample, rice yield ranged between 1,866 and 13,800 kg per hectare (ha) with a national average of 7,135 kg per ha (Table S1 in the appendix). Regional-specific rice growing seasons were compiled from the Ministry of Agriculture of China.

Daily weather data, including T_{min}, T_{max}, rainfall, and sunshine duration, were obtained from the China Meteorological Data Sharing Service System, which reports daily weather information for more than 800 weather stations in China. We merged daily weather data with annual yield data using the coordinates of weather stations and county centroids. Of the 771 single-season rice-producing counties included in the sample, we found that 566 counties had weather stations and 205 counties did not have weather stations. For the 566 counties with weather stations, each county had only one weather station. For the 205 counties without weather stations, we imputed weather information from the nearest contiguous counties.

4. Results

4.1. Results Using GDD as Temperature Variables

We considered two model specifications to examine the impacts of high temperatures and extreme temperature events on rice yield. In Model 1, we included the linear and squared terms of $GDD_{16,30}$, rainfall and sunshine duration, and the linear term of GDD_{30+}. In Model 2, we added cold and heat waves as additional temperature variables.

Table 1 shows that parameter estimates of the linear term of $GDD_{16,30}$ are positive and statistically significant ($p< 0.05$). Parameter estimates of the squared term of this variable are negative and also statistically significant ($p< 0.10$). These results provide suggestive evidence that a bell-shaped relationship between rice yield and temperature may exist. To achieve maximum yield, rice needed approximately 1,550-1,800 growing degree-days, depending on model specifications. The coefficient estimates of GDD_{30+} in both model specifications are statistically significant ($p< 0.01$) and have negative signs, suggesting that heat accumulation from temperatures above 30°C caused severe damage to rice yield.

Parameter estimates of the cold and heat waves variables are also negative and statistically significant ($p< 0.05$), indicating that continuous exposure to temperatures above 30°C and below 0°C was very harmful for rice growth. Holding all other factors constant, one additional heat wave can lead to a reduction of 0.3% in rice yield, while the yield reduction from one additional cold wave is larger, at 0.9%. Continuous exposure to high temperatures above 30°C during the rice growing seasons can negatively affect the photosynthesis process in rice, increase respiration demand and reduce pollen production (Wassmann et al. 2009). Continuous exposure to low temperatures below 0°C can damage rice yield by causing delayed germination and stunted seedling growth during early growth and by inhibiting rooting and tillering during the vegetative phase (Yoshida et al. 1981).

Parameter estimates for rainfall and sunshine duration show similar nonlinear patterns. Rice yield peaked with 85 cm of rainfall over the growing seasons. Rainfall above this level can depress rice yield by preventing timely planting, damaging planted acreage and creating disease pressure (Auffhammer et al. 2012). The optimal amount of sunshine duration needed for rice growth ranged between 1,117 and 1,127 hours. Estimated rainfall and sunshine duration requirements for rice are consistent with the existing agronomic studies (for example, see Zhang et al. 2008), but they are significantly higher than the water and sunshine requirements for corn, soybeans, and cotton (Chen et al. 2016b; Schlenker and Roberts 2009).

4.2. Results Using Temperature Bins as Temperature Variables

Figure 2(A) shows the point estimates and the 95% confidence bands of the temperature variables, which were obtained by estimating Equation (2). The horizontal axis of this figure denotes temperature variables, while the vertical axis of this figure denotes the natural logarithm of rice yield. We found that rice yield increased with temperature up to 29°C and that temperatures above 29°C can cause large reductions in rice yield. For instance, replacing a full day with an average temperature of 29°C with a full day with an average temperature of 36°C is expected to reduce rice yield by 12.5%, holding all else the same. This critical temperature threshold is comparable with those identified for corn, soybeans and cotton (Chen et al. 2016b; Schlenker and Roberts 2009).

Because temperature variables, including temperature bins and cold and heat waves, have different units and exhibit different changing trends, we cannot directly compare the impacts of these temperature variables on rice yield. To overcome this difficulty, we examined the marginal effects per standard deviations (SDs) of the temperature variables, which were computed by multiplying coefficient estimates of the temperature variables by the SDs of the corresponding temperature variables. As shown in Figure 2(B), we found that the largest positive marginal effect per SD was accumulation of heat in the temperature range of 21°C-24°C (+5.4%), while the largest negative marginal effect per SD came from heat accumulation in the temperature range of 33°C-36°C (-4.0%). The marginal effects per SD of cold and heat waves were -0.8% and -1.8%, respectively.

4.3. Robustness Check

We tested the robustness of our key findings to an alternative spatial weights matrix and to alternative variables and data, in five different scenarios. Specifically, in Scenario (1), we used the distance matrix described in Section 2.1. as the spatial weights matrix in the regression analysis. In Scenario (2), a linear time trend and a quadratic time trend by province were used to represent exogenous technological change boosting rice yield. In Scenario (3), we tested the robustness of our results to the chosen lower temperature threshold when computing *GDD*. Following Yoshida et al. (1981), we set the lower and upper temperature thresholds at 20°C and 30°C, respectively, and then replicated the above regression analysis using the linear and squared terms of $GDD_{20,30}$ as temperature variables. Finally, in Scenarios (4) and (5), we examined whether the estimated temperature effects presented above are sensitive to different rice varieties. We replicated the above regression analysis by using the subsample with counties producing Japonica rice only in Scenario (4) and using the subsample with counties producing Indica rice only in Scenario (5).

When conducting these robustness checks, we incorporated cold and heat waves as temperature variables and used GDD and temperature bins as temperature variables, respectively. Table 2 reports the results that were obtained using GDD as temperature variables, while the results obtained using temperature bins as temperature variables are displayed in Figure S2 in the appendix.

We found that parameter estimates of weather variables obtained in Scenarios (1) and (2) are almost identical to our baseline parameter estimates, indicating that our key findings of the negative responses of rice yield to high temperatures and extreme temperature events remained robust to variations in the spatial weights matrix and to different approaches selected to represent technological change for rice yield growth. In Scenarios (3)-(5), the quadratic terms of $GDD_{16,30}$ (or $GDD_{20,30}$) are not statistically significant. However, the linear terms of $GDD_{16,30}$ (or $GDD_{20,30}$) and GDD_{30+} are statistically significant ($p < 0.10$) and have positive and negative signs, respectively. These findings suggest that the accumulation of heat in the temperature range of 16°C (or 20°C) to 30°C increased rice yield, while temperatures above 30°C hurt rice growth. This again indicates the existence of a nonlinear temperature effect on rice yield and shows that rice yield responds negatively to high temperatures. In these three scenarios, our finding of the negative responses of rice yield to extreme temperature events is also broadly consistent with our baseline finding. Figure S2 in the appendix shows that the critical temperature threshold (29°C) identified in the baseline scenario remained remarkably robust.

5. Future Climate Change Impact

We used estimated coefficients of temperature variables to evaluate the future climate impacts on rice yield in China. Projections of future climate variables were taken from WorldClim-Global Climate Data (http://www.worldclim.org/), which provides climate predictions based on the most recent global climate models under four representative concentration pathways (RCPs), including RCP2.6, RCP4.5, RCP6.0, and RCP8.5. The four pathways differ by assumed greenhouse gas (GHG) concentration trajectory. While RCP2.6 assumes that global GHG emissions peak between 2010 and 2020 and decline quickly thereafter, RCP8.5 assumes that GHG emissions continue to rise during this century. The climate variables provided by WorldClim include monthly average minimum and maximum temperatures and monthly total rainfall, for the medium term (2050, average for 2041-2060) and the long term (2070, average for 2061-2080). We selected RCP2.6 and RCP8.5 for this analysis because the two pathways cover the entire range of the projected future GHG emissions changes. Following Warszawski et al. (2014), we used climate data based on the global climate models HadGEM2-ES and NorESM1-M, which represent two distinct predictions for future global temperature changes. We downloaded the data at 2.5-minutes (of a longitude and latitude degree) spatial resolution (about 4.5 kilometers at the equator), which enabled us to obtain future climate variables for all Chinese counties included in our sample.

Figure 3 shows the effects of future warming on average rice yield. We found that warming will reduce rice yield, and that the likely magnitudes of the reductions depend on climate models. Under the HadGEM2-ES model, average rice yield in the medium term is projected to decrease by 13.6-33.6% under RCP2.6 and by 14.3-41.8% under RCP8.5 (Figure 3a). Under the NorESM1-M model, the corresponding yield reductions are smaller, by 10.2-25.7% under RCP2.6 and by 13.6-40.0% under RCP8.5 (Figure 3b). Under RCP8.5, the yield reductions in the long term are projected to be considerably larger than the yield reductions in the medium term (Figures 3c and 3d). Specifically, county-average rice yield is projected to decrease by 13.6-50.5% by 2070 under the HadGEM2-ES model and by 11.0-45.9% under the NorESM1-M model. We found that, under RCP2.6, the predicted reductions in rice yield in the long term are similar in magnitude to the predicted yield reductions in the medium term.

6. Summary and Conclusions

In this article, we analyze a county-level panel of observed rice yield and daily weather outcomes in China, to reconcile the contradictory results in the existing literature with regard to how rice yield responds to temperature changes. By accounting for nonlinearity, we showed that there exists a nonlinear relationship between rice yield and temperature. The critical temperature threshold that we identify and the optimal number of growing degree-days, rainfall, and sunshine duration for rice growth that we estimate are comparable with estimates for other crops (Schlenker and Roberts 2009; Chen et al. 2016b). We also showed that high temperatures and extreme temperature events can cause severe damage to rice yield. These findings are notable for the consistency across rice varieties, model specifications, and estimation strategies.

Holding current rice growing seasons and regions constant, average rice yield in China is projected to decrease by 10-42% by 2050 and by 11-50% by 2070 under future climate change. Two dominant factors driving future yield reductions are the projected increases in GDD_{30+} and the frequency of heat waves (see Table S2 in the appendix). However, one should note that we may have overestimated the projected damages to rice yield that can be attributed to climate change, because coefficient estimates of temperature variables used for prediction were obtained using the observed outcomes in the past decade and cannot capture adaptations that may be undertaken by farmers in the future.

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Tables and Figures

Table 1. Main Regression Results (Dependent Variable: Log Rice Yield ($kg*ha^{-1}$))

Models	Model 1	Model 2
$GDD_{16,30}$	0.2738^{**}	0.3022^{**}
	(2.33)	(2.55)
$GDD_{16,30}$ squared	-0.0884^{*}	-0.0840^{*}
	(-1.74)	(-1.65)
GDD_{30+}	-1.0936^{***}	-1.1384^{***}
	(-5.47)	(-5.65)
Rainfall	0.0922^{**}	0.0894^{**}
	(2.21)	(2.14)
Rainfall squared	-0.0542^{**}	-0.0527^{**}
	(-2.22)	(-2.49)
Sunshine duration	0.2337^{***}	0.2168^{**}
	(2.69)	(2.49)
Sunshine duration squared	-0.1046^{***}	-0.0961^{***}
	(-3.05)	(-2.79)
Heat waves		-0.0027^{**}
		(-2.16)
Cold waves		-0.0091^{***}
		(2.66)

Note: Table lists coefficient estimates and asymptotic *t* statistics in parentheses. Both model specifications used a spatial contiguity matrix as the spatial weights matrix, and controlled for county fixed effects and year fixed effects. N=7,710. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Table 2. Sensitivity Analysis (Dependent Variable: Log Rice Yield (kg*ha^{-1}))

Scenarios	(1) Spatial distance matrix	(2) Regional time trend	(3) Lower temperature threshold set at 20°C	(4) Japonica rice subsample	(5) Indica rice subsample
$GDD_{16\text{-}30}$	0.4202***	0.4697***		0.4064*	0.3180*
	(3.75)	(4.08)		(1.83)	(1.86)
$GDD_{16\text{-}30}$ squared	-0.1096**	-0.1014**		-0.1236	-0.0602
	(-2.27)	(-1.97)		(-1.08)	(-0.98)
GDD_{30+}	-1.0308***	-0.9819***	-1.1252***	-1.1534**	-0.8435***
	(-5.30)	(-4.65)	(-5.52)	(-2.25)	(-4.80)
Rainfall	0.0732*	0.0917**	0.0823**	0.1708**	0.0288
	(1.81)	(2.23)	(2.03)	(2.11)	(0.64)
Rainfall squared	-0.0490**	-0.0495**	-0.0557**	-0.1237**	-0.0130
	(-2.06)	(-2.04)	(-2.33)	(-2.04)	(-0.56)
Sunshine duration	0.2144**	0.1744**	0.2052**	0.3112*	0.1602*
	(2.55)	(1.97)	(2.46)	(1.81)	(1.71)
Sunshine duration squared	-0.1019***	-0.0796**	-0.0967***	-0.1277**	-0.0877*
	(-3.07)	(-2.28)	(-2.93)	(-2.00)	(-1.70)
Heat waves	-0.0035***	-0.0026**	-0.0036***	-0.0039*	-0.0003
	(-2.82)	(-2.17)	(-2.89)	(-1.69)	(-0.24)
Cold waves	-0.0060*	-0.0077**	-0.0079**	-0.0086*	-0.0147**
	(-1.80)	(-2.27)	(-2.39)	(-1.86)	(-2.05)
$GDD_{20,30}$			0.3909***		
			(2.94)		
$GDD_{20,30}$ squared			-1.1432		
			(-1.37)		
N	7,710	7,710	7,710	3,690	4,020

Note: Asymptotic *t*-statistics are shown in parentheses. All scenarios included county fixed effects and year fixed effects, while controlling for the heteroscedasticity, serial correlation and spatial correlations of the error terms. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$.

Figure 1. Spatial Distribution of Single-Season Rice Production in China (Ten-Year Average for the Period 2000–2009)

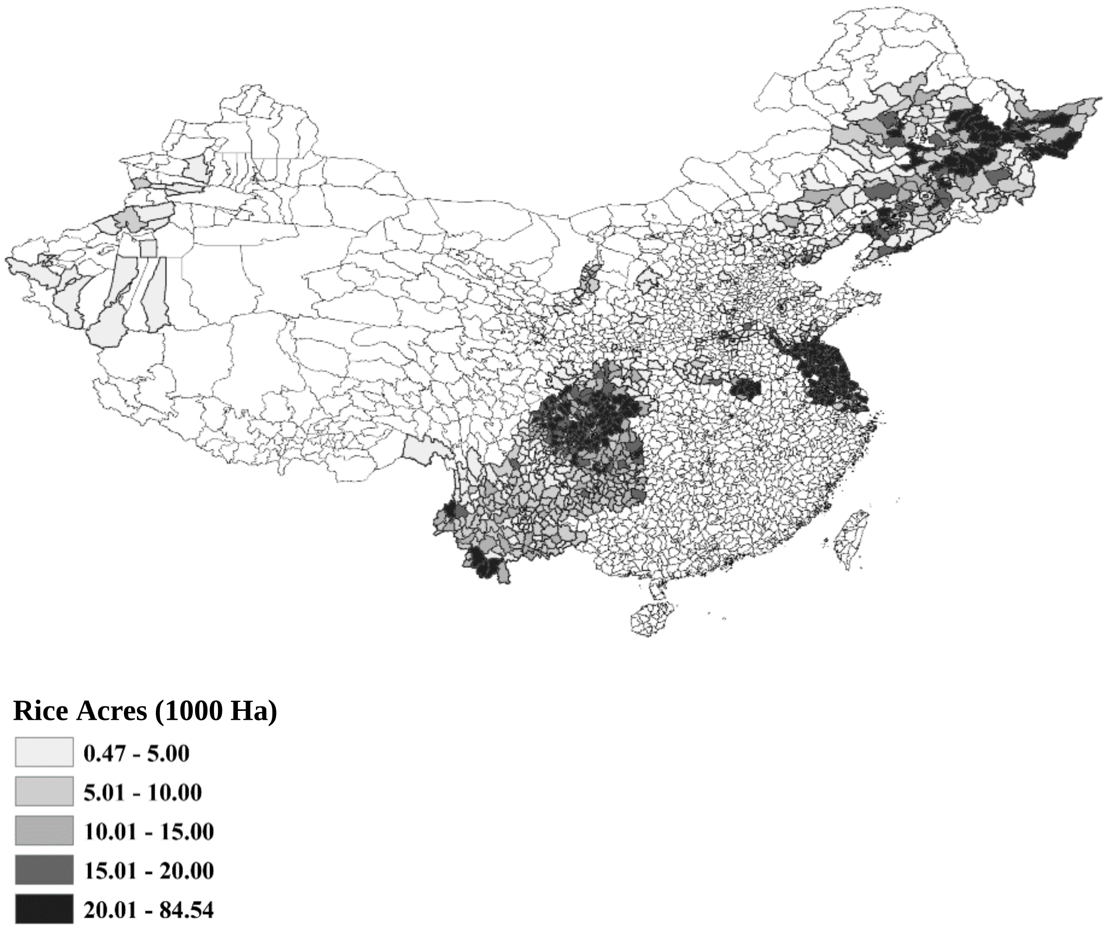
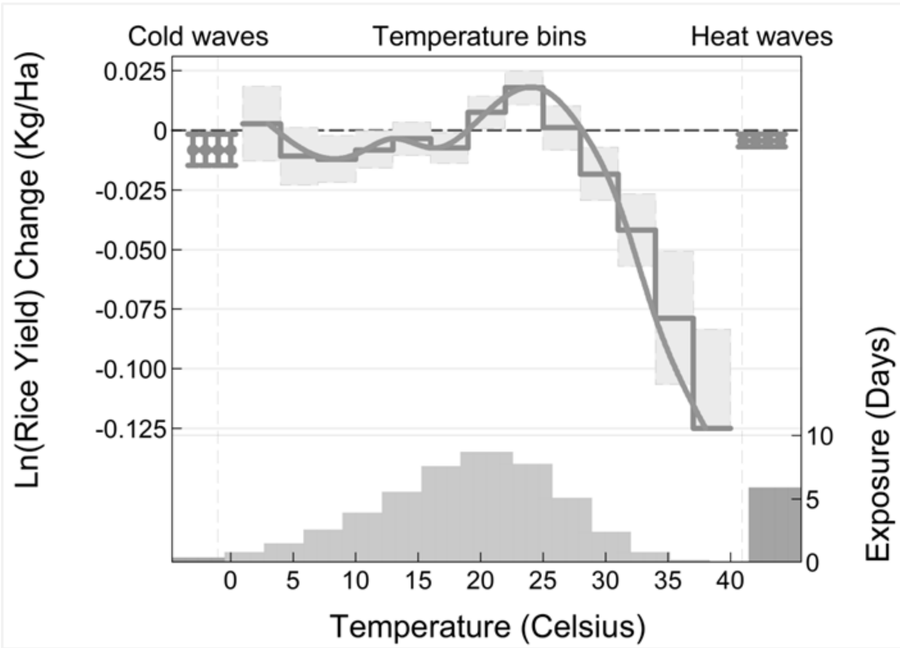
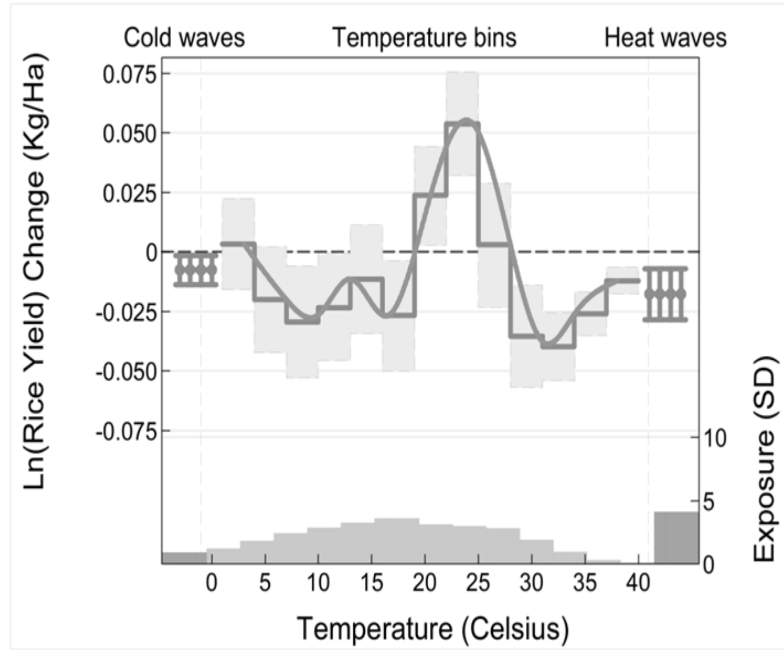


Figure 2. Nonlinear Relationships between Temperature and Rice Yield

(A)

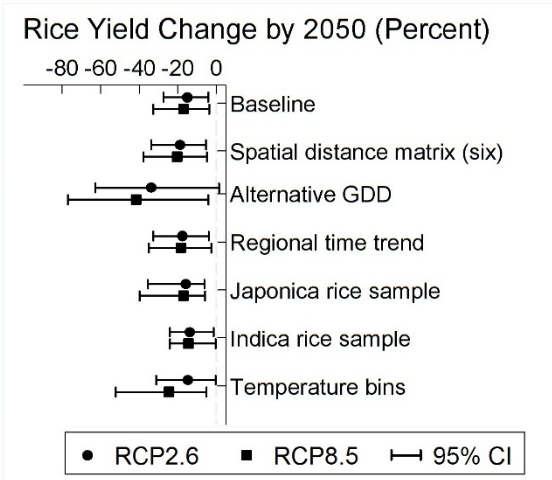


(B)

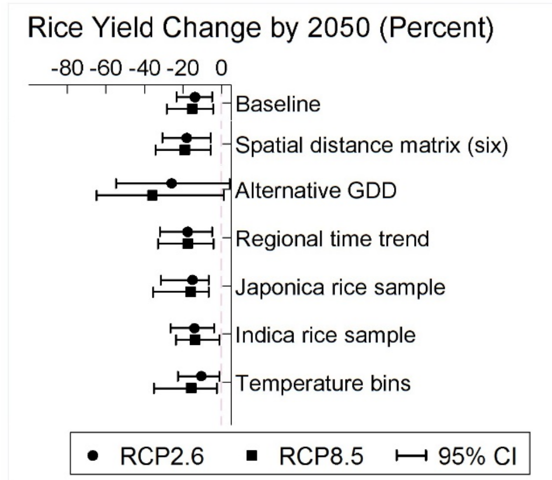


Note: Resulted presented in the graphs were estimated using temperature bins as temperature variables. The left panel (A) shows point estimates and the 95% confidence intervals of the temperature variables. The right panel (B) shows the marginal effects on rice yield per SD of temperature variables. The smooth lines fit coefficient estimates of each 3°C temperature range using an 8th-order polynomial function. Histograms at the bottom of panels (A) and (B) show the distribution of mean and SD of temperature variables in the data, respectively.

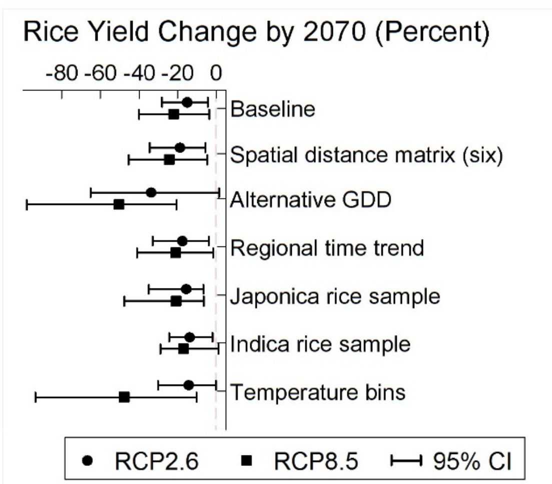
Figure 3. Predicted Impacts of Future Warming on Rice Yield



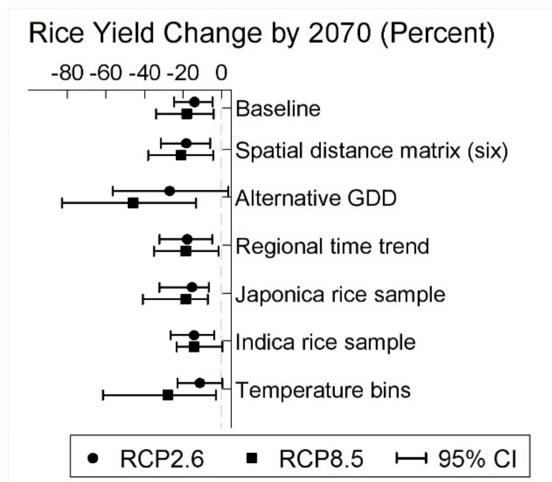
(a) Medium term (HadGEM2-ES)



(b) Medium term (NorESM1-M)



(c) Long term (HadGEM2-ES)



(d) Long term (NorESM1-M)

Note: Panels (a) and (c) show predicted percentage changes in average rice yield in China and the 95% confidence intervals in the medium term and the long term, respectively, under the HadGEM2-ES model. Panels (b) and (d) display the corresponding predictions under the climate model NorESM1-M.

Supporting Material

Table S1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Rice yield ($kg*ha^{-1}$)	7,135	1,523	1,866	13,800
$GDD_{16,30}$ (1000 d)	1.193	0.381	0.054	2.474
GDD_{30+} (1000 d)	0.037	0.042	0	0.352
Heat waves (frequency)	5.879	4.116	0	22
Cold waves (frequency)	0.354	0.929	0	11
Rainfall (100 mm)	7.076	3.136	0.100	20.748
Sunshine duration (1000 hours)	1.118	0.290	0.464	1.935

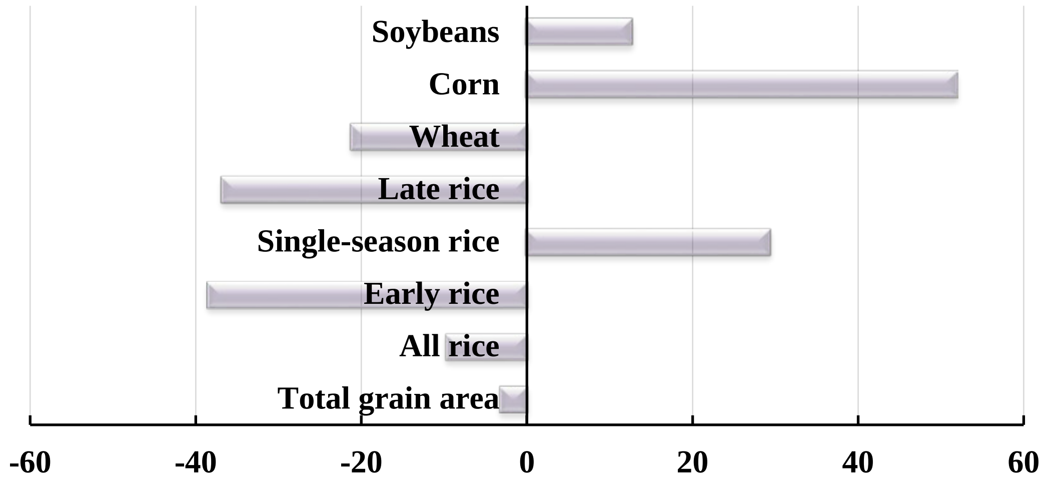
Note: Numbers reported in this table are based on observations from 2000 to 2009. Number of observations=7,710.

Table S2. Predicted Changes in Temperature Variables by HadGEM2-ES and NorESM1-M under Different RCPs

	2041-2060 average		2061-2080 average	
	HadGEM2-ES	NorESM1-M	HadGEM2-ES	NorESM1-M
		RCP2.6		
T_{min} (°C)	0.360 (1.772)	-0.145 (1.747)	0.339 (1.764)	-0.155 (1.748)
T_{max} (°C)	0.699 (1.847)	0.0508 (1.841)	0.647 (1.862)	0.179 (1.854)
$GDD_{16,30}$ (Days)	-0.702 (12.21)	-4.234 (13.32)	-0.842 (12.26)	-3.896 (13.32)
GDD_{30+} (Days)	0.667 (1.643)	0.0796 (1.435)	0.605 (1.613)	0.202 (1.469)
Heat waves (Frequency)	0.573 (2.919)	-0.276 (2.921)	0.526 (2.977)	-0.169 (2.989)
Cold waves (Frequency)	0.102 (0.615)	0.240 (0.698)	0.124 (0.619)	0.216 (0.683)
		RCP8.5		
T_{min} (°C)	1.334 (1.769)	0.781 (1.720)	2.973 (1.807)	1.872 (1.771)
T_{max} (°C)	1.680 (1.878)	0.945 (1.840)	3.328 (1.899)	2.196 (1.905)
$GDD_{16,30}$ (Days)	3.301 (10.77)	0.244 (11.58)	7.770 (9.659)	5.159 (9.874)
GDD_{30+} (Days)	1.660 (2.134)	0.863 (1.698)	3.719 (2.885)	2.140 (2.305)
Heat waves (Frequency)	1.575 (3.223)	0.827 (2.958)	2.822 (3.958)	2.085 (3.422)
Cold waves (Frequency)	-0.050 (0.561)	0.036 (0.560)	-0.211 (0.616)	-0.089 (0.560)

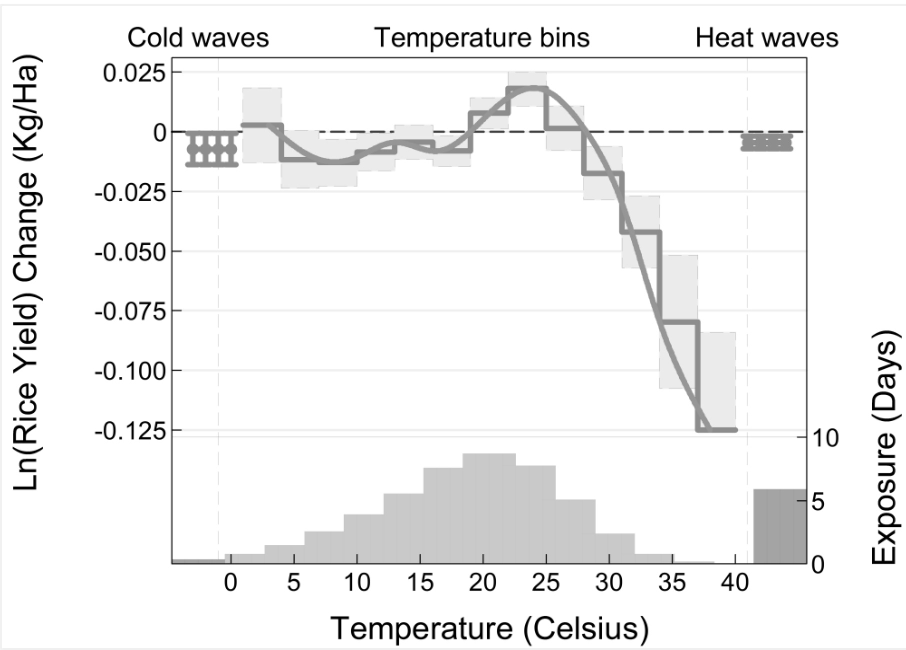
Note: The changes in temperature variables were computed by using the temperature data based on the WordClim database minus sample means of temperature data in the sample. Numbers presented in parentheses are standard deviations.

Figure S1. Percentage Changes in Crop Acreages in China during the Period 1990–2010

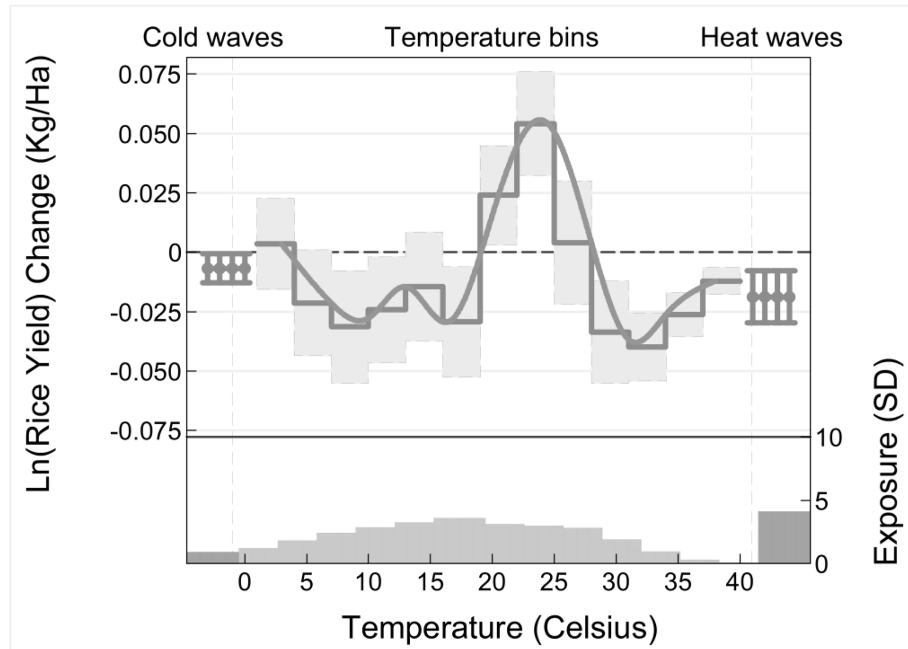


Scenario (1): Spatial Distance Matrix

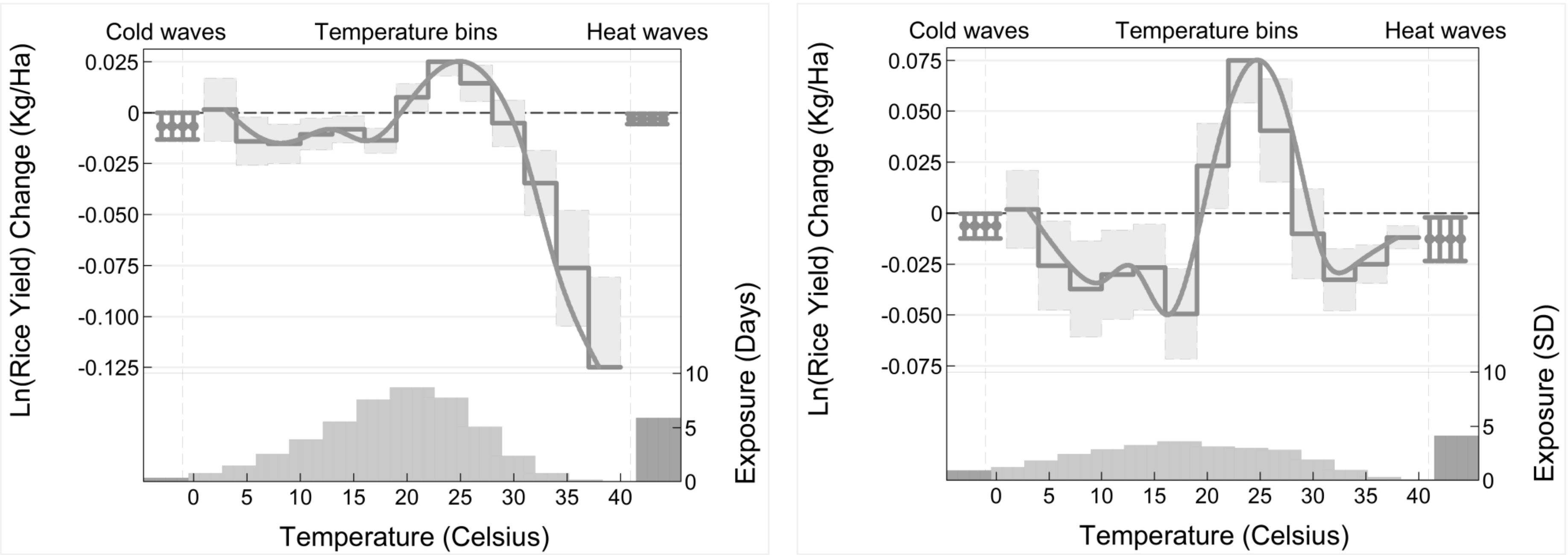
A



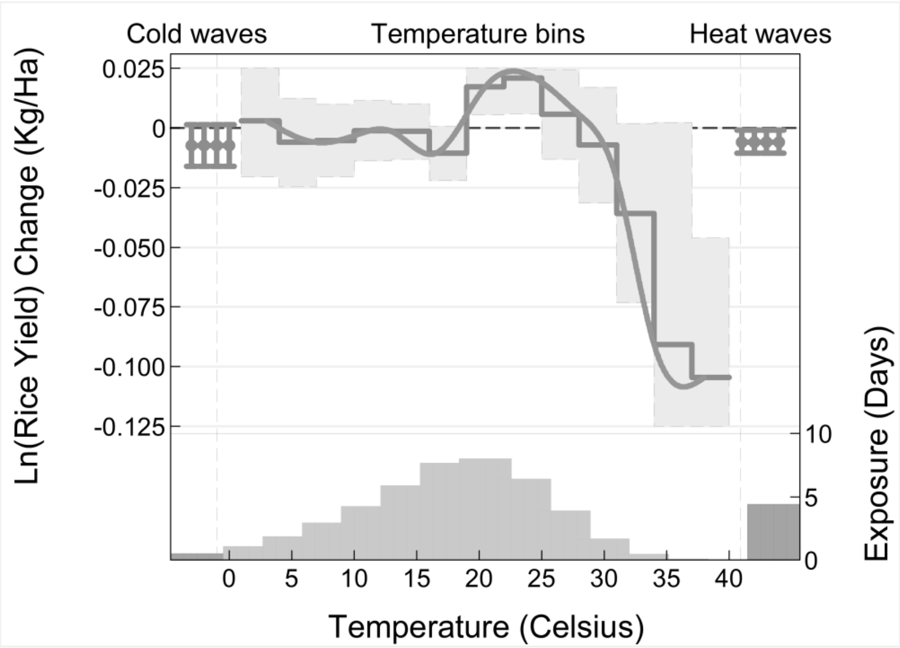
B



Scenario (2): Regional Time Trend



Scenario (4): Japonica Rice Subsample



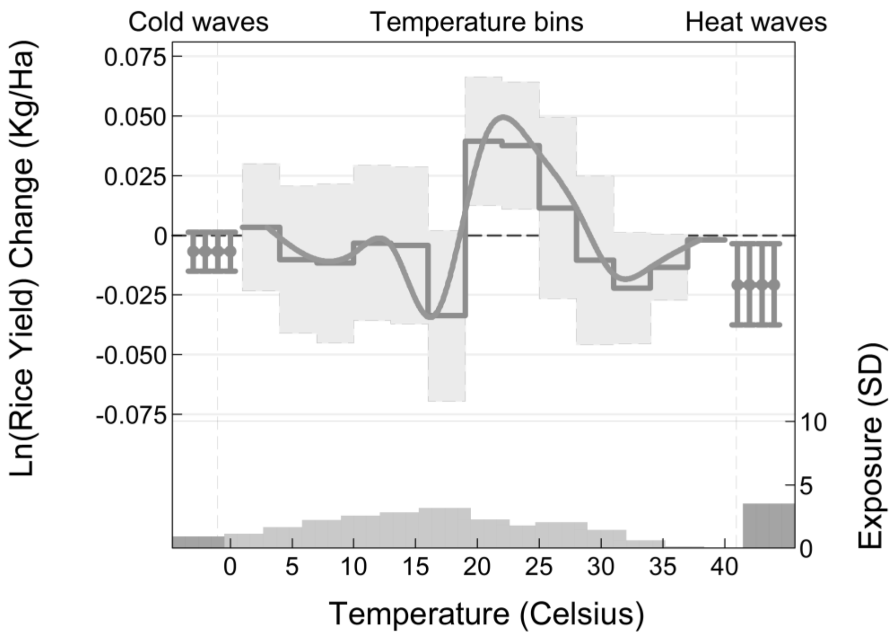
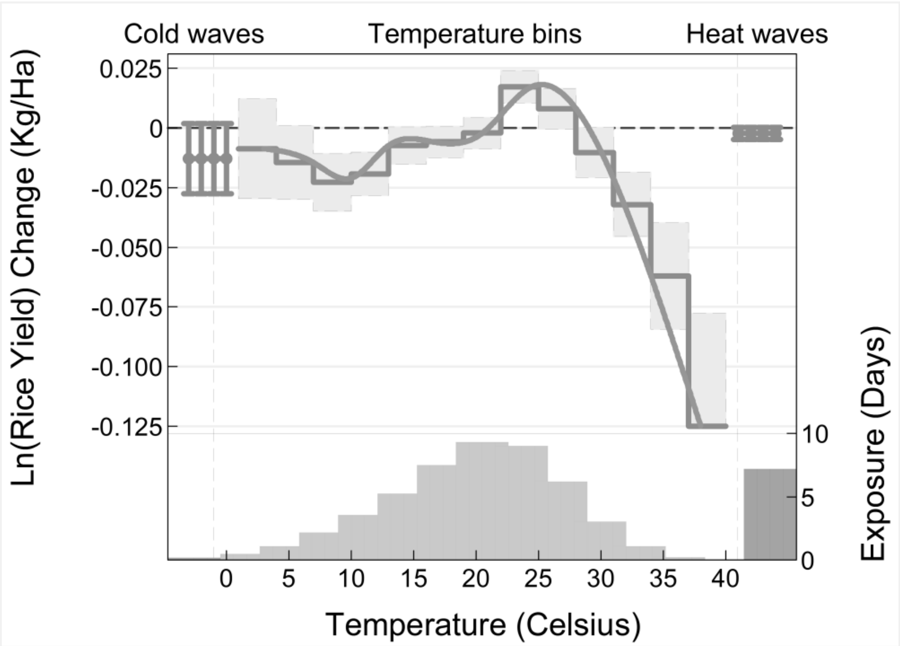
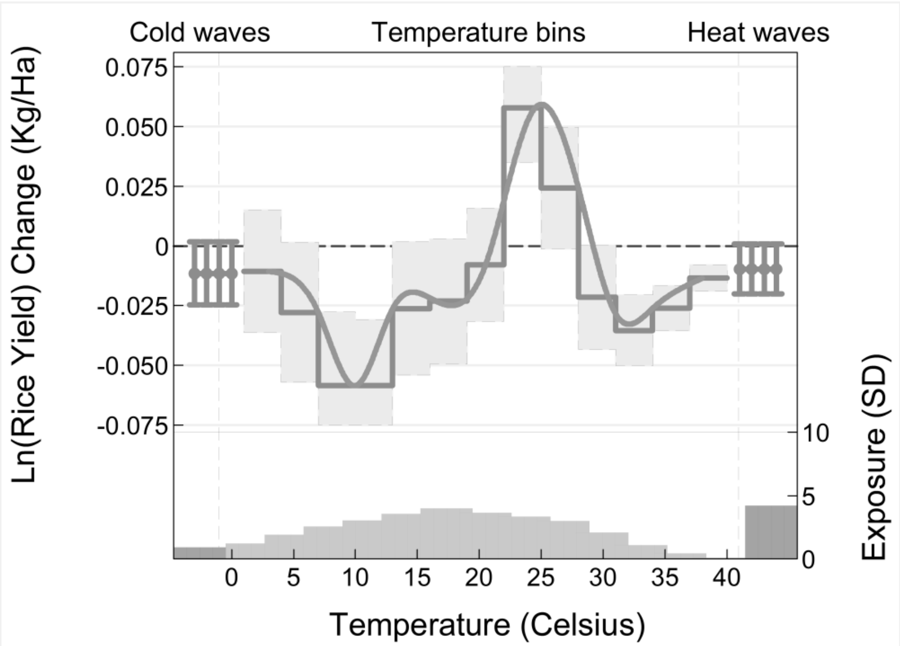


Figure S2. Sensitivity Analysis

Scenario (5): Indica Rice Subsample





Notes: Resulted presented in the graphs were estimated using temperature bins as temperature variables, for scenarios (1), (2), (4) and (5) considered in the robustness check section. The left panels (A) show point estimates and the 95% confidence intervals of the temperature variables. The right panels (B) show the marginal effects on rice yield per SD of temperature variables in these scenarios. The smooth lines fit coefficient estimates of each 3°C temperature range using an 8th-order polynomial function. Histograms at the bottom of panels (A) and (B) show the distribution of mean and SD of temperature variables in the data, respectively.