Rice, Carbon Dioxide, Climate Change, And Feeding The Future

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Abstract

This study investigates the relationship between rice yields, climate change, and carbon dioxide (CO₂). We integrate gridded climate data in the growing seasons and Asian rice yield data reported by the Food and Agriculture Organization with free air carbon dioxide enrichment (FACE) experimental data. Using those data, we estimate prediction models of rice yields that evolve over time and decompose effects of climate, CO₂, and technological progress. The results show that atmospheric CO₂ has significantly increased rice yields, with the contribution accounting for 29% to 33% of the observed yield growth. The results also reveal that increases in temperature decrease rice yields in parts of Asia, implying that both CO₂ mitigation and climate change are yield growth depressing factors. The finding suggests a potential need for more agricultural research and development investment to offset CO₂ mitigation and climate change effects.

Keywords: Rice yield, climate change, CO₂ fertilization effect, gridded climate data

1 Introduction

Globally rice is the most widely consumed food crop (Food and Agriculture Organization 2014, 2016), and population growth is increasing rice demand. Without substantial rice productivity increases, billions may struggle from malnutrition and food insecurity. Declines in rice productivity also can cause conflict and societal instability (Brück and d’Errico 2019). However, rice productivity is facing significant challenges. Agricultural research and development (AGRD) funding is diminishing and limits the potential growth of rice yields (Alston and Pardey 2006; Andersen et al. 2018; Pardey et al. 2016). Some studies show that future rice productivity is threatened by climate change (Ortiz-Bobea et al. 2021; Sinnarong et al. 2019), especially in Asia. A large portion of Asian rice production is in mega deltas, which are vulnerable to sea-level rise and storm surge (Wassmann et al. 2009). The above facts and findings highlight the importance of investigating climate change impacts on rice yields and how rice production might adapt to better feed the future.

There are several factors influencing rice and more generally crop yields. Climate conditions have been found to be key determinants of average crop yields and their variability (IPCC 2014; Jithitikulchai, McCarl, and Wu 2018; Pathak et al. 2018; Raza et al. 2019; Wang et al. 2018). For rice, studies in Thailand and Bangladesh have found that temperature increases reduce rice yields and increase yield variability (Sinnarong et al. 2019, Sarker, Alam, and Gow 2014). Increasing temperature has been found as a cause of rice yield losses in Laos and India (Ishimaru et al. 2016). Zhang, Tao, and Zhang (2016) show that rice yields are generally more sensitive to high temperatures than cold temperatures in China. Collectively these findings suggest the importance of developing integrated adaptation strategies to alleviate potential climate change impacts. Simultaneously, an increase in atmospheric CO₂ has been found to enhance rice yields

(Hasegawa et al. 2013; Kirschbaum 2011). Technical advances as stimulated by research investments are another crucial productivity determinant and can offset possible negative impacts of climate change (Chen, McCarl, and Chang 2012; Villavicencio et al. 2013).

Nevertheless, due to the high correlation between time and CO₂ atmospheric concentration, it is statistically challenging to separately identify CO₂ and technological impacts on rice yields. The conventional way of modeling yield growth due to technological advances is to use time as a technical progress proxy (Attavanich and McCarl 2014; McCarl, Villavicencio, and Wu 2008). However, given the steady advance in CO₂, using this approach captures not only technological advance but also the influence of highly correlated increasing CO₂ (Attavanich and McCarl 2014). As such, one can easily overestimate technological effects on yield growth due to correlated CO₂-induced yield enhancement. Thus, it is important to partition out the CO₂ effect. But to do this, one must overcome a collinearity issue between time and atmospheric CO₂ concentration increases since the correlation of CO₂ concentration with time is above 95% (see Section 3.1). Attavanich and McCarl (2014) addressed this identification challenge for U.S. corn, wheat, sorghum, and cotton by combining the USDA-reported data on yields with free air carbon dioxide enrichment (FACE) experimental data. They found that estimating time as a proxy for yield growth rate without considering CO₂ effects upwardly biased their proxy technological progress rate estimates by as much as 40%.

Herein we address the effects of climate, technological advances, and CO₂ fertilization on Asian rice yield growth. In addition, we forecast the impacts of projected climate change and CO₂ concentration on yield growth under different climate change scenarios. Relevant implications of our findings are discussed at the end of the paper.

2 Estimation equation

To estimate the effect of climate, atmospheric CO₂ concentration, and other factors on rice yield, we conducted an econometric estimation using merged observed and FACE experiment yield data, climate conditions, atmospheric CO₂ concentration, input use data for fertilization and irrigation amounts, a time trend proxying technological advance, a country fixed effect individually, and its interaction term with climate variables. To do this, a rice yield production function is assumed following Just and Pope (1979) and Chen, McCarl, and Schimmelpfennig (2004). In particular, the rice yield functional form is expressed as:

$$\log(y_{itk}) = f(X_{itk}, \boldsymbol{\beta}) + \mu_{itk} = f(X_{itk}, \boldsymbol{\beta}) + h(X_{itk}, \boldsymbol{\alpha})\varepsilon_{itk} \quad (1)$$

where

y_{itk} denotes merged observed (k=1) and FACE experimental (k=2) rice yields in metric ton per hectare in country i in year t ;

$f(\cdot)$ is the mean function consisting of explanatory variables (X_{itk}) in country i in year t for observed (k=1) or FACE (k=2) observations and a corresponding estimated parameter vector ($\boldsymbol{\beta}$);

X_{itk} denotes explanatory variables occurring in country i in year t associated with observation type k, including climate variables, technology-related variables, and global atmospheric CO₂ concentration (in ppm). The climate variables are mean precipitation (in millimeters), annual average maximum temperature (in degrees °C), and the SPEI drought measure developed by Vicente-Serrano, Beguería, and López-Moreno (2010). Technology-related variables include fertilizer application rate (Kg N/ha), percent of land under irrigation, and time (where we include both linear and quadratic terms with 1961=1). Except for SPEI, irrigation rate, and time, the rest of the variables are in their logarithmic forms. We also

included a dummy variable within X_{itk} indicating whether a particular observation is an observation from a FACE experiment. Additionally, since the FACE observations are only available in either China or Japan, we included an interaction term between the FACE dummy and the China dummy variable that controls for possible heterogenous effects between FACE experiments in China and Japan.

μ_{itk} is a heteroskedastic disturbance term with a mean of zero. The disturbance term captures time- and country-variant unobservable effects and can be further decomposed as $h(X_{itk}, \alpha)$ and ε_{itk} . The former, $h(X_{itk}, \alpha)$, is a yield variability function that accounts for heteroskedasticity, estimated as a function of the explanatory factors (X_{itk}) with the corresponding vector of estimated parameters (α). Finally, ε_{itk} is the error term and is assumed distributed with mean zero and unitary variance.

Other time-invariant unobservable effects and their association with climate variation were controlled by country fixed effects in the form of country level dummy variables for all countries. We also introduced interaction terms between the country dummies and the climate variables, so we could examine differential climate effects across countries. Finally, note that since our data incorporates observed and FACE data plus some country data are missing, it does not fully have a balanced panel data structure.

3 Estimation method

In the estimation, we used a three-step feasible generalized least squares (FGLS) method (as discussed in Just and Pope 1979; and Attavanich and McCarl 2014). This approach is applied to correct for heteroscedasticity and estimate the effects of climate and other explanatory variables on rice yield variance. The empirical estimation procedure is as follows:

- First, we estimated $\log(y_{itk}) = f(X_{itk}, \beta) + \mu_{itk}$ by using pooled ordinary least squares

(OLS) and obtained the residuals ($\hat{\mu}_{itk}$).

- Second, we took the first step residuals and then estimated an equation where their square was a function of X_{itk} . Namely, we estimated $\log(\hat{\mu}_{itk}^2) = h(X_{itk}, \boldsymbol{\gamma}) + u_{itk}$ and obtained fitted values $\log(\widehat{\hat{\mu}_{itk}^2})$ and calculated $\sqrt{\exp(\log(\widehat{\hat{\mu}_{itk}^2}))}$.
- Third, we estimated $\log(y_{itk}) = f(X_{itk}, \boldsymbol{\beta}) + \mu_{itk}$ using weighted least squares (WLS) with $\sqrt{\exp(\log(\widehat{\hat{\mu}_{itk}^2}))}$ as weights.

In turn, the values of coefficient vector ($\boldsymbol{\beta}$) from the third stage are those we report below.

4 Data description

A list of data sources that were used in this study is presented in Table S1. Additional notes on the data are:

- The observed rice yield data and irrigation rate data were assembled for 31 Asian countries for the time period from 1961 to 2015 and were drawn from the Food and Agriculture Organization FAOSTAT database (2020). However, the observations are not complete for all countries in all years. For instance, Central Asian countries are missing observations before 1992, and Syria does not have observations after 1996. Overview of rice yields in each country over time is presented in Figure S1.
- Growing season gridded climate data and fertilizer application data for each country were from Jägermeyr et al. (2021). The gridded data were further aggregated to the country level by calculating the weighted average based on each country's rice land acreage.
- The FACE experimental rice yield data arose from studies in Japan and China (Hasegawa et al. 2013; Jing et al. 2016; Sun et al. 2014) and are presented in Table S2.
- The global CO₂ concentration data came from the NOAA Global Monitoring Laboratory

(2020). Drought-based data were incorporated using calculation procedures for the SPEI Global Drought measure from Vicente-Serrano et al. (2010).

- The climate projections data came from the KNMI Climate Change Atlas (2020), as we discuss later.

Summary statistics on the above data are provided in Table S3.

5 Results

5.1 Relationship between rice yields, global CO₂ concentration, and climate

The relationships between rice yields and the key variables are presented in Figure 1. Specifically, Figure 1a shows that global CO₂ concentration is positively correlated with regional Asian rice yields. This also indicates identifying CO₂ fertilization effects independently of time proxied technological progress can be difficult as time and CO₂ are highly correlated (Pearson correlation coefficient = 0.9936). Thus, we follow Attavanich and McCarl (2014) and merge both FACE experimental yield data and historical yield data into a single data set. This approach decreases the Pearson correlation coefficient between CO₂ and time to 0.7707, allowing identification of their separate effects.

Figures 1b and 1c illustrate the relationships between precipitation and maximum temperature with rice yields across different regions. Figure 1b shows that precipitation is negatively associated with rice yields in Central and Southeast Asia but positively associated in drier and hotter West Asia. On the other hand, the average maximum temperature is associated with decreasing rice yields while the temperature beyond the moderate level in Central and East Asia.

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a. Atmospheric CO₂ and rice yields b. Precipitation and rice yields c. Max. temperature and rice yields

Fig. 1. Relationship between CO₂, climate, and Asian regional rice yields over 1961-2016

5.2 Estimation of independent variable impacts on rice yields

To avoid inappropriate estimates caused by non-stationary data, we conducted pre-modeling unit root tests to examine data stationarity. The test method followed Levin-Lin-Chu (Levin et al. 2002) and Im-Pesaran-Shin unit root tests (Im et al. 2003). The test specifications used the inclusion of individual intercepts and the inclusion of both individual intercepts and trends. Table S4 presents the test statistics and indicates that the null hypothesis of non-stationarity under different test specifications and methods is rejected and significant at all the usual testing levels, suggesting that the data doesn't need to be differenced in order to make it stationary.

The estimation results with different model specifications and the final model are presented in Tables S5 and S6, respectively. Overall, the results show that rice yields are significantly increasing with time, reflecting the effect of technological advances. Also, note that excluding the CO₂ atmospheric concentration variable causes the linear time coefficients to be much larger, showing that omitting the CO₂ fertilization effect upwardly biases the estimates for time as a proxy for technology effects by 56% at the mean. Similarly, the linear time coefficients are larger when excluding fertilizer application amounts and irrigation land coverage variables. In addition, we found significant and positive CO₂ concentration effects, indicating a rice yield response to a CO₂ enriched atmosphere which is the well-known C3 CO₂ crop growth stimulation effect (see the review in Korres et al., 2016). Overall, fertilizer application, irrigation rate, CO₂ concentration, and the dummy for FACE observations all significantly increase rice yields. Due to the heterogeneous climate effect across different Asian regions that were present in Figure 1, the overall coefficients on precipitation, average maximum temperature, and SPEI are not significant, but a number of their interaction effects with the country-dummies are significant. Detailed estimation results appear in Table S6.

5.3 Projected effects of climate change

To better illustrate the impact of CO₂ concentration and temperature on rice yields, we used Model 2 of Table S6 to predict the effect of independently varying CO₂ concentration and temperature on rice yields conditional on a wide range of CO₂ concentration and temperature values and constructed Figure 2. The solid lines denote mean estimates and colored shades indicate 95% confidence intervals. In particular, Figure 2a shows the relationship between atmospheric CO₂ concentration and rice yields which is positive and shows ceteris paribus that increases in CO₂ concentration are associated with increased rice yields. Figure 2b shows a negative relationship between maximum temperature and rice yields. Collectively, these results show CO₂ and temperature moves yields in different directions.

Fig. 2. Impact of CO₂ concentration and maximum temperature on rice yields

5.4 The CO₂ fertilization effect on the historical rice yield growth

To further investigate the CO₂ fertilization effect, we used Model 2 in Table S6 to conduct in-sample rice yield growth projections. The estimation, including and excluding the CO₂ fertilization effect, reveals the role CO₂ concentration plays in the rice yield projection model. Specifically, we projected yields using our best-fitted equation under two cases. The first case holds CO₂ concentration constant at the 1990-level, and the other case uses the evolving observed atmospheric CO₂ concentration levels. Figure 3 presents the projected rice yields under these cases. The result shows that regional 1961 to 2015 rice yield growth varies from 47% to 81% when CO₂ concentration is held at 1990-levels; in contrast, that increases to 79% to 123% under the evolving observed CO₂ concentrations. This finding implies that the CO₂ fertilization effect has been responsible for 32% to 42% of the regional rice yield growth over that period.

Fig. 3. Projected regional rice yields during 1990-2015 under constant and evolving CO₂ levels

Note: The blue lines denote the predicted rice yields with CO₂ remaining at the 1990-level. The red lines denote the ones with the evolving CO₂ levels from 1990 to 2015. The colored shades indicate 95% confidence intervals. The results arise from projections with Model 2 in Table S6 and show that rice yield growth is much smaller without the CO₂ influence. In particular, depending on region, yield growth ranges from 47% to 81% when CO₂ is held constant and is much higher with actual CO₂ (79% to 123%, i.e., a 32% to 42% increase).

5.5 Forecasting climate change impact on the future rice yield growth

We also constructed a forecast of rice yields for the years 2016 to 2050 under selected climate change scenarios again using Model 2. We did this for 25 countries, dropping those with small rice production or limited observations (refer to Figure S1). The required covariate values were retrieved from several sources. We used CMIP5¹ climate projections under Representative Concentration Pathway (RCP) scenarios RCP4.5, RCP6.0, and RCP8.5 and the associated CO₂ levels (IPCC 2013). The projected precipitation, maximum temperature, and SPEI are drawn from the KNMI Climate Change Atlas (2020). We used results from Community Earth System Model version 1 coupled with the Community Atmospheric Model version 5 (CESM1-CAM5)(Neale et al. 2012). SPEI projection values used the maximum length of dry spell results from Community Climate System Model 4.0 (Gent et al. 2011). The value of the time trend variable from 2016 to 2100 is a sequence of 56 to 140. In order to identify the effect of climate and CO₂ on future rice yields, the fertilizer usage and irrigation rate were held constant at the 2015 level. Differences among countries are computed using the country dummy variables and their interaction terms with the climate variables.

The projected Asian rice yields under different climate scenarios are shown in Figure 4. The projection indicates that rice yields are expected to grow slowly, even fall in the last two decades of this century under the RCP 4.5 scenario as mitigation proceeds. In contrast, the rice yields are expected to have a significant increase under the RCP 8.5 scenario due to a higher atmospheric CO₂ concentration. The projected Asian rice yields under the RCP 6 scenario are between the RCP 4.5 and RCP 8.5 scenarios.

¹ It is an abbreviation of the Coupled Model Intercomparison Project Phase 5 (CMIP5).

Fig. 4. Projected Asian rice yields under different climate scenarios

Note: The figure shows the projected Asian rice yields under different climate scenarios where climate and CO₂ variables vary in each scenario. The projected Asian rice yields are weighted averages based on the share of country rice production level to total rice production in all study countries in 2015. In order to identify the effect of climate and CO₂ on future rice yields, the fertilizer usage and irrigation rate are assumed to be constant at the 2015 level for the projection duration.

The result in Figure 4 can be further broken down into the regional level (Table 1) and country-level (Table S6) from 2015 to 2050 and 2100 by RCP scenarios. When we formed estimates by Asian subregion, we aggregated the results using weighted averages based on the ratio of country rice production level to total regional rice production in 2015. Table 1 shows that the projected rice yields vary across Asian regions, reflecting the heterogeneous effect of GCM model projected climate change on rice yields across the study regions. Among the distinct RCP scenarios, we see larger growth rates under the RCP 8.5 scenario as climate change and CO₂ concentrations evolve, indicating the positive impacts from CO₂ are dominating the negative temperature.

Table 1. Projected rice yields in 2050 and 2100 by climate scenario and region

Region	2015 Yield (ton/ha)	RCP4.5		RCP6.0		RCP8.5	
		2050 Growth	2100 Growth	2050 Growth	2100 Growth	2050 Growth	2100 Growth
East Asia	6.88	44%	50%	42%	105%	66%	222%
South Asia	3.82	61%	99%	54%	207%	102%	528%
Southeast Asia	4.60	100%	193%	87%	415%	172%	1348%
West Asia	5.39	42%	50%	38%	108%	64%	236%

Note: The forecasted rice yields in 2050 and 2100 under different climate scenarios are estimated by the third stage of the FGLS approach using Model 2 of Table S6 with the CMIP5 projection data. The percentage is the respective growth rate relative to 2015. Darker and lighter green indicate larger and smaller growth rates, respectively.

6 Discussion and conclusions

Above, we find future Asian rice yields are significantly affected by CO₂ levels and climate change. The data show that Asian rice yields increased by 79% to 123% by 2015 relative to 1961. But will this persist?

Our modeling result shows that 32% to 42% of that historical yield increase arose due to increased atmospheric CO₂ concentrations. However, the yield growth was depressed by climate conditions in the form of high maximum temperatures in most Asian countries. Thus, technological developments are not doing as well in increasing rice yields as might otherwise appear, and success with climate-based mitigation policy directed toward atmospheric CO₂ concentration reduction will lower yield levels. This finding implies that future rice yields are subject to the opposing forces of climate change and CO₂ concentration mitigation. Namely, if CO₂ -driven climate change proceeds, yields will grow due to increasing atmospheric, yields will grow due to increasing atmospheric CO₂, but the changing climate will reduce that yield growth rate. On the other hand, if substantial CO₂ mitigation occurs and atmospheric concentrations stabilize or fall, yield growth will slow and possibly decrease. But this will be offset by lesser degrees of climate change and their yield implications.

Ideally, we would have liked to include agricultural research and development (AGRDR) expenditures in this analysis, but we could not do so due to the time length of our data set. In particular, the effects of AGRD investment on rice yields are not instantaneous and, in fact, involve a long lag. Specifically, Alston and Pardey (2006) argue there is a lag of 17 to 25 years, while Huffman and Evenson (2006) assume it is as long as 34 years. However, we could not include such long lags as we could only find AGRD expenditure series for a 20 year period (ASTI 2020; Taiwan National Statistics 2020; World Bank 2020) and including, say, a 17-year lag would require dropping most of our observations. To gain some insight, we calculated the correlation between country yield growth versus 5-year, 10-year, and 15-year lagged AGRD expenditures and found positive correlations of 0.3793, 0.4147, and 0.4838, respectively. This implies that increased AGRD expenditures would increase yield growth.

The current work contains several possible limitations that are suggestive of future research directions. First, while we used a fixed-effect model to consider systematic country effects, we did not incorporate data that could reflect both country-specific differences and commonalities, such as soil quality, degradation, etc. Adding these as independent variables would help further identify the role of CO₂, climate, and other factors. Second, we would like to have a longer AGRD expenditure series, so we could better study links between investments, climate, CO₂, and yield growth. Third, a further study could assess the effects of long-term climate events (e.g., El Niño, decadal climate variability, etc.) on rice yields and develop corresponding climate change adaptation.

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Appendix: Supplementary information

Fig. S1. Historical rice yields by country

Table S1. Data sources

Variables	Duration	Sources
Rice yields (ton/hectare)	1961-2015	Food and Agriculture Organization of the United Nations (2020)
Precipitation (mm)	1961-2015	Jägermeyr et al. (2021)
Temperature (Celsius)	1961-2015	Jägermeyr et al. (2021)
SPEI	1961-2015	Calculated via procedures in Vicente-Serrano et al. (2010) using historical climate. Then projected into the future using data from KNMI Climate Change Atlas (2020).
Irrigation rate	1961-2015	Food and Agriculture Organization (2020)
Fertilizer application (Kg N/ha)	1961-2015	Jägermeyr et al. (2021)
Historical CO ₂ concentration	1961-2015	NOAA Global Monitoring Laboratory (2020)
RCP associated projected climate and CO ₂ concentration (ppm)	2016-2100	KNMI Climate Change Atlas (2020), Meinshausen et al. (2011)
FACE yield and CO ₂ data	1998-2003, 2007-2008, 2010	Hasegawa et al. (2013); Jing et al. (2016); Sun et al. (2014)

Table S2. Free air carbon dioxide enrichment (FACE) experimental data

Area	Country	Year	CO₂	Rice yield (ton/hectare)
Shizukuishi	Japan	1998	642	6.8
Shizukuishi	Japan	1999	629.9	8.4
Shizukuishi	Japan	2000	578.5	8.0
Wuxi	China	2001	577.5	11.8
Wuxi	China	2002	562.4	11.0
Wuxi	China	2003	574.4	9.7
Shizukuishi	Japan	2007	570	6.7
Shizukuishi	Japan	2008	576	7.5
Tsukubamirai	Japan	2010	585	5.3
Shizukuishi	Japan	2007	570	7.9
Shizukuishi	Japan	2008	576	9.0
Tsukubamirai	Japan	2010	585	6.9
Shizukuishi	Japan	2007	570	5.5
Shizukuishi	Japan	2008	576	6.7
Tsukuba	Japan	2010	585	6.4
Shizukuishi	Japan	2007	570	7.0
Shizukuishi	Japan	2008	576	5.7
Tsukubamirai	Japan	2010	585	8.4
Tsukubamirai	Japan	2010	585	5.6
Tsukubamirai	Japan	2010	585	6.1
Tsukubamirai	Japan	2010	585	6.5
Tsukubamirai	Japan	2010	585	5.9

Sources: Hasegawa et al. (2013); Jing et al. (2016); Sun et al. (2014).

Table S3. Summary statistics on data used in estimation

Statistic	N	Mean	St. Dev.	Min	Max
Yield (tonnes/hectare)	1,522	3.31	1.66	0.39	11.83
Precipitation (mm)	1,522	927.78	691.20	0.11	3630.82
Mean max. temperature (Celsius)	1,522	20.94	5.81	11.14	36.64
SPEI (-: drought, +: wet)	1,522	-1.00	5.71	-17.20	16.21
CO ₂ concentration (ppm)	1,522	358.20	36.85	317.64	642.00
Fertilizer application (Kg N/ha)	1,522	56.51	57.29	0.00	450.87
Irrigation rate	1,522	20.62	16.73	0.00	76.20

Table S4. Results from Unit root tests

Levin-Lin-Chu Unit-Root Test		
	Individual Intercepts	Individual Intercepts and Trend
Test statistic	-5.228	-7.539
P-value	0.000	0.000

Im-Pesaran-Shin Unit-Root Test		
	Individual Intercepts	Individual Intercepts and Trend
Test statistic	-17.209	-17.236
P-value	0.000	0.000

Note: The null hypothesis is that the data is non-stationarity. The test used the data excluding FACE observations to remain a panel data structure. The panel data unit root test was conducted in R using *purtest()* from package *plm*.

Table S5. Comparisons of model specifications

	log of rice yield (in ton/hectare)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(precipitation) (in mm)	-0.002 (0.006)	-0.056 (0.098)	-0.082 (0.085)	-0.037 (0.097)	-0.052 (0.094)	-0.046 (0.095)
Log(max. temperature) (in degrees Celsius)	-0.324*** (0.045)	-0.983 (0.993)	-1.074 (0.861)	-0.670 (0.970)	-0.641 (0.931)	-0.827 (0.961)
SPEI (-: Drought, +: Wet)	-0.012*** (0.002)	-0.280*** (0.046)	-0.052 (0.056)	-0.016 (0.054)	0.010** (0.005)	-0.031 (0.055)
Log(atmospheric CO ₂) (in ppm)		2.957*** (0.058)	0.954*** (0.147)	0.747*** (0.151)		1.687** (0.843)
Log(atmospheric CO ₂) x SPEI (in ppm x SPEI)		0.049*** (0.008)	0.011 (0.010)	0.004 (0.009)		0.007 (0.009)
Log(fertilizer usage) (in Kg N/hectare)				0.025** (0.011)	0.019* (0.011)	0.019* (0.011)
Irrigation rate (%)				0.002*** (0.001)	0.002*** (0.001)	0.001** (0.001)
Time (Sequence of 1 to 56)			0.013*** (0.001)	0.011*** (0.002)	0.014*** (0.001)	0.009*** (0.003)
Time squared (Time ²)			-0.00003** (0.00001)	-0.00002 (0.00002)	-0.00001 (0.00002)	-0.00004 (0.00003)
FACE (1: FACE, 0: otherwise)					0.110 (0.082)	-0.564 (0.378)
FACE x China (1: FACE-China, 0: otherwise)					0.515*** (0.106)	0.500*** (0.085)
Constant	2.057*** (0.143)	-13.117*** (3.500)	-1.283 (3.139)	-1.560 (3.518)	2.704 (3.272)	-6.435 (5.864)
Country FE	No	Yes	Yes	Yes	Yes	Yes
Country FE x Climate variables	No	Yes	Yes	Yes	Yes	Yes
Breusch-Pagan test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Degree of freedom	1518	1396	1394	1392	1392	1390
Adjusted R ²	0.054	0.940	0.943	0.945	0.944	0.951

Note: significance levels are marked as follows: *p<0.1, **p<0.05, ***p<0.01. The above results are the third stage of our estimation procedure. The significant Breusch-Pagan test at least at 1% significance level for the first stage results suggests the existence of heteroscedasticity, providing a justification of using the 3-step FGLS approach.

Table S6. Estimated effects of climate, CO₂, and technological progress on rice yields

	log of rice yield (in ton/hectare)	
	Without CO2	With CO2
	(1)	(2)
Log of Precipitation (in mm)	-0.052 (0.094)	-0.046 (0.095)
Log of Max. Temperature (in degrees Celsius)	-0.641 (0.931)	-0.827 (0.961)
SPEI (-: drought, +: wet)	0.010** (0.005)	-0.031 (0.055)
Log of atmospheric CO2 (in ppm)		1.687** (0.843)
SPEI×log(CO2)		0.007 (0.009)
Log of fertilizer application (in Kg N/hectare)	0.019* (0.011)	0.019* (0.011)
Irrigation rate (as a percentage)	0.002*** (0.001)	0.001** (0.001)
Time (Sequence of 1 to 56)	0.014*** (0.001)	0.009*** (0.003)
Time squared	-0.00001 (0.00002)	-0.00004 (0.00003)
FACE	0.110 (0.082)	-0.564 (0.378)
FACE × China	0.515*** (0.106)	0.500*** (0.085)
Log of atmospheric CO2 × SPEI	-32.379** (13.734)	-33.187** (13.392)
Country dummy: Bangladesh	-11.445** (4.710)	-14.272*** (4.847)
Country dummy: Bhutan	-15.822*** (5.000)	-15.029*** (4.872)
Country dummy: Brunei	112.368*** (24.077)	98.199*** (23.210)
Country dummy: Cambodia	-12.095 (8.392)	-11.469 (8.481)
Country dummy: China	1.416 (4.604)	1.959 (4.763)
Country dummy: India	-10.728** (4.769)	-9.646** (4.455)
Country dummy: Indonesia	-23.492*** (4.636)	-24.923*** (4.407)

Country dummy: Iran	1.347 (4.111)	1.350 (4.124)
Country dummy: Iraq	29.985*** (8.675)	27.013*** (9.117)
Country dummy: Japan	6.824* (3.926)	5.680 (3.971)
Country dummy: Kazakhstan	-6.648 (4.555)	-7.670* (4.595)
Country dummy: Kyrgyzstan	-8.551 (7.665)	-7.971 (7.475)
Country dummy: Laos	-10.375 (12.306)	-9.112 (12.825)
Country dummy: Malaysia	15.897*** (5.475)	15.875*** (5.510)
Country dummy: Myanmar	5.842 (9.362)	3.928 (9.693)
Country dummy: Nepal	-11.310*** (3.998)	-11.880*** (4.045)
Country dummy: North Korea	14.769*** (5.222)	13.289** (5.453)
Country dummy: Pakistan	-4.484 (4.108)	-3.087 (3.948)
Country dummy: Philippines	-22.722*** (5.895)	-21.076*** (6.261)
Country dummy: South Korea	-0.529 (3.795)	-1.600 (3.900)
Country dummy: Sri Lanka	1.962 (5.631)	-1.480 (5.793)
Country dummy: Syria	0.887 (20.727)	4.666 (18.734)
Country dummy: Taiwan	5.181 (3.549)	5.225 (3.697)
Country dummy: Tajikistan	-33.583*** (8.722)	-32.583*** (9.284)
Country dummy: Thailand	-12.588*** (4.400)	-15.059*** (4.702)
Country dummy: Turkey	0.027 (3.736)	-0.611 (3.832)
Country dummy: Turkmenistan	30.503*** (11.753)	30.214** (11.992)
Country dummy: Uzbekistan	-24.293 (18.728)	-24.473 (18.373)
Country dummy: Vietnam	-9.937* (18.728)	-10.495* (18.373)

	(5.508)	(6.260)
log(Prec)×Country dummy: Azerbaijan	0.372 (0.400)	0.409 (0.389)
log(Prec)×Country dummy: Bangladesh	-0.00003 (0.124)	0.016 (0.129)
log(Prec)×Country dummy: Bhutan	0.153 (0.176)	0.150 (0.174)
log(Prec)×Country dummy: Brunei	-0.883*** (0.342)	-0.853*** (0.326)
log(Prec)×Country dummy: Cambodia	0.365 (0.288)	0.360 (0.279)
log(Prec)×Country dummy: China	0.246 (0.186)	0.091 (0.174)
log(Prec)×Country dummy: India	0.318* (0.164)	0.314** (0.151)
log(Prec)×Country dummy: Indonesia	0.169 (0.120)	0.162 (0.113)
log(Prec)×Country dummy: Iran	-0.012 (0.099)	-0.014 (0.099)
log(Prec)×Country dummy: Iraq	0.013 (0.102)	0.002 (0.103)
log(Prec)×Country dummy: Japan	-0.231* (0.141)	-0.195 (0.136)
log(Prec)×Country dummy: Kazakhstan	0.033 (0.112)	0.035 (0.112)
log(Prec)×Country dummy: Kyrgyzstan	0.185 (0.355)	0.167 (0.337)
log(Prec)×Country dummy: Laos	0.738** (0.362)	0.705* (0.367)
log(Prec)×Country dummy: Malaysia	-0.033 (0.138)	-0.086 (0.143)
log(Prec)×Country dummy: Myanmar	0.093 (0.203)	0.128 (0.211)
log(Prec)×Country dummy: Nepal	0.365*** (0.132)	0.349*** (0.132)
log(Prec)×Country dummy: North Korea	-0.019 (0.174)	-0.044 (0.179)
log(Prec)×Country dummy: Pakistan	-0.023 (0.097)	-0.042 (0.097)
log(Prec)×Country dummy: Philippines	0.459*** (0.140)	0.447*** (0.144)
log(Prec)×Country dummy: South Korea	-0.150 (0.116)	-0.154 (0.117)

log(Prec)×Country dummy: Sri Lanka	0.048 (0.110)	0.041 (0.112)
log(Prec)×Country dummy: Syria	0.174 (0.179)	0.124 (0.173)
log(Prec)×Country dummy: Taiwan	-0.030 (0.099)	-0.044 (0.100)
log(Prec)×Country dummy: Tajikistan	-0.030 (0.163)	-0.028 (0.167)
log(Prec)×Country dummy: Thailand	0.382** (0.152)	0.428*** (0.162)
log(Prec)×Country dummy: Turkey	0.069 (0.110)	0.069 (0.107)
log(Prec)×Country dummy: Turkmenistan	-0.167 (0.251)	-0.202 (0.249)
log(Prec)×Country dummy: Uzbekistan	-0.127 (0.160)	-0.116 (0.160)
log(Prec)×Country dummy: Vietnam	0.579*** (0.197)	0.410* (0.221)
log(Tmax)×Country dummy: Azerbaijan	9.242** (3.775)	9.431** (3.682)
log(Tmax)×Country dummy: Bangladesh	3.813*** (1.408)	4.705*** (1.426)
log(Tmax)×Country dummy: Bhutan	4.848*** (1.437)	4.577*** (1.381)
log(Tmax)×Country dummy: Brunei	-30.745*** (6.836)	-26.684*** (6.586)
log(Tmax)×Country dummy: Cambodia	2.790 (2.471)	2.617 (2.524)
log(Tmax)×Country dummy: China	-0.969 (1.382)	-0.809 (1.432)
log(Tmax)×Country dummy: India	2.823** (1.389)	2.458* (1.286)
log(Tmax)×Country dummy: Indonesia	9.165*** (1.640)	9.710*** (1.509)
log(Tmax)×Country dummy: Iran	-0.409 (1.270)	-0.433 (1.258)
log(Tmax)×Country dummy: Iraq	-9.420*** (2.680)	-8.477*** (2.815)
log(Tmax)×Country dummy: Japan	-1.596 (1.072)	-1.296 (1.090)
log(Tmax)×Country dummy: Kazakhstan	2.300 (1.473)	2.640* (1.474)
log(Tmax)×Country dummy: Kyrgyzstan	2.773	2.530

	(2.386)	(2.318)
log(Tmax)×Country dummy: Laos	1.501 (3.662)	1.179 (3.808)
log(Tmax)×Country dummy: Malaysia	-5.903*** (1.818)	-5.800*** (1.813)
log(Tmax)×Country dummy: Myanmar	-2.042 (2.768)	-1.522 (2.862)
log(Tmax)×Country dummy: Nepal	3.112** (1.249)	3.331*** (1.245)
log(Tmax)×Country dummy: North Korea	-5.338*** (1.719)	-4.760*** (1.792)
log(Tmax)×Country dummy: Pakistan	1.599 (1.300)	1.085 (1.212)
log(Tmax)×Country dummy: Philippines	6.682*** (1.885)	6.117*** (2.004)
log(Tmax)×Country dummy: South Korea	0.760 (1.092)	1.108 (1.117)
log(Tmax)×Country dummy: Sri Lanka	-0.559 (1.615)	0.469 (1.649)
log(Tmax)×Country dummy: Syria	-0.199 (5.735)	-1.183 (5.181)
log(Tmax)×Country dummy: Taiwan	-1.281 (1.013)	-1.258 (1.051)
log(Tmax)×Country dummy: Tajikistan	11.456*** (2.871)	11.093*** (3.063)
log(Tmax)×Country dummy: Thailand	3.093** (1.256)	3.763*** (1.349)
log(Tmax)×Country dummy: Turkey	0.079 (1.097)	0.284 (1.118)
log(Tmax)×Country dummy: Turkmenistan	-9.879*** (3.608)	-9.755*** (3.688)
log(Tmax)×Country dummy: Uzbekistan	7.746 (5.833)	7.800 (5.721)
log(Tmax)×Country dummy: Vietnam	2.178 (1.830)	2.786 (2.124)
SPEI×Country dummy: Azerbaijan	-0.024 (0.018)	-0.026 (0.016)
SPEI×Country dummy: Bangladesh	-0.013** (0.006)	-0.014*** (0.005)
SPEI×Country dummy: Bhutan	0.009 (0.007)	0.009 (0.007)
SPEI×Country dummy: Brunei	0.018 (0.012)	0.024** (0.011)

SPEI×Country dummy: Cambodia	-0.006 (0.008)	-0.008 (0.008)
SPEI×Country dummy: China	-0.016** (0.007)	-0.015** (0.006)
SPEI×Country dummy: India	-0.010* (0.005)	-0.011** (0.005)
SPEI×Country dummy: Indonesia	-0.013** (0.005)	-0.013** (0.005)
SPEI×Country dummy: Iran	-0.0001 (0.005)	-0.0002 (0.005)
SPEI×Country dummy: Iraq	-0.006 (0.009)	-0.003 (0.008)
SPEI×Country dummy: Japan	-0.001 (0.007)	0.001 (0.007)
SPEI×Country dummy: Kazakhstan	-0.005 (0.006)	-0.005 (0.005)
SPEI×Country dummy: Kyrgyzstan	-0.009 (0.012)	-0.012 (0.011)
SPEI×Country dummy: Laos	-0.033*** (0.012)	-0.036*** (0.012)
SPEI×Country dummy: Malaysia	-0.010* (0.006)	-0.008 (0.005)
SPEI×Country dummy: Myanmar	-0.019*** (0.006)	-0.020*** (0.006)
SPEI×Country dummy: Nepal	-0.003 (0.005)	-0.003 (0.005)
SPEI×Country dummy: North Korea	0.010 (0.012)	0.016 (0.012)
SPEI×Country dummy: Pakistan	-0.004 (0.005)	-0.005 (0.005)
SPEI×Country dummy: Philippines	-0.015*** (0.006)	-0.017*** (0.005)
SPEI×Country dummy: South Korea	-0.001 (0.007)	-0.001 (0.006)
SPEI×Country dummy: Sri Lanka	-0.015*** (0.005)	-0.015*** (0.005)
SPEI×Country dummy: Syria	-0.016 (0.024)	-0.024 (0.022)
SPEI×Country dummy: Taiwan	-0.009* (0.005)	-0.008* (0.005)
SPEI×Country dummy: Tajikistan	-0.003 (0.011)	-0.008 (0.011)
SPEI×Country dummy: Thailand	0.0003	0.001

	(0.005)	(0.005)
SPEI×Country dummy: Turkey	-0.013**	-0.012**
	(0.005)	(0.005)
SPEI×Country dummy: Turkmenistan	0.008	0.006
	(0.009)	(0.009)
SPEI×Country dummy: Uzbekistan	0.015	0.012
	(0.011)	(0.011)
SPEI×Country dummy: Vietnam	-0.015**	-0.017***
	(0.006)	(0.006)
Constant	2.704	-6.435
	(3.272)	(5.864)
Country FE	Yes	Yes
Country FE × Climate variables	Yes	Yes
Breusch-Pagan test (p-value)	0.000	0.000
Degree of freedom	1392	1390
Adjusted R2	0.944	0.951

Note: significance levels are marked as follows: *p<0.1, **p<0.05, ***p<0.01. Models (1) and (2) in this table are the same as Models (5) and (6) in Table S5 but with detailed interaction term coefficients. The above results are the third stage of our estimation procedure. The significant Breusch-Pagan test at least at 1% significance level for the first stage results suggests the existence of heteroscedasticity, providing a justification of using the 3-step FGLS approach.

Table S7. Projected rice yield growth by climate scenario and country for 2050 and 2100

Region	Country	Regional weights	2015 Yield (ton/ha)	RCP4.5		RCP6.0		RCP8.5	
				2050 Growth	2100 Growth	2050 Growth	2100 Growth	2050 Growth	2100 Growth
East Asia	China	91.4%	6.89	42%	47%	40%	102%	64%	215%
	Japan	4.7%	6.63	65%	66%	62%	123%	87%	237%
	North Korea	0.8%	6.34	-22%	-33%	-22%	-20%	-19%	-5%
	South Korea	2.5%	7.22	103%	128%	96%	232%	143%	494%
	Taiwan	0.7%	6.28	43%	44%	40%	94%	62%	194%
South Asia	Afghanistan	0.2%	2.50	63%	74%	58%	143%	90%	299%
	Bangladesh	22.7%	4.51	62%	116%	53%	251%	111%	701%
	Bhutan	0.0%	3.81	51%	99%	41%	223%	95%	636%
	India	68.5%	3.61	62%	95%	55%	196%	100%	478%
	Nepal	2.1%	3.36	63%	104%	54%	218%	105%	563%
	Pakistan	4.5%	3.72	46%	63%	40%	136%	74%	318%
	Sri Lanka	2.1%	3.87	59%	74%	55%	146%	88%	317%
Southeast Asia	Brunei	0.0%	0.81	-75%	-92%	-71%	-96%	-84%	-99%
	Cambodia	4.8%	3.34	11%	34%	6%	104%	37%	300%
	Indonesia	31.4%	5.34	187%	382%	161%	818%	319%	2857%
	Laos	2.1%	4.25	21%	41%	19%	102%	47%	255%
	Malaysia	1.4%	2.86	21%	-2%	22%	12%	22%	22%
	Myanmar	13.5%	3.87	37%	37%	36%	81%	55%	164%
	Philippines	9.3%	3.90	102%	190%	90%	392%	173%	1131%
	Thailand	14.3%	2.85	93%	146%	82%	288%	145%	731%
	Vietnam	23.2%	5.76	37%	68%	31%	155%	70%	405%
West Asia	Iran	69.5%	4.43	47%	53%	43%	110%	69%	234%
	Iraq	3.2%	4.48	-51%	-65%	-50%	-63%	-53%	-67%
	Turkey	27.2%	7.94	41%	53%	38%	115%	66%	258%

Note: The forecasted rice yields in 2050 and 2100 under different climate scenarios are estimated using projections from the equation resulting from the third stage of the FGLS approach estimation for Model 2 in Table S6 when evaluated with the CMIP5 projection data. The percentage is the total yield growth since 2015. Darker and lighter green indicate larger and smaller growth rates, respectively. The regional weights, which are based on the ratio of country rice production level to total regional rice production in 2015, are used for calculating the regional weighted average projection.