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DILEMMA OF CO_2 MITIGATION: EFFECTS OF CLIMATE, CO_2, AND TECHNOLOGICAL PROGRESS ON RICE YIELDS

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Rice feeds billions of populations, and its yields are sensitive to climate change, carbon dioxide (CO_2), and technological progress. This study estimates a model of these effects using Asian rice yield data merged with free air carbon dioxide enrichment (FACE) experimental data. A three-stage generalized least squares model is developed to quantify their effects on mean rice yields and their variance. The results show that CO_2 concentration has significantly contributed to increased rice yields, accounting for 16–26% of observed yield growth over 1990–2015. This indicates that if significant CO_2 mitigation occurs, the CO_2 fertilization effect will diminish, inducing a yield reduction. This finding suggests that increased agricultural research and development investments are needed to overcome not only adverse climate change effects but also to counteract CO_2 mitigation effects on rice yields.

Keywords: Rice yield; climate change; CO_2 fertilization effect; gridded climate data.

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1. Introduction

Rice is the most widely consumed food crop globally (Food and Agriculture Organization, 2016). Increasing rice yields is vital in feeding a growing population (Brück and d'Errico, 2019), especially critical in Asia, which produces and consumes approximately 90% of the world's rice (Food and Agriculture Organization, 2018). However, rice yield growth faces significant challenges, particularly due to climate change effects (Ortiz-Bobea *et al.*, 2021; Sinnarong *et al.*, 2019). Rising temperatures associated with climate change have been found to negatively impact rice yields (Ishimaru *et al.*, 2016; Pattanayak and Kumar, 2014). Meanwhile, as a C3 crop, rice yields benefit from enhanced atmospheric CO_2 levels through the so-called CO_2 fertilization effect (Hasegawa *et al.*, 2013; Kirschbaum, 2011; Xu *et al.*, 2017). Namely, efforts to limit climate change by reducing net CO_2 emissions are also expected to negatively affect rice yield growth. These facts raise a dilemma between continuing climate change and climate change mitigation. To understand the future potential of rice yield growth, it is crucial to understand its driving factors and to develop appropriate adaptation strategies for sustainable rice yield growth.

This study aims to identify and separate out the respective effects of climate, atmospheric CO_2 concentration, and technological advances on Asian rice yield growth. It also estimates the potential yield loss induced by the absence of the CO_2 fertilization effect, which will likely occur if more ambitious CO_2 mitigation takes place. As such the study contributes to the literature by quantifying the CO_2 fertilization effect on Asian rice yield using free air carbon dioxide enrichment (FACE) data. The findings provide insights into the extent to which the CO_2 fertilization effect has contributed to historical rice yield growth and its potential role in future yield growth under varying climate change scenarios.

2. Background on Rice Yield, CO_2, and Climate

Previous studies have shown that climate conditions are key determinants of mean rice yields and their variability (Castro-Llanos *et al.*, 2019; Pathak *et al.*, 2018). Studies in Thailand and Bangladesh have found that increasing temperatures reduce rice yields and increase yield variability (Sinnarong *et al.*, 2019; Sarker *et al.*, 2014). Additionally, higher temperatures have been identified as a cause of rice yield losses in Laos, India and China (Ishimaru *et al.*, 2016; Pattanayak and Kumar, 2014; Zhang *et al.*, 2016). Precipitation has also been shown to be a key determinant of rice yields in Japan (Tanaka *et al.*, 2011). Considering both climate effects Shrestha *et al.* (2016) project Vietnamese rice yields will decrease by 1.3–23.1% during winter and increase by 2.1–6.7% during summer. Thus, it is important to consider climate effects in models that estimate future rice yields.

Technological advancement in rice yields has also been strong in the recent past decades. Much effort has addressed rice yield enhancement via breeding, genetic manipulation, fertilization, and management improvement. To capture this, studies commonly use a time variable (i.e., a sequential number) as a proxy to capture the technological impacts (Chen *et al.*, 2012; Villavicencio *et al.*, 2013).

In addition to technological innovation, the CO_2 fertilization effect is also contributing to the C3 rice crop yield growth. CO_2 concentration has risen from about 330 parts per million (ppm) in July 1973 to 426 ppm in July 2024 (US National Oceanic and Atmospheric Administration (NOAA), 2024). From the statistical identification standpoint, the impacts of technological progress and the CO_2 fertilization effect on rice yield growth can easily be confounded because atmospheric CO_2 concentration exhibits a correlation of about 95% with time (Attavanich and McCarl, 2014). As a result, it is not clear how much rice yield growth comes from technological progress versus that from the CO_2 fertilization effect. In the context of the large global dialogue over greenhouse gas control, CO_2 emissions may begin to taper off, which can diminish future rice yields. Thus, it is important to separately estimate the CO_2 effect and the technological progress effects on rice yield growth.

3. Methodology

A viable approach to independently identify CO_2 fertilization and technological progress effects on rice yields has to overcome the collinearity between atmospheric CO_2 concentration and time as a proxy for technological advance. Attavanich and McCarl (2014) addressed this identification challenge for U.S. corn, wheat, sorghum, and cotton by combining the historical crop yield data with FACE experimental data. They found that the effect of proxy technological progress on crop yield growth without considering CO_2 effects can be upwardly biased by as much as 40% when not accounting for the CO_2 effect. This study applies a similar methodology to Asian rice yields by combining Asian-based FACE data with regional historical yield and climate data.

3.1. *Analytical model specification*

A rice yield production function is used as shown in Eq. (1). The model follows developments in Just and Pope (1979) and Chen *et al.* (2004) and is

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

where $\log(y_{it})$ denotes the logarithmic rice yield in country i in year t. $f(X_{it}, \boldsymbol{\beta})$ is a function consisting of explanatory variables (X_{it}) in country i in year t with corresponding estimated parameters ($\boldsymbol{\beta}$). μ_{it} is a heteroskedastic error term, which captures unobservable effects and contains two components: $h(X_{it}, \boldsymbol{\alpha})$ and ε_{it}. This error term specification assumes that $h(X_{it}, \boldsymbol{\alpha})$ is a function accounting for heteroskedasticity in yields as influenced by the explanatory variable X_{it} and its associated estimated parameters ($\boldsymbol{\alpha}$). ε_{it} is an error term, and its distribution follows $N(0, 1)$. Under those assumptions, $f(X_{it}, \boldsymbol{\beta})$ gives the response of mean rice yield to the explanatory variables X_{it} while $h(X_{it}, \boldsymbol{\alpha})^2$ captures the influence of the same explanatory variables (X_{it}) on yield variance (Just and Pope, 1978). The resulting distribution of the estimated log (y_{it}) will be $N(f(X_{it}, \boldsymbol{\beta}), h(X_{it}, \boldsymbol{\alpha})^2)$ (Chen *et al.*, 2004; Wooldridge, 2019).

The first-stage empirical estimation form of Eq. (1) is

$$\begin{aligned}\log(y_{it}) &= f(X_{it}, \boldsymbol{\beta}) + \mu_{it}\\ &= \beta_0 + \beta_1 \log(\mathrm{PRE}_{it}) + \beta_2 \log(\mathrm{TEM}_{it}) + \beta_3 \mathrm{SPEI}_{it} + \beta_4 \log(\mathrm{CO2}_t)\\ &\quad + \beta_5 \mathrm{SPEI}_{it} \cdot \log(\mathrm{CO2}_t) + \beta_6 \log(\mathrm{FER}_{it}) + \beta_7 \mathrm{IRR}_{it} + \beta_8 \mathrm{Trend}_t + \beta_9 \mathrm{FACE}_{it}\\ &\quad + \delta_i + \boldsymbol{\gamma_1} \log(\mathrm{PRE}_{it}) \cdot \delta_i + \boldsymbol{\gamma_2} \log(\mathrm{TEM}_{it}) \cdot \delta_i + \boldsymbol{\gamma_3} \mathrm{SPEI}_{it} \cdot \delta_i + \mu_{it}, \end{aligned} \tag{2}$$

where the (X_{it}) terms include annual mean precipitation (PRE_{it}), annual average maximum growing season temperature (TEM_{it}), the SPEI drought measure (SPEI_{it}) (Vicente-Serrano *et al.*, 2010a, 2010b), yearly atmospheric CO_2 concentration ($\mathrm{CO2}_t$), fertilizer application amount (FER_{it}), percent of land under irrigation (IRR_{it}), time trend (Trend_t, which is a sequence of number starting with $1961 = 1$), and a FACE dummy variable ($\mathrm{FACE}_{it} = 1$ if the observation is from the FACE experiments, 0 if otherwise). We also include a country fixed effect (δ_i), and an interaction term between climate variables and δ_i.

Herein the time variable captures the technological progress that is not associated with irrigation and fertilizer (e.g., advances in rice variety, tillage, monitoring system, machinery, etc.). In addition, because only China and Japan have FACE observations, our dataset is not fully a balanced panel data. Except for SPEI, the percentage of land irrigated, time trend, and FACE dummy variable, the rest of the variables are in logarithmic form to derive corresponding elasticities (i.e., rice yield change rate respect to each explanatory variable). $\boldsymbol{\gamma_1}$, $\boldsymbol{\gamma_2}$, and $\boldsymbol{\gamma_3}$ are vectors of coefficients, accounting for interaction effects between climate and country fixed effects.

As estimating the CO_2 effect on rice yields is the focus of this study, the model specification presented in Eq. (2) allows us to minimize the potential endogeneity concerns related to the atmospheric CO_2 concentration via the following considerations. First, the atmospheric CO_2 concentration is highly correlated with technological progress advancement (Attavanich and McCarl, 2014). Therefore, to eliminate the concern of the key variation left in the error term and being a potential endogeneity source, we include the time variable as the proxy of technological progress advancement, as described in the previous paragraph. The inclusion of the time trend variable as an explanatory variable significantly eliminates the unobserved effect correlated with atmospheric CO_2 concentration in the error term. Second, following common approaches in the literature (Blanc and Schlenker, 2017; Chen *et al.*, 2004; McCarl *et al.*, 2008; Schlenker and Roberts, 2009), other time-invariant unobservable effects in each country were controlled by country fixed effects, which mitigates the possible endogeneity bias caused by country-specific omitted variables or unobserved factors. Third, climate is another potential factor that is correlated with atmospheric CO_2 concentration. Hence, our model includes a set of climate variables (i.e., precipitation, temperature, SPEI, and their interaction terms with country fixed effects) as explanatory variables, which reflect differential climate effects across countries and mitigate the climate-related unobserved country-level variation correlated with atmospheric CO_2 concentration in the error term.

3.2. *Empirical estimation method and procedure*

To estimate the analytical model in Sec. 3.1, we apply a three-stage feasible generalized least squares (FGLS) method (Just and Pope, 1979; Attavanich and McCarl, 2014). This method was chosen due to the following considerations: first, our dataset includes different countries over multiple years, and the cross-country data usually exhibits heteroscedastic features, which can affect estimation efficiency. The three-stage FGLS can address this heteroscedasticity. Additionally, when it comes to investigating crop yields, not only the mean effect on yield but also the effect on yield variance is of interest. The three-stage FGLS allows us to estimate the effects of climate and other explanatory variables on both mean rice yield and variance. The empirical three-stage FGLS estimation procedure is as follows:

(i) Estimate Eq. (2) $\log(y_{it}) = f(X_{it}, \boldsymbol{\beta}) + \mu_{it}$ using pooled ordinary least squares (OLS) to obtain the residuals $(\hat{\mu}_{it})$.

(ii) Use the residuals $(\hat{\mu}_{it})$ from stage (i) in stage (ii) estimation, where the square of $\hat{\mu}_{it}$ is the dependent variables and is estimated as a function of X_{it}. Namely, we estimated

$$\begin{aligned}\log(\hat{\mu}_{it}^2) &= \log[h(X_{it}, \boldsymbol{\alpha})^2] + \log(\varepsilon_{it}^2)\\ &= \log[\alpha_0 + \alpha_1 \log(\mathrm{PRE}_{it}) + \alpha_2 \log(\mathrm{TEM}_{it}) + \alpha_3 \mathrm{SPEI}_{it} + \alpha_4 \log(\mathrm{CO2}_t)\\ &\quad + \alpha_5 \mathrm{SPEI}_{it} \cdot \log(\mathrm{CO2}_t) + \alpha_6 \log(\mathrm{FER}_{it}) + \alpha_7 \mathrm{IRR}_{it} + \alpha_8 \mathrm{Trend}_t\\ &\quad + \alpha_9 \mathrm{FACE}_{it} + \delta_i + \boldsymbol{\alpha_{10}} \log(\mathrm{PRE}_{it}) \cdot \delta_i + \boldsymbol{\alpha_{11}} \log(\mathrm{TEM}_{it}) \cdot \delta_i\\ &\quad + \boldsymbol{\alpha_{12}} \mathrm{SPEI}_{it} \cdot \delta_i]^2 + \log(\varepsilon_{it}^2). \end{aligned} \tag{3}$$

This results in fitted values of $\widehat{\log(\hat{\mu}_{it}^2)}$ and enables us to calculate $\sqrt{\exp(\widehat{\log(\hat{\mu}_{it}^2)})}$, which will be used in stage (iii) to correct for the heteroskedasticity in Eq. (2).

(iii) Conduct a third stage adjusted estimation of the terms in Eq. (1), where the fitted results from stage (ii) divide the dependent variable and constant for the error term to correct for heteroskedasticity by estimating:

$$\frac{\log(y_{it})}{\sqrt{\exp(\widehat{\log(\hat{\mu}_{it}^2)})}} = \frac{f(X_{it}, \boldsymbol{\beta})}{\sqrt{\exp(\widehat{\log(\hat{\mu}_{it}^2)})}} + \frac{\mu_{it}}{\sqrt{\exp(\widehat{\log(\hat{\mu}_{it}^2)})}}, \tag{4}$$

where the weighted least squares (WLS) method is used with $\sqrt{\exp(\widehat{\log(\hat{\mu}_{it}^2)})}$ as weights.

In these steps, the estimated coefficients from stage (ii) capture the effects of explanatory variables on the rice yield variance, and the estimated coefficients from stage (iii) reflect the effects of explanatory variables on mean rice yield after removing heteroskedasticity.

4. Data Description

The data we used include country-level rice yields, climate, technology-related data, and global CO_2 concentration data and country-specific FACE data. The data sources for this information are presented in Table 1. Rice yield data were assembled for 19 Asian countries from 1961 to 2015 from a database maintained by the Food and Agriculture Organization (2022). Due to widespread rice production and limited FACE observational data, we only used data from 19 Asian countries. A list of chosen countries and corresponding group classification are: (1) the East Asia group where we included data from China, Japan, South Korea, and Taiwan (2) the South Asia group where we included data from Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka, and (3) the Southeast Asia group where we included data from Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, and Vietnam.

For climate data in these countries, we retrieved fine scale gridded climate data from (Jägermeyr *et al.*, 2021) that were defined on a 0.25° latitude–longitude grid. The retrieved gridded climate data include growing season precipitation (in millimeters) and average growing season maximum temperature (in°C). We then aggregated the grid-level climate data to the country-level using a weighted average based on each grid's rice land acreage. The study duration is limited to 2015 because the gridded climate data were only available up to 2015 at the time of conducting this study. We also computed an SPEI Drought measure following Vicente-Serrano *et al.* (2010a, 2010b). Values of SPEI span over both positive and negative ranges, with the positive observations indicating wet conditions and the negative ones indicating dry conditions.

Table 1. Data sources.

Variables	Duration	Sources
Rice yields (tonne/ha)	1961–2015	Food and Agriculture Organization (2022)
Precipitation (mm)	1961–2015	Jägermeyr *et al.* (2021)
Temperature (°C)	1961–2015	Jägermeyr *et al.* (2021)
SPEI	1961–2015	Calculated following Vicente-Serrano *et al.* (2010a, 2010b)
Percentage of land irrigated (%)	1961–2015	Food and Agriculture Organization (2022)
Fertilizer application (kg N/ha)	1961–2015	Jägermeyr *et al.* (2021)
Historical CO_2 concentration (ppm)	1961–2015	NOAA Global Monitoring Laboratory (US National Oceanic and Atmospheric Administration (NOAA), 2020)
FACE yield and CO_2 data	1998–2003, 2007–2008, 2010	Hasegawa *et al.* (2013), Jing *et al.* (2016), Sun *et al.* (2014)

Table 2. Summary statistics on data used in estimation.

Statistic	N	Mean	St. Dev.	Min	Max
Yield (tonne/ha)	1078	3.33	1.75	0.70	12.17
Precipitation (mm)	1078	1158	567	81	3,631
Mean max. growing season temp. (°C)	1078	20.34	5.28	11.14	31.82
SPEI (−: drought, +: wet)	1078	−0.91	5.06	−15.77	11.25
CO_2 concentration (ppm)	1078	360	47.36	318	642
Fertilizer application (kg N/ha)	1078	52	53	0.001	251
Percent of land irrigated (%)	1078	22	17	0.80	76

Table 3. Pearson correlation coefficient between CO_2 concentration and time.

	Without FACE data	With FACE data
Correlation coefficient	0.9939	0.6529

Regarding CO_2 concentration data (in ppm), we used two datasets in constructing the model: observed atmospheric CO_2 concentration from the NOAA Global Monitoring Laboratory (US National Oceanic and Atmospheric Administration (NOAA), 2020) and the control CO_2 concentration levels used in the FACE experiments. The FACE data we used arose from field experiments in Japan (25 observations) and China (8 observations) (Hasegawa *et al.*, 2013; Jing *et al.*, 2016; Sun *et al.*, 2014) and are presented in Table S1. FACE data were needed as they exhibit systematic CO_2 variation independent of time, lowering the correlation of CO_2 with time and allowing the CO_2 effect to be separately identified (Attavanich and McCarl, 2014).

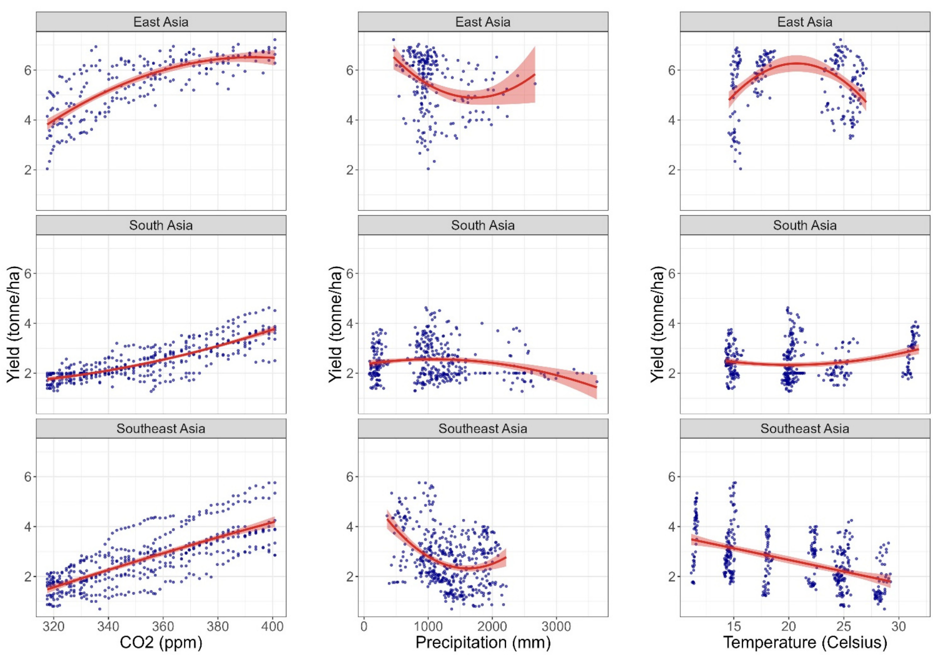
The technological-related data we used include irrigation prevalence and fertilizer application. The irrigation prevalence data were retrieved from the Food and Agriculture Organization (2022) and represent the percentage of land in each country under irrigation from 1961 to 2015. The fertilizer data give application rates (in kg N/ha) that were developed on a gridded basis by Jägermeyr *et al.* (2021). Those data were also aggregated to the country-level, following the same procedures used for the gridded climate data. Time series data for rice yield, climate, fertilization rate, and percentage of land irrigated by country are presented in Figs. S1–S6. Summary statistics on the data are provided in Table 2. A correlation analysis between time and CO_2 (Table 3) shows a correlation coefficient of 0.9939, raising the multicollinearity and separate effects identification issue, as we discussed above. Including the FACE data, as done in Attavanich and McCarl (2014), lowers the correlation coefficient to 0.6529, allowing the identification of the separate time and CO_2 effects.

5. Data Exploration and Model Specification Tests

5.1. *Relationship between rice yields, CO_2 concentration, and climate*

Figure 1 shows the scatter plots between rice yields in tonnes per hectare and key variables (i.e., atmospheric CO_2, precipitation, and growing season maximum temperature) in three Asian regions. Specifically, the scatter plots show observed values of rice yields on the vertical axis and associated CO_2 concentrations (Fig. 1(a)), precipitation (Fig. 1(b)), and growing season maximum temperature (Fig. 1(c)) on the horizontal axis in rows for the three Asian regions. The red lines in the plots are lines estimated from the OLS method where rice yield is the dependent variable, and atmospheric CO_2, precipitation, and growing season maximum temperature with their squared terms are the independent variables for the respective scatter plots.

Figure 1(a) shows upward sloping fitted lines of rice yield versus CO_2 indicating a positive correlation in all regions between CO_2 and rice yields. Figure 1(b) shows rice yield relationships with precipitation and indicates that the effect of precipitation on rice yields varies across Asian region. Figure 1(c) shows rice yield relationships with average growing season maximum temperature are heterogeneous, including an inverse U-shaped one in East Asia and a negative relationship with rice yields in Southeast Asia. Note that there are gaps in observed temperatures in Fig. 1(c) because the average growing season maximum temperature clusters in different countries.



(a) Atmospheric CO_2 (b) Precipitation (c) Temperature

Figure 1. Relationship between CO_2, climate, and rice yields over 1961–2015.

Table 4. Unit root test results.

	Individual intercepts	Individual intercepts and trend
Levin–Lin–Chu unit root test		
Test statistic	−3.206	−4.685
p-value	0.001	0.000
	Individual intercepts	Individual intercepts and trend
Im–Pesaran–Shin unit root test		
Test statistic	−13.107	−12.687
p-value	0.000	0.000

Notes: The null hypothesis is that the data are nonstationarity. The dataset without FACE observations was used to retain a panel data structure for the above unit root tests. The panel data unit root test was conducted in R using *purtest*() from the *plm* package (Croissant *et al.*, 2025).

These heterogeneous climate effects motivate us to include the climate and country intersection terms in our model (Sec. 3.1).

5.2. *Model specification tests*

Several statistical tests were conducted before the three-stage FGLS estimation. First, we examined data stationarity using unit root tests developed by Levin–Lin–Chu (Levin *et al.*, 2002) and Im–Pesaran–Shin (Im *et al.*, 2003). The tested specifications used cases with individual intercepts and with both individual intercepts and trends. Table 4 presents the resultant test statistics that indicate rejection of the null hypothesis of nonstationarity, suggesting that the data do not need to be transformed to make them stationary. We also tested for heteroskedasticity in the first-stage model using a Breusch–Pagan test (Breusch and Pagan, 1979) and found heteroscedasticity was present at the 99% level of significance, motivating the use of the three-stage FGLS approach.

6. Estimation Results

This section presents the estimation results on the effects of climate, CO_2 and technical progress. For brevity, we only report results from the second and third stages of our FGLS estimation. To allow exploration of the importance of the CO_2 concentration effect and its effect on technological progress effects, we estimated model versions with and without the atmospheric CO_2 concentration variable present.

6.1. *Impacts of CO_2, technology, and climate on mean rice yields*

Columns (1) and (2) in Table 5 demonstrate the importance of considering the atmospheric CO_2 concentration and including FACE observations in the model.

Table 5. Selected estimation results for mean rice yield and variability.

	Effects on mean yield [log (tonne/ha)]		Effects on yield variance [log $(\text{tonne/ha})^2$]	
	(1) Without CO_2	(2) With CO_2	(3) Without CO_2	(4) With CO_2
Log of precipitation (in mm)	0.024	−0.006	0.524	0.235
	(0.094)	(0.103)	(1.058)	(1.077)
Log of max. temperature (in °C)	0.139	−0.243	−2.086	−5.379
	(0.947)	(1.072)	(11.267)	(11.464)
SPEI (−: drought, +: wet)	0.013***	−0.077	−0.187***	−2.102**
	(0.005)	(0.050)	(0.054)	(0.951)
Log of atmospheric CO_2 (in ppm)		1.347**		4.285
		(0.579)		(6.868)
Log of atmospheric $CO_2 \times$ SPEI		0.015*		0.330**
		(0.009)		(0.162)
Log of fertilizer application (in kg N/ha)	0.070***	0.060***	0.003	−0.063
	(0.008)	(0.010)	(0.149)	(0.162)
Percentage of land irrigated	0.005***	0.005***	0.007	0.008
	(0.0005)	(0.0005)	(0.015)	(0.015)
Time (sequence of 1−56)	0.011***	0.006**	−0.012	−0.022
	(0.0004)	(0.003)	(0.010)	(0.033)
FACE dummy	0.135**	−0.399	1.413***	−0.272
	(0.056)	(0.248)	(0.502)	(3.027)
Constant	−0.136	−6.509	−0.362	−13.011
	(3.336)	(5.049)	(38.739)	(55.342)
Country FE	Yes	Yes	Yes	Yes
Country FE × Climate variables	Yes	Yes	Yes	Yes
Degrees of freedom	998	996	998	996
Number of countries	19	19	19	19
Observations	1078	1078	1078	1078
Adjusted R^2	0.960	0.957	0.215	0.216
F-statistic	326.608***	299.881***	4.729***	4.664***

Notes: Significance levels are marked as follows: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Columns (1) and (2) are the third-stage FGLS results, and columns (3) and (4) are the second-stage FGLS results. The full reporting on all the included variables is in Table S2.

Column (1) shows the omission of the CO_2 concentration variable leads to a significantly larger coefficient estimate for the time variable as a proxy for technological progress, leading to an upwardly biased estimate of the technological progress effect on mean rice yields. Column (2) shows that adding the CO_2 variable makes the technological progress effect smaller. In particular, including FACE observations reduces the correlation between the time trend variable and the CO_2 concentration variable, in turn, allowing us to identify both CO_2 and technological progress effects. These results indicate that using only the time trend variables over the historical yield data tends to confound time with the CO_2 effect due to the high correlation (Table 3 and Fig. 1(a)). Thus, the inclusion of the FACE observations allows us to separately identify respective effects. The FACE observations also add a larger variation in CO_2 values in the data (with values up to 642 ppm as shown in Fig. S7), which helps improve prediction validity because future CO_2 values are projected to be well out of the range of the observed CO_2 levels in the historical data (ranging from 318 ppm to 401 ppm).

The effects of CO_2, technology, and climate on mean rice yields estimated from the third-stage FGLS with the full model specification are presented in column (2) of Table 5. The results show that CO_2 atmospheric concentration enhances rice yields, reflecting the well-known C3 CO_2 crop growth fertilization effect (Korres *et al.*, 2016). Additionally, we find the amount of fertilizer application, irrigated land proportion, and time as a proxy for technological progress all have a positive effect on mean rice yields.

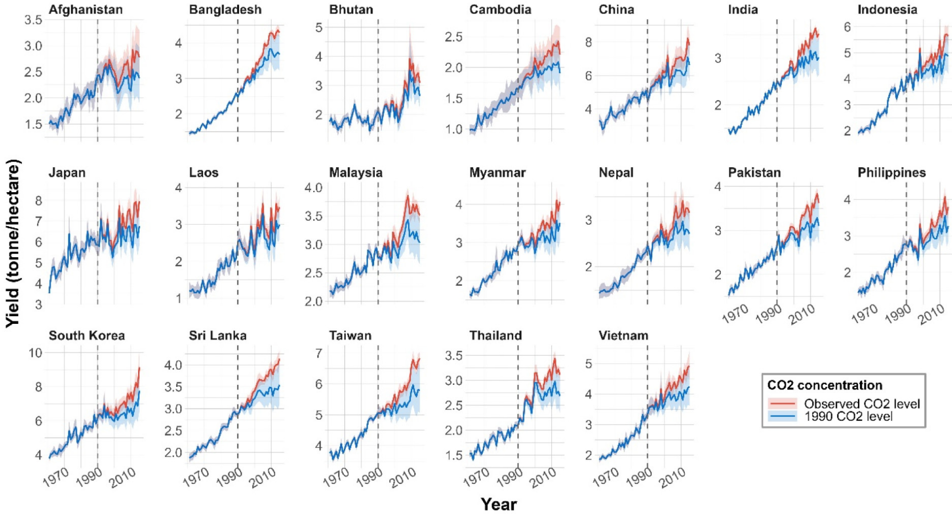
Climate variables have various impacts on rice yields and differ by country, as shown in Fig. 1. Specifically, higher precipitation has a negative impact on yields in Japan but a positive impact in India, Nepal, Philippines, and Thailand. Higher average growing season maximum temperature has a positive effect on yields in Indonesia and Bhutan but a negative effect in Malaysia. Wetter climate (i.e., higher SPEI) is expected to decrease rice yields in Bangladesh, China, India, Indonesia, Laos, Myanmar, Philippines, Sri Lanka, and Taiwan. The above country-dependent climate impacts are captured by interaction effects between the climate variables and country-dummy variables. Detailed estimation results, including the country and interaction coefficients, are given in Table S2.

6.2. *CO_2 fertilization effects on rice yield growth*

To separate out the impact of the CO_2 fertilization effect on the past rice yield growth, we used the estimated equation in column (2) of Table 5 and predicted historical rice yields from 1990 to 2015 with and without changing the CO_2 levels. To do so, we investigate two cases in which, starting in 1990, we maintain CO_2 at 1990 levels versus a case where we use the evolving observed atmospheric CO_2 concentration levels. Figure 2 presents the predicted rice yields by country under the constant and evolving CO_2 scenarios. The result shows that, without CO_2 evolution, the regional rice yield, on average, would have increased by 21% by 2015 relative to 1990. However, with CO_2 evolution, the regional yield increased by 41%. Namely, the CO_2 fertilization effect contributed an estimated 20% of the regional rice yield growth over 1990–2015. The countries with the largest yield growth from the evolving CO_2 fertilization are China (26%), Bangladesh (25%), and South Korea (22%), and the country with the least growth is Afghanistan (16%).

6.3. *Impacts of CO_2, technology, and climate on rice yield variance*

The estimated coefficients from the second stage of FGLS show the effects of CO_2, technology, and climate factors on rice yield variability. Those coefficients are given in columns (3) and (4) of Table 5. The *F*-statistic reported in columns (3) and (4) of Table 5 is significant at the 1% level, implying that CO_2, technology, and climate factors



Notes: The blue lines after 1990 show the estimated rice yields with CO_2 held fixed at the 1990 level. The red lines after 1990 show the estimated rice yields with the evolving observed CO_2 levels. The colored shades indicate 95% confidence intervals.

Figure 2. Estimated rice yields during 1990–2015 under constant and evolving CO_2 levels.

collectively influence rice yield variance. This result was also found in Attavanich and McCarl (2014) and McCarl *et al.* (2008). Additionally, the results show increasing SPEI (i.e., less drought with a wetter climate) reduces rice yield variability. On the other hand, the interaction of the SPEI and CO_2 effects leads to increases in rice yield variance, implying that the combination of wetter climate and CO_2 effects leads to larger rice yield variability. Regarding country-dependent climate effects on rice yield variance, higher precipitation is expected to reduce yield variance in the Philippines. A higher average growing season maximum temperature is anticipated to lower yield variability in Bangladesh and Myanmar but increase yield variability in Nepal and Taiwan. Detailed estimation results on yield variability, including the country and interaction coefficients, are given in Table S2.

7. Discussion: Implications for Future Rice Yield Growth

Our in-sample prediction in Sec. 6.2 suggests, on average, 20% of the regional rice yield growth over 1990–2015 was attributed to the CO_2 fertilization effect. Herein suppose we project future growth under climate change while partitioning out the CO_2 effect. Specifically, we assess the pure climate effect (i.e., holding CO_2 concentration constant and evolving climate), pure CO_2 effect (i.e., holding climate constant and evolving CO_2 concentration), and both effects (i.e., evolving both climate and CO_2 concentration). To do so, we used CMIP5[1] climate projections drawn from the

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

KNMI Climate Change Atlas (2020) under Representative Concentration Pathway (RCP) scenarios RCP 4.5, RCP 6, and RCP 8.5 (Intergovernmental Panel on Climate Change, 2013). For climate projections, we used projections from the Community Earth System Model version 1 coupled with the Community Atmospheric Model version 5 (CESM1–CAM5) (Neale *et al.*, 2010). For SPEI projections, we used the maximum length of dry spell results from Community Climate System Model 4.0 (Gent *et al.*, 2011). CMIP5 climate projections were used because they contain the information needed for SPEI projections. Fertilizer application and percentage of land irrigated were held constant at 2015 levels. For CO_2 projections, we used the IPCC CO_2 levels associated with the chosen RCPs under the evolving cases. When estimating the pure climate effect, we held CO_2 constant at the 1990 level. When estimating the pure CO_2 effect, we held climate variables constant at the 1990 level and evolved CO_2 concentration. Country-level projections were computed using the interaction terms between the climate variables and country dummy variables.

Figure 3 shows the climate and CO_2 effects on rice yields in the three Asia subregions under the RCPs. The results show that rice yields are projected to increase due to the pure climate effect (the blue boxes that involve maintaining CO_2 concentrations at the 1990 level), but those increases are much lower compared to the ones with the pure CO_2 effect (the green boxes that involve holding climate at 1990 levels while evolving CO_2 concentrations) or when both effects are included (the red boxes). That is because the pure climate effect does not exhibit the CO_2 fertilization effect, which helps enhance rice yields. The average yield reduction difference due to the absence of the CO_2 fertilization effect (i.e., the difference between black dots in red and blue boxes) over 2016–2100 is 34–36% under RCP 4.5, 40–41% under RCP 6, and 54–56% under RCP 8.5. The difference in rice yield contributions between the pure climate effect and both effects

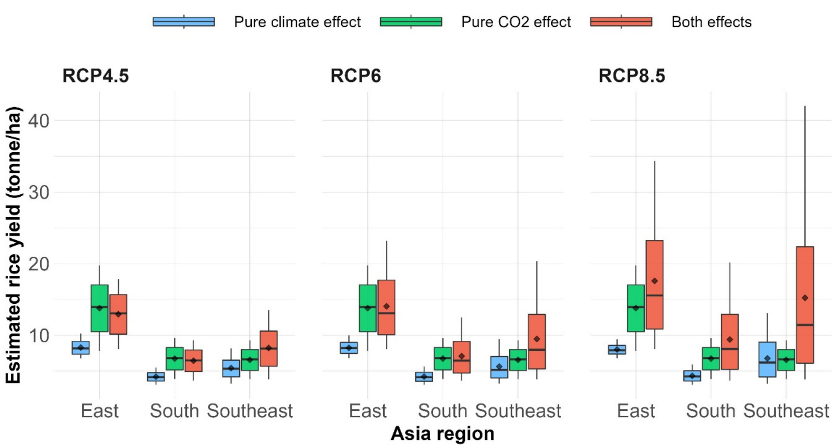
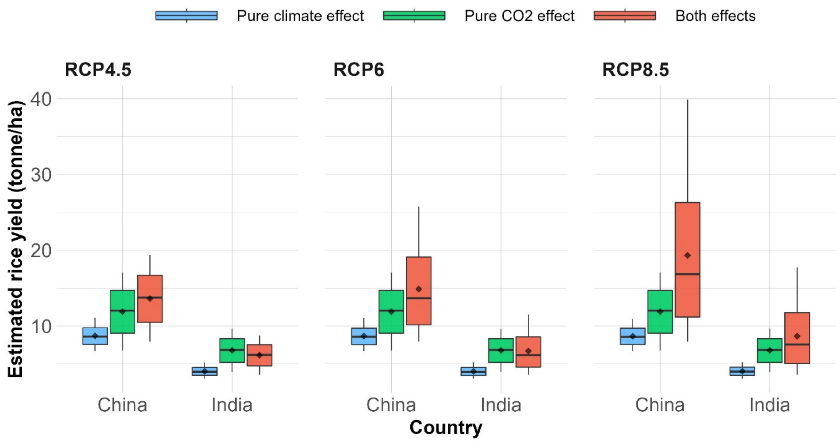


Figure 3. Projected rice yield comparison with and without the climate and CO_2 fertilization effects over 2016–2100 (by Asian subregion).



Note: For references, the observed rice yields in 2015 are 6.9 tonne/ha in China and 3.6 tonne/ha in India.

Figure 4. Projected rice yield comparison with and without the climate and CO_2 fertilization effects in India and China over 2016–2100.

is larger under RCP 8.5 than under RCP 4.5 and RCP 6 due to the larger CO_2 and climate effects under RCP8.5.

Examining the climate and CO_2 effects in the world's two largest rice-producing countries, China and India, which account for 28% and 26% of global rice production (US Department of Agriculture, 2024), reveals significant CO_2 contributions to future yield growth. Figure 4 shows that China is expected to have 36%, 42%, and 55% lower yields by 2100 if we don't consider the CO_2 effect (i.e., the difference between black dots in red and blue boxes) under the three RCPs (4.5, 6, and 8.5). Correspondingly, India is estimated to have yields that are lower by 35%, 40%, and 53% under the same three RCPs. Clearly the CO_2 effect is a major contributor to future rice yield growth.

8. Conclusions

This study examined the effects of climate, CO_2 fertilization, and technological progress on rice yields in the selected Asian countries. The results show that, on average, rice yields in the sample countries increased by 41% in 2015 relative to 1990 levels. However, when the impact of a CO_2-enriched atmosphere was removed, the increase was only 21%, indicating that 20% of the yield growth was attributable to increases in CO_2 concentration. On the other hand, we find average yield reductions over 2016–2100 due to the absence of the CO_2 fertilization effect and its intersection effect with climate are estimated at 34–36% under RCP 4.5, 40–41% under RCP 6, and 54–56% under RCP 8.5. Importantly, CO_2 mitigation efforts can lead to a reduction in yield growth rate by diminishing the above CO_2 fertilization effect, emphasizing the critical need for proactive adaptation strategies to ensure sustainable rice production in the face of both the reduced CO_2 and climate change challenges.

Based on this study's findings, some adaptation strategies can mitigate the adverse impacts of climate change on rice production while enhancing future rice yields to meet the demands of a growing population. First, the positive coefficient for the percentage of land irrigated in column (2) of Table 5 highlights the importance of expanding irrigation infrastructure to support yield growth. This strategy is especially critical for countries with low amounts of rice land irrigated but may not hold much potential in regions where rice is already highly irrigated. Second, the fertilization coefficient in column (2) of Table 5 suggests that increased fertilizer application is another possible adaptation (as argued in Shrestha *et al.* (2016)). However, extensive fertilizer applications may deteriorate water quality. Third, the positive coefficient of the time variable in column (2) of Table 5 suggests that technological progress can also enhance rice yields via varietal advancement, improved tillage, improved pest management, pest and moisture monitoring systems, and improved machinery, among other possibilities.

This study has a number of limitations. First, although agricultural research and development investment is widely recognized as a key determinant of crop yield growth (Alston and Pardey, 2006; Andersen *et al.*, 2018; Huang, 2021; Pardey *et al.*, 2016), it could not be directly analyzed in this study due to data limitations and the 17- to 34-year lag involved between investment and full returns (Alston and Pardey, 2006; Huffman and Evenson, 2006). Second, we treated each country as a homogeneous region; for areas like China, we could certainly improve things with more regionalized data.

There are several potential research developments for future work. First, FACE experiments are very costly, leading to a scarcity of such data. Since the rice FACE data are limited, if any new rice-based FACE data emerge, it would be desirable to update this analysis. Second, as mentioned above, it would be useful to work with less aggregate sub-country-level data. Third, while this study employed a fixed-effects model to account for systematic country effects, it did not include variables capturing country-specific characteristics, such as soil quality, degradation, etc., and adding more related explanatory variables could improve the results. Fourth, further studies could devote attention to studying the R&D expenditure effect and how it could help in adaptation. Finally, investigating the impacts of long-term climate events (e.g., El Niño, decadal climate variability) and extremes (droughts, flooding, and heatwaves) on rice yields would be a valuable avenue for further study as climate change is influencing their frequency and intensity as well (Fan *et al.*, 2017; Huang *et al.*, 2020; Intergovernmental Panel on Climate Change, 2012, 2022; Wang *et al.*, 2021).

Supplementary Information

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