Environment for Development

Discussion Paper Series June 2014; revised Sept. 2014 ■ EfD DP 14-13-REV

# The Economic Impact of Weather Variability on China's Rice Sector

Shuai Chen, Xiaoguang Chen, and Jintao Xu

# Environment for Development Centers

**Central America**
Research Program in Economics and Environment for Development in Central America
Tropical Agricultural Research and Higher Education Center (CATIE)
Email: centralamerica@efdinitiative.org

**Chile**
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción
Email: chile@efdinitiative.org

**China**
Environmental Economics Program in China (EEPC)
Peking University
Email: china@efdinitiative.org

**Ethiopia**
Environmental Economics Policy Forum for Ethiopia (EEPFE)
Ethiopian Development Research Institute (EDRI/AAU)
Email: ethiopia@efdinitiative.org

**Kenya**
Environment for Development Kenya
University of Nairobi with
Kenya Institute for Public Policy Research and Analysis (KIPPRA)
Email: kenya@efdinitiative.org

**South Africa**
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town
Email: southafrica@efdinitiative.org

**Sweden**
Environmental Economics Unit
University of Gothenburg

Email: info@efdinitiative.org

**Tanzania**
Environment for Development Tanzania
University of Dar es Salaam
Email: tanzania@efdinitiative.org

**USA (Washington, DC)**
Resources for the Future (RFF)
Email: usa@efdintiative.org

The Environment for Development (EfD) initiative is an environmental economics program focused on international research collaboration, policy advice, and academic training. Financial support is provided by the Swedish International Development Cooperation Agency (Sida). Learn more at www.efdinitiative.org or contact info@efdinitiative.org.

# The Economic Impact of Weather Variability on China's Rice Sector

Shuai Chen, Xiaoguang Chen, and Jintao Xu

## Abstract

This paper provides the first county-level analysis of the impacts of weather variability on rice yield in China, by compiling a unique panel on irrigated single-season rice and daily weather data. We found that temperature and solar radiation had statistically significant impacts on rice yield during the vegetative and ripening stages, while the effects of rainfall on yield were not significant. 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 in China. Consistent with other studies, higher daily maximum temperature during the vegetative and ripening stages reduced rice yield in China, while the impacts of solar radiation on rice yield varied across the plant's growth stages. Adaptation of rice production to higher temperatures effectively reduced the adverse impacts of weather variability on rice yield. Combined, our results indicate that weather variability caused a net economic loss of $25.2 million to $60.7 million to China's rice sector in the past decade, depending on model specifications and econometric estimation strategies.

**Key Words:** agriculture, rice, climate change, China, temperature

**JL Codes:** Q54, Q10

## Contents

# The Economic Impact of Weather Variability on China's Rice Sector

Shuai Chen, Xiaoguang Chen, and Jintao Xu*

## 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 (Lobell et al. 2011; 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 depend heavily on agriculture. The objective of this article is to provide empirical evidence on the impact of weather variability on rice yield in China, using a unique county-level panel on rice yield and weather.

Rice is the most important food crop in China's agricultural economy, accounting for 30% of the total grain area, 50% of the total grain output, and nearly 40% of the nation's caloric intake (Huang and Rozelle 1996; NBS 2000-2009). China is also the world's largest rice producer, accounting for 28% of world rice production in 2012 (Fao 2012). Therefore, how weather variations affect China's rice sector is of critical importance to the welfare of China's domestic population of 1.4 billion and can have profound impacts on rice supply and prices worldwide.

Many studies have evaluated the impacts of temperature and solar radiation on rice yield. The predominant tool was agronomic research based on field trials and greenhouse experiments. The growth of the rice plant can be divided 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. These agronomic studies found that higher daily average temperature ($T_{\text{ave}}$) and decreased solar radiation (global dimming) reduce rice yield (Krishnan et al. 2007; Seshu and Cady 1984; Wassmann et al. 2009; Yoshida and Parao 1976), with the effects varying across the plant's three growth stages. Recent studies

* Shuai Chen, College of Environmental Science and Engineering, Peking University, Beijing, China 100871, email: chen__shuai@163.com. Xioguang Chen, Research Institute of Economics and Management, Southwestern University of Finance and Economics, No. 55 Guanghuacun Street, Chengdu, China 610074, email: cxg@swufe.edu.cn. Jintao Xu, National School of Development, Peking University, Beijing, China 100871, email: xujt@pku.edu.cn. Authorship is alphabetical. All correspondence should be addressed to Xiaoguang Chen.

discovered that rice yield responded differently to daily maximum temperature ($T_{max}$) and daily minimum temperature ($T_{min}$), and that the impacts of temperature and solar radiation could potentially be confounding (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 insignificant. In contrast, 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 $T_{min}$ but was positively correlated with higher $T_{max}$, while the radiation impacts varied by growth stage. Despite these findings, in a review article on the impacts of climate change on rice yield, Wassmann et al. (2009) concluded that "research into the effect of high night temperature is not understood well and should be prioritized."

A few studies have evaluated the impacts of climate change on rice yield in China (Chen et al. 2014; Zhang et al. 2010). Using data from 20 experiment stations, Zhang et al. (2010) showed that rice yield was positively correlated with temperature. Based on province-level data, Chen et al. (2014) found that higher average temperature raised single cropping rice yield, but reduced the yield of double cropping rice. Crop simulation models have also been used to assess the climate impact on rice yield in China (Yang et al. 2014; Yao et al. 2007). However, fundamental aspects of these models have been questioned (Schlenker et al. 2006), because they cannot represent real agricultural settings and because they ignore farmers' contemporaneous responses to changing climate conditions.

This article estimates the relationship between weather variables and rice yield in China, using a newly available county-level panel. The dataset includes county-specific rice yield and daily weather outcomes that spanned most Chinese counties from 2000 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 $T_{max}$, $T_{min}$, rainfall, and solar radiation. This detail enabled us to construct county-specific weather variables across three growth stages of rice for all rice-producing counties. We also used estimated coefficients of weather variables to quantify the net economic impact of weather variability on China's rice sector over the sample period.

To conduct the analysis, we developed a fixed-effects spatial error model to estimate the link between rice yield and weather variables. The model controlled county fixed effects to remove the unobserved factors that are unique to each county and do not vary over time (e.g., soil quality and crop production/management practices), and year fixed effects to remove the unobserved factors that are common to all counties in a given year (such as seed variety). We also controlled for the potential spatial correlations of the error terms. In addition to weather variables, we included socioeconomic variables in some model specifications. These estimation strategies are expected to increase the precision of coefficient estimates of weather variables.

In contrast to nearly all previous studies focusing on rice production in tropical/subtropical regions, we found that higher $T_{\min}$ during the vegetative stage increased rice yield in China. Consistent with other studies, higher $T_{\max}$ during the vegetative and ripening stages reduced yield. Although farmers actively undertook steps to adapt rice production to higher temperatures, our estimates indicate that the changes in weather conditions caused a net economic loss of approximately $25.2-$60.7 million in China's rice sector during the past decade. As the first county-level analysis estimating the relationship between weather and rice yield in China, we provide new evidence on the effect of high nighttime temperature on rice yield. Our results may also generate important public policy implications for the formation of China's future national and global climate strategies.

## Empirical Model

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

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

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

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 $T_{\max}$ and $T_{\min}$ and sums of solar radiation and rainfall for three rice growth stages (a total of twelve weather variables). Other control variables are denoted by $A_{r,t}$, which includes economic variables (i.e., output-input price ratios that control for the effect of the use of inputs on rice yield, such as fertilizer and labor) and farmers' contemporaneous climate adaptation behaviors. We also controlled both county-level fixed effects (represented by $\alpha_r$) and year fixed effects (denoted by $\lambda_t$) to remove the unobserved factors unique to each county or common to all counties in a given year. $\varepsilon_{r,t}$ are the error terms that represent the impacts of factors other than weather, economic, and adaptation variables on rice yield. $\beta$ is the parameter vector that gives the responses of rice yield to weather variations.

In addition to weather variables, to capture the effects of the change in rice price and prices of inputs used for rice production on yield, we included output-input price ratios as additional explanatory variables in some model specifications (as in Welch et al. 2010). We used lagged rice price in year *t*-1 as a proxy for expected rice price in year *t* (Braulke 1982; Nerlove 1956). Because of the limited data on other input prices, we included fertilizer price index and wage as input prices and constructed rice-fertilizer and rice-labor price ratios. Because other input prices (such as chemicals and machinery) are unlikely to be highly correlated with weather, the exclusion of these variables is not expected to have a significant impact on coefficient estimates of $\beta$ . Here, the use of province-level price data is reasonable, because Chinese farmers usually operate small farms[1] and thus are price takers in rice, labor, and fertilizer markets. However, the two price ratios may be endogenous, as argued by Roberts and Schlenker (2013). Drawing on their work, we used weather variables in the previous year as instruments to address this potential endogeneity issue. As shown in the results section, regression results were only marginally different if the two price ratios were considered to be exogenous.

Most rice production in China is irrigated. However, farmers can still take adaptation actions, such as adjusting crop production practices, investing in new technology to save irrigated water, and increasing irrigation water usage in warmer seasons, to mitigate the adverse effects of weather change on yield (Howden et al. 2007). These adaptation behaviors can affect rice yield, and the need for these behaviors is largely dependent on local weather variations. Therefore, omitting these adaptation variables from a regression model may cause biased estimates of the true weather effects. With the lack of other relevant information, we used the ratio of irrigated acres to total planted acres of all crops in a county as a proxy to control for the possibility of farmers' contemporaneous adaptation behaviors. This variable is also potentially endogenous because it reflects farmers' responses to changes in weather conditions. To address this issue, we used the irrigation ratio in the previous year to serve as the instrument for farmers' irrigation behavior in the current year. Past irrigation behavior is a good instrument because it affects farmers' irrigation behaviors in subsequent periods due to the large investment made in irrigation infrastructure, such as vertical wells and irrigation canals. But it has zero covariance with unobserved factors affecting rice yield in the current period. Unobserved factors might stem from the omission of input use, unanticipated pest problems, and regional-specific agricultural

[1] China's per capita farmland is about 0.13 hectare (ha), which is 40% less than the global average; see http://faostat.fao.org/site/377/default.aspx#ancor.

production practices. With the use of the instrumental variable, we lost the observations in 2000. To make results comparable across different model specifications, we used the data consistently for years 2001-2009 for all model specifications.

As shown in Equation (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 $\text{var}[\phi_{r,t}] = \sigma^2$, $\rho$ 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. We first 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. Under the spatial contiguity matrix, the (*r, r'*) element of the spatial matrix is unity if counties *r* and *r'* share a common boundary, and 0 otherwise. The contiguity matrix is then normalized so that the elements in each row sum to unity. However, the spatial contiguity matrix allows the possibility that counties share only a single boundary point (such as a shared corner point on a grid of counties). Thus, we considered two alternative 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 the county *r*. All spatial panel models controlled for spatial fixed effects and were estimated using maximum likelihood (Anselin 1988).

## Data

County-specific total rice production and planted acres were obtained from the National Bureau of Statistics of China (NBS) for years 2000-2009. From the same source, we obtained total planted and irrigated acres of all crops for all rice-producing counties in China. 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. This gave us 6,939 observations with 771 counties. The sample represented about 50% of the total rice production in China. As shown in Table 1, rice yield varied substantially in the sample**,** ranging between

1,842-14,240 kg·ha$^{-1}$ with an average of 7,138 kg·ha$^{-1}$. Rice growing seasons in different areas were obtained from the Department of Agriculture of China.[2]

Weather data were obtained from the China Meteorological Data Sharing Service System (CMDSSS), which records daily $T_{\mathrm{min}}$, $T_{\mathrm{max}}$, $T_{\mathrm{ave}}$, rainfall, and solar radiation for 820 weather stations in China. The CMDSSS measures solar radiation using the number of hours in each day during which the sunshine is above 200 megawatts/cm$^2$. The dataset also contains exact coordinates of each weather station, enabling them to be merged with our county-level yield data. 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 climatic information from the contiguous counties for counties without a weather station.

Trends for $T_{\mathrm{min}}$, $T_{\mathrm{max}}$, $T_{\mathrm{ave}}$, and solar radiation during the three rice-growth stages are shown in Figure 1. On average, the observed $T_{\mathrm{min}}$ and $T_{\mathrm{max}}$ 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, a phenomenon known as global dimming (Huang et al. 2006; Ramanathan et al. 2005).

We obtained province-level economic data on rice price and fertilizer price indices from the China Yearbook of Agricultural Price Surveys (NBS 2012). County-specific labor costs are not available. Labor costs were measured using average wage for farm labor and obtained from the NBS.[3]

## Empirical Results

### *Data Correlations*

Before presenting our regression results, we first examined the presence of spatial correlations of the error terms in the regression model by performing Moran's *I* test (Anselin 1988) for each of our three spatial weighting matrices. We also supplemented Moran's *I* test with three alternative tests, namely the Lagrange Multiplier (LM) ERR test, the Likelihood Ratio (LR) test and the Wald test. We conducted these tests using the same set of explanatory variables as in the estimation of the yield equations, including weather, economic, and adaptation variables. As

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

[3] http://data.stats.gov.cn/workspace/index?m=fsnd.

shown in Table 2, these test results indicate that spatial correlations of the error terms in the regression model are quite large. The parameters of spatial correlations are 0.69 under the contiguity matrix and the distance matrix that weights the six nearest neighbors, and become smaller (0.62) under the distance matrix that weights 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 a spatial weighting matrix. We examined the robustness of our results using other spatial weighting matrices.

Table 3 presents the correlations of weather variables. We found that: (*i*) $T_{\min}$ and solar radiation were moderately (and positively) correlated in the vegetative and reproductive stages, but the correlation of the two variables in the ripening stage was not statistically significant; (*ii*) $T_{\min}$ and solar 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.

### *Regression Results*

We conducted the spatial error analysis using five different model specifications. In Model (1), we included the three $T_{\min}$ variables as the only explanatory variables to examine the variations in rice yield during the sample period. In Model (2), we added the three solar radiation variables as additional explanatory variables. In Model (3), we included the $T_{\max}$ variables to examine whether daily maximum temperature played a significant role in influencing county-average rice yield. In Model (4), we incorporated rainfall. Lastly, in Model (5), we added the two price ratios and the irrigation ratio and examined whether the inclusion of these variables affects our coefficient estimates of weather variables. All model specifications included time-invariant county fixed effects to control for the possibility of unobserved characteristics within each county and year fixed effects to remove the unobserved factors common to all counties in a given year.

Table 4 shows parameter estimates of weather variables for different model specifications. 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, with the exception of radiation in Model (2), where $T_{\min}$ and radiation are the only explanatory variables. Rice yield was not significantly affected by the temperature and radiation variables during the reproductive stage in any of the model specifications considered here.

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 in China had a positive impact on rice yield. For instance, in Model (5) with weather, economic and adaption variables, a 1°C increase in $T_{\min}$ during the vegetative stage increased rice yield by 133.3 $kg \cdot ha^{-1}$. Existing literature emphasizes 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), cause low pollen viability, and hasten crop maturity during the ripening stage (Mohammed and Tarpley 2009a). Agronomic studies also suggest that if $T_{\min}$ is above 25°C during the vegetative stage, it can lead to significant damage to rice growth 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 are greater than 25°C. We also found that average $T_{\min}$ during the three rice-growth stages in our sample were 6.5-9.4°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 may 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).

Higher $T_{\max}$ had negative impacts on rice yield during the vegetative and ripening phases, which is in agreement with well-established previous assessments (Lobell and Field 2007; Wassmann et al. 2009). Higher $T_{\max}$ hurts rice growth through altered pollen germination and spikelet fertility, increased respiration rates, and decreased membrane thermal stability (Mohammed and Tarpley 2009b; Mohammed and Tarpley 2009a; Wassmann et al. 2009).

Coefficient estimates of other weather and socioeconomic variables have expected signs. We found that the impacts of radiation on yield varied by growth stage. Estimated effect of radiation on rice yield is negative during the vegetative stage and is positive during the ripening stage, which is similar to the findings in other regions (for example, see Welch et al. 2010). Parameter estimates of rice-fertilizer and rice-labor price ratios are positive, but not statistically significant (see results in last column of Table 4). To control for the effect of possible adaptation to changes in weather conditions on rice yield, in Model (5) we added the ratio of irrigated acres to total planted acres in a county. When this adaptation variable is included, the results show that adaptation had a positive effect on rice yield, suggesting that adaptation of rice production effectively reduced the negative effects of higher temperatures on yield. In light of the fact that most rice production in China is irrigated, it is not surprising to see that rainfall had an insignificant impact on rice yield across the model specifications considered here.

We found that the addition of radiation in Model (2) only modestly affected parameter estimates of $T_{\min}$ as compared to Model (1), which is not surprising given the small correlation between $T_{\min}$ and radiation. Because $T_{\min}$ and radiation were highly correlated with $T_{\max}$, the inclusion of $T_{\max}$ in Model (3) doubled the parameter estimate of $T_{\min}$ during the vegetative phase as compared to the parameter estimates in Models (1)-(2), while reducing the parameter estimate of solar radiation during the vegetative stage by 35%. The addition of $T_{\max}$ also made the effect of radiation on yield insignificant during the reproductive stage, and significant ($p<0.05$) during the ripening stage. Therefore, our results confirm the necessity of jointly analyzing the impacts of $T_{\max}$, $T_{\min}$ and solar radiation on rice yield, and excluding $T_{\max}$ can lead to biased parameter estimates of $T_{\min}$ and radiation and their statistical significance. Parameter estimates of the temperature and radiation variables changed modestly with the inclusion of rainfall and price and irrigation ratios, which shows the robustness of our results.

### *Marginal Effects*

Table 4 shows how rice yield changed when the temperature and radiation variables increased by an additional unit, holding all other variables in the regression constant. However, the weather variables have different units and exhibited different patterns of change over time, which prevented effective comparison of the marginal effects of the weather variables. To overcome this difficulty, we computed the marginal effects by multiplying parameter estimates of the weather variables, whose parameter estimates are statistically significant, by the standard deviations (SDs) of the corresponding weather variables. As shown in Table 5, the two largest marginal effects per SD were for $T_{\max}$ and $T_{\min}$ during the vegetative stage (-54.0 $\text{kg}\cdot\text{ha}^{-1}$ and 53.9 $\text{kg}\cdot\text{ha}^{-1}$), respectively, followed by $T_{\max}$ during the ripening stage (-38.5 $\text{kg}\cdot\text{ha}^{-1}$). The marginal effects per SD of radiation during the vegetative and ripening stages were opposite, -32.3 $\text{kg}\cdot\text{ha}^{-1}$ and 33.1 $\text{kg}\cdot\text{ha}^{-1}$, respectively, and the absolute values of their marginal affects were smaller than those of the temperature variables.

### *Sensitivity Analysis*

The results presented above regarding the impacts of weather variability on rice yield make intuitive sense. In this section, we examine how robust they are across different spatial weighting matrices, econometric estimation strategies and variables. 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 without using instrumental variables to address the potential endogeneity of the two price ratios and irrigation ratio, and assumed that they were exogenous. In Scenarios (1)-(3), we used the same set of explanatory variables as in Model (5) in the baseline analysis. Lastly, in Scenario (4), we used average temperature ($T_{ave}$) instead of $T_{min}$ and $T_{max}$ as temperature variables to examine the temperature effects on rice yield. Results are presented in Table 6.

In Scenarios (1)-(2), signs, statistical significance and magnitudes of parameter estimates of weather variables are only slightly different from the baseline estimates, despite the considerable difference in the spatial weighting matrices used. That indicates that our results are generally insensitive to the chosen spatial weighting matrix. In Scenario (3), with endogenous price and irrigation ratios, we found that estimated coefficients of the weather variables changed marginally as compared to the baseline estimates. The parameter estimate of the rice-fertilizer price ratio now is positive and statistically significant, indicating that the increase in fertilizer prices might have resulted in reduced use of fertilizer and might have had detrimental effects on county-average rice yield. The parameter estimate of the rice-labor price ratio is positive, but statistically insignificant. In Scenario (4), we used daily $T_{ave}$ as temperature variables rather than $T_{min}$ and $T_{max}$. Consistent with the previous studies (Welch et al. 2010), the impacts of $T_{ave}$ on rice yield were not statistically significant for rice's three growth stages.

### *Economic Impact of Weather Variability on China's Rice Sector*

Estimated parameters of the weather variables were used to investigate the net economic impact of weather variability on China's rice sector. We first used these coefficient estimates to measure the change ($\delta_t$) in rice yields for years 2001-2009 that have resulted from the changes in weather conditions relative to year 2000:

$$\delta_t = E(Y \mid Z_{2000}, A_t) - E(Y \mid Z_t, A_t) \tag{3}$$

where $E(Y \mid Z_{2000}, A_t)$ denotes the expected rice yield with 2000 levels of weather outcomes and socioeconomic variables in year $t$= 2001-2009, and $E(Y \mid Z_t, A_t)$ represents the expected rice yield with all variables in year $t$. In other words, $\delta_t$ measures the change in rice yield because of weather variability. Using Equation (1), we can rewrite (3) as:

$$\delta_t = \beta(Z_{2000} - Z_t) \tag{4}$$

where $\beta$ is the coefficient vector of the relationship between weather and rice yield. Replacing $\beta$ with its estimated coefficients provides an estimate of $\delta_t$.

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 2001-2009), to get a rough estimate of the change in total rice production in China in the past decade due to weather variations. We multiplied the change in total rice production by its market price in 2009 to get an estimate of the net economic impact of weather variability on China's rice sector.

As shown in Figure 2, the most noticeable result is that increased $T_{\min}$ had a positive economic impact, whereas higher $T_{\max}$ had a negative economic impact. Declining radiation had a positive impact during the vegetative stage, while the effect was negative during the ripening stage. The sum of the absolute values of the positive impact of $T_{\min}$ and radiation during the vegetative stage was smaller than the sum of the absolute values of the negative impact of $T_{\max}$ and radiation during the ripening stage. Combined, these results indicate that weather variability resulted in a net economic loss of approximately \$38.4 million in China's rice sector in the past decade. The signs and magnitudes of the estimated economic impact were robust across the scenarios considered in the sensitivity analysis, ranging between \$25.2 million and \$60.7 million.

## Conclusions

This article is the first county-level analysis of the impacts of weather variability on rice yield in China. Using a unique county-level panel on rice yield and daily weather data in China over multiple years, we investigated the impacts of weather variability on rice yield, while controlling for unobserved factors that varied across counties over time and the potential spatial correlations of these unobserved factors. Using estimated coefficients of weather variables, we also estimated the net economic impact of weather variability on China's rice sector.

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 differences in the data analyzed, particularly by the difference between China and other countries in the average minimum temperatures. Our finding 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, and a positive impact of increased radiation during the ripening stage are consistent with the existing literature.

Given the large correlation between $T_{\max}$ and $T_{\min}$ in our data, our results confirmed the necessity to jointly analyze the impacts of $T_{\max}$ and $T_{\min}$. We found that excluding $T_{\max}$ caused biased parameter estimates of $T_{\min}$ and radiation and their statistical significance. The exclusion of $T_{\max}$ in the regression analysis can even lead to directional change in the assessment of the economic impact of weather variability on China's rice sector (see Figure 3).

Our finding of a positive impact of increased proportion of land under irrigation provided the empirical evidence that adaptation of rice production to changing weather conditions effectively reduced the negative impacts of higher temperatures on rice yield. Omitting this adaptation variable in the regression analysis can overestimate the net economic impact of weather variability by $22 million (see Figure 3). There are many other possible adaptation actions that rice farmers can take, such as changing the locations or seasons in which rice is grown and adjusting production practices (Howden et al. 2007). The lack of relevant information on these adaptation behaviors constrained us from accounting for their impacts on rice yield.

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 are 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, our dataset covered observations for the past decade only, yet our results are remarkably significant and robust. With a longer time period of observations, the net economic cost because of weather variability could be even larger. Third, our analysis focused on the impacts of the changes in temperature, precipitation, and radiation, but did not consider the impact of $CO_2$ fertilization on crop yields. Laboratory studies have found that higher $CO_2$ fertilization may offset yield reductions due to warmer climate (Long et al. 2006).

## References


Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht, Boston: Kluwer Academic Publishers.

Braulke, M. 1982. A Note on the Nerlove Model of Agricultural Supply Response. *International Economic Review* 23(1): 241-244.

Chen, C., G.-s. Zhou, and L. Zhou. 2014. Impacts of Climate Change on Rice Yield in China from 1961 to 2010 Based on Provincial Data. *Journal of Integrative Agriculture* 13(7): 1555-1564.

FAO (2012) Faostat-Agriculture, Food and Agricultural Organizations of the United Nations. Available online at: http://www.fao.org/corp/statistics/en/, pp. Food and Agricultural Organizations of the United Nations.

Howden, S. M., J.-F. Soussana, F. N. Tubiello, N. Chhetri, M. Dunlop, and H. Meinke. 2007. Adapting Agriculture to Climate Change. *Proceedings of the National Academy of Sciences of the United States of America* 104(50): 19691-19696.

Huang, J., and S. Rozelle. 1996. Technological Change: Rediscovering the Engine of Productivity Growth in China's Rural Economy. *Journal of Development Economics* 49(2): 337-369.

Huang, Y., R. E. Dickinson, and W. L. Chameides. 2006. Impact of Aerosol Indirect Effect on Surface Temperature over East Asia. *Proceedings of the National Academy of Sciences of the United States of America* 103(12): 4371-4376.

Kanno, K., T. Mae, and A. Makino. 2009. High Night Temperature Stimulates Photosynthesis, Biomass Production and Growth During the Vegetative Stage of Rice Plants. *Soil Science and Plant Nutrition* 55(1): 124-131.

Krishnan, P., D. K. Swain, B. Chandra Bhaskar, S. K. Nayak, and R. N. Dash. 2007. Impact of Elevated Co2 and Temperature on Rice Yield and Methods of Adaptation as Evaluated by Crop Simulation Studies. *Agriculture, Ecosystems & Environment* 122(2): 233-242.

Lobell, D. B., and G. P. Asner. 2003. Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields. *Science* 299(5609): 1032.

Lobell, D. B., M. Banziger, C. Magorokosho, and B. Vivek. 2011. Nonlinear Heat Effects on African Maize as Evidenced by Historical Yield Trials. *Nature Clim. Change* 1(1): 42-45.

Lobell, D. B., and C. B. Field. 2007. Global Scale Climate–Crop Yield Relationships and the Impacts of Recent Warming. *Environmental Research Letters* 2(014002): 1-7.

Long, S. P., E. A. Ainsworth, A. D. B. Leakey, J. Nösberger, and D. R. Ort. 2006. Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising Co2 Concentrations. *Science* 312(5782): 1918-1921.

McCarl, B. A., X. Villavicencio, and X. Wu. 2008. Climate Change and Future Analysis: Is Stationarity Dying? *American Journal of Agricultural Economics* 90(5): 1241-1247.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw. 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis. *The American Economic Review* 84(4): 753-771.

Mohammed, A.-R., and L. Tarpley. 2009b. Impact of High Nighttime Temperature on Respiration, Membrane Stability, Antioxidant Capacity, and Yield of Rice Plants. *Crop Sci.* 49(1): 313-322.

Mohammed, A. R., and L. Tarpley. 2009a. High Nighttime Temperatures Affect Rice Productivity through Altered Pollen Germination and Spikelet Fertility. *Agricultural and Forest Meteorology* 149(6-7): 999-1008.

NBS. 2000-2009. *China Statistical Database.* National Bureau of Statistics of China.

———. 2012. *China Yearbook of Agricultural Price Survey*: National Bureau of Statistics of China, Chinese Statistics Press.

Nerlove, M. 1956. Estimates of the Elasticities of Supply of Selected Agricultural Commodities. *Journal of Farm Economics* 38(2): 496-509.

Olesen, J. E., and M. Bindi. 2002. Consequences of Climate Change for European Agricultural Productivity, Land Use and Policy. *European Journal of Agronomy* 16(4): 239-262.

Peng, S., J. Huang, J. E. Sheehy, R. C. Laza, R. M. Visperas, X. Zhong, G. S. Centeno, G. S. Khush, and K. G. Cassman. 2004. Rice Yields Decline with Higher Night Temperature from Global Warming. *Proceedings of the National Academy of Sciences of the United States of America* 101(27): 9971-9975.

Ramanathan, V., C. Chung, D. Kim, T. Bettge, L. Buja, J. T. Kiehl, W. M. Washington, Q. Fu, D. R. Sikka, and M. Wild. 2005. Atmospheric Brown Clouds: Impacts on South Asian Climate and Hydrological Cycle. *Proceedings of the National Academy of Sciences of the United States of America* 102(15): 5326-5333.

Roberts, M. J., and W. Schlenker. 2013. Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the Us Ethanol Mandate. *American Economic Review* 103(6): 2265-2295.

Schlenker, W., W. M. Hanemann, and A. C. Fisher. 2006. The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions. *Review of Economics and Statistics* 88(1): 113-125.

Schlenker, W., and M. J. Roberts. 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences of the United States of America* 106(37): 15594-15598.

Seshu, D. V., and F. B. Cady. 1984. Response of Rice to Solar Radiation and Temperature Estimated from International Yield Trials. *Crop Sci.* 24(4): 649-654.

Wassmann, R., S. V. K. Jagadish, S. Heuer, A. Ismail, E. Redona, R. Serraj, R. K. Singh, G. Howell, H. Pathak, and K. Sumfleth. 2009. Climate Change Affecting Rice Production: The Physiological and Agronomic Basis for Possible Adaptation Strategies. In L.S. Donald (ed.), *Advances in Agronomy,* vol. 101, pp. 59-122, Academic Press, an imprint of Elsevier.

Welch, J. R., J. R. Vincent, M. Auffhammer, P. F. Moya, A. Dobermann, and D. Dawe. 2010. Rice Yields in Tropical/Subtropical Asia Exhibit Large but Opposing Sensitivities to Minimum and Maximum Temperatures. *Proceedings of the National Academy of Sciences of the United States of America* 107(33): 14562-14567.

Yang, J., W. Xiong, X.-g. Yang, Y. Cao, and L.-z. Feng. 2014. Geographic Variation of Rice Yield Response to Past Climate Change in China. *Journal of Integrative Agriculture* 13(7): 1586-1598.

Yao, F., Y. Xu, E. Lin, M. Yokozawa, and J. Zhang. 2007. Assessing the Impacts of Climate Change on Rice Yields in the Main Rice Areas of China. *Climatic Change* 80(3-4): 395-409.

Yoshida, S., and F. Parao. 1976. *Climatic Influence on Yield and Yield Components of Lowland Rice in the Tropics*. Proceedings of the Symposium on Climate and Rice (International Rice Research Institute, Los Baños, Philippines), pp. 471-491.

Yoshida, S., T. Satake, and D. Mackill. 1981. High Temperature Stress. IRRI Res. Pap. 67, 1-15.

Zhang, T., J. Zhu, and R. Wassmann. 2010. Responses of Rice Yields to Recent Climate Change in China: An Empirical Assessment Based on Long-Term Observations at Different Spatial Scales (1981-2005). *Agricultural and Forest Meteorology* 150(7-8): 1128-1137.

Ziska, L., and P. Manalo. 1996. Increasing Night Temperature Can Reduce Seed Set and Potential Yield of Tropical Rice. *Functional Plant Biology* 23(6): 791-794.

## Tables and Figures

### Table 1. Summary Statistics: Means (SDs) of Rice Yield, Temperature, Rainfall, and Solar Radiation

| Variable | Rice-growth stage | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Yield ($kg \cdot ha^{-1}$) | | 7,138.9 | 1,480.2 | 1,842.1 | 14,240.0 |
| $T_{min}$ (°C) | *Vegetative* | 15.2 | 4.0 | 0.7 | 26.2 |
| | *Reproductive* | 20.7 | 3.0 | 1.7 | 27.3 |
| | *Ripening* | 16.4 | 3.8 | -2.1 | 25.4 |
| $T_{max}$ (°C) | *Vegetative* | 25.3 | 3.4 | 9.2 | 34.3 |
| | *Reproductive* | 29.4 | 2.9 | 14.7 | 37.3 |
| | *Ripening* | 25.8 | 2.8 | 11.9 | 35.4 |
| $T_{ave}$ (°C) | *Vegetative* | 19.8 | 3.6 | 5.0 | 29.2 |
| | *Reproductive* | 24.5 | 2.8 | 9.8 | 31.7 |
| | *Ripening* | 20.4 | 3.0 | 4.9 | 29.6 |
| Radiation (hours) | *Vegetative* | 5.9 | 1.9 | 1.8 | 11.4 |
| | *Reproductive* | 5.8 | 1.9 | 0.8 | 12.0 |
| | *Ripening* | 5.4 | 2.0 | 0.8 | 10.4 |
| Rainfall (cm) | *Vegetative* | 43.2 | 20.4 | 0.2 | 135.9 |
| | *Reproductive* | 18.4 | 12.3 | 0.0 | 96.6 |
| | *Ripening* | 18.3 | 13.2 | 0.0 | 98.7 |

*Note*: Numbers are based on single-season rice growing counties in China for years 2001-2009. Means for $T_{min}$, $T_{max}$, $T_{ave}$, and sums for radiation and rainfall. Number of observations = 6939.

### Table 2. Tests for the Presence of Spatial Correlations of the Error Terms of the Spatial Error Model

| Spatial weighting matrix | Contiguity matrix | Distance matrix(six) | Distance matrix(four) |
|---|---|---|---|
| Moran-*I* *N(0,1)* | 18.62 | 19.75 | 18.28 |
| LM-ERR $\chi^2(1)$ | 306.91 | 337.95 | 300.51 |
| LRatio $\chi^2(1)$ | 250.21 | 252.24 | 257.47 |
| Walds $\chi^2(1)$ | 4076.55 | 2357.80 | 3429.14 |
| Parameter of spatial correlation | 0.69 | 0.69 | 0.62 |

*Note*: We used three spatial weighting matrices to examine the sensitivity of our results to proposed weighting matrices. Under the spatial contiguity matrix, the (*r, r'*) element of the matrix is unity if counties *r* and *r'* share a common boundary, and 0 otherwise. The matrix is then normalized so that the elements in each row sum to unity. Distance matrices are inverse distance weighting matrices that weight the six and four nearest neighbors, respectively, according to their physical distance, and assign zero to other counties. The distance matrices are then normalized to have row sums of unity. We examined the presence of the spatial correlations of the error terms by performing Moran's *I* test, the Lagrange Multiplier (LM) ERR test, the Likelihood Ratio (LRatio) test and the Wald test.

**Table 3. Correlations among Weather Variables by Rice Growth Stage**

| Phase | Variable | $T_{min}$ | $T_{max}$ | Radiation |
|---|---|---|---|---|
| *Vegetative* | $T_{max}$ | 0.5950* | - | - |
| | Radiation | 0.1232* | 0.4984* | - |
| | Rainfall | -0.1165* | -0.3300* | -0.2819* |
| *Reproductive* | $T_{max}$ | 0.5172* | - | - |
| | Radiation | 0.0806* | 0.6886* | - |
| | Rainfall | -0.1298* | -0.4875* | -0.4222* |
| *Ripening* | $T_{max}$ | 0.5096* | - | - |
| | Radiation | -0.0277 | 0.5783* | - |
| | Rainfall | -0.1016* | -0.4221* | -0.2842* |

*Note*: *$p$<0.05.

**Table 4. Regression Results: Impacts of Weather, Economic and Adaptation Variables on Rice Yield (kg·ha$^{-1}$)**

| Variables | Model (1): $T_{min}$ only | Model (2): add radiation | Model (3): add $T_{max}$ | Model (4): add rainfall | Model (5): add economic and adaptation variables |
|---|---|---|---|---|---|
| $T_{min}$: vegetative | 55.95$^{**}$ | 65.85$^{**}$ | 134.68$^{***}$ | 136.29$^{***}$ | 133.30$^{***}$ |
| | (2.15) | (2.51) | (4.03) | (4.07) | (3.95) |
| $T_{min}$: reproductive | -0.13 | -4.38 | -13.53 | -13.88 | -6.94 |
| | (-0.01) | (-0.25) | (-0.62) | (-0.63) | (-0.29) |
| $T_{min}$: ripening | -3.73 | -15.17 | 1.00 | 4.27 | 9.62 |
| | (-0.20) | (-0.81) | (0.04) | (0.18) | (0.38) |
| Radiation: vegetative | | -72.65$^{***}$ | -46.96$^{**}$ | -49.65$^{**}$ | -55.24$^{***}$ |
| | | (-3.99) | (-2.23) | (-2.33) | (-2.57) |
| Radiation: reproductive | | 17.38$^{*}$ | 4.96 | 4.75 | 10.16 |
| | | (1.88) | (0.36) | (0.34) | (0.72) |
| Radiation: ripening | | 19.29 | 42.21$^{**}$ | 43.04$^{**}$ | 42.10$^{**}$ |
| | | (1.44) | (2.27) | (2.31) | (2.22) |
| $T_{max}$: vegetative | | | -80.76$^{***}$ | -86.09$^{***}$ | -81.23$^{***}$ |
| | | | (-3.36) | (-3.53) | (-3.29) |
| $T_{max}$: reproductive | | | 9.66 | 9.72 | -5.34 |
| | | | (0.49) | (0.48) | (-0.21) |
| $T_{max}$: ripening | | | -48.41$^{**}$ | -54.92$^{**}$ | -47.97$^{**}$ |
| | | | (-2.32) | (-2.48) | (-1.96) |
| Rainfall: vegetative | | | | -1.12 | -1.27 |
| | | | | (-1.26) | (-1.38) |
| Rainfall: reproductive | | | | 0.20 | 0.50 |
| | | | | (0.15) | (0.36) |
| Rainfall: ripening | | | | -1.12 | -0.98 |
| | | | | (-0.85) | (-0.73) |
| Price ratio: rice/fertilizer | | | | | 996.57 |
| | | | | | (0.35) |
| Price ratio: rice/wage | | | | | 2561.47 |
| | | | | | (0.58) |
| Irrigation ratio | | | | | 474.25$^{***}$ |
| | | | | | (5.44) |
| *Parameter of spatial correlation* | 0.3869 | 0.3849 | 0.3769 | 0.3739 | 0.3819 |
| *N* | 6939 | 6939 | 6939 | 6939 | 6939 |
| $R^2$ | 0.8025 | 0.8034 | 0.8046 | 0.8048 | 0.8064 |

*Note*: 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.

$^{*}$ $p < 0.1$,

$^{**}$ $p < 0.05$,

$^{***}$ $p < 0.01$.

### Table 5. Marginal Effects of Weather Variables Expressed per SD: Regression Model that Included Weather, Economic and Adaption Variables

| Variable | Growth phase | SD based on residual variation | Marginal effect ($kg \cdot ha^{-1}$ per SD) |
|---|---|---|---|
| $T_{min}$ | *Vegetative* | 0.404 °C | 53.854 |
| Radiation | *Vegetative* | 0.585 hour | -32.328 |
| | *Ripening* | 0.787 hour | 33.149 |
| $T_{max}$ | *Vegetative* | 0.666 °C | -54.058 |
| | *Ripening* | 0.802 °C | -38.472 |

*Note*: Marginal effects are shown only for weather variables whose parameter estimates are statistically significant (see Model 5 in Table 4) and were calculated by multiplying parameter estimates by the SDs of the corresponding weather variables. SDs refer to residual variation after removing variation explained by fixed effects for counties and years.

### Table 6. Sensitivity Analysis: Impacts of Weather, Economic and Adaptation Variables on Rice Yield ($kg \cdot ha^{-1}$)

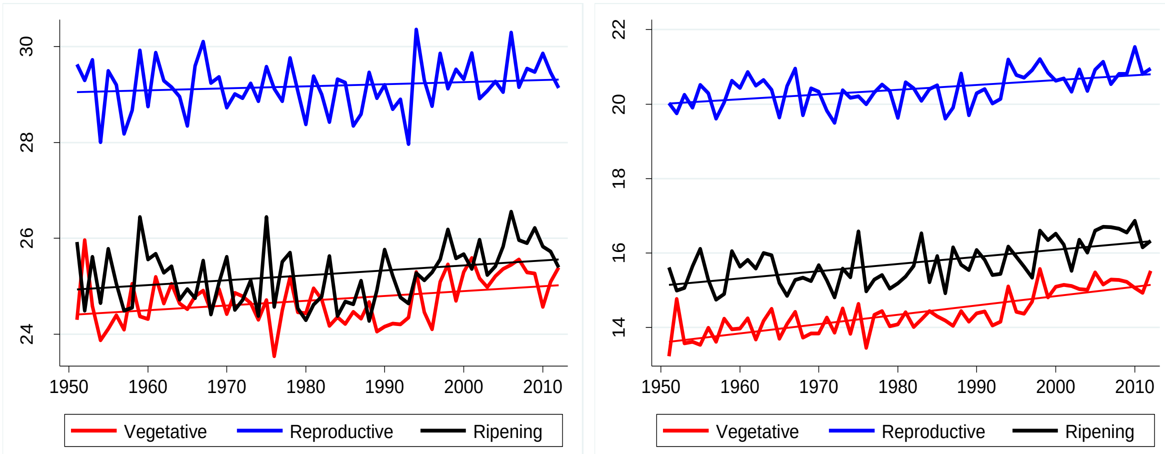
| | Model 5 in Table 4 | Model 5 with Distance matrix(six) | Model 5 with Distance matrix(four) | Model (5) with endogenous socioeconomic variables | Model (5) using $T_{ave}$ as temperature variables |
|---|---|---|---|---|---|
| $T_{min}$: vegetative | 133.30*** | 138.97*** | 138.85*** | 127.91*** | |
| | (3.95) | (4.03) | (4.21) | (3.84) | |
| $T_{min}$: reproductive | -6.94 | -10.62 | -12.75 | -6.71 | |
| | (-0.29) | (-0.43) | (-0.55) | (-0.31) | |
| $T_{min}$: ripening | 9.62 | 16.88 | 21.98 | 1.61 | |
| | (0.38) | (0.64) | (0.88) | (0.07) | |
| Radiation: vegetative | -55.24*** | -56.45*** | -56.48*** | -50.38*** | -84.09*** |
| | (-2.57) | (-2.59) | (-2.66) | (-2.37) | (-4.18) |
| Radiation: reproductive | 10.16 | 8.07 | 6.47 | 4.55 | 24.25** |
| | (0.72) | (0.56) | (0.46) | (0.33) | (2.04) |
| Radiation: ripening | 42.10** | 38.94** | 43.39** | 45.21** | 28.62* |
| | (2.22) | (2.02) | (2.33) | (2.43) | (1.79) |
| $T_{max}$: vegetative | -81.23*** | -80.10*** | -86.33*** | -101.07*** | |
| | (-3.29) | (-3.16) | (-3.59) | (-4.07) | |
| $T_{max}$: reproductive | -5.34 | 2.23 | 8.75 | 9.58 | |
| | (-0.21) | (0.09) | (0.35) | (0.47) | |
| $T_{max}$: ripening | -47.97** | -44.93* | -55.22** | -52.22** | |
| | (-1.96) | (-1.79) | (-2.30) | (-2.37) | |
| Rainfall: vegetative | -1.27 | -1.16 | -1.64* | -1.20 | -0.67 |
| | (-1.38) | (-1.24) | (-1.81) | (-1.35) | (-0.73) |
| Rainfall: reproductive | 0.50 | 0.87 | 0.89 | 0.51 | 0.46 |
| | (0.36) | (0.62) | (0.66) | (0.37) | (0.34) |
| Rainfall: ripening | -0.98 | -0.86 | -1.21 | -0.99 | -0.15 |
| | (-0.73) | (-0.62) | (-0.92) | (-0.75) | (-0.12) |
| Price ratio: rice/fertilizer | 996.57 | 691.57 | 175.78 | 502.97* | 595.61 |
| | (0.35) | (0.24) | (0.06) | (1.72) | (0.17) |
| Price ratio: rice/wage | 2561.47 | 2794.78 | 1043.05 | 269.88 | 2765.78 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.58) | (0.62) | (0.25) | (0.95) | (0.62) |
| Irrigation ratio | 474.25*** | 467.19*** | 456.32*** | 163.53*** | 472.77*** |
| | (5.44) | (5.37) | (5.21) | (3.01) | (5.42) |
| $T_{ave}$: vegetative | | | | | 15.93 |
| | | | | | (0.62) |
| $T_{ave}$: reproductive | | | | | -12.48 |
| | | | | | (-0.61) |
| $T_{ave}$: ripening | | | | | -34.29 |
| | | | | | (-1.49) |
| *Parameter of spatial correlation* | 0.3819 | 0.4059 | 0.3179 | 0.3669 | 0.3819 |
| $R^2$ | 0.8064 | 0.8053 | 0.8055 | 0.8064 | 0.8041 |

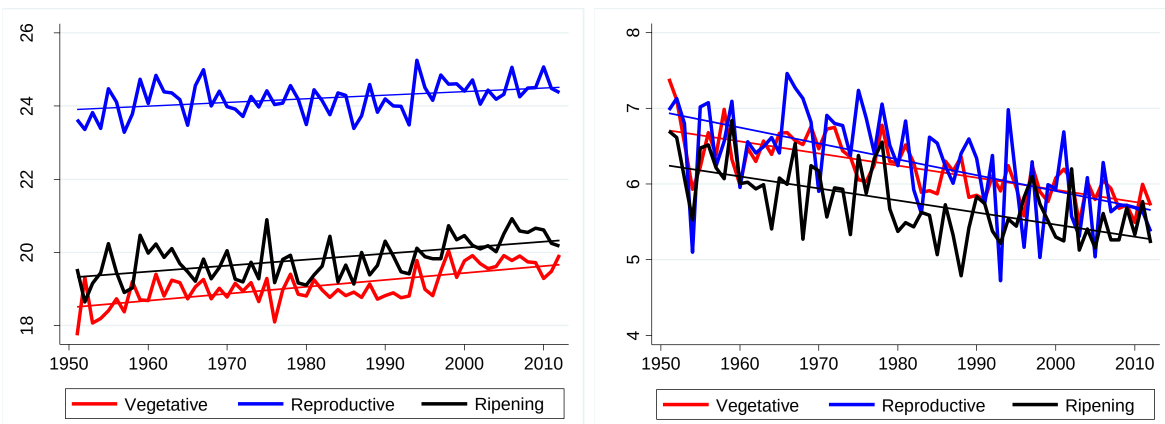
*Note*: We considered four scenarios in sensitivity analysis. In Scenarios (1) and (2), we used distance matrices as the spatial weighting matrices in the spatial error analysis. In Scenario (3), we did not use instrumental variables to address the endogeneity issue of the economic and climate adaptation variables. Scenario (4) included $T_{ave}$ (average temperature) instead of $T_{min}$ and $T_{max}$ as temperature variables. 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 $T_{min}$, $T_{max}$ and $T_{ave}$, hours for solar radiation, and cm for rainfall. Asymptotic t-statistics are shown in parentheses. Number of observations = 6939.

$^{*}$ $p < 0.1$,
$^{**}$ $p < 0.05$,
$^{***}$ $p < 0.01$.

## Figure 1. Yearly Temperature and Solar Radiation by Rice-growth Stage in China, 1950-2010

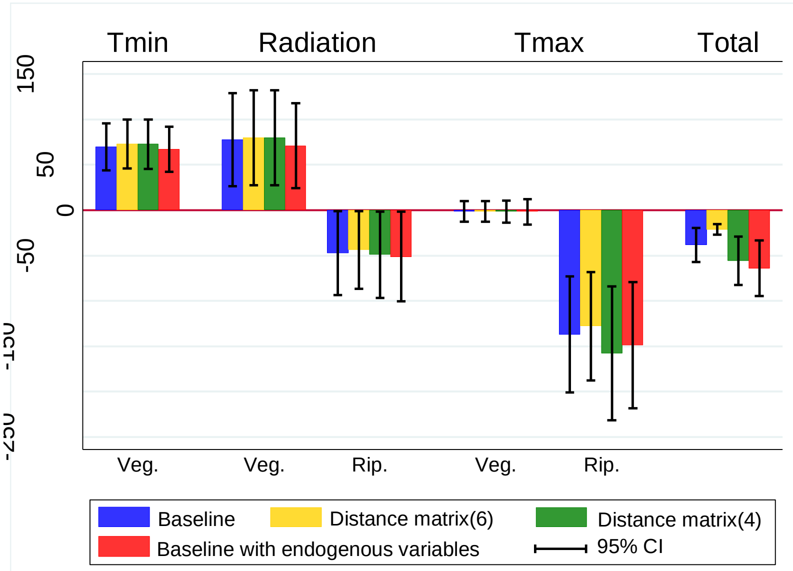



(a) $T_{max}$ (b) $T_{min}$



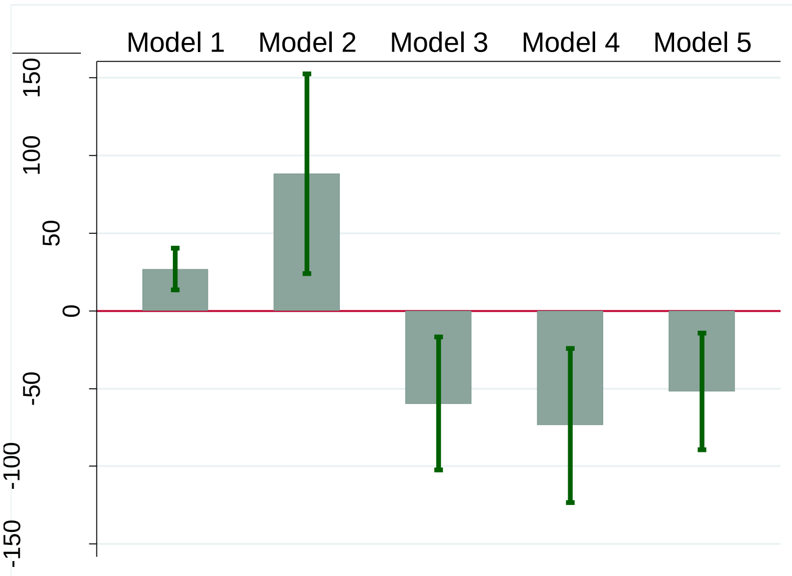

(c) $T_{ave}$ (d) Solar radiation

**Figure 2. Economic Impacts of Temperature and Radiation on China's Rice Sector Due to Weather Variability 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 2001-2009 if weather conditions were maintained at the 2000 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 to obtain the net economic loss due to weather variability. National average rice price in China was RMB 2.1 per kg. The average exchange rate assumed here is RMB 6.8 per US$. Different colors represent the economic impacts of different weather variables. Bars show 95% confidence bands.

**Figure 3. Economic Impacts of Weather Variability on China's Rice Sector under Alternative Model Specifications ($ million)**




*Note*: Model 1 included $T_{min}$ only. Model 2 added radiation. Model 3 added $T_{max}$. Model 4 added rainfall. Model 5 added economic and adaptation variables. Bars show 95% confidence bands.