Asia-Pac. J. Atmos. Sci., 53(1), 21-30, 2017
DOI:10.1007/s13143-017-0001-z pISSN 1976-7633 / eISSN 1976-7951

Spatially Distinct Response of Rice Yield to Autonomous Adaptation Under the CMIP5 Multi-Model Projections

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(Manuscript received 3 May 2016; accepted 5 August 2016)

Abstract: Rice (*Oryza sativa* L.) is a very important staple crop, as it feeds more than half of the world's population. Numerous studies have focused on the negative impacts of climate change on rice production. However, there is little debate on which region of the world is more vulnerable to climate change and how adaptation to this change can mitigate the negative impacts on rice production. We investigated the impacts of climate change on rice yield, based on simulations combining a global crop model, M-GAZE, and Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model projections. Our focus was the impact of mitigating emission forcings (representative concentration pathway RCP 4.5 vs. RCP 8.5) and autonomous adaptation (i.e., changing crop variety and planting date) on rice yield. In general, our results showed that climate change due to anthropogenic warming leads to a significant reduction in rice yield. However, autonomous adaptation provides the potential to reduce the negative impact of global warming on rice yields in a spatially distinct manner. The adaptation was less beneficial for countries located at a low latitude (e.g., Cambodia, Thailand, Brazil) compared to mid-latitude countries (e.g., USA, China, Pakistan), as regional climates at the lower latitudes are already near the upper temperature thresholds for acceptable rice growth. These findings suggest that the socioeconomic effects from rice production in low-latitude countries can be highly vulnerable to anthropogenic global warming. Therefore, these countries need to be accountable to develop transformative adaptation strategies, such as adopting (or developing) heat-tolerant varieties, and/or improve irrigation systems and fertilizer use efficiency.

Key words: Rice production, climate change, adaptation, CMIP5, M-GAZE

1. Introduction

Because rice feeds more than half of the world's population, sustainable rice production is essential for food security (Masutomi et al., 2009; Wang et al., 2015). Climate change will threaten sustainable rice production, as both temperature and precipitation play an important role by constraining heat accumulation and water availability that determine the growth, development, and ultimately grain yield of rice (Lobell and Burke, 2008; Asseng et al., 2011; Watson and Challinor, 2013). In addition, most of the developing countries in which rice production accounts for a significant part of their economy have predominantly traditional rain-fed agriculture (Ramirez-Villegas et al., 2012). Therefore, these countries, which tend to highly depend on regional or local climate conditions, may face further vulnerability and risk from future climate change.

Most crop modeling studies have consistently reported that the impact of climate change on crop production is likely to be negative rather than positive (Schlenker and Lobell, 2010; IPCC, 2014), although there are specific crops in certain locations that may benefit from global warming (Tao and Zhang, 2013). Lobell et al. (2013) demonstrated that +2°C warming of extremely warm days can reduce maize (*Zea mays* L.) yields in the USA, due to intensified water stress. According to the Intergovernmental Panel on Climate Change (IPCC, 2014), the negative impact on crop yield is also evident in some high-latitude regions. There is also a large amount of literature (Peng et al., 2004; Iizumi et al., 2011) that focuses on the impact of climate change on rice yield, but somewhat less focus has been placed on the relative vulnerability among major rice-producing countries.

If it is impossible to avoid the impact of elevated greenhouse gases (GHGs), we should seek to find an alternative way to reduce or minimize the negative impact on crop production. An adaptation strategy tailored to climate change could be effective for maintaining sustainable and reliable rice production (Anwar et al., 2011; Osborne et al., 2013; Seo, 2013). In soybean (*Glycine max* L.) and spring wheat (*Triticum aestivum* L.), adaptation can either offset yield losses or even increase yield by shifting the crop growing season to a cooler period of the year or switching to a crop variety that exploits an extended growing season under the A1B emission scenario (Osborne et al., 2013). IPCC (2014) demonstrated that adaptation can improve crop yields by the equivalent of +15% to +18% of current yields, but the effectiveness of adaptation is highly variable.

In this study, we assessed the impact of climate change on rice yield and the importance of an adaptation strategy, using a

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biophysical principal-based global crop model, M-GAEZ, combined with CMIP5 multi-model projections. Analyses involved comparing rice yields from four experimental sets, with and without an adaptation strategy, under RCP4.5 and RCP8.5 scenarios, and based on the top-ranked 14 countries that account for up to 90% of total rice production (Bangladesh, Brazil, Cambodia, China, Indonesia, India, Japan, Myanmar, Pakistan, Philippines, South Korea, Thailand, USA, and Vietnam; FAOSTAT, 2011). To the best of our knowledge, there is minimal literature on the potential impact of climate change on crop production, taking adaptation strategy into consideration and using a large number of newly generated CMIP5 global projections. In this regard, the updated assessment presented in this study can provide an opportunity to build on previous findings.

2. Description of crop model, experimental design, and climate data used

To estimate changes in global rice yields, assuming a warmer climate, we employed the biophysical principal-based global crop model, M-GAEZ (Masutomi et al., 2009). This model is based on the Global Agro-ecological Zones (GAEZ) model, originally developed through collaboration between the International Institute for Applied Systems Analysis (IIASA) and the FAO (Fischer et al., 2002). The final output of M-GAEZ is potential yield at each grid cell, with spatial resolution of 2.5 arc min (~5 km). Various input data were used to control both biophysical and management conditions for each grid cell (Table 1). While the biophysical conditions are constrained by climate, terrain, soil type, maximum available soil moisture, and CO_2 concentration, the management conditions are locally assigned based on water management scheme (irrigated or non-irrigated), cropping system (single or double), and different socioeconomic conditions on a national scale. Climate variables such as maximum and minimum temperature, precipitation, wind speed, and solar radiation, derived from 26 CMIP5 global climate models (Taylor et al., 2012) (GCMs; Table 2), were used as inputs to M-GAEZ simulations for a historical period (1990s: 1990-1999) and the future (2080s: 2080-2089). Future climate is projected under the IPCC Representative Concentration Pathway (RCP, Moss et al., 2010) trajectories for the period 2080 through 2089. To quantify the effect of mitigating GHGs emissions, two different RCP scenarios, namely RCP4.5 and RCP8.5, are adopted. While RCP4.5 is a stabilization scenario after about 2060 without overshooting pathways to 4.5 W m^{-2}, RCP8.5 is a rising pathway leading to 8.5 W m^{-2} by 2100 which is known as the business-as-usual scenario. Carbon dioxide (CO_2) varied according to emissions scenarios and periods (i.e., 361 ppm in the 1990s, 531 ppm for RCP4.5 and 758 ppm for RCP8.5 in the 2080s). The different CO_2 concentrations were used to modulate CO_2 fertilization in M-GAEZ. It was necessary to disaggregate climate variables to M-GAEZ operation systems in both temporal and spatial resolution. First, climate variables were converted into a daily time-scale by linear interpolation, as they were obtained monthly. Then all inputs with different spatial resolution were disaggregated to the same resolution of M-GAEZ, using the bilinear interpolation method.

To examine the adaptation effect on rice yields, we adopted two autonomous adaptation measures considered in Hasegawa et al. (2014). Crop variety and planting date in each grid cell varied to maximize the yields in accordance with future climate conditions. Major rice varieties with different growth periods, such as four Japonica (105, 120, 135, and 150 days) and four Indica (105, 120, 135, and 150 days) varieties, were considered to select the best variety. Planting date was shifted a selected period forward or backward to adjust to a suitable environment for rice planting under given climatological conditions. In addition, an experiment without adaptation was performed, assuming that the best crop variety and the planting date in a changing climate would remain the same as historical climate conditions. We also considered the proportions in correspondence of the region where multiple cropping was imposed (i.e., double cropping) when calculating the yields in M-GAEZ.

Our analysis focused on changes in rice yield derived from four experimental sets, the combination of two emission scenarios (RCP4.5 and RCP8.5) and two options (with and without adaptation). We denoted RCP45_Adaptation (RCP85_Adaptation) and RCP45_No Adaptation (RCP85_No Adaptation) as the experiments from RCP4.5 (RCP8.5) scenarios

Table 1. Input data for the M-GAEZ model (modified from Masutomi et al., 2009).

Item	Data Name	Original Resolution	Reference
Maximum available soil moisture	Digital soil map of the world	5 min × 5 min	FAO (2002)
Soil type	Digital soil map of the world	5 min × 5 min	FAO (1995)
Elevation	GTOPO30	30 s × 30 s	USGS (1996)
Climate	26 CMIP5 GCMs	$1^o \times 1^o$	See Section 2.1
Cultivated area	Major crop dataset	5 min × 5 min	Leff et al. (2004)
Irrigated area	Global map of irrigated area	5 min × 5 min	Siebert et al. (2005)
Country boundary	Gridded population of the world	2.5 min × 2.5 min	CIESIN (2005)
Fertilization use	World development indicators	Country by country	World Bank (2006)
CO_2 Concentration	Representative Concentration Pathways	Constant globally	van Vuuren et al. (2011)

Table 2. Description of CMIP5 participant GCMs used in this study.

No	Model	Institution	Resolution (Lon. × Lat.)
1	ACCESS1-0	CSIRO-BOM	$1.875^o \times 1.25^o$
2	BCC-CSM1-1	BCC	$2.8125^o \times 2.8125^o$
3	CanESM2	CCCma	$2.8125^o \times 2.8125^o$
4	CCSM4	NCAR	$1.25^o \times 0.9375^o$
5	CESM1-CAM5	NCAR	$1.25^o \times 0.9375^o$
6	CNRM-CM5	CNRM-CERFACS	$1.40625^o \times 1.40625^o$
7	CSIRO-Mk3-6-0	CSIRO-QCCCE	$1.875^o \times 1.875^o$
8	FGOALS-g2	LASG-CESS	$2.8125^o \times 2.8125^o$
9	GFDL-CM3	NOAA GFDL	$2.5^o \times 2^o$
10	GFDL-ESM2G	NOAA GFDL	$2.5^o \times 2^o$
11	GFDL-ESM2M	NOAA GFDL	$2.5^o \times 2^o$
12	GISS-E2-R	NASA/GISS	$2.5^o \times 2^o$
13	HadGEM2-AO	NIMR/KMA	$1.875^o \times 1.24^o$
14	HadGEM2-CC	MOHC	$1.875^o \times 1.24^o$
15	HadGEM2-ES	MOHC	$1.875^o \times 1.24^o$
16	INM-CM4	INM	$2^o \times 1.5^o$
17	IPSL-CM5A-LR	IPSL	$3.75^o \times 1.875^o$
18	IPSL-CM5A-MR	IPSL	$3.75^o \times 1.875^o$
19	IPSL-CM5B-LR	IPSL	$3.75^o \times 1.875^o$
20	MIROC5	AORI	$1.40625^o \times 1.40625^o$
21	MIROC-ESM	JAMSTEC, AORI, NIES	$2.8125^o \times 2.8125^o$
22	MIROC-ESM-CHEM	JAMSTEC, AORI, NIES	$2.8125^o \times 2.8125^o$
23	MPI-ESM-LR	MPI-M	$1.875^o \times 1.875^o$
24	MPI-ESM-MR	MPI-M	$1.875^o \times 1.875^o$
25	MRI-CGCM3	MRI	$1.125^o \times 2.25^o$
26	NorESM1-M	NCC	$2.5^o \times 1.875^o$

with adaptation (abbreviation “Adaptation”) and without adaptation (abbreviation “No Adaptation”), respectively. Each experiment set was composed of 26 ensemble members from multi-GCMs.

3. Results

a. Validation of M-GAEZ performance

Because this study was based on one crop model, the robustness of the results seemed to be rather limited, as conclusions might be crop model-dependent. Although this study did not provide the ensemble projections derived from multiple crop models, we assessed the basic performance of M-GAZE in simulating yield potential under the current climatic conditions (1990s) to justify the use of one crop model. To validate the performance of M-GAEZ, we performed the two types of M-GAZE simulations forced by NCEP/NCAR reanalysis and CMIP5 GCMs during the 1990s, and compared them against yield estimates from the Food and Agriculture Organization of the United Nations Statistical database (FAOSTAT).

Figure 1 presents the interannual variation in potential rice yield averaged over the top-ranked 14 countries that account for up to 90% of global rice production. The FAOSTAT estimation shows that rice yields gradually increased during the 1990s. This pattern agrees well with the average global yields observed by Lobell and Gourdji (2012). They reported an increase in rice yield, which has been fairly linear over the past 50 years (1961-2000), on a global scale, and explained that this increase was partly due to advances in technology such as greater use of irrigation, chemical inputs, and modern crop varieties. The M-GAEZ model does not consider these technological aspects, so the growth trend of rice yield extracted from FAOSTAT was applied to the M-GAEZ model. Both simulations (NCEP/NCAR and multi-model ensemble [MME]) tended to provide estimates similar to the observed pattern, although there was a systematic overestimation of yields. The simulated yields forced by the CMIP5 MME (26 GCMs) were more similar to observed estimates in terms of

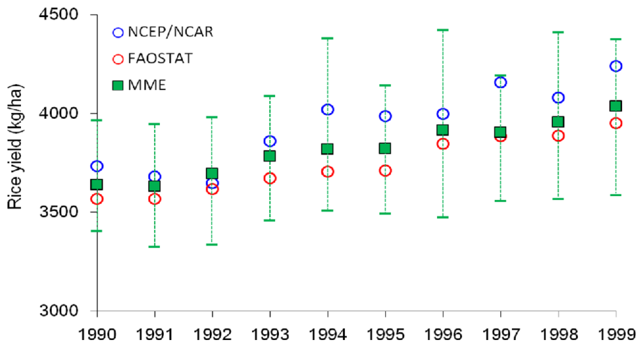

Fig. 1. Interannual variation in rice yield that is regionally averaged over the top-ranked 14 countries derived from observations (FAOSTAT: red open circle) and simulations forced by the NCEP/NCAR (blue open circle) reanalysis and CMIP5 MME (green closed square). Green dashed line indicates the uncertainty range of individual GCMs.

quantitative and qualitative behaviors than those forced by NCEP/NCAR reanalysis, which is typically considered equivalent to observations. There were large discrepancies between the simulated and observed yields when comparing them based on individual GCM and individual countries. For example, the upper and lower values bounded by individual GCMs (green dashed line in Fig. 1) indicate the large uncertainty range. However, MME seemed to reduce the error compared to individual GCM, mostly by smoothened up (i.e., positive bias) and down (i.e., negative bias) fluctuations.

In addition to the gross features of M-GAZE performance based on regional averages (Fig. 1), we also accessed the detailed characteristics of individual countries. Figure 2 presents a comparison between simulated and observed yields based on 14 individual countries and corresponding to 10 years from 1990 to 1999. In contrast to the regional average, the simulation forced by NCEP/NCAR reanalysis had better performance than that from MME when looking at individual countries. Despite the relatively large scatter in Indonesia and Japan, the simulated yields derived from NCEP/NCAR reanalysis were highly correlated with observed estimates. These results clearly demonstrate that M-GAZE is capable of reproducing the main features of yields, in terms of observed regional and temporal variation. If climate variables are derived from GCMs, M-GAZE might contain further uncertainty due to input data, in addition to model physics imperfection. Nevertheless, the simulated yield forced by MME was reasonable.

These results provide some confidence in the ability of M-GAZE to simulate rice yields under current climate conditions. Thus, M-GAZE may be a useful tool for examining the responses of rice yield to changing climatic conditions attributed to global warming. In the next section, we analyze rice yield in response to RCP emissions scenarios.

b. Regional dependence of rice yield changes and adaptation effects

The CMIP5 MME projections, forced by RCP4.5 and RCP8.5 scenarios, showed significant warming and large variation in precipitation, which are in line with the results presented in IPCC (2013) (Fig. 3). In general, the changes in temperature and precipitation derived from RCP4.5 and RCP8.5 projections showed a similar regional pattern but at different magnitudes. The degree of warming was higher in the RCP8.5 projection than in the RCP4.5 projection, in accordance with the emissions forcing. On the other hand, precipitation exhibited substantial spatial variation and less spatial consistency, especially at the low- and mid-latitudes. More importantly, the areas where the mean MME (i.e., signal) was higher than the inter-model spread (i.e., noise) were limited over arable land for rice (two rectangles in Fig. 3 and analysis domain for Fig. 4), indicating a large uncertainty of precipitation changes over this region.

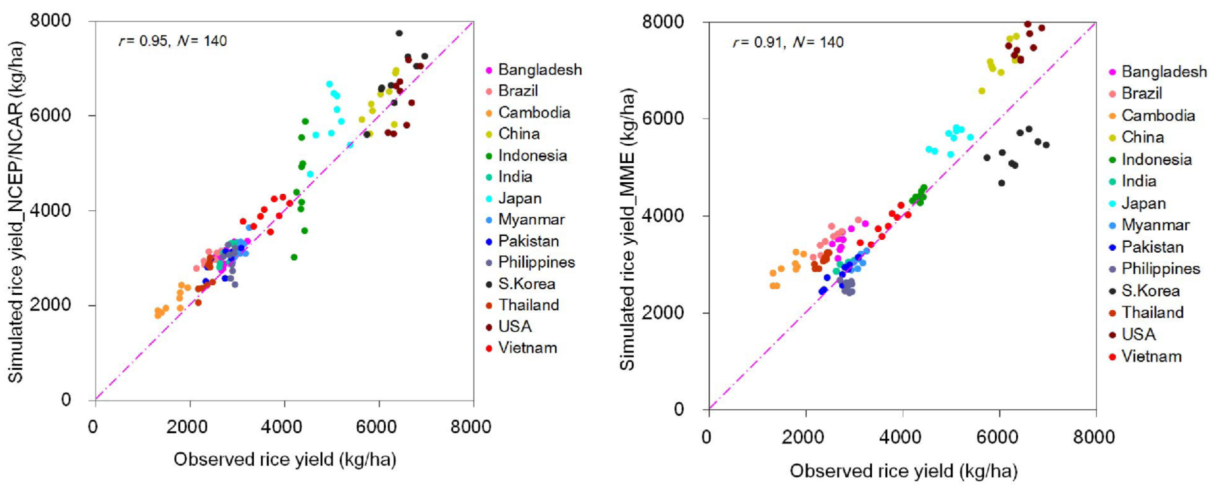

Fig. 2. Scatterplots of observed rice yield (x-axis) vs. simulated rice yield (y-axis) forced by the (a) NCEP/NCAR reanalysis and (b) CMIP5 MME in the 14 top-ranked rice-producing countries. Individual countries have 10 values with the same color corresponding to 10 years from 1990 to 1999.

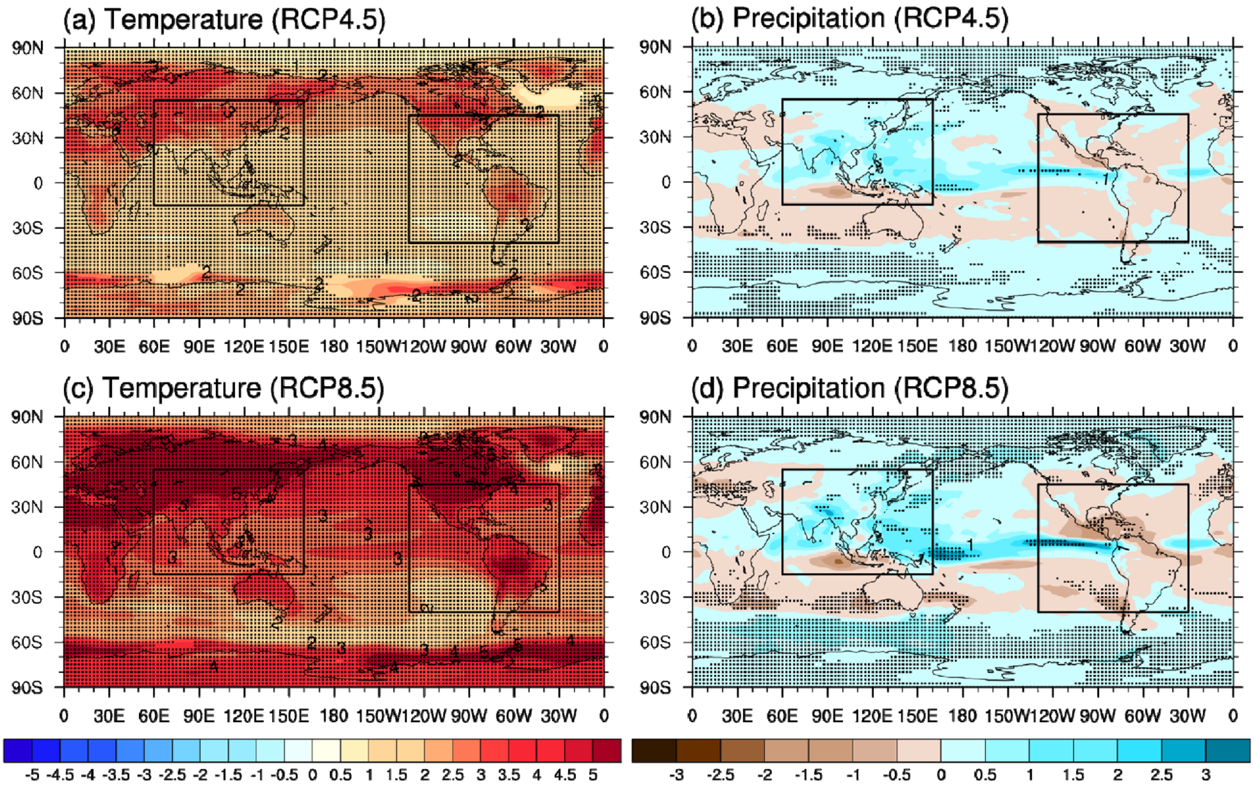

Fig. 3. Spatial distribution of multi-model mean changes (2080s-1990s) in temperature (a, c: degree) and precipitation (b, d: mm d^{-1}) for the summer season (JJA) derived from 26 CMIP5 global projections forced by RCP4.5 (a, b) and RCP8.5 (c, d) emission scenarios. Superimposed dots indicate the areas where the signal-to-noise ratio (SNR) is more than one, indicating agreement of model projection is significantly higher than inter-model spread. The SNR measures the ratio of multi-model ensemble mean change (i.e. signal) to the standard deviation of the change from each GCM (i.e. noise) (Tebaldi et al., 2011). The two black rectangles indicate the area where the top-ranked 14 countries of rice production are located.

These changes in temperature and precipitation might affect the rice production environment by altering not only surface energy but also the moisture budget. Figure 4 presents the spatial distribution of the ensemble mean (26 members) of changes in rice yield (2080s-1990s) derived from four sets of experiments. Rice without the ability to adapt well showed substantial yield reductions in most regions. The impact of adverse warming on rice yield was stronger in RCP8.5 than in RCP4.5. Although changes in precipitation were projected to be different between Asia and America (Fig. 3), both regions had consistently lower rice yields in the 2080s, indicating lower sensitivity of rice yield to changes in precipitation than in temperature. Applying adaptive measures (shifting planting date and switching rice variety) reduced the degree of decrease in yield in all areas and even shifted from a decreasing phase to an increasing phase in some areas. There continued to be large areas with a decreasing phase, especially in mid-China, Southeast Asia, and Brazil. Because all changes satisfied the required signal-to-noise ratio of greater than one (i.e., 26 MME > one standard deviation of 26 models), these regional changes in response to emissions forcings tended to justify a high level of confidence from a statistical standpoint.

To provide a more quantitative perspective of regional variability and the range of uncertainty, we provided the changes in rice yield corresponding to 26 each single member, as well as their ensemble mean based on the 14 top-ranked countries (Fig. 5). For experiments without adaptation, the ensemble mean of 14 countries had a robust negative impact on rice yield, except for South Korea under the RCP4.5 scenario. Compared to the RCP4.5 projection, the RCP8.5 projection produced a markedly wider range of yields and more severe yield losses. In particular, Cambodia, Thailand, and Brazil remained vulnerable to the impacts of aggressive increases in GHG concentrations (e.g., RCP8.5 scenario) on rice production, although adaptation slightly mitigated the negative impacts.

The effectiveness of adaptation showed a strong regional dependence, varying among the individual countries. In general, there was a large yield increase in temperate climates and relatively less improvement in tropical climate zones located at lower latitudes. The effectiveness of shifting planting dates and switching rice varieties was marginal in Cambodia, Thailand, and Brazil. On the other hand, yield improvements in China, Pakistan, and USA were dramatic when the adaptation measures were applied.

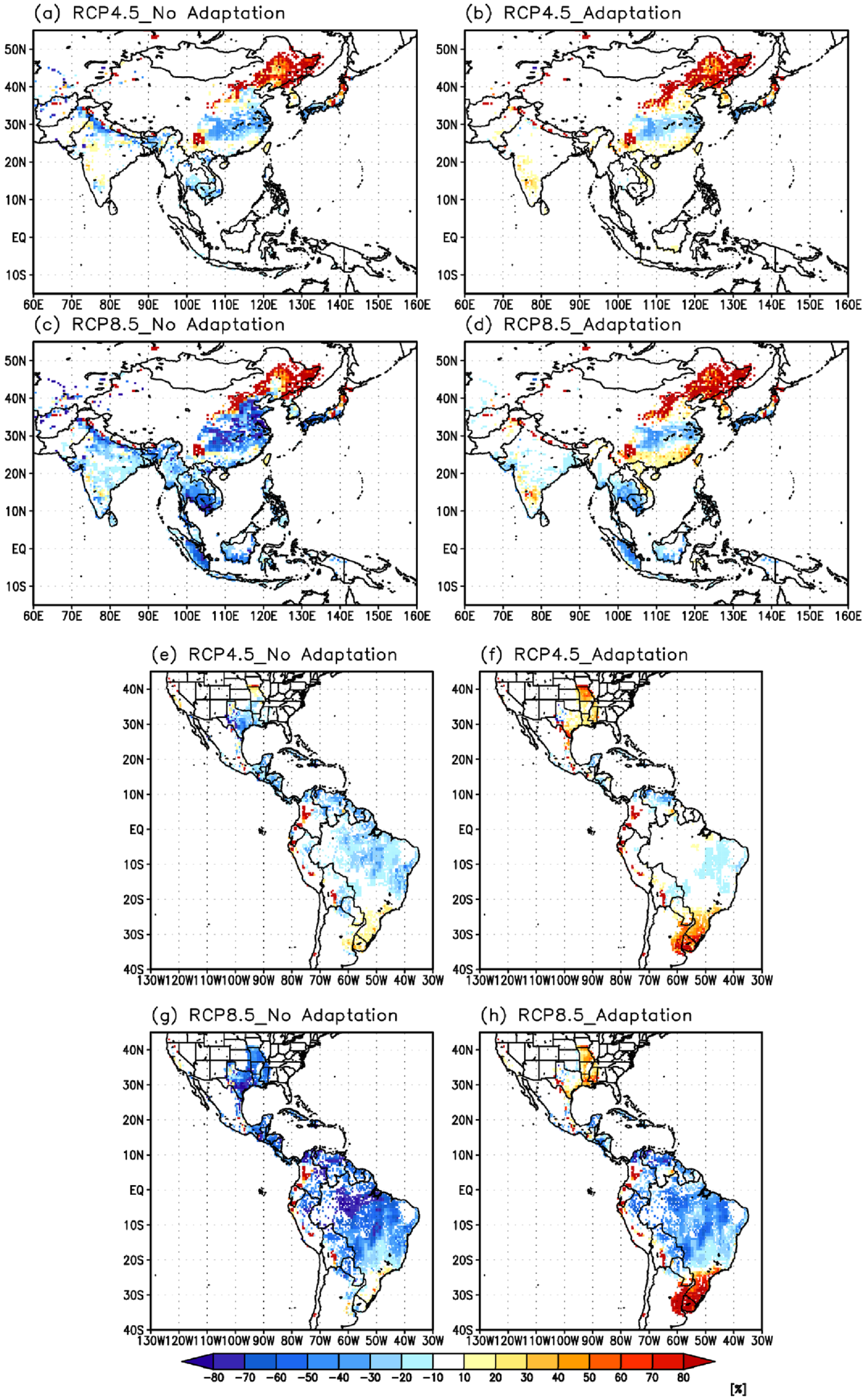

Fig. 4. Spatial distribution of rice yield changes (2080s-1990s: %) derived using 26 GCMs projections under RCP4.5 and RCP8.5 scenarios over Asia (a-d) and America (e-h). All changes have a signal-to-noise ratio greater than one (e.g., 26 multi-model mean > one standard deviation of 26 models).

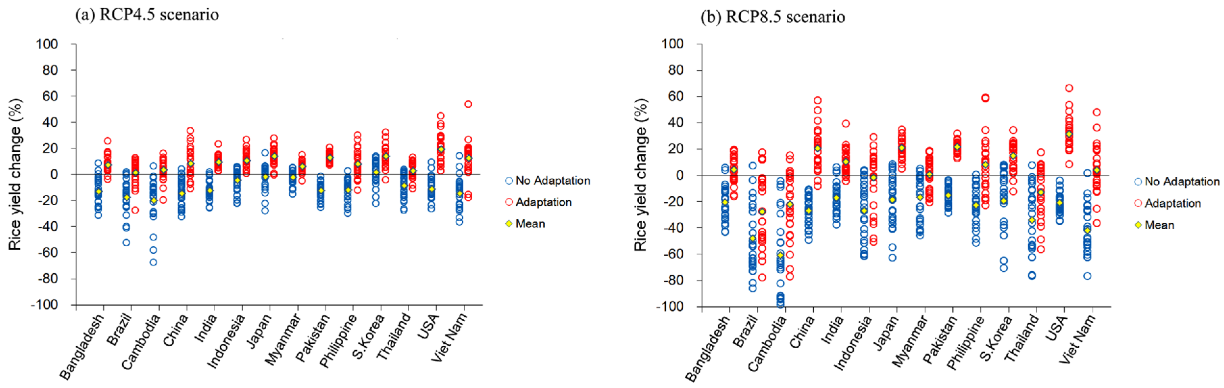

Fig. 5. Area-averaged changes (2080s-1990s) in rice yield derived from RCP4.5 (a) and RCP8.5 (b) projections based on the top 14 rice-producing countries. Blue (red) circles denote the results without (with) an adaptation strategy from individual CMIP5 global projections (26 GCMs), while yellow diamonds indicate multi-model mean values.

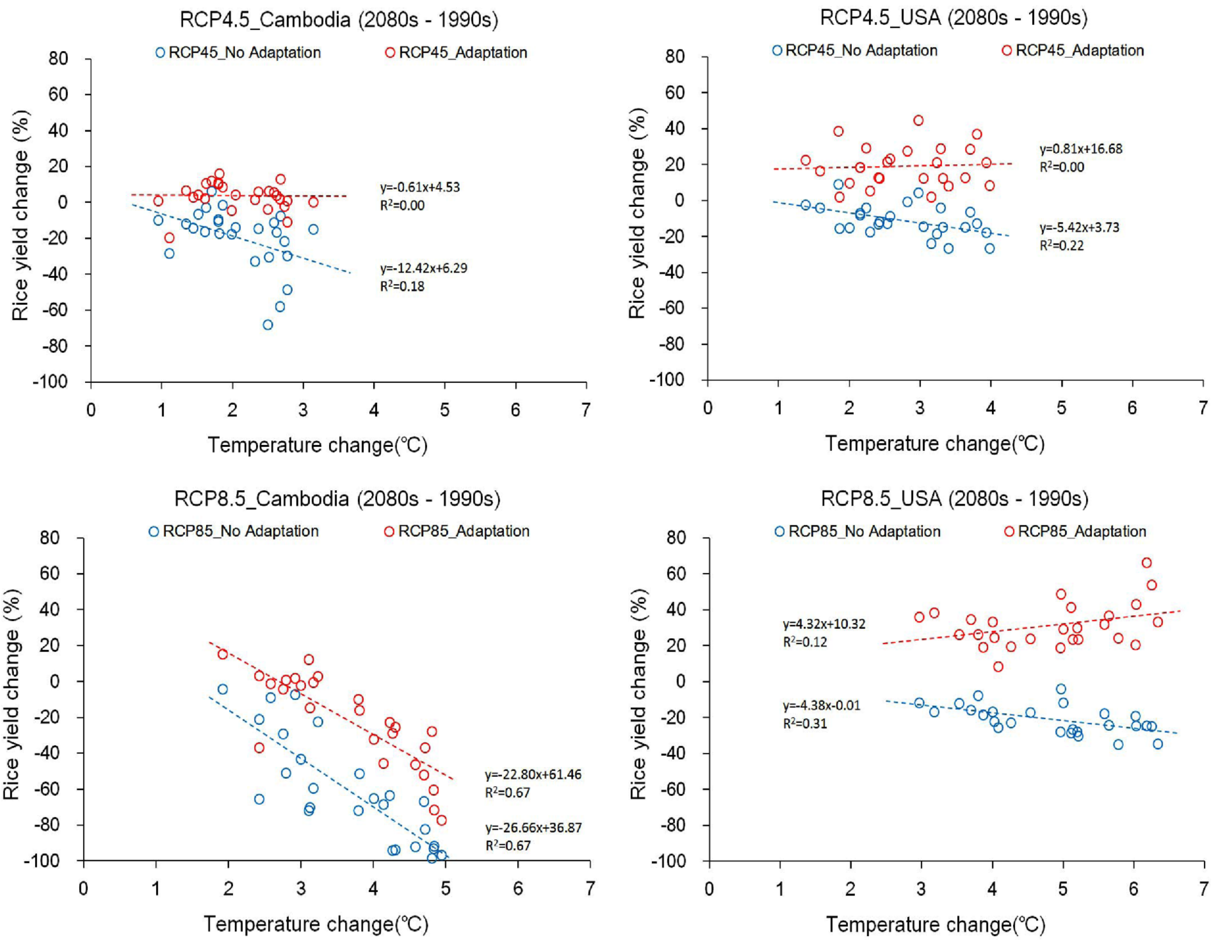

Fig. 6. Relative changes (2080s-1990s) in yield vs. changes in temperature averaged over Cambodia (left) and the USA (right) under the RCP4.5 and RCP8.5 scenarios. Blue (red) open circle indicates the simulations without (with) adaptation and ordinary least squares regression lines with the same color are added.

c. Sensitivity of rice yield to temperature and precipitation changes

To gain insight into the main causes of rice yield fluctuations, we investigated the sensitivity of regional rice yields to changes in temperature and precipitation. This analysis focused on two representative countries, Cambodia and USA, because these exhibited different changes in rice yield (Fig. 5).

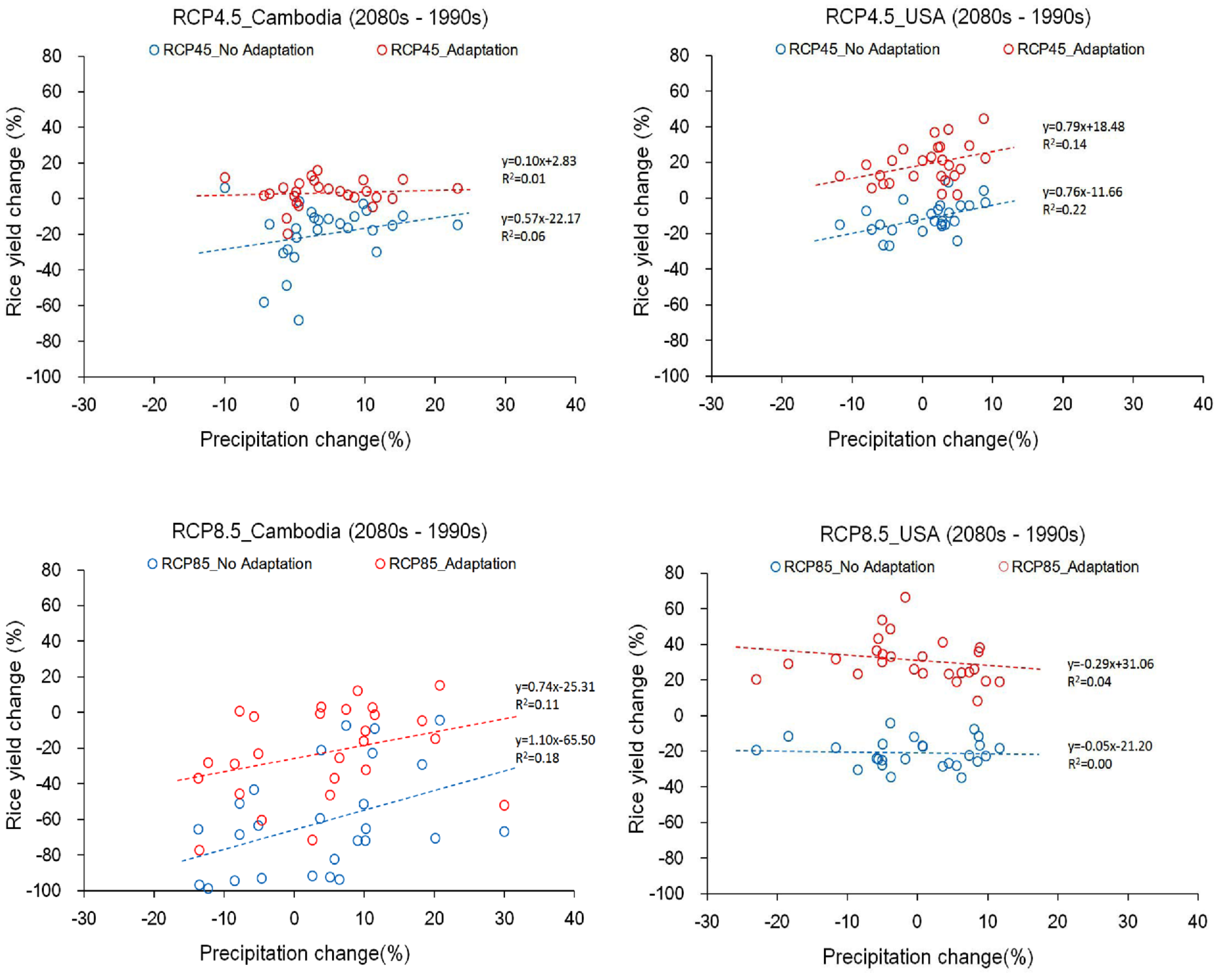

Fig. 7. Relative changes (2080s-1990s) in yield vs. changes in precipitation averaged over Cambodia (left) and the USA (right) under the RCP4.5 and RCP8.5 scenarios. Blue (red) open circle indicates the simulations without (with) adaptation and ordinary least squares regression lines with the same color are added.

While rice production in Cambodia was very vulnerable in the 2080s (3.3% for RCP4.5 and −22.3% for RCP8.5), despite the positive effects of adaptation, the USA experienced the largest yield gain by focusing on adaptation (18.9% for RCP4.5 and 31.2% for RCP8.5).

Figure 6 presents the changes in rice yields as a function of temperature changes in Cambodia and the USA. In Cambodia, the RCP4.5 and RCP8.5 projections showed very different variations in rice yield in response to increased temperature, whereas yields in the USA were relatively less sensitive to extensive warming. Although temperatures increased by more than 6°C in RCP8.5 projections, changes in yield were similar for RCP45_No Adaptation and RCP85_No Adaptation.

When applying the adaptation measures, the differential responses in Cambodia and USA were more clearly explained under the RCP8.5 scenario, showing a strong negative correlation with temperature (Cambodia: $R^2 = 0.67$, USA: $R^2 = 0.31$). Interestingly, the magnitude of the yield loss (gain) in Cambodia (USA) was proportional to the degree of warming. The key for explaining such a different response is related to their respective reference climates. The high-temperature threshold for suitable growth of the rice varieties considered in this study commonly ranges from 29.5°C to 32.5°C, and the average temperature for Cambodia from 1960 to 1990 was 26.7°C (http://sdwebx.worldbank.org/climateportal/index.cfm). This means that the climate governing Cambodia was already near the high-temperature threshold for suitable rice growth. Therefore, there was limited ability to moderate the acceleration of crop development through simply shifting the planting date and switching rice varieties. On the other hand, because the average temperature of the state of Arkansas, the largest rice-producing region in the USA, was in the range 15-18°C (www.ncdc.noaa.gov), there was sufficient potential to improve rice production in the warmer climate conditions. There was also an opportunity to adopt new crop varieties and to delay the planting schedule to minimize warming effects and the associated shortening of the growing season.

Unlike the large sensitivity of rice yield to changes in temperature, the relationship between changes in precipitation and rice yield were less clear (Fig. 7). For example, it's hard to find the relevant coefficient of determination (e.g. R^2) from the regression line shown in Fig. 7. However, this does not necessarily mean that rice yields are less affected by changes in precipitation. In general, changes in precipitation characterized by less consistency and large uncertainty from GCMs projections were partly responsible for underestimating the role of precipitation in crop yield responses to climate change. Another possible explanation may be related to the water-retention capacity of rice paddies. Because rice paddies help relieve water constraints, unlike other rain-fed crops that are immediately affected by variable precipitation, the direct responses to precipitation changes were reduced. However, this interpretation is not valid under water-limited conditions. Indeed, Watson and Challinor (2013) emphasized that, beyond temperature, errors in precipitation data have the most significant impact on yield data in target regions with limited precipitation. In addition, because the M-GAZE model includes the assumption that irrigation systems are not subject to water stress and rice is widely irrigated, these factors can contribute to the poor correlation between rice production and precipitation.

4. Summary and Discussion

This study demonstrated that a warmer climate, caused by elevated GHG concentrations, has a strong negative impact on rice production in the top 14 rice-producing countries. To alleviate the negative impact on rice production, it is necessary to adapt to the climatic changes by shifting planting dates and switching rice varieties. However, the effectiveness of adaptation is highly dependent on the regional climate. For example, the local temperature of Cambodia is close to the upper boundary for suitable rice cultivation, so this country has little opportunity to make adjustments that moderate the negative warming impacts related to anthropogenic climate change. These findings imply that countries located in lower latitudes within tropical climates (Cambodia, Thailand, Brazil) are more vulnerable to climate change than other countries. Therefore, to avoid or minimize the adverse impacts of climate change on rice production, these countries must adopt alternative strategies such as growing (or developing) heat-tolerant varieties, improving (or expanding) irrigation systems, and increasing the efficiency of fertilizer use.

Due to the strong relationship between agriculture and climate, it is reasonable to anticipate that changing climate conditions would make rice production more vulnerable to yield losses. However, the impacts of climate change on agriculture are still a topic of debate, as the response of yield to climate change is quite nonlinear, depending on the selected climate model, emissions scenarios, region, crop variety, accuracy of input records, methodology (empirical or process-based model), and many assumptions incorporated into crop models. Although we carefully selected the crop model, input data, and GCMs, we could not account for investments in new varieties, irrigation systems, and other technological changes. Nevertheless, considering the consensus that temperatures will continue to increase in response to GHG emissions, our findings have important implications for countries with economies that are largely dependent on rice production.

Acknowledgements. This research was supported by the APEC Climate Center and a grant (14AWMP-B082564-01) from the Advanced Water Management Research Program funded by the Ministry of Land, Infrastructure, and Transport of Korea. We thank Dr. Takahashi from National Institute for Environmental Studies (NIES) and Professor Masutomi from Ibaraki University in Japan for providing M-GAZE model and technical support on the work.

Edited by: Tianjun Zhou

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