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China feels the heat: negative impacts of high temperatures on China's rice sector*

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We analysed a county-level data set of single-season rice yield and daily weather outcomes in China to examine the effects of temperature on China's rice sector. We found that rice yield exhibited highly nonlinear responses to temperature changes: rice yield increased with temperature up to 28°C and decreased sharply with higher temperatures. Holding current growing seasons and regions constant, average rice yield in China is projected to decrease by 10–19 per cent by 2050 and 11–33 per cent by 2070 due to future warming under the global climate models HadGEM2-ES and NorESM1-M. These results imply that future warming poses a major challenge for Chinese rice farmers and that the effectiveness of adaptations will depend on how well they reduce the negative temperature impacts on rice yield because of very hot days.

Key words: China, global warming, nonlinear temperature effects, rice yield.

1. Introduction

Given growing scientific evidence demonstrating that the earth is becoming warmer, agricultural vulnerability to rising temperature has been extensively studied (see a detailed review in Dell *et al*. 2014). With a few exceptions (Welch *et al*. 2010; Lobell *et al*. 2011; Chen *et al*. 2016a,b; Zhang *et al*. 2017), most of the economic analyses examining the impacts of warming on agriculture have focused on developed countries (for example, see Mendelsohn *et al*. 1994; Schlenker *et al*. 2006; Deschênes and Greenstone 2007; Schlenker and Roberts 2009). There is an urgent need for rigorous studies to evaluate the impacts of warming on agriculture in developing countries, which are home to over 70 per cent of the world's poor and heavily depend on agriculture.

The purpose of this article is to evaluate the responses of rice yield in China to temperature variations and assess the impact of future warming on rice yield in China. China's rice sector provides a compelling setting to study the impacts of warming on agriculture in developing countries for several reasons. First, rice is the most important food crop in China's agricultural

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Seniority of authorship is shared.

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economy, and it is widely produced and consumed in the country. According to the National Bureau of Statistics of China (NBS), rice accounts for about 30 per cent of the total grain area in China, 50 per cent of the nation's grain output and roughly 35 per cent of the total grain consumption in China while corn, soybeans and wheat account for approximately 26 per cent, 10 per cent and 23 per cent, respectively (NBS 1999–2009). Second, China has witnessed significant warming. Annual mean surface temperature has increased by 0.5–0.8°C over the past century, which is considerably higher than the average global temperature rise over the same period (Ding *et al.* 2007). Third, existing studies show inconsistent findings regarding how rice yield responds to temperature changes. Several studies used the similar data sets to analyse the effects of temperature on rice yields in China, but obtained mixed results (a detailed review is presented below). By accounting for nonlinearity, we attempt to reconcile these contradictory results.

At present, China has three main rice cropping systems, namely: single-season rice; double-cropped rice; and multiple-cropped rice. The latter two rice cropping systems involve various combinations of early rice, middle rice and late rice production. In this article, we analysed the effects of temperature changes on single-season rice yield for two reasons. First, single-season rice is widely produced across China's agricultural heartland (Figure 1). Second, due to increased labour costs, many Chinese farmers have reduced the production of double-cropped and multiple-cropped rice and increased single-season rice production. Figure S1 in Appendix S1 shows that the total planted area of early rice and late rice in China declined by 38 per cent and 37 per cent, respectively during the period 1990–2010, while the total planted area of single-season rice increased by 30 per cent over the same period.

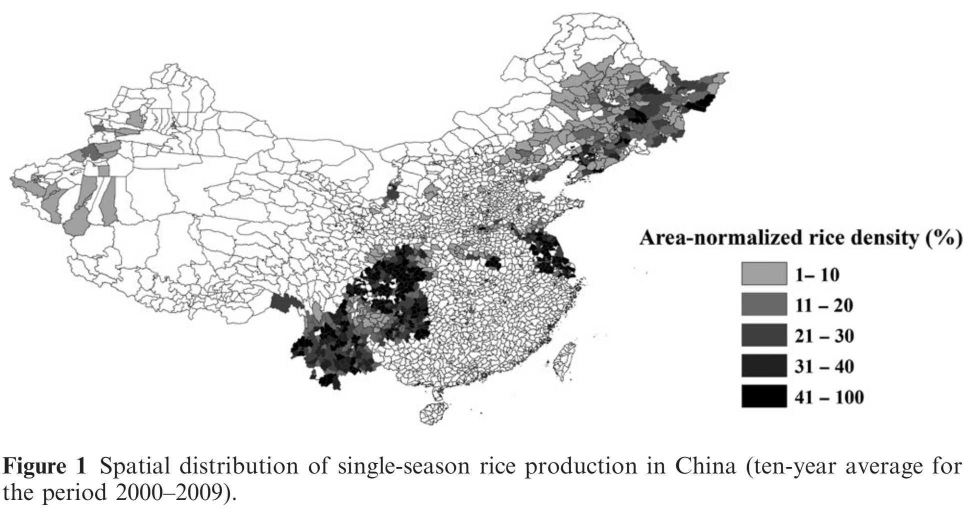


Figure 1 Spatial distribution of single-season rice production in China (ten-year average for the period 2000–2009).
Note: This map shows area-normalised rice production density, which is the ratio of a county's single-season rice planted area to that county's total grain area.

Using a county-level panel data set of annual single-season rice yield and daily weather observations in China over the period 2000–2009, we developed a fixed-effects spatial error model to estimate the link between temperature and rice yield. To account for the potential nonlinear relationship between rice yield and temperature, we followed the approach of Schlenker and Roberts (2009) and constructed temperature variables using temperature bins that measure accumulation of heat for each 3°C temperature interval. To account for the simultaneous variations in weather variables, the regression model also included rainfall and sunshine duration as additional weather variables. Moreover, to minimise the potential estimation biases originating from omitted variables, the regression model controlled for county fixed effects, year fixed effects and spatial correlation of the error terms.

We found that single-season rice yield exhibited negative responses to high temperatures and that the relationships between rice yield and weather variables were highly nonlinear. Rice yield increased with temperature up to 28°C, and temperatures above 28°C during rice growing seasons were harmful for rice growth. We also discovered that rice yield peaked with approximately 800 mm of rainfall and 900 hours of sunshine hours over the growing seasons. These findings remained robust to variations in rice varieties and econometric estimation strategies. Using estimated coefficients of temperature variables, we evaluated the impact of future warming on single-season rice yield in China. Holding current rice growing seasons and regions fixed, county-average single-season rice yield in China is projected to decline by 10–19 per cent by 2050 and 11–33 per cent by 2070 due to future warming under the global climate models HadGEM2-ES and NorESM1-M.

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

We contribute to the existing literature in two ways. First, we provide the first empirical evidence of the nonlinear temperature effects on rice yield. This finding reconciles seemingly contradictory results about how rice yield responds to temperature in the existing literature. Second, we add to the sparse economic literature examining the impact of warming on agriculture in developing countries. We show that if no additional adaptation is undertaken, future global warming is expected to cause a sizeable negative effect on rice yield in China. Given the importance of rice in China's agricultural economy, our findings may stimulate policy discussions about how to mitigate climate change and what strategies should be developed to adapt Chinese agriculture to future warming.

The rest of the paper is organised as follows: Section 2 introduces the empirical model. Section 3 describes data sources. Section 4 presents main regression results and considers a number of robustness checks. Section 5 projects future climate impacts on rice yield. Section 6 concludes the paper.

2. Empirical model

Several recent studies suggest that if weather affects farmers' input use and climate adaptation behaviours, one should only incorporate weather variables as explanatory variables (and control for other time-invariant factors) to obtain the total marginal effects of weather on crop yields (e.g. see McCarl *et al.* 2008, Schlenker and Roberts 2009; Welch *et al.* 2010). If non-weather factors, such as prices of inputs and output, are included as additional explanatory variables, estimated coefficients of weather variables should be interpreted as the partial effects of weather on yields. That is because controlling for these non-weather factors may absorb some of the overall effects of weather on yields. The regression model that we developed is presented below:

$$\log Y_{r,t} = \sum_{m} \alpha^{m} \mathrm{TempBin}^{m}_{r,t} + \beta \mathrm{Weather}_{r,t} + c_r + \theta_t + \varepsilon_{r,t} \tag{1}$$

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

Here, $\log Y_{r,t}$ represents the natural logarithm of average single-season rice yield in county r and year t. Following Schlenker and Roberts (2009), we constructed temperature variables using temperature bins for each 3°C temperature interval. $\mathrm{TempBin}^{m}_{r,t}$ denotes heat accumulation in county r and year t when temperature falls into the m^{th} temperature bin during rice growing seasons and is constructed using a fitted sine curve. We divided daily temperatures during rice growing seasons, measured in °C, into fourteen bins, each of which was 3°C wide. We defined $\mathrm{TempBin}^{1}_{r,t}$ = heat accumulation when temperature was into the range of [0°C, 3°C)[1] , $\mathrm{TempBin}^{2}_{r,t}$ = heat accumulation when temperature was into the range of [3°C, 6°C), and so on. Finally, $\mathrm{TempBin}^{14}_{r,t}$ = heat accumulation when temperature was above 39°C.

[1] Because daily $T_{\min}$ during single-season rice growing seasons was above 0°C for all regions in our sample, the first temperature bin was selected to range from 0°C to 3°C.

The implicit assumption is that the temperature effect on rice yield is consistent within each bin, which is reasonable given the small size of each temperature bin.

To account for the simultaneous variations in weather variables and isolate the effects of temperature on rice yield, linear and quadratic terms of the sums of rainfall and sunshine duration during rice growing seasons were also included as explanatory variables and represented by $\text{Weather}_{r,t}$. County fixed effects (c_r) were incorporated to account for unobserved regional heterogeneity that was specific to county r, such as soil quality. Year fixed effects (θ_t) were also included to account for the unobserved factors that were the same to all counties in a given year, such as global CO_2 concentrations. $\varepsilon_{r,t}$ are the error terms. α^m are the coefficients of interest. The main hypothesis was to test whether $\alpha^m = 0$, to test the null hypothesis that temperature had no effect on rice yield.

As shown in Equation (2), the error terms $\varepsilon_{r,t}$ were allowed to be spatially correlated across single-season rice-producing counties. ρ is the parameter of spatial correlation, and $W_{r,r'}$ is a prespecified spatial weights matrix that describes the spatial dependence of county r with its neighbours. $\varphi_{r,t}$ are the error terms that are independently normally distributed with $\mathrm{E}\left[\varphi_{r,t}\right] = 0$ and $\mathrm{var}\left[\varphi_{r,t}\right] = \sigma_r^2$. The error terms $\varepsilon_{r,t}$ are spatially correlated for at least two reasons. First, some spatially correlated explanatory variables, such as agricultural policies implemented in certain regions or production practices used by neighbouring rice-producing counties, are omitted as explanatory variables in Equation (1). Second, nearby rice-producing counties may share the similar local characteristics (such as soil type) or experience with pest problems in a particular growing season. If these factors cannot be incorporated as explanatory variables in Equation (1), then the error terms $\varepsilon_{r,t}$ are expected to be spatially correlated.

In the baseline analysis presented below, we first adopted a spatial contiguity matrix that assigns 1 to neighbouring single-season rice-producing counties sharing common boundaries and 0 to other counties. We also considered a distance weights matrix in the robustness check session. The distance weights matrix assigned positive weights to the six adjacent single-season rice-producing counties relative to county r and 0 to other counties. The positive weights in the distance weights matrix were computed using the inverses of the geographical distances between the centroids of counties. This distance weights matrix is referred to as KNN(6) in the remainder of the paper.

We estimated the regression models (1)-(2) using a two-step procedure. We first estimated the parameter of spatial correlation $\hat{\rho}$ using the generalised method of moments approach and premultiplied the original data by $I - \hat{\rho}W$, where I and W denote the identity matrix and the spatial weights matrix, respectively. Using the transformed data, we then estimated the models using the approach introduced in Hsiang (2010) to allow for the heteroscedasticity and serial correlation of the error terms. Thus, our estimation strategy allows for spatial correlation, serial correlation and heteroscedasticity of the error terms.

3. Data

Data used for this analysis were assembled from several sources. We obtained county-level single-season rice yield for the period 2000–2009 from the NBS. In the sample, rice yield ranged approximately between 1,900 and 13,700 kg per hectare (ha) with a national average of 7,100 kg per ha (Table S1 in the Appendix S1). Regional-specific rice growing seasons were compiled from the Ministry of Agriculture of China.

Daily weather data, including $T_{\min}$, $T_{\max}$, average temperature, rainfall and sunshine duration, were obtained from the China Meteorological Data Sharing Service System, which reports daily weather information for more than 800 weather stations in China. We merged daily weather data with annual yield data using the coordinates of weather stations and county centroids. Of the 771 single-season rice-producing counties included in the sample, we found that 566 counties had weather stations and 205 counties did not have weather stations. For the 566 counties with weather stations, each county has only one weather station. For the 205 counties without weather stations, we imputed their weather information from the nearest contiguous counties among the 2,806 counties in China. As a robustness check, we constructed weather variables for all single-season rice-producing counties by taking a spatially weighted average of weather data from their neighbouring counties and using the inverses of the geographical distances between the centroids of counties as the weights. A county's neighbours were defined as those that share common boundaries.

4. Results

4.1 Spatial correlation of the error terms

Table 1 reports test statistics for the presence of spatial correlation of the error terms. To examine whether the error terms are spatially correlated, we performed four tests, including Moran's *I* test, the Lagrange multiplier (LM) ERR test, the likelihood-ratio (LR) test and the Wald test. When conducting these tests, we used the same set of explanatory variables as in Equation (1). The test results in Table 1 indicate that the spatial correlation of the error terms is statistically significant and large. The parameter of spatial correlation is 0.42 under the contiguity matrix and 0.36 under the KNN(6). These test statistics suggest that the error terms are spatially correlated and that the true *t*-statistics would be overestimated if the spatial correlation of the error terms was not considered in the regression analysis.

4.2 Effects of temperature on rice yield

Figure 2a shows the point estimates and the 95 per cent confidence bands of the temperature variables. The horizontal axis of this figure denotes temperature variables, while the vertical axis of this figure denotes the natural logarithm of rice yield. We found that rice yield increased with temperature up to 28°C and that temperatures above 28°C can cause large reductions in rice yield. For instance, replacing a full day with an average temperature of 28°C with a full day with an average temperature of 36°C is expected to reduce rice yield by 15.1 per cent, holding all else constant. High temperatures reduce rice yield mainly by negatively affecting the photosynthesis process in rice, increasing respiration demand and reducing pollen production (Wassmann *et al.* 2009). This critical temperature threshold is comparable with those identified for corn, soybeans and cotton (Schlenker and Roberts 2009; Chen *et al.* 2016a).

Because temperature bins have different means and exhibit different changing trends, it is not appropriate to directly compare their marginal impacts on rice yield. To overcome this difficulty, we examined the marginal effects per standard deviations (SDs) of the temperature variables, which were computed by multiplying coefficient estimates of each temperature bin by the corresponding SD. As shown in Figure 2b, we found that the largest positive marginal effect per SD was accumulation of heat in the temperature range of 21–24°C (+4.2 per cent), while the largest negative marginal effect per SD came from heat accumulation in the temperature range of 30–33°C (−4.0 per cent).

Parameter estimates for rainfall and sunshine duration show similar nonlinear patterns (Table S2 in the Appendix S1 reports point estimates of these weather variables). Rice yield peaked with 830 mm of rainfall over the growing seasons. Rainfall above this level can depress rice yield by preventing timely planting, damaging planted area and creating disease pressure (Auffhammer *et al.* 2012). The optimal amount of sunshine duration needed for rice growth is estimated to be 912 hours. Estimated rainfall and sunshine duration requirements for rice are consistent with the existing agronomic

Table 1 Tests for the presence of spatial correlation of the error terms

Spatial weights matrix	Contiguity matrix	KNN(6)
Moran-I ~ N(0,1)	18.72	26.16
LM-ERR ~ $\chi^2(1)$	245.20	218.97
LR ~ $\chi^2(1)$	372.35	350.81
Wald ~ $\chi^2(1)$	13296.00	10383.42
Parameter of spatial correlation	0.42	0.36

Note: Two spatial weights matrices were used to examine the existence of spatial correlation of the error terms. Under the spatial contiguity matrix, the (*r*, *r*’) element of the matrix is unity if counties *r* and *r*’ share a common boundary and zero otherwise. KNN(6) is an inverse distance matrix that weights the six nearest neighbours according to their physical distance, and assign zero to other counties.

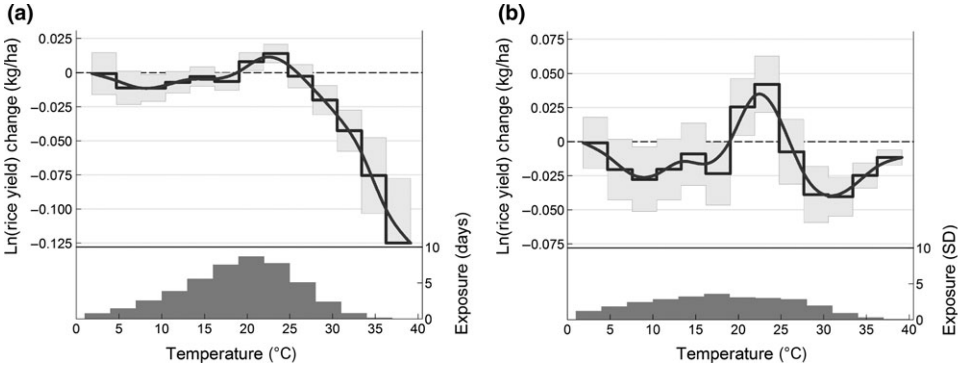


Figure 2 Nonlinear relationships between temperature and rice yield.
Note: Results presented in the two panels were estimated using temperature bins as temperature variables. The left panel (a) shows point estimates and the 95 per cent confidence intervals of the temperature variables. The right panel (b) shows the marginal effects on rice yield per SD of temperature variables. The smooth lines fit coefficient estimates of each 3°C temperature range using an eighth-order polynomial function. Histograms at the bottom of panels (a) and (b) show the distribution of mean and SD of temperature bins in the data, respectively. Because the coefficient estimate of $\text{TempBin}_{r,t}^{14}$ when temperature was above 39°C is considerably larger than the coefficient estimates of other bins (see Table S2 in the Appendix S1), it was omitted in the two panels to make the figure compact. Standard errors were adjusted for spatial correlation and serial correlation and are robust to heteroscedasticity.

studies (e.g. see Zhang *et al.* 2008), but they are significantly higher than the water and sunshine requirements for corn, soybeans and cotton (Schlenker and Roberts 2009; Chen *et al.* 2016a).

4.3 Robustness check

We tested the robustness of our key findings to an alternative spatial weights matrix and to alternative variables and samples in five different scenarios. Specifically, in Scenario (1), we used the distance matrix KNN(6) described in Section 2 as the spatial weights matrix in the regression analysis. In Scenario (2), a linear time trend and a quadratic time trend by province were used to represent exogenous technological change boosting rice yield. In Scenarios (3) and (4), we examined whether the estimated temperature effects presented above are sensitive to different rice varieties. We replicated the above regression analysis using the subsample with counties producing Japonica rice only in Scenario (3) and using the subsample with counties producing Indica rice only in Scenario (4). Finally, in Scenario (5), we constructed weather variables for all single-season rice-producing counties by taking a spatially weighted average of weather data from their neighbours as mentioned above and then replicated the aforementioned regression analysis. Table S2 in the Appendix S1 reports point estimates of weather variables for these scenarios, while Figure S2 in the Appendix S1 depicts the point estimates and the 95 per cent confidence bands of the temperature variables.

We found that our key finding of the negative responses of rice yield to high temperatures remained robust to variations in the spatial weights matrix and to a different approach used to represent technological change for rice yield growth. This finding also remained robust to different rice varieties and a different approach used to construct weather variables. Figure S2 in the Appendix S1 shows that the critical temperature threshold (28°C) identified in the baseline scenario remained remarkably robust.

5. Future climate change impact

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

Following Hsiang *et al.* (2017), we used a three-step process to construct county-level projections of daily $T_{\min}$ and $T_{\max}$. First, we constructed monthly probability distribution functions of $T_{\min}$ and $T_{\max}$ for all single-season rice-producing counties included in the sample, based on historical daily observations from 1981 to 2010. Second, we computed the projected changes in monthly average $T_{\min}$ and $T_{\max}$ for all counties in our sample, which are the differences between the projected monthly average minimum and maximum temperatures based on the WorldClim database and the corresponding average temperature data based on the historical data from 1981 to 2010. Third, we assumed that the distributions of $T_{\min}$ and $T_{\max}$ in the twenty-first century mirror the distributions obtained in the first step based on the historical data. That allowed us to obtain the distributions of daily $T_{\min}$ and $T_{\max}$ in the medium term and the long term for the two forcing pathways considered (RCP2.6 and RCP8.5).

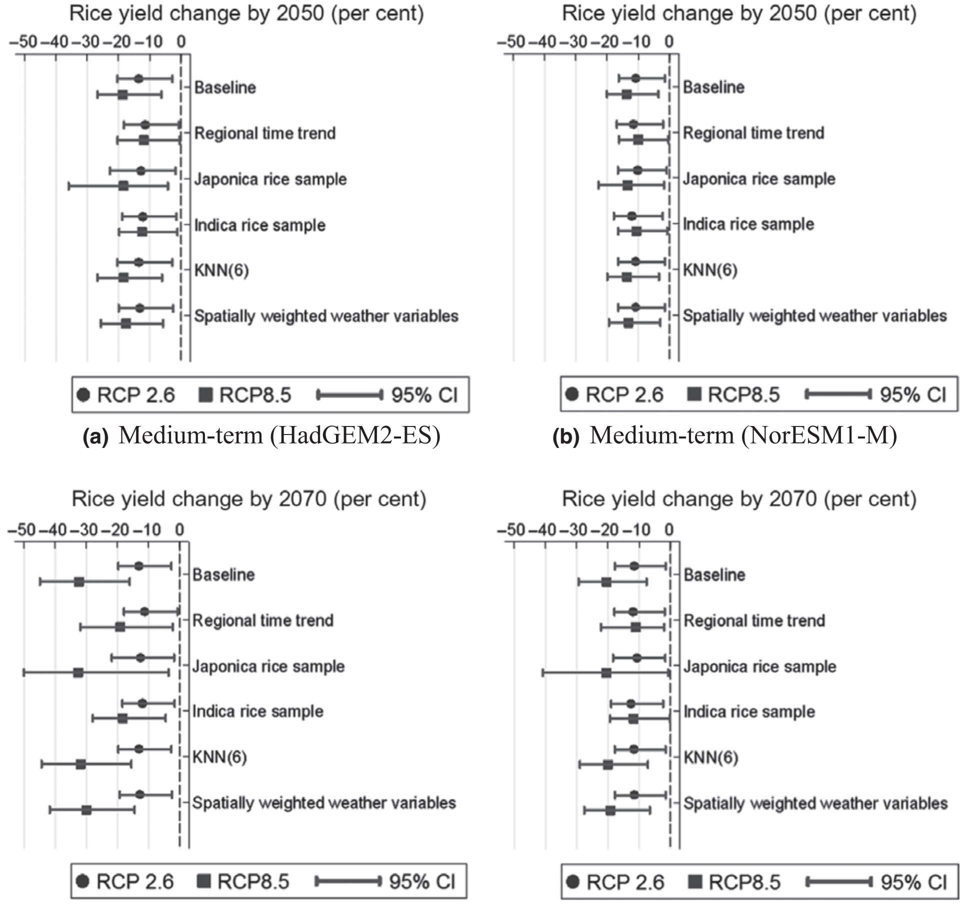
We then calculated the projected changes in temperature bins across regions, which are the differences between the temperature bins computed based on the constructed daily T_{min} and T_{max} data for the twenty-first century and the average temperature bins in our sample (2000–2009). Using the coefficient estimates of the temperature bins, we predicted county-specific changes in rice yield, weighted by each county's share in total single-season rice production, to obtain the estimates of the impacts of future warming on rice yield.

Figure 3 shows the effects of future warming on average rice yield. We found that warming will reduce rice yield and that the likely magnitudes of the reductions depend on climate models. Under the HadGEM2-ES model, average rice yield in the medium-term is projected to decrease by 11.4–13.5 per cent under RCP2.6 and 11.9–18.6 per cent under RCP8.5 (Figure 3a). Under the NorESM1-M model, the corresponding yield reductions are smaller by 10.2–12.0 per cent under RCP2.6 and 9.9–13.7 per cent under RCP8.5 (Figure 3b). Under RCP8.5, the yield reductions in the long-term are projected to be considerably larger than the yield reductions in the medium-term (Figures 3c,d). Specifically, county-average rice yield is projected to decrease by 18.2–32.7 per cent by 2070 under the HadGEM2-ES model and 11.0–20.5 per cent under the NorESM1-M model. We found that under RCP2.6, the predicted reductions in rice yield in the long-term are similar in magnitude to the predicted yield reductions in the medium-term.

6. Summary and conclusions

To develop efficient adaptation strategies to combat future climate change, policy makers and crop scientists need to understand the impacts of global warming on agriculture, which is particularly important for developing nations. In this paper, we analysed a county-level panel of observed single-season rice yield and daily weather outcomes in China, to estimate the link between weather and rice yield and to predict the impacts of future warming on rice yield. By accounting for nonlinearity, we showed a nonlinear relationship between rice yield and temperature. The critical temperature threshold and the optimal rainfall and sunshine duration for rice growth are comparable with estimates for other crops (Schlenker and Roberts 2009; Chen *et al.* 2016a,b). We showed that high temperatures above this critical temperature threshold can cause severe damage to rice yield. These findings are notable for the consistency across rice varieties, model specifications and estimation strategies.

Using estimated coefficients of weather variables, we showed that holding current rice growing seasons and regions constant, average rice yield in China is projected to decrease by 10–19 per cent by 2050 and 11–33 per cent by 2070 under future climate change. The dominant factors driving future yield reductions are the projected increases in temperature bins above 28°C (see Table S3 in the Appendix S1). Here, one should note that we may have



(a) Medium-term (HadGEM2-ES)
(b) Medium-term (NorESM1-M)
(c) Long-term (HadGEM2-ES)
(d) Long-term (NorESM1-M)

Figure 3 Predicted impacts of future warming on rice yield.
Note: Panels (a) and (c) show predicted percentage changes in average rice yield in China and the 95 per cent confidence intervals in the medium-term and the long-term, respectively, under the HadGEM2-ES model. Panels (b) and (d) display the corresponding predictions under the climate model NorESM1-M.

overestimated the projected damages to rice yield that can be attributed to climate change for two reasons. First, coefficient estimates of temperature variables used for prediction were obtained using the observed outcomes in the past decade and cannot capture adaptations that may be undertaken by farmers in the future. Second, when predicting the impacts of future warming on rice yield, we assumed that the growing seasons and regions of single-season rice remained unchanged in the twenty-first century. However, farmers may change rice growing seasons and areas as an adaptation strategy to cope with future warming.

Another major caveat is that our regression results may be subject to omitted variable bias. Our analysis focused on the impacts of changes in temperature, rainfall and sunshine duration on rice yield and did not consider the impact of CO_2 fertilisation, air pollution and/or industrial pollution on rice yield. Laboratory studies have found that higher CO_2 fertilisation may offset yield reductions due to warmer climate (Long *et al*. 2006). Several studies have shown that rice yields decline with elevated ozone concentrations in the atmosphere (Ainsworth 2008).

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Summary statistics.

Table S2. Regression results (dependent variable is log rice yield (kg/ha)).

Table S3. Predicted changes in temperature variables by HadGEM2-ES and NorESM1-M under different RCPs.

Figure S1. Percentage changes in crop area in China during the period 1990–2010.

Figure S2. Sensitivity analysis.