Assessing the impacts of temperature variations on rice yield in China

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Abstract: Using a unique county-level panel on single-season rice yield and daily weather outcomes from 1996 to 2009, we examined the impacts of temperature variations on rice yield in China. We have five key findings: (*i*) in contrast to nearly all previous studies focusing on rice production in tropical/subtropical regions, we discovered that higher daily minimum temperature during the vegetative stage increased rice yield; (*ii*) consistent with previous assessments, we found that increased daily maximum temperature during the vegetative and ripening stages reduced rice yield; (*iii*) the impacts of solar radiation and rainfall on rice yield differed across the plant's growth stages; (*iv*) estimated weather effects on yield differed by rice variety; and (*v*) weather variations caused a net economic loss of $21.6-88.2 million during the sample period, depending on model specifications and econometric estimation strategies.

Keywords: agriculture, rice, weather, China, temperature.

1. Introduction

Most studies assessing the impacts of rising temperature on agriculture have focused on the developed world (Lobell and Asner 2003; McCarl et al. 2008; Mendelsohn et al. 1994; Olesen and Bindi 2002; Schlenker et al. 2006; Schlenker and Roberts 2009). With a few exceptions (Chen et al. 2015; Lobell et al. 2011a; Welch et al. 2010), there has been little research using high quality data to address similar issues in developing countries, which are home to over 70% of the world's poor and heavily depend on agriculture. The objective of this article is to provide empirical evidence on the temperature effects on rice yield in China, using a unique county-level panel on rice yield and daily weather outcomes.

Rice is the most important food crop in China's agricultural economy. It accounts for about 30% of the total grain area, nearly 50% of the total grain output, and roughly 35% of the nation's annual grain consumption (NBS 1996-2009). China is also the world's largest rice producer, accounting for 28% of the world's rice production in 2012 (FAO 2012). Therefore, examining whether and the extent to which changing weather conditions have affected China's rice sector is the important first step before efficient climate adaptation and mitigation strategies can be developed to combat climate change.

Many studies have evaluated the impacts of variations in temperature and solar radiation on rice yield. According to the growth characteristics of the rice plant, agronomic studies usually divide the growing season of rice into three main stages, namely the vegetative stage from germination to panicle initiation, the reproductive stage from panicle initiation to flowering, and the ripening stage from flowering to mature grain. Early studies found that higher daily average temperature (T_{ave}) and decreased solar radiation can reduce rice yield (Krishnan et al. 2007; Seshu and Cady 1984; Wassmann et al. 2009; Yoshida and Parao 1976), but the temperature and radiation effects on yield varied across rice's three growth stages. Recent studies discovered that rice yield responded differently to daily maximum temperature (T_{max}) and daily minimum temperature (T_{min}) (Peng et al. 2004; Welch et al. 2010; Ziska and Manalo 1996). For instance, using the data at the International Rice Research Institute farm, Peng et al. (2004) found that rice yield responded negatively to rising T_{min}, while the effect of T_{max} on yield was statistically insignificant. Welch et al. (2010) analyzed the data from farm-managed fields to estimate the effects of temperature and solar radiation on rice yield in tropical/subtropical Asia. Similar to Peng et al. (2004), they showed that rice yield was negatively affected by higher T_{min}. Different from Peng et al. (2004), they found that higher T_{max} had a positive impact on rice yield, while the radiation impacts on yield varied by growth stage. Despite these findings, in a review article, Wassmann et al. (2009) concluded that "research into the effect of high night temperature is not understood well and should be prioritized".

Crop simulation models have been the primary tool used to predict the changes in rice yield in China under different climate change scenarios (Chavas et al. 2009; Lin et al. 2005; Yang et al. 2014; Yao et al. 2007). While crop simulation models are useful for projecting the impacts of future climate change on crop yields, they do not consider the effects of economic factors (such as input prices) and human's responses to changing climatic conditions on yields. Hence, they cannot represent real agricultural settings. A few studies have evaluated the temperature effects on rice yield in China, using statistical approaches and observed data based on either field trials or statistical yearbooks released by the National Bureau of Statistics of China (NBS) at the provincial scale (Chen et al. 2014; Tao et al. 2006; Zhang et al. 2010). However, due to the differences in the data utilized and research methods they yielded mixed results. For instance, using data from 20 experiment stations, Zhang et al. (2010) showed that rice yield was positively correlated with T_{min},T_{max}, and T_{ave}. But, Tao et al. (2006) showed that higher T_{min} reduced rice yield in Eastern and Southern China, which was also based on the data collected at experimental stations. Chen et al. (2014) analyzed province-level data from 1961 to 2010, and found that higher T_{ave} raised single-cropping rice yield, but reduced the yield of double-cropping rice. Based on the province-level data from 1950 to 2002, Tao et al. (2009) found that rice yield was positively correlated with T_{max} and T_{min} in Northeast China.

This article aims to evaluate the responses of rice yield to temperature variations in China, using a newly available county-level panel. The panel includes county-specific rice yield and daily weather outcomes that spanned most Chinese counties from 1996 to 2009. Here, we focused on single-season rice, which is widely produced across the nation and accounts for about 50% of the total rice production in China. The weather data include daily T_{max}, T_{min}, T_{ave}, rainfall, and solar radiation. The fine-scale weather data enabled us to construct county-specific weather variables across three growth stages of rice for all single-season rice-producing counties in China.

We developed a fixed-effects spatial error model to estimate the link between rice yield and temperature variables. In addition to T_{min} and T_{max}, the model also included rainfall and solar radiation as weather variables, while controlling for county fixed effects to remove the effects of the time-invariant unobserved factors that are unique to each county (e.g. soil quality and tradition of agricultural production). The model also controlled for year fixed effects to remove the effects of the unobserved factors that are common to all counties in a given growing season (e.g. global CO_2 concentrations). We also included economic variables in one model specification to examine the responses of rice yield to changes in rice price and prices of inputs used for rice production. Moreover, we controlled for the potential spatial correlations of the error terms. These estimation strategies are expected to increase the precision of coefficient estimates of weather variables. Japonica rice and Indica rice are the two main rice varieties planted in China. To examine if estimated weather effects on yield differed by rice variety, we also estimated the spatial error model using Japonica rice-producing counties and Indica rice-producing counties, respectively. Using estimated coefficients of weather variables, we quantified the net economic impact of weather variations on China's rice sector over the sample period. Our results may generate important public policy implications for the formation of China's future national and global climate strategies.

2. Materials and Methods

The spatial error model developed to estimate the relationship between weather variables and rice yield is shown in Eq. (1) and (2):

$$Y_{r,t} = Z_{r,t}\beta + E_{r,t}\gamma + \alpha_r + \lambda_t + \varepsilon_{r,t} \tag{1}$$

$$\varepsilon_{r,t} = \rho \sum_{r'} W_{r,r'}\varepsilon_{r',t} + \phi_{r,t} \tag{2}$$

where $Y_{r,t}$ denotes county-average rice yield in county *r* and year *t*. $Z_{r,t}$ represents weather variables, including the means of daily $T_{\max}$, $T_{\min}$, and solar radiation, and sums of rainfall for three rice growth stages (a total of twelve weather variables). Economic variables are denoted by $E_{r,t}$, which includes several output-input price ratios in order to control for the effects of changes in input uses and rice price on rice yield. We also controlled for county-level fixed effects (represented by α_r) and year fixed effects (denoted by λ_t) to remove the effects of unobserved factors that are unique to each county and/or are common to all counties in a given year on yield. $\varepsilon_{r,t}$ are the error terms. β is the parameter vector that gives the responses of rice yield to weather variations.

When constructing output-input price ratios, we used lagged rice price in year *t*-1 as a proxy for expected rice price in year *t*, which is similar to Chen et al. (2015) and Braulke (1982). We included price indices for fertilizer, pesticides, and fuels, and wage as input prices and constructed rice-fertilizer, rice-pesticide, rice-fuel, and rice-labor price ratios. These price ratios may be endogenous, as argued by Roberts and Schlenker (2013). Drawing on their work, we used weather variables and crop inventories in the previous year as instruments to address this potential endogeneity issue.

Several studies in the literature have used weather variables only as explanatory variables to examine the weather effects on crop yields (see McCarl et al. 2008; Schlenker and Roberts 2009; Welch et al. 2010). Estimated coefficients of weather variables in these studies are interpreted as the total marginal effects of weather on yields, which are the sum of the direct effects of weather on yields (through the effects on crop physiology) and the indirect effects of weather on yields (through the effects on farmers' input use). Hence, if we include $E_{r,t}$ as explanatory variables in Eq. (1) in addition to weather variables, estimated β should be considered as the partial effects of weather on rice yield, because controlling for $E_{r,t}$ might absorb some of the overall effects of weather on yield. In the empirical analysis, we considered one model specification with $E_{r,t}$ as explanatory variables to examine whether rice yield reponded to changes in rice and input prices, and to examine if our coefficient estimates of weather variables are sensitive to the inclusion of economic variables.

As shown in Eq. (2), we allowed the error terms $\varepsilon_{r,t}$ to be spatially correlated across counties. $\phi_{r,t}$ are the error terms that are independently normally distributed with $E[\phi_{r,t}] = 0$ and $\text{var}[\phi_{r,t}] = \sigma^2$, ρ is the parameter of spatial correlation, and $W_{r,r'}$ is a pre-specified spatial weighting matrix that describes the spatial dependence of counties with their neighbors. We used three different spatial weighting matrices to examine the robustness of our coefficient estimates of weather variables. In the baseline, we used a spatial contiguity matrix because crop production in a county is more likely to be influenced by its neighboring counties that share the same boundary. We also considered two alternative inverse distance weighting matrices that weigh the six and four nearest counties relative to county *r*, respectively, according to their physical distance, and assign zero weights to other counties. The relative weights in each of the two distance weighting matrices are determined based on their distances to the centroid of county *r*.

3. Data

County-specific total rice production and planted acres were obtained from the NBS for years 1996-2009. Rice yield was computed as the total rice production in a county divided by the total rice-planted acres in that county. Several rice cropping systems are practiced in China, including single-season rice, double cropped rice (a combination of early and late rice production technology), and multiple cropped rice. The dataset only reports total rice production and total rice planted acres for rice-producing counties, and does not contain details on yields for early rice and late rice in regions with double or multiple rice cropping systems. Therefore, to accurately match yield data with our weather data, we selected counties with single-season rice production only. Fig.1 shows that single-season rice is primarily produced in the Three Northeast provinces (Heilongjiang, Jilin, and Liaoning) and Southwest mountainous areas. Central China, the Huang-Huai plain area, and Northwest inland area also produce a small amount of sing-season rice. This gave us 10,794 observations with 771 counties, representing about 50% of the total rice production in China. Rice yield varied substantially in the sample**,** ranging between

1,788-14,240 kg·ha^{-1} with an average of 7,125 kg·ha^{-1} (see Tables S-1, S-2 in the appendix). Rice growing seasons in different areas were obtained from the Department of Agriculture of China[1].

Weather data were obtained from the China Meteorological Data Sharing Service System (CMDSSS), which records daily T_{min}, T_{max}, T_{ave}, rainfall, and solar radiation for 820 weather stations in China. The dataset also contains exact coordinates of each weather station, enabling them to be merged with our county-level yield data. Fig. 1 displays the spatial distribution of single-season rice-producing counties and weather stations included in our sample. Of the 771 counties, about 566 counties have at least one weather station. For counties with several weather stations, we constructed weather variables by taking a simple average of these weather variables across these stations. We imputed the weather information from the nearest adjacent counties for counties without a weather station. Trends for T_{min}, T_{max}, T_{ave}, and solar radiation during the three rice-growth stages are shown in Fig. S-1 in the appendix. On average, the observed T_{min} and T_{max} increased by 0.217°C and 0.094°C per decade, respectively, during the period 1950-2010. Average daily solar radiation decreased by 0.161 hours per decade over the same period.

Because county-level data on rice price and input prices are not available in public data sources, we constructed the price ratios at the provincial scale. We obtained province-level rice price from the China Yearbook of Agricultural Price Surveys (NBS 2012). Price indices for fertilizer, pesticides, and fuels, and labor costs measured using average wage for farm labor were obtained from the NBS[2].

[1] Available at: http://zzys.agri.gov.cn/nongshi.aspx

[2] The Chinese-language version of the webpage is available at: http://data.stats.gov.cn/workspace/index;jsessionid=0921DCCDD689B3EDA1BC074063BEAAD1?m=fsnd.

4. Empirical Results

4.1. Data Correlations

We performed several tests to examine the presence of spatial correlations of the error terms in the regression model for each of our three spatial weighting matrices, including Moran's *I* test (Anselin 1988), the Lagrange Multiplier (LM) ERR test, the Likelihood Ratio (LR) test and the Wald test. We conducted these tests using weather and economic variables as explanatory variables. These test results indicate that spatial correlations of the error terms in the regression model are quite large (Table S-3). The parameters of spatial correlations are 0.71 and 0.69, respectively, under the contiguity matrix and the distance matrix that weighs the six nearest neighbors, and become smaller (0.63) under the distance matrix that weighs the four nearest neighbors. These test statistics indicate that omitting the spatial correlations can lead to a significant overestimate of the true *t*-statistics (Schlenker et al. 2006). In the baseline analysis presented below, we employed the contiguity matrix as our spatial weighting matrix. We examined the robustness of our results using other spatial weighting matrices.

We also found that weather variables were correlated during the sample period (Table S-4). Specifically, we found that: (*i*) $T_{\min}$ and radiation were moderately (and positively) correlated during the vegetative and reproductive stages, but the correlation of the two variables became negative during the ripening stage; (*ii*) $T_{\min}$ and radiation were positively correlated with $T_{\max}$ during the three growth stages; and (*iii*) $T_{\max}$, $T_{\min}$ and solar radiation were negatively correlated with rainfall. These test results suggest that all weather variables should be incorporated in the regression analysis to obtain consistent estimates of the weather effects on rice yield.

4.2. Regression Results: Sample with all single-season rice-producing counties

We conducted the spatial error analysis using two different model specifications. In model (1), we included weather variables, namely $T_{\min}$, $T_{\max}$, radiation, and rainfall as explanatory variables to examine the variations in rice yield during the sample period. In model (2), we added the price ratios and examined whether the inclusion of these variables affects our coefficient estimates of weather variables. The two model specifications included time-invariant county fixed effects and year fixed effects, and controlled for the spatial correlations of the error terms.

Table 1 shows parameter estimates of weather variables for the two model specifications considered here. We found that the responses of rice yield to temperature and radiation variables varied by growth stage. $T_{\min}$, $T_{\max}$, and radiation had statistically significant impacts on rice yield during the vegetative stage. $T_{\max}$ and radiation also had significant impacts on rice yield during the ripening stage. Rice yield was not significantly affected by the temperature and radiation variables during the reproductive stage.

In contrast to nearly all previous studies focusing on rice production in tropical and subtropical regions (Mohammed and Tarpley 2009b; Peng et al. 2004; Seshu and Cady 1984; Welch et al. 2010; Yoshida and Parao 1976; Ziska and Manalo 1996), we found that higher $T_{\min}$ during the vegetative stage had a positive impact on rice yield in China. For instance, in model (1) with weather variables only, a 1°C increase in $T_{\min}$ during the vegetative stage increased rice yield by 44.2 $kg \cdot ha^{-1}$ (p<0.10). Existing studies emphasize that increased $T_{\min}$ can damage rice yield because it can increase respiration losses during the vegetative stage (Mohammed and Tarpley 2009b; Peng et al. 2004), and hasten crop maturity during the ripening stage (Mohammed and Tarpley 2009a). Agronomic studies suggest that if $T_{\min}$ is above 25°C during the vegetative stage, it can lead to significant damage to rice yield by reducing plant height, tiller number, and total dry weight (Yoshida et al. 1981). However, less than 1% of the observations of $T_{\min}$ during the vegetative stage in our sample were greater than 25°C. We also found that average daily $T_{\min}$ during the vegetative stage in our sample were 6.6-9.5°C lower than that in tropical and subtropical Asia (see table S2 in Welch et al. 2010). Therefore, the difference in the data analyzed between this article and the previous studies might explain the differences in the estimated effects of $T_{\min}$ on rice yield. Greenhouse experiments for rice showed a positive impact of elevated $T_{\min}$ on rice yield during the vegetative stage (Kanno et al. 2009).

Coefficient estimates of other weather variables have expected signs. Higher $T_{\max}$ had negative impacts on rice yield during the vegetative and ripening stages ($p<0.05$), which is in agreement with well-established previous assessments (Lobell and Field 2007; Wassmann et al. 2009). The radiation impacts on yield differed by growth stage. Estimated effect of radiation on rice yield was negative during the vegetative stage ($p<0.01$) and was positive during the ripening stage ($p<0.05$), which is similar to the findings in other regions (for example, see Welch et al. 2010). Rainfall had small but negative impact on rice yield during the reproductive stage ($p<0.05$). Prior studies found that variations in rainfall in the past several decades have depressed rice yield in many regions of the world (Auffhammer et al. 2012; Lobell et al. 2011b).

Statistical significance, signs, and magnitudes of weather variables changed modestly with the inclusion of economic variables in model (2), which shows the robustness of our results. Coefficients of rice-fertilizer, rice-labor, and rice-fuel price ratios are positive and statistically significant, which indicates that the increases in prices of fertilizer, labor and fuels might have resulted in reduced use of these inputs and might have had detrimental effects on county-average rice yield. Coefficient estimate of rice-pesticide price ratio has expected sign, but is not statistically significant.

4.3. Regression Results: Japonica rice vs. Indica rice

Japonica rice and Indica rice are the two main rice varieties planted in China. They differ substantially in their physicochemical properties (Kang et al. 2006), and genetic traits (Huang et al. 2012). To examine if the weather effects on yield estimated above differed by rice variety, we divided our sample into two subsamples: Japonica rice-producing counties and Indica rice-producing counties[3], and then replicated the above analysis.

As shown in the last four columns of Table 1, the temperature effects on yield differed substantially between Japonica rice and Indica rice. Specifically, the effect of higher $T_{\min}$ on Indica rice yield was positive and statistically significant during the vegetative stage (p<0.01), which is similar to the finding presented above, but the effect of higher $T_{\min}$ on Japonica rice yield was found to be insignificant. Elevated $T_{\max}$ still had negative effects on yields for the two types of rice, but the negative temperature effects occurred during different growth stages. We found that higher $T_{\max}$ negatively affected Japonica rice yield during the ripening stage (p<0.10), and that the negative effects of elevated $T_{\max}$ on Indica rice yield occurred during the vegetative stage (p<0.01) and the reproductive stage (p<0.10).

Radiation and rainfall impacts on yield also differed considerably by rice variety. We found that signs and statistical significance of coefficient estimates of radiation and rainfall variables for Japonica rice are quite close to the findings without separating the sample into subsamples by rice variety. Radiation had a positive effect on Indica rice yield during the reproductive stage (p<0.05), while the effect of rainfall on Indica rice yield was not significant.

Parameter estimates of rice-fertilizer, rice-labor, and rice-fuel price ratios are positive and statistically significant for Japonica rice (p<0.01), while coefficient estimate of rice-pesticide

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[3] We obtained information on rice varieties planted in different regions from China Rice Data Center, see http://www.ricedata.cn/variety/

price ratio is not significant. Coefficient estimates of these economic variables are not statistically significant for Indica rice, which might stem from the use of province-level price data. The inclusion of economic variables does not affect coefficient estimates of weather variables in both cases.

4.4. Sensitivity Analysis

We examined the robustness of estimated coefficients of weather variables across different spatial weighting matrices, variables, and data. Specifically, in Scenarios (1)-(2), we used two distance matrices that assign weights to the six and four nearest neighboring counties, respectively, and zero to other counties, as our spatial weighting matrices. In Scenario (3), we replicated the above analysis using T_{ave} instead of T_{min} and T_{max} as temperature variables to examine the temperature effects on rice yield. In the sample, about 205 rice-producing counties do not have weather stations. When constructing weather variables for these counties, we used the weather information from their neighboring counties. To examine if our results are sensitive to this, we eliminated counties without weather stations in the sample and replicated the above analysis in Scenario (4). In all scenarios considered here, we used model specification (2) with weather and economic variables as explanatory variables. We conducted the sensitivity analyses using the entire sample with all single-season rice-producing counties, and subsamples with Japonica and Indica rice-producing counties, respectively. Results are presented in Fig. 2.

In Scenarios (1)-(2), signs, statistical significance, and magnitudes of parameter estimates of weather variables are only modestly different from the baseline estimates. That indicates that our results are generally insensitive to the chosen spatial weighting matrix. In Scenario (3), we used T_{ave} as temperature variables rather than T_{min} and T_{max}. Consistent with the previous assessments (for example, see Chen et al. 2014), we found negative effects of higher T_{ave} on rice yield during the vegetative stage (p<0.10) in the sample with all single-season rice-producing counties. Higher T_{ave} also negatively affected Indica rice yield during the reproductive stage (p<0.05). Estimated weather effects on rice yields in Scenario (4) are similar to our baseline findings.

4.5. Economic Impact of Weather Variations on China's Rice Sector

We used estimated parameters of the weather variables to investigate the net economic impact on China's rice sector stemming from variations in weather conditions. To do so, we first used these coefficient estimates to measure the change in rice yields for years 1996-2009 that have resulted from the changes in weather conditions relative to year 1996:

$$\delta_t = E(Y \mid Z_{1996}, E_t) - E(Y \mid Z_t, E_t) \tag{3}$$

where $E(Y \mid Z_{1996}, E_t)$ denotes the expected rice yield with the 1996 levels of weather outcomes and economic variables in year t= 1996-2009, and $E(Y \mid Z_t, E_t)$ represents the expected rice yield with all variables in year t = 1996-2009. Therefore, δ_t measures the change in rice yield because of weather variations. Using Eq. (1), we can rewrite Eq. (3) as:

$$\delta_t = \beta(Z_{1996} - Z_t) \tag{4}$$

where β is the coefficient vector of the relationship between weather and rice yield. Replacing β with its estimated coefficients provides an estimate of δ_t.

We then multiplied the yield change in each county by county-level rice-planted acres in 2009, summed over all rice-producing counties and all years (from 1996-2009), to get a rough estimate of the change in total rice production in China during the sample period due to weather variations. We multiplied the change in total rice production by its market price in 2009 and then subtracted associated production costs, to get an estimate of the net economic impact of weather variations on China's rice sector[4].

As shown in Fig. 3, the most noticeable result is that variations in weather conditions during the sample period had a positive economic impact on Indica rice, whereas the economic impact of weather variations on Japonica rice was negative. The absolute value of the positive economic impact on Indica rice was smaller than the absolute value of the negative economic impact on Japonica rice. Combined, these results indicate that changing weather conditions resulted in a net economic loss of approximately $21.6-49.2 million in China's rice sector over the sample period, depending on scenarios. The negative economic impacts associated with weather variations were larger in the sample with all single-season rice-producing counties, ranging between $29.1 million and $88.2 million.

5. Conclusions

Using a unique county-level panel on rice yield and daily weather outcomes in China, we examined the impacts of changing weather conditions on rice yield, and estimated the net economic impact on China's rice sector stemming from weather variations. The most surprising finding is that T_{min} had a large and positive impact on rice yield during the vegetative stage. The difference in the estimated effects of T_{min} on rice yield between this article and the previous studies focusing on rice production in tropical/subtropical regions is primarily driven by the differences in the data analyzed. Our findings of a negative impact on rice yield of higher T_{max} during the vegetative and ripening stages, a negative impact of increased radiation during the vegetative stage, a positive impact of increased radiation during the ripening stage, and a

[4] We thank one referee for pointing this issue out. Here, we can only measure the direct impact of weather variations on rice production and cannot measure the indirect impact of weather shocks to market prices of rice.

negative impact of rainfall during the reproductive stage, are consistent with the existing literature.

Our further analysis showed that the weather effects on yield differed by rice variety. The finding of the positive effect of higher T_{min} on yield only holds for Indica rice, while Japonica rice yield did not respond to the variations in daily T_{min}. Higher T_{max} negatively affected Japonica and Indica rice yields, with the negative temperature effects varying by growth stage. Responses of Japonica rice to changes in radiation and rainfall were found to be quite close to that when all single-season rice-producing counties were included in the empirical analysis. Radiation had a positive effect on Indica rice yield during the reproductive stage, while the effect of rainfall on Indica rice yield was found to be insignificant. Coefficient estimates of weather variables remain robust across various model specifications, estimation strategies, and data. Weather variations caused a net economic loss of $21.6-88.2 million during the sample period, depending on scenarios.

Three caveats apply. First, our parameter estimates were based on single-season rice in China. Chen et al. (2014) found that yield responses of double- and multi-cropped rice to weather variables were different from those of single-season rice. Therefore, caution should be made when using the results presented in this article to explain the responses of double- and multi-cropped rice to weather shocks. Second, due to the lack of county-level economic data, we used province-level price data and constructed the economic variables, which might cause insignificant coefficient estimates of the price ratios in some scenarios. Third, our analysis focused on the temperature, radiation, and rainfall effects on rice yield, but did not consider the impacts of CO_2 fertilization on yield. Laboratory studies have found that higher CO_2 fertilization may offset yield reductions due to warmer climate (Long et al. 2006).

Table 1 Regression Results: Impacts of Weather and Economic Variables on Rice Yield ($kg \cdot ha^{-1}$)

	All single-season rice		Japonica rice		Indica rice	
Model specification	(1)	(2)	(1)	(2)	(1)	(2)
T_{min}: vegetative	44.17*	44.50*	-14.82	-13.65	134.28***	134.13***
	(1.65)	(1.66)	(-0.35)	(-0.33)	(3.98)	(3.96)
T_{min}: reproductive	19.63	14.76	7.10	2.98	41.50	38.81
	(1.02)	(0.77)	(0.25)	(0.10)	(1.50)	(1.39)
T_{min}: ripening	13.04	10.48	38.48	35.05	20.22	24.75
	(0.62)	(0.49)	(1.18)	(1.07)	(0.70)	(0.85)
T_{max}: vegetative	-73.11***	-76.61***	-20.87	-29.93	-100.33***	-97.51***
	(-3.35)	(-3.49)	(-0.59)	(-0.84)	(-3.84)	(-3.72)
T_{max}: reproductive	-13.67	-14.36	11.00	5.21	-40.65*	-41.36*
	(-0.75)	(-0.79)	(0.38)	(0.18)	(-1.85)	(-1.86)
T_{max}: ripening	-45.28**	-43.91**	-54.57*	-62.89*	-31.02	-34.31
	(-2.25)	(-2.18)	(-1.68)	(-1.94)	(-1.29)	(-1.41)
Radiation: vegetative	-86.95***	-91.23***	-94.57***	-101.02***	-6.48	-0.90
	(-4.25)	(-4.45)	(-3.05)	(-3.24)	(-0.25)	(-0.03)
Radiation: reproductive	12.75	14.10	-16.57	-11.11	33.52**	34.30**
	(0.97)	(1.07)	(-0.83)	(-0.55)	(2.04)	(2.06)
Radiation: ripening	42.65**	41.95**	66.06**	67.91**	-3.59	-6.12
	(2.27)	(2.23)	(2.26)	(2.31)	(-0.16)	(-0.28)
Rainfall: vegetative	-0.52	-0.76	-0.33	-1.19	-0.67	-0.44
	(-0.47)	(-0.69)	(-0.16)	(-0.57)	(-0.67)	(-0.44)
Rainfall: reproductive	-2.80**	-3.07**	-5.86**	-6.59***	1.45	1.49
	(-2.01)	(-2.21)	(-2.47)	(-2.78)	(1.05)	(1.07)
Rainfall: ripening	0.18	0.43	1.21	1.73	-1.55	-1.73
	(0.12)	(0.27)	(0.39)	(0.56)	(-1.12)	(-1.25)
Price ratio						
rice/labor		111.63***		162.52***		-22.97
		(3.54)		(3.35)		(-0.54)
rice/fertilizer		483.63***		572.41**		116.97
		(2.79)		(2.26)		(0.43)
rice/pesticide		171.29		65.78		116.02
		(1.03)		(0.27)		(0.41)
rice/fuel		283.06**		561.84***		-315.20
		(2.25)		(2.78)		(-1.50)
N	10,794	10,794	5,166	5,166	5,628	5,628

Note: Results presented in the first two columns are based on the entire sample with all single-season rice-producing counties. Results presented in the third and fourth columns are based on the subsample with Japonica rice-producing counties only, while results presented in the last two columns are based on the subsample with Indica rice-producing counties only. All model specifications considered the spatial correlations of the error terms, and included fixed effects for counties and years in addition to the variables shown above. Units for explanatory variables: °C for T_{min} and T_{max}, hours for radiation, and cm for rainfall. Asymptotic *t*-statistics are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

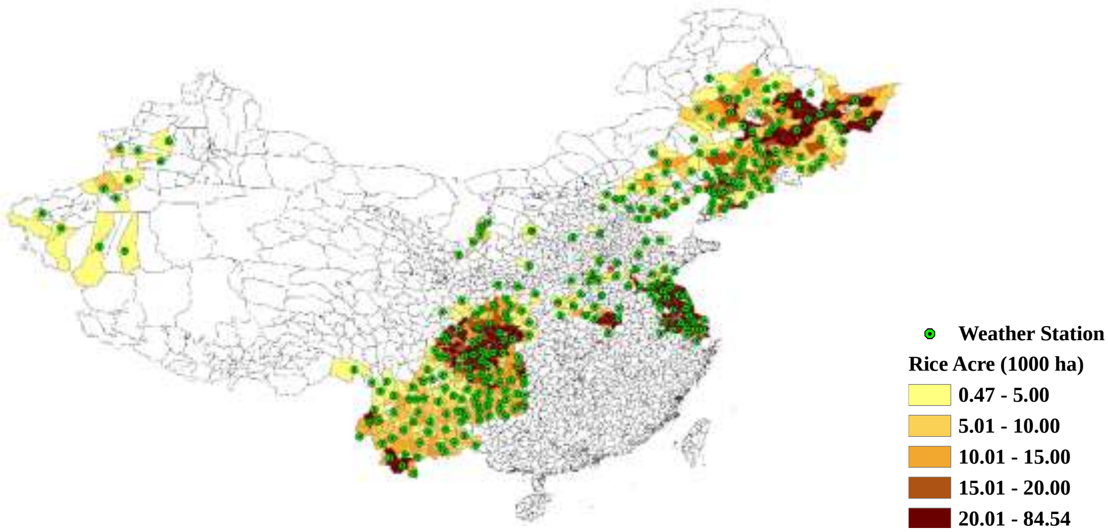
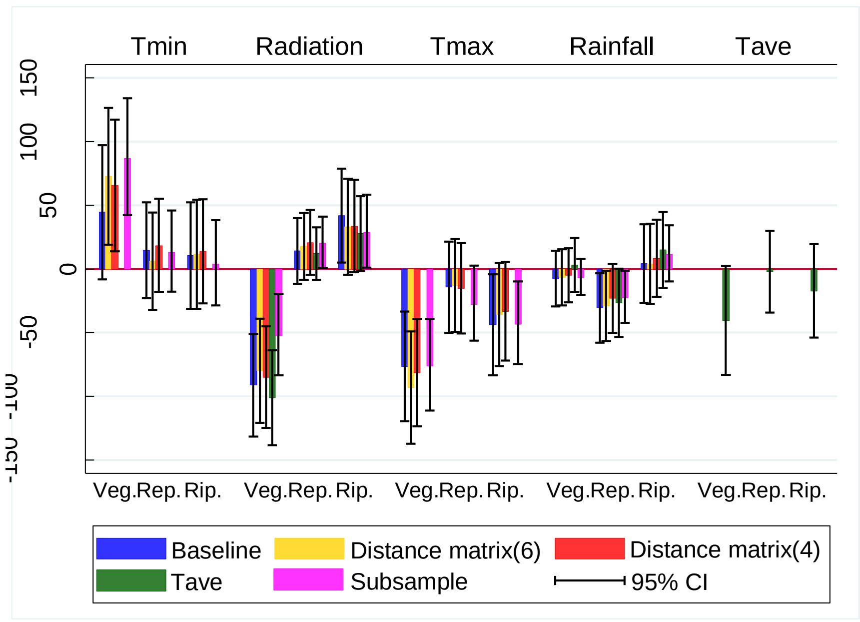
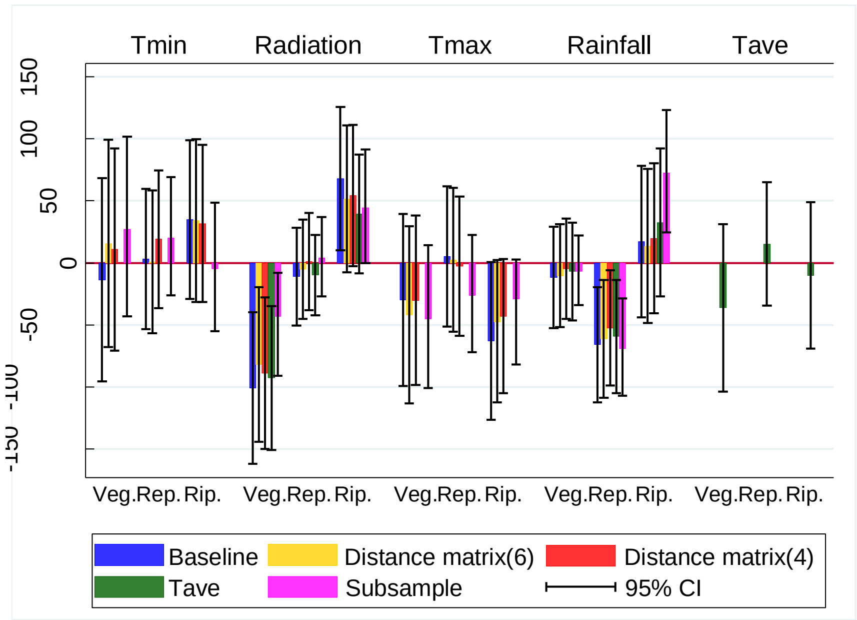


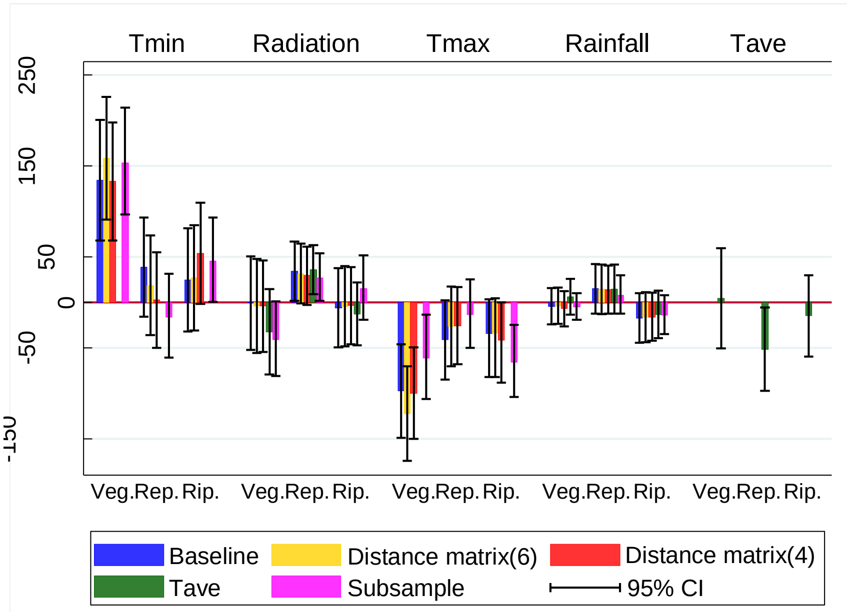
Fig. 1 Spatial distribution of single-season rice production and weather Stations in China



(a) All single-season rice



(b) Japonica rice



(c) Indica rice

Fig. 2 Impacts of weather on rice yields
Note: Results presented in panel (a) are based on the entire sample with all single-season rice-producing counties. Results presented in panels (b) and (c) are based on the subsample with Japonica rice and Indica rice-producing counties, respectively. We considered four scenarios in the sensitivity analysis. In Scenarios (1) and (2), we used two distance matrices that assign weights to the six and four nearest neighboring counties, respectively, and zero to other counties, as our spatial weighting matrices. Scenario (3) used T_{ave} instead of T_{min} and T_{max} as temperature variables. In Scenarios (4), we conducted the spatial error analysis by excluding counties without weather stations from the sample. Parameter estimates are interpreted as the marginal effects of per-unit change in the temperature (°C), radiation (hour), and precipitation (10cm) variables on rice yields. Each cluster shows the impacts of a given variable on rice yields, varied by rice-growth phase (vegetative, reproductive, and ripening). Bars show 95% confidence bands.

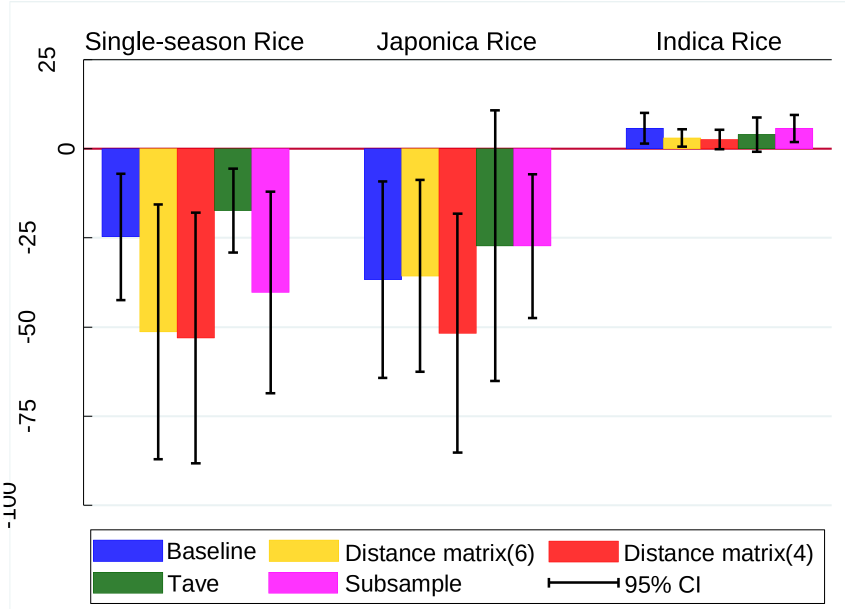


Fig. 3 Economic impacts of weather variations on China's rice sector under alternative scenarios ($ million)

Note: To compute the economic impact on China's rice sector resulting from the changes in weather conditions, we first calculated the change in rice yield for years 1996-2009 if weather conditions were maintained at the 1996 levels. We then multiplied the rice yield change by county-specific planted acres in 2009 to estimate county-level production change, and summed across all counties and all years in the sample to get the total rice production loss. We multiplied the total rice production loss by its price in 2009 and subtracted the associated production costs to obtain the net economic loss due to weather variations. National average rice price in China was RMB 2.1 per kg. The average exchange rate assumed here is RMB6.8 per US$. Different colors represent the economic impacts of different weather variables. Bars show 95% confidence bands.