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Abstract

Rice is arguably the world's most important food crop. Expansions in rice crop productivity are vital to future food security and highly related to climate factors. This study econometrically investigates the impacts of CO_2 fertilization effects, climate, and ocean-related decadal climate variability (DCV), on rice yields using Asian and African data. To allow identification of CO_2 effects, the study includes data from free air carbon dioxide enrichment (FACE) experimentation. The result indicates that actual pure technological progress is 44.7% smaller than what we observe if the growth of CO_2 concentration would not have existed. The result also shows that warmer sea surface temperature in the West Pacific tends to have lower rice yields in our samples. The forecasting rice yield result given different warming scenarios suggests that rice yields are predicted to rise significantly by 134.6% in 2100 under the RCP8.5 scenario due to the larger CO_2 fertilization effect. However, under greater CO_2 mitigation (RCP4.5 and RCP6 scenarios), growth rates fall to 31.7% and 67.9%, respectively. This raises a joint challenge of maintaining high productivity while mitigating future CO_2 emissions.

Keywords Decadal climate variability, rice yield, fertilization effect, climate change.

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1 Introduction

Climate change can induce substantial economic losses by the end of the century (Martinich and Crimmins 2019). Among all sectors, agriculture is particularly vulnerable. Climate conditions are key drivers of agricultural productivity and the variability of food production (Selvaraju, Gommes, and Bernardi 2011). Previous studies also have indicated how climate affects agricultural production and production location. Sinnarong et al. (2019) show that increasing temperatures reduces mean rice production and increases production variation. Cho, McCarl, and Wu (2015) examine crop mix and find that the temperature and the amount of precipitation cause changes in crop production location.

Climate effects of ocean phenomena are also important. One ocean-related phenomenon is decadal climate variability (DCV), which has been found to influence climatic conditions and crop yields (Jithitikulchai 2014; Jithitikulchai 2018; Jithitikulchai, McCarl, and Wu 2018). The DCV index consists of Pacific Decadal Oscillation (PDO)(Mantua et al. 1997), the Tropical Atlantic Sea Surface Temperature Gradient (TAG)(Mehta 1998; Mehta and Delworth 1995), and the Western Pacific Warm Pool Sea Surface Temperature (WPWP)(Wang and Mehta 2008). Each component has two phases which involve sea level temperatures above or below the long-term average. Across the three phenomena with each in having one of two states, there are eight possible joint conditions. Those joint phase conditions have been found to be associated with the long-run ocean temperature and can impact multi-year drought and precipitation patterns (Latif and Barnett 1994; Mehta, Wang, and Mendoza 2013), which greatly influence crop yields. For example, Jithitikulchai, McCarl, and Wu (2018) found that the DCV phases influence U.S. crop yields while Mehta, Rosenberg, and Mendoza (2012) found impacts in the Missouri River Basin.

Technical advance in crop production is a crucial determinant of food supply adequacy and can offset possible negative impacts of climate change (McCarl, Villavicencio, and Wu 2008; Miao, Hennessy, and Babcock 2012). The conventional way of modeling such advance is to use a linear and quadratic time trend as a proxy. However, this approach not only captures technological advance effect but also captures the effects of increases in CO_2 concentrations (Attavanich and McCarl 2014). Its omissions fail to capture possible strong effects that would be reduced under climate change mitigation. To identify CO_2

concentration effect, one must overcome a collinearity issue between time as a proxy for technological progress and time increasing CO_2 emissions. To reduce the correlation between these two variables, Attavanich and McCarl (2014) combine observed yields and free air carbon dioxide enrichment (FACE) experimental data. In turn, they find for the U.S. that CO_2 biases upwards estimated rates of technological progress.

This study investigates climate, DCV, and CO_2 fertilization effects on rice yields over time using historical data from Asian and African countries, coupled with FACE experiment data. The results can contribute to understanding how climate change affects rice yields in Africa and Asia and sheds light on future food supplies.

2 Empirical Methodology

To estimate the effect of climate, DCV, CO_2 fertilization effect, and technological progress on rice yields, the rice yield function is assumed as a stochastic production function (Just and Pope 1979). Following Attavanich and McCarl (2014), we can express the rice yield function as:

$$log(y_{it}) = f(X_{it}, \beta) + \mu = f(X_{it}, \beta) + h(X_{it}, \alpha)\varepsilon_{it} \quad \text{Eq. (1)}$$

where y_{it} denotes rice yields in country i in year t; X_{it} is a set of explanatory variables in country i in year t, including mean precipitation, mean temperature, a drought measure - Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010), global CO_2 concentration, DCV joint phase combination dummies, irrigation rate, and time as a proxy for technological progress (including both linear and quadratic terms). We also include dummy variables indicating whether a particular observation is part of the FACE data. Country fixed effects and interaction terms between DCV dummies and country dummies are also included.

To properly model variance effects, a three-step feasible generalized least squares (FGLS) method is employed (Just and Pope 1979; Attavanich and McCarl 2014). Specifically, the empirical estimation procedure is one that corrects for heteroskedasticity as follows:

First, estimate $log(y_{it}) = f(X_{it}, \beta) + \mu$ by using ordinary least squares (OLS) and obtain residuals ($\hat{\mu}$).

Second, estimate $\hat{\mu}^2 = g(X, \gamma) + u$ and obtain fitted values $\widehat{\hat{\mu}^2}$ and calculate $\sqrt{exp(\widehat{\hat{\mu}^2})}$.

Lastly, we estimate the $log(y_{it}) = f(X_{it}, \beta) + \mu$ model using weighted least squares (WLS) with $\sqrt{exp(\widehat{\hat{\mu}^2})}$ as weights.

We also need to take DCV effects on climate and, in turn, climate effects on yield into account. In particular, the marginal total effect of DCV, combing the indirect effect of phase on climate and the climate effect on yield along with any direct effects can be expressed as follows:

$$\frac{\Delta log(Yield_{it})}{\Delta DCV_{k,t}} = \frac{\Delta \hat{f}}{\Delta DCV_{k,t}} + \frac{\Delta \hat{g}}{\Delta Climate_{i,t}} \frac{\Delta Climate_{i,t}}{\Delta DCV_{k,t}} \quad \text{Eq. (2)}$$

where $\hat{f}$ captures the direct climate and DCV effects on rice yields and $\hat{g}$ is effects of DCV phases on climate variables (precipitation and temperature). Given that the term $\frac{\Delta \hat{f}}{\Delta Climate_{i,t}} \frac{\Delta Climate_{i,t}}{\Delta DCV_{k,t}}$ presents the indirect DCV effect on rice yields through weather variables. $Climate_{i,t}$ denotes precipitation and temperature variables in country i in year t. Note that $DCV_{k,t}$ in $\frac{\Delta log(Yield_{it})}{\Delta DCV_{k,t}}$ is a dummy variable indicating different types of DCV events, k is from 1 to 8. The marginal effect of $\frac{\Delta log(Yield_{it})}{\Delta DCV_{k,t}}$ need to be transformed by the following procedure:

$$\delta = \frac{\Delta log(Yield_{it})}{\Delta DCV_{k,t}} = log(Yield_{it})|_{DCV=1} - log(Yield_{it})|_{DCV=0} = log\left(\frac{Yield_{it}|_{DCV=1}}{Yield_{it}|_{DCV=0}}\right) \quad \text{Eq. (3)}$$

With exponential transformation at the both side of Eq.(3), the marginal effect of DCV on rice yields turns to be:

$$exp(\delta) = \frac{Yield_{it}|_{DCV=1}}{Yield_{it}|_{DCV=0}} \quad \text{Eq. (4)}$$

The percentage change in rice yields caused by switching the DCV status from the base scenario to other scenarios is

$$\left[\frac{Yield_{it}|_{DCV=1} - Yield_{it}|_{DCV=0}}{Yield_{it}|_{DCV=0}}\right] \times 100\% = [exp(\delta) - 1] \times 100\% \quad \text{Eq. (5)}$$

3 Data

The data sources employed are summarized in Table 1. This study uses rice data from 59 countries: 26 African countries and 23 Asian countries from 1961 to 2016. The country-level rice yield data were drawn from Food and Agriculture Organization of the United Nations (2020). The country-level climate data came from the Climatic Research Unit (CRU), University of East Anglia (2020). DCV data were obtained from the National Oceanic and Atmospheric Administration (2020), and the global CO_2 concentration is from Meinshausen et al. (2011). SPEI data was retrieved from SPEI Global Drought Monitor. FACE data are from experiments in Japan and China (Hasegawa et al. 2013; Sun et al. 2014; Jing et al. 2016). The summary statistics for these data are given in the Appendix.

4 Empirical Results

This section first addresses stationarity of the data then goes on to investigate effects of climate, CO_2 on rice yields, as well as impacts of DCV on both rice yields and climate. It then examines the robustness check on the technological progress effect with and without considering global CO_2 concentrations. Finally, forecasted impacts of global warming and CO_2 fertilization effect on future rice yields are investigated.

4.1 Testing for Non-stationarity

Statistical inference requires the satisfaction of the stationary assumption. Thus, panel unit-root tests using the Levin-Lin-Chu method (Levin, Lin, and Chu 2002) are conducted. The result of the panel unit-root tests is available in the Appendix. The results indicate that the series are stationary, suggesting no need to difference or detrend the data before the estimation.

4.2 Direct and Indirect Effects on Rice Yields

The estimation results for rice yields are shown in Table 3, where four model specifications are presented: both African and Asian observations with and without the CO_2 concentration variable (Model 1 and 2), and Asian observations alone with and without the CO_2 concentration variable (Model 3 and 4). Generally, we find climate and CO_2 influences. Precipitation has a positive effect on rice yields in Model 1 and 2, and the impact of temperature on rice yield is negative in the Asia only models (Model 3 and 4). The

inclusion of the CO_2 concentration variable reduces the magnitude of the trend variable's coefficient as we discuss below.

The direct effects of DCV phase combinations are presented by joint phase combination where we denote positive (+) and negative (−) phases for the three phenomena. All models include a country fixed effect and drop the intercept so that it is more straightforward to interpret the eight DCV coefficients. Other model specifications are available in the Appendix.

The result indicates that (PDO-TAG+WPWP+) induces the highest rice yield among all DCV scenarios across different model specifications, and the rice yield is generally lower under (PDO+TAG+WPWP-). The indirect effects of DCV on rice yield through climate effects (precipitation and temperature), are shown in Table 4. Under (PDO+TAG+WPWP+), the precipitation is expected to be higher among all scenarios in Africa and Asia. The temperature is relatively lower in (PDO-TAG-WPWP-) scenario compared to other scenarios.

For interpretation, the DCV coefficients in Table 3 and 4 need to be transformed by using Eq.(5). Figure 1 shows the total DCV effect on rice yields in both Africa and Asia relative a base case of negative phases for all three DCV cases (PDO-TAG-WPWP-). There we see the rice yield is expected to be 7.36% higher when the DCV status switches from (PDO-TAG-WPWP-) to (PDO-TAG+WPWP+). Rice yields are estimated to be 101.45%, 75.68%, and 75.04% lower compared to the base scenario under the (PDO+TAG+WPWP+), (PDO-TAG-WPWP+) and (PDO+TAG-WPWP+), respectively. The results indicate that the rice yield tends to be lower when WPWP+ occurs. The underlying reason is that higher temperature tends to reduce the rice yield (Table 3), which echoes findings in Sinnarong et al. (2019). Then the occurrence of WPWP+ tends to have a higher temperature (Table 4). Thus, the combination of the effect leads to a lower rice yield.

The robustness check of excluding FACE data is shown in Figure 3. The upward bias of the technological progress estimate becomes wildly large without including FACE data. This outcome indicates a numerical instability issue, which is caused by nearly perfect collinearity (correlation = 0.9936) and could make the coefficients very sensitive to small changes in the model. Namely, the exclusion of FACE data

makes the estimate of technological progress problematic. Therefore, it is necessary to include the FACE observations to prevent the above numerical instability concern.

4.3 Technological Progress and CO_2

Over time CO_2 has been steadily rising, and a simple correlation with time is 0.99. Nevertheless, the global CO_2 concentration and the trend variable reflect very different things. The former enhances yields through the CO_2 fertilization effect; the latter captures technological progress effect (e.g., advances in rice varieties, farming practices, equipment, etc.). Under climate mitigation or greenhouse gas emission efforts, the CO_2 effect would be reduced. Thus, it is important to separate the effects of both variables, and this requires addressing the associated multicollinearity problem.

Including FACE data decreases correlation between the global CO_2 concentration and the time trend variable. In our data the correlation between the global CO_2 concentration and the trend variable without including FACE data is 0.9936, while it reduces to 0.9135 with FACE data. Using only Asian observations, the correlation further decreases to 0.8287. Figure 2 shows differences in the coefficients of the trend variables (both linear and quadratic terms) with and without including the global CO_2 concentration variable based on the models in Table 3. The left-hand side trend graph in Figure 2 shows results form Models 1 and 2 of Table 3, while the right side shows results from Models 3 and 4. The dashed lines, which hold the global CO_2 concentration variable constant, indicate the trajectory of the sum of the technological progress and CO_2 effects. On the other hand, the solid lines, represent the trajectory of the sole technological progress effect without the influence of CO_2. The discrepancies between the solid and dash lines in both different sets of data become larger as time passes, implying that CO_2 concentrations are responsible for a substantial amount of the projected and future crop yield growth. Namely, actual pure technological progress is substantially smaller than what we observe, which is biased upward by CO_2. In the combined Africa and Asia model, 57.3% of the observed technical progress is coming from the CO_2 effect. The bias is 44.7% in the Asia alone model.

4.4 Forecasting Impacts of Climate Change on Rice Yield

Since this study investigates both impacts of climatic variables and global CO_2 concentration on rice yields in Africa and Asia, the model estimated in Section 4.1 allows to forecast the rice yield conditional on different global warming scenarios. According to Representative Concentration Pathway (RCP) scenarios from IPCC (2013), global warming projections up to 2100 are predicted to increase by 1.8°C, 2.2°C, and 3.7°C in RCP4.5, RCP6.0, and RCP8.5, respectively. The global CO_2 concentration projection from Meinshausen et al. (2011) indicates that the CO_2 concentration was 384.8 ppm in 2008 and is projected to increase to 538.4 ppm, 669.7 ppm, and 935.9 ppm in 2100 given RCP4.5, RCP6.0, and RCP8.5 scenarios, respectively.

Based on the above RCP projections, the forecasting marginal impacts of global warming and growing CO_2 concentration on rice yields are illustrated in Figure 4, where Model 2 is used and only varies the temperature and CO_2 concentration variables given other things constant at 2016 level. The result shows that the positive effect of growing CO_2 concentration on rice yields outweighs the negative effect of increasing temperature in the RCP8.5 scenario. Thus, the rice yield is predicted to rise significantly under the RCP8.5 scenario due to the larger CO_2 fertilization effect. However, the growth of rice yields is relatively small under the RCP4.5 and RCP6 scenarios because the negative effect of increasing temperature is closer to the positive effect of growing CO_2 concentration. Specifically, the forecasting rice yield result suggests that rice yields are predicted to rise significantly by 134.6% in 2100 under the RCP8.5 scenario due to the larger CO_2 fertilization effect. However, under greater CO_2 mitigation (RCP4.5 RCP6 scenarios), growth rates fall to 31.7% and 67.9%, respectively. This raises a joint challenge of maintaining high productivity while mitigating future CO_2 emission.

5 CONCLUSION

This study investigates rice yields considering impacts of climate, decadal climate variability (DCV), and CO_2 fertilization on rice yields using historical data from Asian and African countries coupled with FACE experiment data results. The forecasts of long-term rice yields given different warming scenarios are also explored.

The findings of the study first indicate that CO_2 is giving us a false reading on technological advance and in fact is the driver of 44% to 57% of what we observe. This means that climate change induced emission control will reduce crop yield growth. The finding is consistent with Attavanich and McCarl (2014).

The forecasting result shows that the positive effect of growing CO_2 concentration on rice yields outweighs the negative effect of increasing temperature in the RCP8.5 scenario. Thus, the rice yield is predicted to rise significantly under the RCP8.5 scenario due to the larger CO_2 fertilization effect. Nevertheless, rice yields are expected to be relatively flat under the RCP4.5 and RCP6 scenarios since the negative effect of increasing temperature and the positive effect of growing CO_2 concentration have similar magnitude.

The DCV phenomena involve the complex relationship between atmosphere and ocean. The estimated DCV effects on weather variables suggest that the precipitation is expected to be higher in (PDO+TAG+WPWP+) compared to other scenarios in Africa and Asia. The temperature is relatively lower in (PDO-TAG-WPWP-) scenario among all scenarios. The result shows that the occurrence of WPWP+ tends to have a higher temperature in our samples. This outcome leads to lower rice yields in all WPWP+ scenarios since higher temperature tends to reduce the rice yield, which echoes the finding of Sinnarong et al. (2019). Thus, rice yields are estimated to be 101.45%, 75.68%, and 75.04% lower compared to the base scenario under the (PDO+TAG+WPWP+), (PDO-TAG-WPWP+) and (PDO+TAG-WPWP+), respectively.

Granular DCV effects on rice yields and local weather in the subcontinent or county level would be worth exploring in future studies. Comparisons between the impact of DCV and other ocean-related indexes on crop yields are also a potential research topic. Besides, similar yield estimation and forecast could be improved further if more FACE data in broader coverage of countries are available.

This study contributes to climate change implications for both existing literature and empirical work. The implication of interplay between growing CO_2 concentration and temperature in the forecasting results sheds light on the importance of considering growing CO_2 concentration when future researchers estimate crop yields, particularly in the context of climate change. The finding of the DCV effects on weather

variables and rice yields allows policymakers, agricultural, and hydrological agents to understand how to react in advance to potential changes in precipitation and temperature under known DCV information.

Reference

Attavanich, W., and B.A. McCarl. 2014. "How Is CO2 Affecting Yields and Technological Progress? A Statistical Analysis." *Climatic Change* 124 (4): 747–62. https://doi.org/10.1007/s10584-014-1128-x.

Cho, S.J., B.A. McCarl, and X.M. Wu. 2015. "Climate Change Adaptation via US Land Use Transitions: A Spatial Econometric Analysis." In *2015 Annual Meeting, January*. http://ageconsearch.umn.edu/bitstream/196684/2/CHO_SAEA2015_submit0112.pdf.

Climatic Research Unit (CRU), University of East Anglia. 2020. "CRU TS Version 4.03." 2020. https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/crucy.1905151143.v4.03/new_countries/.

Food and Agriculture Organization of the United Nations. 2020. "FAOSTAT." 2020. http://www.fao.org/faostat/en/#data/QC.

Hasegawa, T., H. Sakai, T. Tokida, H. Nakamura, C. Zhu, Y. Usui, M. Yoshimoto, et al. 2013. "Rice Cultivar Responses to Elevated CO2 at Two Free-Air CO2 Enrichment (FACE) Sites in Japan." *Functional Plant Biology* 40 (2): 148–159.

IPCC. 2013. "Climate Change 2013: The Physical Science Basis." In *Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Jing, L.Q., Y.Z. Wu, S.T. Zhuang, Y.X. Wang, J.Q. Zhu, Y.L. Wang, and L.X. Yang. 2016. "Effects of CO2 Enrichment and Spikelet Removal on Rice Quality under Open-Air Field Conditions." *Journal of Integrative Agriculture* 15 (9): 2012–2022.

Jithitikulchai, T. 2014. “Essays on Applied Economics and Econometrics: Decadal Climate Variability Impacts on Cropping and Sugar-Sweetened Beverage Demand of Low-Income Families.” Texas A&M University.

———. 2018. “Influence of Decadal Climate Variability on Growing Degree Day, Precipitation, and Drought in Crop-Growing Seasons.” *Climate* 6 (2): 43. https://doi.org/10.3390/cli6020043.

Jithitikulchai, T., B.A. McCarl, and X.M. Wu. 2018. “Decadal Climate Variability Impacts on Climate and Crop Yields.” *Journal of Agricultural and Applied Economics*, 1–22.

Just, R.E., and R.D. Pope. 1979. “Production Function Estimation and Related Risk Considerations.” *American Journal of Agricultural Economics* 61 (2): 276–284.

Latif, M., and T.P. Barnett. 1994. “Causes of Decadal Climate Variability over the North Pacific and North America.” *Science* 266 (5185): 634–637.

Levin, A., C.F. Lin, and C.S.J. Chu. 2002. “Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties.” *Journal of Econometrics* 108 (1): 1–24.

Mantua, N.J., S.R. Hare, Y. Zhang, J.M. Wallace, and R.C. Francis. 1997. “A Pacific Interdecadal Climate Oscillation with Impacts on Salmon Production.” *Bulletin of the American Meteorological Society* 78: 1069–1079.

Martinich, J., and A. Crimmins. 2019. “Climate Damages and Adaptation Potential across Diverse Sectors of the United States.” *Nature Climate Change* 9 (5): 397–404.

McCarl, B.A., X. Villavicencio, and X.M. Wu. 2008. “Climate Change and Future Analysis: Is Stationarity Dying?” *American Journal of Agricultural Economics* 90 (5): 1241–47. https://doi.org/10.1111/j.1467-8276.2008.01211.x.

Mehta, V. M., and T. Delworth. 1995. “Decadal Variability of the Tropical Atlantic Ocean Surface Temperature in Shipboard Measurements and in a Global Ocean-Atmosphere Model.” *Journal of Climate* 8 (2): 172–190.

Mehta, V.M. 1998. “Tropical Ocean Surface Temperatures at Decadal–Multidecadal Timescales. Part I: The Atlantic Ocean.” *Journal of Climate* 11 (9): 2351–2375.

Mehta, V.M., N.J. Rosenberg, and K. Mendoza. 2012. “Simulated Impacts of Three Decadal Climate Variability Phenomena on Dryland Corn and Wheat Yields in the Missouri River Basin.” *Agricultural and Forest Meteorology* 152: 109–124.

Mehta, V.M., H. Wang, and K. Mendoza. 2013. “Decadal Predictability of Tropical Basin Average and Global Average Sea Surface Temperatures in CMIP5 Experiments with the HadCM3, GFDL-CM2. 1, NCAR-CCSM4, and MIROC5 Global Earth System Models.” *Geophysical Research Letters* 40 (11): 2807–2812.

Meinshausen, M., S.J. Smith, K.V. Calvin, J.S. Daniel, MLT Kainuma, J.F. Lamarque, K.M. Matsumoto, et al. 2011. “The RCP Greenhouse Gas Concentrations and Their Extensions from 1765 to 2300.” *Climatic Change* 109 (1–2): 213.

Miao, R., D.A. Hennessy, and B.A. Babcock. 2012. “Investment in Cellulosic Biofuel Refineries: Do Waivable Biofuel Mandates Matter?” *American Journal of Agricultural Economics* 94 (3): 750–62. https://doi.org/10.1093/ajae/aar142.

National Oceanic and Atmospheric Administration (NOAA). 2020. “Extended Reconstructed Sea Surface Temperature (ERSST) V5.” 2020. https://www.ncdc.noaa.gov/data-access/marineocean-data/extended-reconstructed-sea-surface-temperature-ersst-v5.

Selvaraju, R., R. Gommes, and M. Bernardi. 2011. “Climate Science in Support of Sustainable Agriculture

and Food Security." *Climate Research* 47 (1–2): 95–110.

Sinnarong, N., C.C. Chen, B.A. McCarl, and B.L. Tran. 2019. "Estimating the Potential Effects of Climate Change on Rice Production in Thailand." *Paddy and Water Environment* 17 (4): 761–769.

Sun, C., L. Wang, T. Liu, D. Guo, Y. Chen, W. Wu, Y. Wang, and J. Zhu. 2014. "Effects of Free-Air CO2 Enrichment on Adventitious Root Development of Rice under Low and Normal Soil Nitrogen Levels." *The Crop Journal* 2 (4): 207–212.

Vicente-Serrano, S.M., S. Beguería, J.I. López-Moreno, M. Angulo, and A. El Kenawy. 2010. "A Global 0.5 Gridded Dataset (1901–2006) of a Multi-Scalar Drought Index Considering the Joint Effects of Precipitation and Temperature." *Journal of Hydrometeorology* 11 (4): 1033–1043.

Wang, H., and V.M. Mehta. 2008. "Decadal Variability of the Indo-Pacific Warm Pool and Its Association with Atmospheric and Oceanic Variability in the NCEP–NCAR and SODA Reanalyses." *Journal of Climate* 21 (21): 5545–5565.

Table 1. Data Sources

Variables	Duration	Sources
Rice yields (hg/ha)	1961-2016	Food and Agriculture Organization of the United Nations (2020)
DCV	1961-2016	National Oceanic and Atmospheric Administration (2020)
Precipitation (mm)	1961-2016	Climatic Research Unit (CRU), University of East Anglia (2020)
Temperature (Celsius)	1961-2016	Climatic Research Unit (CRU), University of East Anglia (2020)
SPEI	1961-2016	Vicente-Serrano et al. (2010)
Irrigation rate	1961-2016	Food and Agriculture Organization of the United Nations (2020)
Global CO_2 concentration (ppm)	1961-2016	Meinshausen et al. (2011)
FACE data	Refer to Table 2	Hasegawa et al. (2013); Sun et al. (2014); Jing et al. (2016)

Table 2. FACE data

Year	Country	Area	CO_2 (ppm)	Rice yields (g/m^2)
1998	Japan	Shizukuishi	642.0	679.2
1999	Japan	Shizukuishi	629.9	838.4
2000	Japan	Shizukuishi	578.5	797.9
2001	China	Wuxi	577.5	1182.9
2002	China	Wuxi	562.4	1103.8
2003	China	Wuxi	574.4	971.7
2007	Japan	Shizukuishi	570.0	546.0
2008	Japan	Shizukuishi	576.0	672.0
2010	Japan	Tsukuba	585.0	642.0

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

Table 3. DCV Effects on the Rice Yield (Direct Effects)

	Rice yield (log hg/ha)			
	All data		Asia only	
	(1)	(2)	(3)	(4)
PDO-TAG-WPWP-	9.90***	8.74***	11.90***	10.75***
	(0.67)	(1.17)	(0.62)	(1.19)
PDO+TAG+WPWP+	9.86***	8.70***	11.93***	10.78***
	(0.67)	(1.18)	(0.62)	(1.19)
PDO+TAG+WPWP-	9.86***	8.70***	11.93***	10.78***
	(0.67)	(1.17)	(0.62)	(1.19)
PDO-TAG+WPWP+	9.95***	8.79***	11.94***	10.78***
	(0.67)	(1.17)	(0.62)	(1.19)
PDO+TAG-WPWP+	9.92***	8.76***	11.91***	10.75***
	(0.67)	(1.17)	(0.62)	(1.19)
PDO+TAG-WPWP-	9.93***	8.78***	11.92***	10.76***
	(0.67)	(1.17)	(0.62)	(1.18)
PDO-TAG+WPWP-	9.92***	8.77***	11.91***	10.76***
	(0.67)	(1.17)	(0.62)	(1.18)
PDO-TAG-WPWP+	9.93***	8.77***	11.94***	10.78***
	(0.67)	(1.17)	(0.62)	(1.19)
Precipitation (log mm)	0.09*	0.08*	-0.01	-0.02
	(0.04)	(0.04)	(0.06)	(0.06)
Temperature (log Celsius)	-0.31	-0.31	-0.90***	-0.91***
	(0.24)	(0.24)	(0.20)	(0.20)
CO2 (ppm)		0.004		0.004
		(0.003)		(0.003)
SPEI	-0.002	0.01	0.0004	0.01
	(0.001)	(0.010)	(0.002)	(0.020)
I(CO2 × SPEI)		0.0000		0.0000
		0.0000		(0.0001)
Irrigation rate	0.003**	0.003**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Trend	0.02***	0.01***	0.01***	0.01***
	(0.002)	(0.003)	(0.002)	(0.004)
Sq. Trend	-0.0001***	-0.0002***	0. 0000	0. 0000
	0.0000	(0.0001)	0.0000	(0.0001)
FACE dummy	0.21**	-0.6	0.21**	-0.59
	(0.11)	(0.67)	(0.08)	(0.68)
Num. of countries	59	59	23	23
Adjusted R^2	0.7666	0.7666	0.8038	0.8036
Country FE	Yes	Yes	Yes	Yes
Observations	2,996	2,992	1,086	1,084

Note: *p<0.1;**p<0.05;***p<0.01

Table 4. DCV Effects on the Weather Variables (Indirect Effects)

	Precipitation (log mm)			Temperature (log Celsius)		
	(1)	(2)	(3)	(4)	(5)	(6)
PDO-TAG-WPWP-	6.83***	5.79***	5.71***	3.05***	2.55***	2.54***
	(0.040)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
PDO+TAG+WPWP+	6.80***	5.76***	5.88***	3.07***	2.57***	2.57***
	(0.060)	(0.020)	(0.060)	(0.020)	(0.004)	(0.010)
PDO+TAG+WPWP-	6.79***	5.75***	5.82***	3.07***	2.56***	2.55***
	(0.040)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
PDO-TAG+WPWP+	6.84***	5.80***	5.74***	3.07***	2.56***	2.55***
	(0.050)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
PDO+TAG-WPWP+	6.81***	5.77***	5.83***	3.08***	2.58***	2.58***
	(0.050)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
PDO+TAG-WPWP-	6.80***	5.76***	5.75***	3.06***	2.54***	2.55***
	(0.040)	(0.020)	(0.040)	(0.020)	(0.004)	(0.010)
PDO-TAG+WPWP-	6.86***	5.81***	5.82***	3.06***	2.55***	2.55***
	(0.050)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
PDO-TAG-WPWP+	6.80***	5.76***	5.71***	3.07***	2.57***	2.58***
	(0.050)	(0.020)	(0.050)	(0.020)	(0.004)	(0.010)
Num. of countries	59	59	59	59	59	59
Observations	3,313	3,241	3,313	3,313	2,747	3,313
Country FE	No	Yes	Yes	No	Yes	Yes
Interaction (DCV × Country FE)	No	No	Yes	No	No	Yes
Adjusted R2	0.0005	0.9795	0.9798	0.0006	0.9943	0.9944

Note: *p<0.1;**p<0.05;***p<0.01

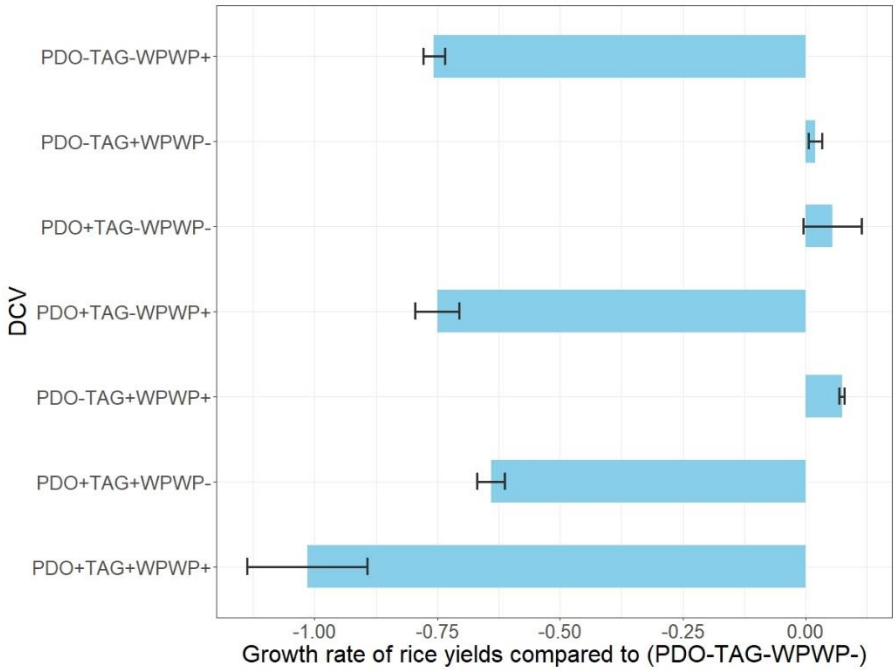

Figure 1. Total DCV Effect on Rice Yields in All Samples

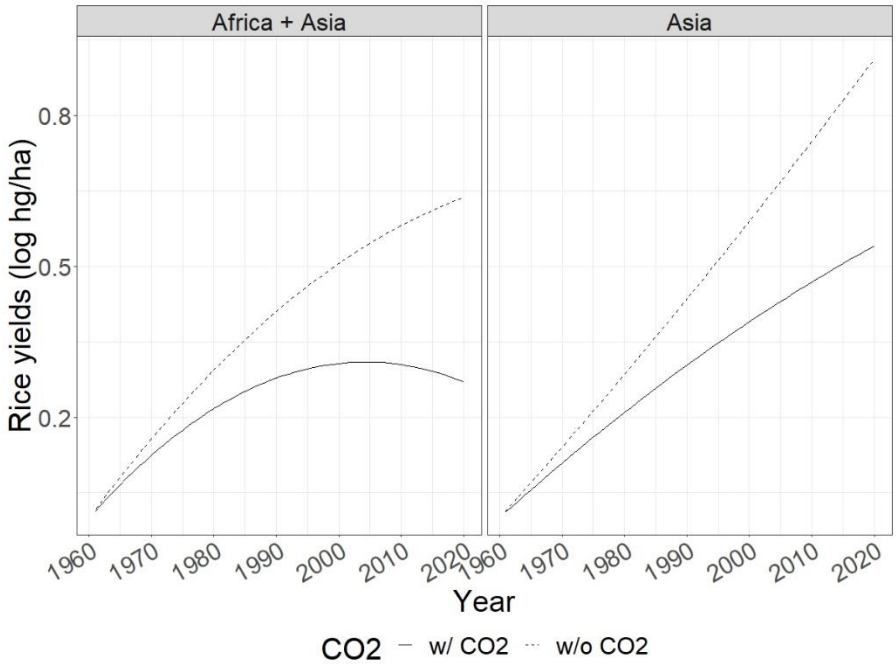

Figure 2. Differences in the Coefficients of the Trend Variables

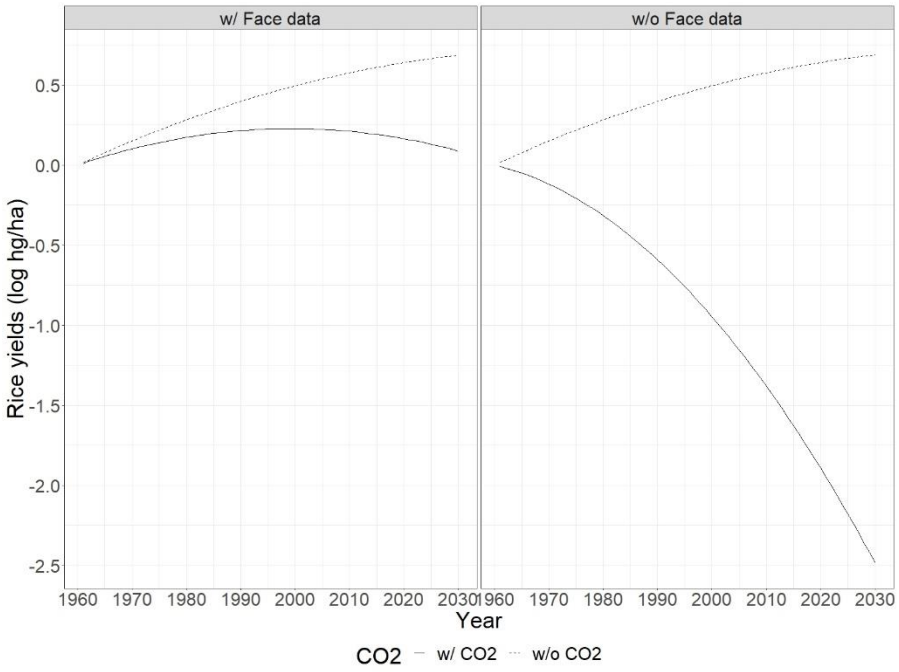

Figure 3. Differences in the Coefficients of the Trend Variables with and without FACE data

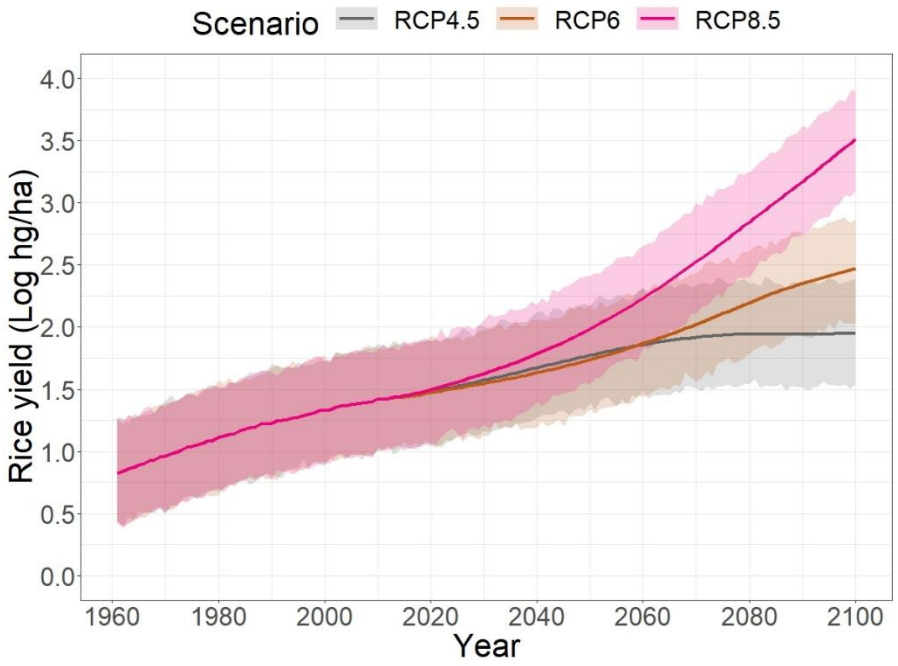

Figure 4. Forecasting Rice Yields Conditional on RCP Warming Scenarios

Appendix

Table A1. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Yield (hg/ha)	3,313	25,313.8	16,443.3	2,034	13,415	31,759	118,290
Precipitation (mm)	3,313	1,232.40	755.93	26.8	630.2	1,698.1	3,569.0
Mean temperature (Celsius)	3,313	22.58	5.86	4.62	21.55	26.61	29.35
SPEI (-: drought, +: wet)	3,313	-1.46	6.85	-24.5	-6.49	2.98	17.71
CO_2 concentration (ppm)	3,313	354.49	28.23	317.64	331.11	375.8	642
Irrigation rate	3,313	10.08	18.22	0	0.2	11.3	103.4
Trend	3,313	28.54	16.16	1	15	43	56
PDO+TAG+WPWP+	3,313	0.07	0.26	0	0	0	1
PDO+TAG+WPWP-	3,313	0.14	0.35	0	0	0	1
PDO-TAG+WPWP+	3,313	0.12	0.33	0	0	0	1
PDO+TAG-WPWP+	3,313	0.11	0.31	0	0	0	1
PDO+TAG-WPWP-	3,313	0.18	0.38	0	0	0	1
PDO-TAG+WPWP-	3,313	0.12	0.33	0	0	0	1
PDO-TAG-WPWP+	3,313	0.11	0.31	0	0	0	1
PDO-TAG-WPWP-	3,313	0.14	0.35	0	0	0	1
FACE dummy	3,313	0.003	0.05	0	0	0	1

Table A2. Panel Unit-root Test

	Difference stationary	**Trend stationary**
z statistic	-4.1652	-7.2168
P-value	0.00001	0.00000

Note: The above panel data unit-root tests apply the Levin-Lin-Chu method (Levin, Lin, and Chu 2002)using both Africa and Asia data without FACE observations. The null hypothesis is the series are found to have a unit-root. The result of the panel unit-root test suggests no need to difference the data before the estimation.

Table A3. DCV Effects on the Rice Yield (Different Model Specifications)

	Rice yield (log hg/ha)					
	(1)	(2)	(3)	(4)	(5)	(6)
PDO-TAG-WPWP-	9.93***	10.58***	9.93***	10.83***	8.74***	
	(0.030)	(0.160)	(0.170)	(1.470)	(1.170)	
PDO+TAG+WPWP+	9.96***	10.57***	9.91***	10.80***	8.70***	
	(0.040)	(0.170)	(0.170)	(1.480)	(1.180)	
PDO+TAG+WPWP-	9.93***	10.56***	9.90***	10.79***	8.70***	
	(0.030)	(0.160)	(0.170)	(1.470)	(1.170)	
PDO-TAG+WPWP+	9.90***	10.58***	9.95***	10.86***	8.79***	
	(0.030)	(0.160)	(0.170)	(1.470)	(1.170)	
PDO+TAG-WPWP+	10.14***	10.58***	9.95***	10.84***	8.76***	
	(0.030)	(0.170)	(0.180)	(1.470)	(1.170)	
PDO+TAG-WPWP-	9.88***	10.60***	9.95***	10.85***	8.78***	
	(0.020)	(0.160)	(0.170)	(1.470)	(1.170)	
PDO-TAG+WPWP-	9.91***	10.57***	9.94***	10.85***	8.77***	
	(0.030)	(0.160)	(0.170)	(1.470)	(1.170)	
PDO-TAG-WPWP+	10.04***	10.62***	9.96***	10.85***	8.77***	
	(0.030)	(0.170)	(0.170)	(1.470)	(1.170)	
Precipitation (log mm)		-0.15***	-0.09***	-0.09***	0.08*	0.08*
		(0.010)	(0.010)	(0.010)	(0.040)	(0.040)
Temperature (log Celsius)		-0.66***	-0.44***	-0.45***	-0.31	-0.3
		(0.020)	(0.020)	(0.020)	(0.240)	(0.230)
CO_2 (ppm)		0.01***	0.01***	0.002	0.004	0.004
		(0.000)	(0.000)	(0.005)	(0.003)	(0.003)
SPEI			-0.06***	-0.03	0.01	0.01
			(0.020)	(0.020)	(0.010)	(0.010)
I(CO_2 * SPEI)			0.0001***	0.0001	0	0
			(0.0001)	(0.0001)	0.0000	0.0000
Irrigation rate			0.01***	0.01***	0.003**	0.003*
			(0.001)	(0.001)	(0.001)	(0.001)
Trend				0.01*	0.01***	0.01***
				(0.005)	(0.003)	(0.003)
Sq. Trend				0.00000	-0.0002***	-0.0001**
				(0.0001)	(0.0001)	(0.0001)
FACE dummy				0.07	-0.6	-0.63
				(1.000)	(0.670)	(0.670)
Adjusted R^2	0.0141	0.2984	0.4249	0.4276	0.7666	0.7656
Country FE	No	No	No	No	Yes	Yes
Observations	3,313	3,313	3,298	3,297	2,992	2,999

Note: *p<0.1;**p<0.05;***p<0.01

Table A4. DCV Effects on the Rice Yield (Different Samples)

	Rice yield (log hg/ha)			
	All data			
	(1)	(2)	(3)	(4)
PDO-TAG-WPWP-	9.90***	8.74***	9.97***	1.31
	(0.67)	(1.17)	(0.67)	(2.83)
PDO+TAG+WPWP+	9.86***	8.70***	9.94***	1.27
	(0.67)	(1.18)	(0.67)	(2.83)
PDO+TAG+WPWP-	9.86***	8.70***	9.94***	1.27
	(0.67)	(1.17)	(0.67)	(2.83)
PDO-TAG+WPWP+	9.95***	8.79***	10.02***	1.35
	(0.67)	(1.17)	(0.67)	(2.83)
PDO+TAG-WPWP+	9.92***	8.76***	9.99***	1.32
	(0.67)	(1.17)	(0.67)	(2.83)
PDO+TAG-WPWP-	9.93***	8.78***	10.01***	1.34
	(0.67)	(1.17)	(0.67)	(2.83)
PDO-TAG+WPWP-	9.92***	8.77***	10.00***	1.34
	(0.67)	(1.17)	(0.67)	(2.83)
PDO-TAG-WPWP+	9.93***	8.77***	10.00***	1.32
	(0.67)	(1.17)	(0.67)	(2.83)
Precipitation (log mm)	0.09*	0.08*	0.08*	0.07
	(0.04)	(0.04)	(0.04)	(0.04)
Temperature (log Celsius)	-0.31	-0.31	-0.33	-0.32
	(0.24)	(0.24)	(0.24)	(0.24)
CO_2 (ppm)		0.004		0.03***
		(0.003)		(0.010)
SPEI	-0.002	0.01	-0.002	0.003
	(0.001)	(0.010)	(0.001)	(0.020)
I(CO_2 × SPEI)		0		0
		0.0000		0.0000
Irrigation rate	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Trend	0.02***	0.01***	0.02***	-0.01
	(0.002)	(0.003)	(0.002)	(0.010)
Sq. Trend	-0.0001***	-0.0002***	-0.0001***	-0.0004***
	0.0000	(0.0001)	0.0000	(0.0001)
FACE dummy	0.21**	-0.6		
	(0.11)	(0.67)		
Num. of countries	59	59	59	59
Adjusted R^2	0.7666	0.7666	0.7644	0.7648
Country FE	Yes	Yes	Yes	Yes
Observations	2,996	2,992	2,986	2,987

Note: *p<0.1;**p<0.05;***p<0.01

Table A4. DCV Effects on the Rice Yield (Different Samples)(Cont.)

	Rice yield (log hg/ha)			
	Asia only			
	(5)	(6)	(7)	(8)
PDO-TAG-WPWP-	11.90***	10.75***	12.02***	6.62*
	(0.62)	(1.19)	(0.61)	(3.53)
PDO+TAG+WPWP+	11.93***	10.78***	12.04***	6.64*
	(0.62)	(1.19)	(0.62)	(3.53)
PDO+TAG+WPWP-	11.93***	10.78***	12.05***	6.64*
	(0.62)	(1.19)	(0.62)	(3.53)
PDO-TAG+WPWP+	11.94***	10.78***	12.05***	6.65*
	(0.62)	(1.19)	(0.62)	(3.53)
PDO+TAG-WPWP+	11.91***	10.75***	12.02***	6.61*
	(0.62)	(1.19)	(0.61)	(3.53)
PDO+TAG-WPWP-	11.92***	10.76***	12.03***	6.63*
	(0.62)	(1.18)	(0.61)	(3.53)
PDO-TAG+WPWP-	11.91***	10.76***	12.03***	6.62*
	(0.62)	(1.18)	(0.62)	(3.53)
PDO-TAG-WPWP+	11.94***	10.78***	12.04***	6.64*
	(0.62)	(1.19)	(0.62)	(3.53)
Precipitation (log mm)	-0.01	-0.02	-0.02	-0.02
	(0.06)	(0.06)	(0.06)	(0.06)
Temperature (log Celsius)	-0.90***	-0.91***	-0.93***	-0.91***
	(0.20)	(0.20)	(0.20)	(0.20)
CO_2 (ppm)		0.004		0.02
		(0.003)		(0.010)
SPEI	0.0004	0.01	0.0004	-0.003
	(0.002)	(0.020)	(0.002)	(0.020)
I(CO_2 × SPEI)		0		0
		(0.0001)		(0.0001)
Irrigation rate	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Trend	0.01***	0.01***	0.01***	-0.001
	(0.002)	(0.004)	(0.002)	(0.010)
Sq. Trend	0	0	0	-0.0002
	0.0000	(0.0001)	0.0000	(0.0001)
FACE dummy	0.21**	-0.59		
	(0.08)	(0.68)		
Num. of countries	23	23	23	23
Adjusted R^2	0.8038	0.8036	0.8014	0.8014
Country FE	Yes	Yes	Yes	Yes
Observations	1,086	1,084	1,080	1,077

Note: *p<0.1;**p<0.05;***p<0.01

Figure A1. Rice Yield Trends in Each Country

Note: The duration is from 1961 to 2016. African countries are in red, and Asian countries are in green.

Figure A2. Distribution of the Rice Yield Variable (Original and Logarithm Forms)

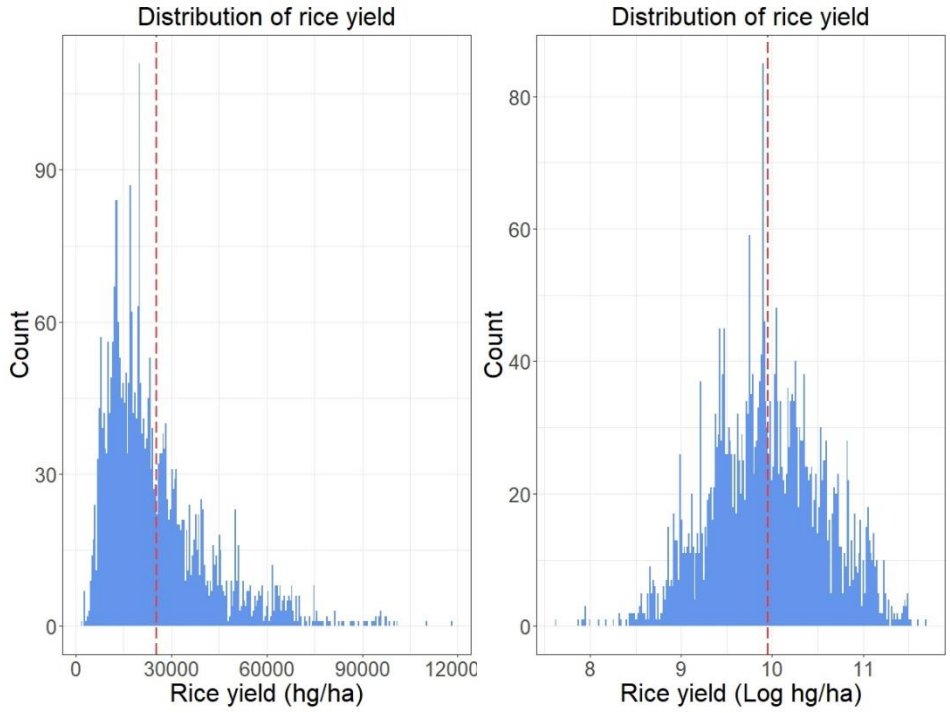
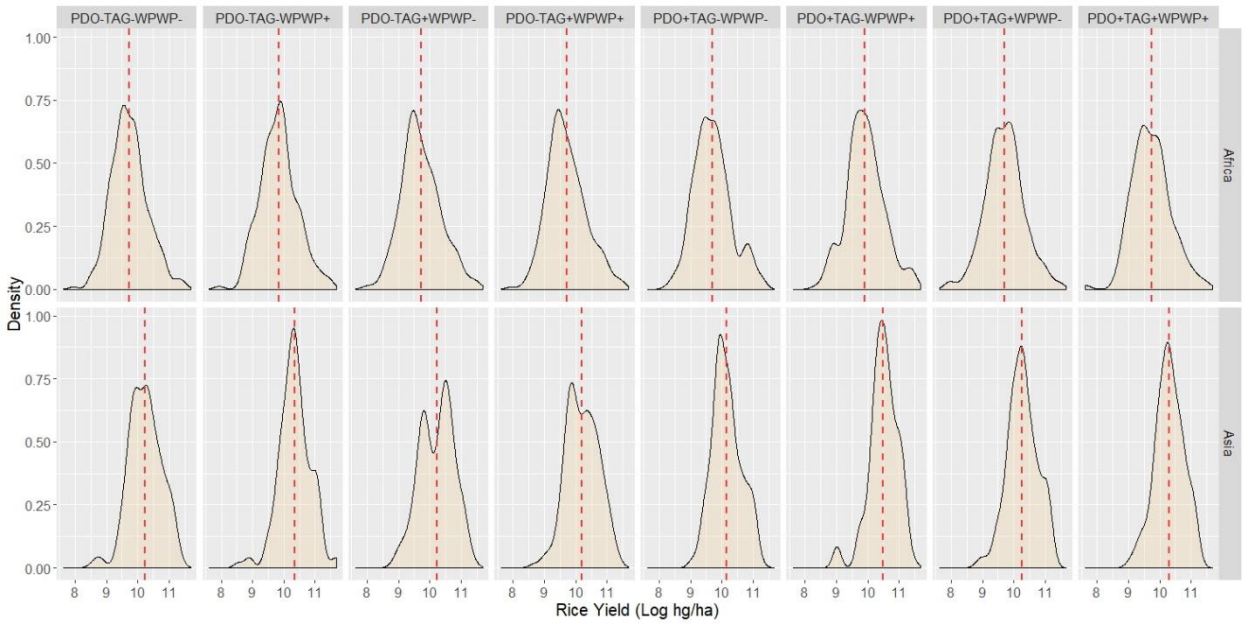
Figure A3. Distribution of Rice Yields under Different DCV Scenarios