Quantifying the Yield Sensitivity of Modern Rice Varieties to Warming Temperatures: Evidence from the Philippines

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Abstract

This study examines the relationship between yields of modern rice varieties and three major weather variables — maximum temperature, minimum temperature, and precipitation. Data from a long-running farm-level survey in the Philippines, with rich information on planted rice varieties, allows us to estimate fixed effect econometric models of rice yields. We find that increases in temperature, especially minimum temperatures, have substantial negative impacts on rice yields. Yield response to temperatures vary across different varietal groups. Early modern varieties, bred primarily for higher yields, pest resistance, and/or grain quality traits, demonstrate improved heat-stress resistance relative to traditional varieties. Moreover, the most recent varietal group bred for better tolerance to abiotic stresses are even more resilient to warming temperatures. These results provide some evidence that public investments in breeding rice varieties more tolerant to warming temperatures have been successful, and continued investments in these breeding efforts are warranted.

Keywords: Central Luzon, climate change, rice yield, rice varieties.

JEL Classification Numbers: Q12, Q16, Q18

1 Introduction

Rice is the most important food crop in the world, with nearly half of the world's population relying on it for sustenance every day. It is the main staple food across a number of Asian countries, and it is also becoming an increasingly important food crop in Africa and in Latin America (Ricepedia (2019)). Over 144 million farms cultivate rice across an area of about 167 million hectares (ha) in more than 100 countries (FAOSTAT (2019)). Rice-based farming systems have also been the main source of income for a large proportion of rural farmers located in a number of developing countries (Ricepedia (2019)).

Given the importance of rice as a major food staple and a source of income for farmers worldwide, a key challenge is to find strategies that would maintain or improve rice productivity in the future even in the presence of climate change. Based on the recent climate assessment reports of the Intergovernmental Panel on Climate Change (IPCC), global warming has intensified over the last 50 years and this warming trend is predicted to persist in the future (see the Figure S1). A warming climate has the potential to adversely affect rice yields and rice quality (Peng et al. (2004); Iizumi et al. (2006); Lyman et al. (2013); Kawasaki and Uchida (2016)). For example, extreme high temperatures can lead to spikelet sterility and consequently reduce rice yields (Nguyen et al. (2014); Bheemanahalli et al. (2016)). These adverse warming effects then have the potential to compromise food security in counties that rely on it as a food staple.

One strategy that may help address the climate change challenge in rice production is development and use of newer rice varieties that are better able to adapt to a progressively warming climate. Over the years, development and adoption of new rice varieties have been utilized to overcome a variety of production challenges that have historically arisen in this sector. Since the Green Revolution in the 1960s, there have been development and consequent adoption of several generations of modern rice varieties (MVs) aimed at addressing various production challenges such as lodging, low fertilizer responsiveness, pest problems, and adverse weather conditions (see next section for more details). The release and subsequent adoption of these MVs have led to remarkable increases in rice yields over time (Barker et al. (1985), Hayami and Otsuka (1994), Otsuka et al. (1994), Estudillo and Otsuka (2006)), especially as compared to the traditional rice varieties (TVs), which was the only rice varietal group available prior to the Green Revolution.

With this history of rice varietal development over time, it is likely that there is heterogeneity in each variety's (or varietal group's) yield response to weather variables. The objective of this study is to determine the yield response of different rice varietal groups to warming temperatures. To achieve this objective, we utilize farm-level survey data collected every four to five years from 1966 to 2016 in the Central Luzon region of the Philippines (Moya (2015); Laborte et al. (2015)). Examining the Philippine case is especially relevant since it is one the top ten rice-producing countries in the world (FAOSTAT (2019)), and the pattern of varietal adoption in this country is representative of other major rice-producing countries like India, Indonesia, Bangladesh, and Vietnam (Brennan and Malabayabas (2011); Pandey et al. (2012)). Since farmers are tracked over time in the data set utilized, we are able to develop fixed effects econometric models, which then allows us to identify "varietal-group-specific" yield response to several weather variables (e.g., minimum temperature, maximum temperature, and precipitation).[1] Therefore, the study results provide interesting insights as to the effectiveness of prior rice varietal development efforts, specifically in terms of mitigating the adverse impacts of climate change.

Due to concerns about the effect of climate change on agriculture, there is now a large literature that used econometric methods to examine how weather variables influence crop yield outcomes (See, for example, Auffhammer et al. (2006), Welch et al. (2010); Sarker et al. (2012); Lyman et al. (2013) and Kawasaki and Uchida (2016) for rice; Schlenker and Roberts (2009) for corn; Tack et al. (2015) for wheat). There is also another strand of literature that explores the determinants and economic impacts of particular climate change adaptation practices for different crops (See: Chen et al. (2014); Wang et al. (2010); Deressa et al. (2009); Di Falco et al. (2011); Butler and Huybers (2013); Huang et al. (2015)). Despite this rich literature on climate change adaptation and climate change effects on yields, to the best of our knowledge, there has been a limited number of studies that investigated how the yield impact of weather variables may vary depending on the rice variety, or the rice varietal group, used by farmers. Tack et al. (2016), using a long time-series of field trial data in the U.S., examined variety-specific yield response to higher temperatures for wheat, but not for rice. Hasan et al. (2016) examined how the yield response of TVs differ from higher-yielding rice varieties (HYVs), using more aggregate region-specific data from Bangladesh. We have not found any study that have used individual farm-level data to econometrically examine the relationship between rice varietal use and yield response to weather variables.

[1] As noted in Launio et al. (2008) and Laborte et al. (2015) there are numerous specifically-named MVs that have been released in the Philippines since 1966 and it would have been impossible to estimate yield response for each of these specifically-named rice varieties. Hence, in this study, we focus on the yield response of varietal groups (as further defined below) to weather variables.

Our main contribution is to disentangle the warming effects on rice yields by allowing for and econometrically identifying varietal-group-specific effects. This is important because it will allow us to know which rice varietal group is most effective in mitigating the adverse effects of warming temperatures, and whether the older MVs had some climate change mitigation features. Although not all previously released rice MVs are widely used anymore (Laborte et al. (2015)), it is still important to determine whether these older varietal groups have historically contributed to climate change mitigation, especially because they were not specifically bred for this purpose (see more discussion on this issue below). If these climate change mitigation effects are present for these earlier MVs, then these are important "spillover" rice breeding effects that need to be recognized. But more importantly, given that newer rice varieties were developed to be more tolerant to adverse climatic conditions, providing empirical evidence to show the climate change mitigation effects of these newer varieties on farmers' fields allows one to see whether more recent breeding efforts to produce "climate-change-tolerant-traits" has indeed been successful.

The second contribution is that we exploit actual farm-level panel data in our analysis, rather than using more aggregate rice production data (e.g., district-level, province-level) or experimental field trial data, which are the two most commonly used data types in previous literature. The novel data set used in this study allows one to better examine rice yield response under actual farmer-managed field conditions. The data set used is also unique in terms of the decades-long time period it spans, which is relatively rare in terms of the few climate change studies that utilize individual farm-level data sets. Furthermore, the farm-level data set we have also has rich information on the rice varieties used, as well as the other inputs utilized by the grower (e.g., fertilizer, insecticide). Much of the individual data sets used for climate change studies in the past do not have rich varietal information that would allow one to estimate variety-specific (or varietal-group-specific) yield response to weather variables. Disregarding heterogeneity in the yield response of specific rice varieties may lead to inaccurate inferences regarding the yield effects of warming. Hence, having this unique and novel data set gives us the rare opportunity to study the interactions of rice varietal traits and the environment it grows in, over a long period of time.

The rest of the paper is organized as follows. Section 2 introduces the empirical setting and data sources, as well discusses pertinent background on rice varietal development in the Philippines. Section 3 illustrates the modeling framework that examines the heterogeneity in the resilience of each varietal group's yield with respect to weather variables. Section 4 explains the estimation results. Section 5 provides various robustness checks and Section 6 discusses the conclusions.

2 Empirical Setting and Data Sources

The empirical setting for this study covers six major rice-producing provinces from two administrative regions in the Philippines: (a) La Union and Pangasinan provinces in Region I (called the Ilocos region), and (b) Nueva Ecija, Pampanga, Bulacan, and Tarlac provinces in Region III (usually called the Central Luzon region). For the purpose of this study (and consistent with Laborte et al. (2015)), the six provinces in the study area are collectively referred to here as Central Luzon. In 2013, the total harvested area in the six provinces was 0.9 million ha, with majority of these under irrigation (82%). Average rice yield in the study area was 4.7 tons per ha, per cropping season in 2013, which is slightly higher than the national average. Rice is planted twice a year: (a) the wet season (WS) production that ranges from May/June to September/October, and (b) the dry season (DS) production that ranges from November/December to March/April (Moya (2015)). The average farm size in the study area is around 1 ha (Moya (2015)). Like many other countries of the world, the Philippines (and the study area under consideration) have experienced significant warming trends over the years. Estimates from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) suggest that, between 1951 to 2010, average maximum and minimum temperatures in the Philippines have increased by 0.36°C and 1.0°C, respectively.

As previously mentioned, Philippine rice varietal development and utilization roughly follows the pattern for other major rice-producing countries in Asia (Brennan and Malabayabas (2011); Pandey et al. (2012)). The first-generation MVs (called MV1) were released from the mid-1960s to the mid 1970s, which included the IR5 to IR34 varieties developed by the International Rice Research Institute (IRRI) and the C4 series developed by the University of the Philippines (UP). Specifically, the release of IRRI's IR8 variety in the Philippines and India is widely considered as the event that ignited the Green Revolution for rice production. Compared to TVs, MV1 achieved higher yields primarily due to their resistance to lodging, their ability to make more efficient use of solar energy, and their responsiveness to fertilizer (Launio et al. (2008)). Although MV1 are typically higher-yielding (relative to TVs) they were more susceptible to pests and diseases. The second-generation MVs (called MV2) were released in the mid-1970s to mid-1980s and included such IRRI-developed varieties like IR36 to IR62. These MV2 varieties incorporated multiple pest and disease resistance traits (relative to MV1). The third-generation MVs (called MV3) were developed and released between the mid-1980s to the late-1990s, and incorporated better grain quality and stronger host plant resistance (Launio et al. (2008)). Lastly, the fourth-generation MVs (called MV4) were released after 1995. In this period, public rice breeding programs started to focus on the research and development of varieties specifically for adverse rice production environments, such as those subject to salinity, floods, and drought (Laborte et al. (2015)).[2]

The main data source utilized for this study is from the so-called "Central Luzon Loop Survey" or simply the "Loop Survey." It is called the "Loop Survey" because of the sampling strategy used, where the farm households included in the sample are located along the loop of the main highway that passes through the six provinces (Figure 1). Face-to-face interviews were conducted to collect various socio-demographic, input use, and rice production information from the sample respondents (See Moya (2015) for more details on how the survey was conducted over the years and the different sets of information collected). The loop survey data included WS information for the following cropping years: 1966, 1974, 1986, 1999, 2003, 2008, 2011 and 2015; while DS information was available for 1967, 1975, 1987, 1998, 2004, 2007, 2012 and 2016.

Note that the loop survey collected production and input use data for each parcel (or field) the farmer uses (i.e., there could be three rice parcels for a particular farm household, and input use information, say on fertilizer, was collected for each of the three parcels, where the input applied for each parcel may vary). However, there was no unique identifier used to consistently track parcels over time. Hence, only a farm-level panel data set can be constructed with the loop survey since only the farm households can be uniquely tracked over time (and not the parcels for each farm household). Nevertheless, we still "carry-over" the parcel level data rows (for each farm household) and run our empirical models using parcel-level observations. But, as discussed further in the next section, we can only account for farm-level fixed effects (and not parcel-level fixed effects) given the data structure described here.

As noted above, the loop survey includes data for two growing seasons (DS and WS).

[2]As noted in Laborte et al. (2015), there was an additional varietal group called MV5 that refers to modern rice varieties released after 2005. However, these varieties do not have substantially different characteristics relative to MV4. Hence, varieties classified as MV5 in Laborte et al. (2015) is still considered MV4 in this study.

It is likely that the rice yield effect of weather variables varies by season. From 1966 to 1975, only around 20% of farmers in the Central Luzon region can plant a DS rice because of lack of irrigation. For this reason, our DS sample has a relatively small number of observations. Given the limited size of the dry season data, we focus on the analysis of the WS data. Another major concern is that yield response to weather variables and input use are likely to vary depending on whether the farm is irrigated or not. Thus, pooling them together and fitting the model for this kind of pooled data is inappropriate. With the construction and operation of large scale irrigation systems and wide use of small pumps used for irrigation, the population of farmers having access to irrigated water was growing rapidly for the period considered. In the data set we used for empirical analysis, 79% of observations are irrigated operations. For this reason, in this study, the sample of interest were limited to irrigated rice production planted in the WS.

Aside from the loop survey data, we also collected monthly average of daily values for minimum temperature (in °C) and maximum temperature(in °C), and monthly total precipitation (in mm/month)) from the following sources: (a) the WorldClim data (version 1.4) for 1960-1990, and (b) the University of East Anglia's Climatic Research Unit (CRU) data (version 3.23) for years 1990-2016.[3] Since these data sets are at higher spatial resolutions (i.e., 0.5 degree resolutions for the CRU data), a climate downscaling tool (called ClimDown) was used to produce climatic data corresponding to the municipality level[4] where each loop survey household is located (See Mosier et al. (2014) for more information on this downscaling process). Therefore, the climate data in this dataset are at the municipality level, and reported at a monthly time-scale for the years covered in the loop survey. This climate data were then merged to the loop survey data in order to have one unified data set to run our empirical models.

3 Modeling Framework

We use multivariate regression methods to estimate econometric models of the following general form:

$$\ln(y_{ijmt}) = \alpha_j + f(\mathbf{tmin}_{kmt}, \mathbf{tmax}_{kmt}, \mathbf{prec}_{mt}, \mathbf{V}_{ijmt}; \delta, \beta, \psi) + \gamma \mathbf{X}_{ijmt} + \eta t + \varepsilon_{ijmt} \quad (1)$$

[3]See http://wwww.worldclim.org/version1 for the WorldClim data and https://crudata.uea.ac.uk/cru/data/hrg/ for the CRU data. For more information on how these two data sets were constructed see Hijmans et al. (2005) and Harris et al. (2014), respectively.

[4] Administrative unit data were collected from the Global Administrative Areas (GADM) database located at http://www.gadm.org.

where $\ln(y_{ijmt})$ is the natural log of rice yield y (in kg/ha) for parcel i and farm j, located in municipality m, for year t. The other terms in Equation (1) is described as follows. The parameter α_j accounts for unobservable time-invariant farm-level fixed effects such as soil quality and farmer management ability. The function $f(\cdot)$ is what we call the climate function that includes the following explanatory variables: (a) a vector of weather variables: municipality-level maximum and minimum temperature for a particular kth growing phase, as well as cumulative growing season precipitation; and (b) a vector of parcel-level rice varietal group dummy variables $\mathbf{V}_{ijmt}$.

For the purpose of having a more parsimonious model (and more easily interpretable results), we classify the hundreds of varieties in the Loop Survey data set into three main varietal groups: the "TV" group, the "Early MVs" group, and the "Recent MVs" group.[5] The TV group is the omitted category in the regressions, which includes the varieties prior to the Green Revolution. Rice varieties commonly considered as MV1, MV2 and MV3 are included in the "Early MVs" group, where "Early MV" is a dummy variable equal to one if the rice variety planted is either considered as MV1, MV2, or MV3, zero otherwise. In addition, rice varieties commonly classified as MV4 are included in the "Recent MVs" group, where it is represented as a dummy variable equal to one if the rice variety planted is commonly considered as MV4, zero otherwise.

The term $\mathbf{X}_{ijmt}$ is a vector of control variables that include parcel level input applications (e.g., fertilizer use, pesticide applications, and labor), as well as other farmer/farm socio-demographic characteristics (e.g., age, land tenure). The term ηt is a linear time trend that is common to all farms in the sample and, in previous studies, it typically represents technological evolution. However, note that use of rice varietal group dummies in the specification allows us to separate at least the "varietal development" part of the technological change from this time trend. The term ε_{ijmt} is the parcel-level idiosyncractic error term, and δ, β, ψ, and γ are parameter vectors to be estimated.

Note that the farm-level fixed effects (α_j) allows one to control for potential endogeneity caused by farm-level, time-invariant unobservables that do not vary across parcels within a farm (i.e., like unobserved farmer management ability). Given that farm size in our data only averages around 1 to 2 hectares, it is reasonable to expect that these farm-level fixed effects adequately controls for potential endogeneity caused by time invariant

[5]This means that, for the purpose of parsimony, we did not use the more common MV1 to MV4 varietal group classification as described in the previous section (and as utilized in previous studies like Launio et al. (2008) and Laborte et al. (2015)).

unobservables. Furthermore, we cluster standard errors at the village level to account for potential correlations among the parcels within a farm and the spatial correlations among farms within a village.

3.1 Climate Function Specification

To estimate Equation (1), the function $f(\mathbf{tmin}_{kmt}, \mathbf{tmax}_{kmt}, \mathbf{prec}_{mt}, \mathbf{V}_{ijmt}; \delta, \beta, \psi)$ needs to be specified. The weather variables used are minimum temperature (*tmin*), maximum temperature (*tmax*), and precipitation (*prec*), which are the same weather variables typically used in previous studies (Welch et al. (2010); Hasan et al. (2016)).[6] Note however that these weather variables were only available at the municipality level (m), and not at the farm or parcel level. As discussed further below, we also run an alternative specification with the following weather variables: *tavg*, *dtr*, and *prec*. In this case, the variable *tavg* is mean temperature (in °C), *dtr* represents the diurnal temperature range (which is equal to the difference between *tmax* and *tmin*), and *prec* is cumulative precipitation fo the entire season (as previously defined). This alternative specification is also used in Welch et al. (2010).

In our main empirical specification, we use *tmin* and *tmax* by k growing phase, instead of by month. We decided to do this in order to have a parsimonious specification, to facilitate estimation, and for ease of interpretation. Since our focus is on the WS, it is important to note that this growing season spans 3-6 months and the lengths of the growing season varies across provinces. One can then designate the main growing phases in each season as $k = 1, 2, 3$, where 1 = vegetative phase, 2 = reproductive phase, and 3 = ripening phase. For example, $tmax_{3mt}$ would represent the maximum temperature for the ripening phase ($k = 3$).

However, the raw climate data set only contain the monthly average of daily minimum temperatures and maximum temperatures, as well as the monthly cumulative precipitation (i.e., the sum of daily observations within a month). To construct weather variables by growing phase, we need to assign the monthly weather values to each growing phase for each year and across all provinces in the survey data. Therefore, data on the "rice growing windows" (i.e., the dates from planting to harvesting) for each growing season in the data are required. For this purpose, we utilized the RiceAtlas (Laborte et al. (2017)), which

[6] Minimum temperature is normally associated with nighttime temperatures and maximum temperature is associated with daytime temperatures. Welch et al. (2010) have shown that these two variables may have differing effects on rice yields.

contains the planting and harvesting dates for all of the provinces covered by Central Luzon Loop Survey. However, the RiceAtlas mainly focused on the "growing windows" from 1979 onwards, while the Loop survey data covers a longer period of time (i.e. from 1966 to 2016). Information about "growing windows" for the earlier years of the Loop survey is not available. Thus, we needed to make reasonable assumptions about the months to include in each phase for earlier years of the Loop survey data. Before 1979, when TVs and MV1 are the major varieties adopted, growing seasons typically lasted around 5 to 6 months, and the wet season starts around June and ends in November. The vegetative phase usually lasts 75-95 days (i.e., 3 months), with the duration of both the reproductive and ripening phases around one month (see http://www.knowledgebank.irri.org/step-by-step-production/pre-planting/crop-calendar). Based on the information above, for the years prior to 1979, we take the average weather values from June to September as the vegetative phase value, the average of September and October as the reproductive phase value, and the average of October and November as ripening phase value. With the adoption of MV2, the average growth period declined from about 150 days in the 1960s and 1970s to about 110-120 days in the 1980s and 1990s (Moya (2015)). For growing seasons after 1979, the RiceAtlas provides accurate planting and harvesting dates, and we therefore use this information to properly assign the monthly weather values to appropriate growing season phases for these years.

Another major component of the climate function $f(\cdot)$ is the rice varietal group dummies ($\mathbf{V}_{ijmt}$). In this study, we designate TV as the base group (e.g., the omitted category) and then use the notation V^r to represent the 2 other varietal groups we defined in the previous section (i.e., $r = 1, 2$ corresponds to 1 = "Early MVs" and 2 = "Recent MVs"(or MV4), respectively. The area planted to each varietal grouping (for each survey year) are presented in Figure 2.

Given the notations discussed above, the climate function $f(\cdot)$ can then be fully specified as follows:

$$\begin{aligned}\sum_{r=1}^{2}\beta^r\mathbf{V}^r_{ijmt} + \sum_{k=1}^{3}\delta_{1k}\mathbf{tmin}_{kmt} + \sum_{k=1}^{3}\delta_{2k}\mathbf{tmax}_{kmt} + \delta_3\mathbf{prec}_{mt} + \delta_4(\mathbf{prec}_{mt})^2 + \\ \sum_{k=1}^{3}\sum_{r=1}^{2}\psi^r_{1k}(\mathbf{tmin}_{kmt}\times\mathbf{V}^r_{ijmt}) + \sum_{k=1}^{3}\sum_{r=1}^{2}\psi^r_{2k}(\mathbf{tmax}_{kmt}\times\mathbf{V}^r_{ijmt}) + \\ \sum_{r=1}^{2}\psi^r_3(\mathbf{prec}_{mt}\times\mathbf{V}^r_{ijmt}) + \sum_{r=1}^{2}\psi^r_4((\mathbf{prec}_{mt})^2\times\mathbf{V}^r_{ijmt})\end{aligned} \tag{2}$$

Quadratic precipitation terms is added to the climate function to allow for nonlinear precipitation effects, which is similar to the specification used in previous research (Tack et al. (2015), Lobell et al. (2011), Schlenker and Lobell (2010)). The climate-MV interaction terms makes it possible to examine whether there is heterogeneity in each varietal groups' response to weather variables.

3.2 Specification of Control Variables

The next component of Equation (1) that needs to be specified is the vector $\mathbf{X}_{ijmt}$, which accounts for a number of control variables such as parcel-level input applications and other socio-demographic farm characteristics. Including these variables in the specification allows us to control for observable time-varying factors that can influence rice yields, thereby improving the accuracy and efficiency of our estimations.

The input application variables included in the specification are: nitrogen fertilizer applications (in kg/ha), labor use (in man-days/ha), land size(ha). These are considered as major determinants of rice yields (Moya (2015)). Socio-demographic characteristic included in the specification are land tenure status, age and education of household head (in number of years). Land tenure status is represented by a dummy variable *Own* where this variable is equal to 1 if the land is owned, and it is zero otherwise (e.g., share tenant, fixed rent leaseholder, or other tenurial arrangement). Table 1 provides descriptive statistics for the "economic variables" included in the empirical model, and Table 2 presents the summary statistics for the weather variables.

3.3 Marginal Effects

One of the main goals of this study is to investigate heterogeneity in the yield response of different rice varietal groups to weather variables. The yield response is measured by the marginal effect of changes in weather variables on rice yield. Given the climate function specified in Equation (2), the marginal effect of minimum and maximum temperatures can be calculated using the following:

$$\frac{\partial y}{\partial \mathbf{tmin}_k} = \delta_{1k} + (\psi^r_{1k} \times \mathbf{V}^r_{ijmt}), \tag{3}$$

$$\frac{\partial y}{\partial \mathbf{tmax}_k} = \delta_{2k} + (\psi^r_{2k} \times \mathbf{V}^r_{ijmt}) \tag{4}$$

where $\mathbf{V}^r_{ijmt}$ is the parcel-level rice varietal group dummy variables. For example, suppose the rice variety adopted belongs to the "Early MVs" group, then $\mathbf{V}^1_{ijmt} = 1$. In this case, the marginal yield effect of a one unit change in the minimum (maximum) temperature for the kth phase is $\delta_{1k} + \psi^r_{1k}$ $(\delta_{2k} + \psi^r_{2k})$ (i.e., the coefficient associated with the weather variable plus the coefficient associated with the interaction of the weather variables and the varietal grouping dummy). Because TV is designated as the base varietal grouping, the marginal effects of weather variables $\mathbf{tmin}_{kmt}$ and $\mathbf{tmax}_{kmt}$ on TV rice yield are δ_{1k} and δ_{2k}, respectively. On the other hand, the marginal effect of growing season cumulative precipitation is:

$$\frac{\partial y}{\partial \mathbf{prec}} = \delta_3 + (2 \times \delta_4 \times \mathbf{prec}) + (\psi^r_3 \times \mathbf{V}^r_{ijmt}) + (2 \times \psi^r_4 \times \mathbf{prec} \times \mathbf{V}^r_{ijmt}) \tag{5}$$

The simple marginal effect expressions in Equations (3) and (4) can easily be interpreted if there are only a few weather variables to consider for each growing phase, and if there are only one or two rice varietal groups. However, as seen in Equations (3) and (4) above, our empirical model includes six "temperature-growing-phase" variables for each of two MV groups. Given the number of parameters involved, drawing sensible and consistent inferences using the simple marginal effect expressions in Equation (3) and (4) would be difficult and complex. As such, for ease of interpretation and to facilitate making inferences, we focus on estimating the marginal effect of a particular "warming scenario", where we are interested in the cumulative marginal effect of a 1°C increase in both *tmin* and *tmax* in all three rice-growing phases (or for a particular phase).[7] The marginal effect of this specific "warming scenario" can then be calculated respectively for the TVs, Early MVs, and MV4 as follows:

$$\sum_{k=1}^{3} \frac{\partial y \mid V = \text{TV}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{TV}}{\partial \mathbf{tmax}_k} = \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} \tag{6}$$

$$\begin{aligned} \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{tmax}_k} &= \\ \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} + \sum_{k=1}^{3} \psi_{1k1} + \sum_{k=1}^{3} \psi_{2k1} \end{aligned} \tag{7}$$

$$\begin{aligned} \sum_{k=1}^{3} \frac{\partial y \mid V = \text{MV4}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{MV4}}{\partial \mathbf{tmax}_k} &= \\ \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} + \sum_{k=1}^{3} \psi_{1k2} + \sum_{k=1}^{3} \psi_{2k2} \end{aligned} \tag{8}$$

[7] Even though the specific "warming scenario" discussed here is mainly for the purpose of facilitating interpretation, it is important to note that minimum and maximum temperatures in the Philippines tend to move together and are usually positively correlated (See Welch et al. (2010); Peng et al. (2004)). Our data also supports this behavior (See Supplementary Figure S2 and Supplementary Table S3). Therefore, the base "warming scenario" examined here is still is fairly reasonable based on this positive correlation between *tmin* and *tmax*. Nevertheless, given that minimum and maximum temperatures is likely not to move together in *exactly* 1°C intervals in reality, we also explore marginal effects for the case where *tmin* and *tmax* changes based on projections from climate models (See Section 4 below).

From these equations, we can calculate the warming yield response of Early MVs and the Recent MVs (MV4) as compared to TVs. This allows us to make inferences on whether or not the Early MVs and/or MV4 are more resilient to warming temperatures relative to the TVs.

On the other hand, for calculating the impact of cumulative precipitation (*prec*), we can directly derive the marginal effect because we utilize a single cumulative growing-season precipitation variable in the specification, instead of precipitation in each of the three growing phases. For example, the estimated marginal effect of a 1mm increase in the cumulative precipitation for the TVs, Early MVs and MV4 can be calculated as follows:

$$\frac{\partial y \mid V = \text{TV}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} \tag{9}$$

$$\frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} + \psi_{31} + 2 \times \psi_{41} \times \mathbf{prec} \tag{10}$$

$$\frac{\partial y \mid V = \text{MV4}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} + \psi_{32} + 2 \times \psi_{42} \times \mathbf{prec} \tag{11}$$

Given that a squared precipitation term and its interaction with the varietal group dummy are included in Equation (2), the marginal impacts of precipitation in Equations (9) to (11) are a function involving the value of *prec*. In this study, we calculate the marginal impact of cumulative precipitation at the mean of *prec*. In addition, we also measure and report the marginal effect of a 1 standard deviation increase in precipitation (at the mean of *prec*).

4 Estimation Results

The fully specified empirical model for this study is primarily based on Equations (1) and (2) above. However, in this section, we also present estimation results from four other more parsimonious models, which then build towards the full specification results from Equations (1) and (2). The first parsimonious model (Model 1) is our baseline where we do not include the interactions terms between the temperature variables and the varietal group dummies, for all three growth phases. In Model 1, we only include the interaction of *tmin* for the vegetative growing phase with the varietal group dummmies, and the interaction of *tmax* for the ripening phase with the varietal group dummies.[8] In addition,

[8]The vegetative rice-growing phase *tmin* and the ripening phase *tmax* were chosen in this baseline model based on a preliminary run of the empirical model without any interactions, but including all the individual *tmin* and *tmax* variables in all phases (i.e., vegetative, reproductive, and ripening phases). In this preliminary run, the parameters associated with the *tmin* in the vegetative phase and and *tmax* in the ripening phase are the largest. Therefore, this preliminary run suggests that *tmin* during the vegetative

the baseline model also includes the *tmin* and *tmax* variables in all phases individually, the fixed effects, and the time trend. The second parsimonious model (Model 2) includes the interactions of the *tmin* and *tmax* variables in all growing phases (e.g., the vegetative, reproductive, and ripening phases), instead of just the varietal group interactions with the vegetative phase *tmin* and the ripening phase *tmax*, plus the remaining variables in Model 1. Next, the third parsimonious model (Model 3) adds on the *prec* and squared *prec* terms to Model 2. The fourth parsimonious model (Model 4) then includes all variables of Model 3 and adds the interactions of *prec* and squared *prec* with varietal grouping dummy variables. Lastly, the fully specified model is Model 5, where all the economic variables (i.e., input application variables and socio-economic variables) are included in the specification, in addition to the variables in Model 4 (i.e., this is the full expressions from Equations (1) and (2)). The parameter estimates for all of these models are presented in Supplementary Table S1 in the Appendix.

The pertinent marginal effects for Models 1 to 5 under a variety of warming scenarios are presented in Table 3.[9] Marginal effects for the "baseline" model (Model 1) and the corresponding P-values are in columns 2 and 3. Model 2 results are presented in columns 4 and 5. Marginal effects and their P-values for Model 3 are in columns 6 and 7. Marginal effects and their P-values for Model 5 are in columns 8 and 9. Lastly, the marginal effects and their P-values based on the full specification are shown in columns 10 and 11.

For all model specifications, a warming scenario that increases *tmin* and *tmax* by 1°C in all growing phases substantially reduces rice yields, though some of the estimated warming effects are not statistically significant at the usual levels of significance (i.e., see warming scenario in the top panel of Table 3). The magnitudes of our marginal effects ranges from -7% (for MV4 in the "baseline" model) to -28% (for the TVs under Model 3). Results presented in the other two warming scenarios, where only *tmin* or *tmax* are increased separately by 1°C (see middle panels of table 3), indicate that *tmin* is the likely source of the observed negative yield impact of warming. This result is consistent with results from Welch et al. (2010) where *tmin* effects were also found to be the stronger determinant of rice yield losses due to warming temperatures. It is also

phase and *tmax* during the ripening phase had the largest impact on rice yields. Therefore, we decided to have an initial parsimonious baseline model that only include the climate-varietal-group interactions for these two variables.

[9] The warming scenario considered in Table 3 is a 1°C increase in *tmin* and *tmax*. We also provide the marginal effects for a warming scenario that increases *tmin* and *tmax* by 1 standard deviation in Supplementary Table S2 and Supplementary Figure S3 in the Appendix. The pattern of results in both cases are similar.

important to note that the estimated adverse warming effects observed in Model 3 and Model 4 became higher (relative to the effects in Models 1 and 2), as one controls for precipitation and its interactions. However, the observed marginal effects in Model 5 are lower than the estimates in Models 3 and 4 after a set of economic variables are added to the specification. This suggests that controlling for precipitation and possible time-varying confounding factors may be important in our empirical context.[10]

Another important result from Table 3 is the heterogeneity of the warming impacts across the three varietal groups examined. In Figure 3, we graphically present the marginal percentage yield effects of the main warming scenario (e.g, a 1°C increase in both *tmin* and *tmax* across the vegetative, reproductive, and ripening phases) for the three varietal groups. For all five model specifications, the warming impact is lowest for the MV4 varietal group (Recent MVs).[11] This result provides some farm-level evidence that rice breeding efforts to improve tolerance to abiotic stresses have indeed resulted in more resilience to warming temperatures. In addition, we observe in Figure 3 that the negative warming effect on yields is smaller for the Early MVs as compared to the TVs (across all model specifications). This is suggestive of a "spillover" warming tolerance effect from early rice breeding efforts that were targeted primarily for increasing yields, improving pest resistance, and/or enhancing quality traits (rather than enhancing tolerance to abiotic stresses).

Next, we utilize the parameter estimates from our fixed effects models to investigate how projected future climate change will likely influence potential rice yields of the three varietal groups examined in this study.[12] To complete this climate projection and rice yield simulation exercise, we utilize the projected climate change values from PAGASA, the main meteorological government agency in the Philippines. The climate change values from PAGASA are the projected change in seasonal minimum temperature, maximum temperature, and precipitation from the average over the period 1971-2000 to the average over the period 2011-2040. These projected changes are generated based on the statistical

[10] It should be noted here that although including farm inputs in the specification can help control for confounding factors, it can also raise endogeneity concerns especially if there are parcel-level unobservables not adequately controlled for by the farm-level-fixed effects. Nonetheless, this concern is mitigated by the result that the magnitudes of the estimated effects in Models 3 to 5 are roughly similar.

[11] In Figure 3, there is clearly variation in the estimated magnitudes of the marginal effects. However, the confidence bands do not clearly suggest that the marginal effects are statistically different across varietal groups. This may simply be due to sample size limitations in the data and perhaps test power issues, which we believe does not wholly invalidate the inferences made.

[12] Simulating the effect of projected future climate on rice yields also provides additional insights relative to the 1°C warming scenario examined in Table 3 since this simulation exercise do not implicitly assume that *tmin* and *tmax* change by the same amount (i.e., *dtr* is not assumed to be constant in the future climate projections).

downscaling of three global climate models (GCMs): (1) the BCM2, (2) the CNCM3, and (3) MPEH5; and two plausible emissions scenarios: (1) the A1B emmission scenario, and (2) the A2 emmission scenario.[13]

The projected changes in monthly average of daily *tmin* and *tmax*, as well as projections of percentage change of monthly cumulative *prec* for each of the six provinces in this study are presented in Supplementary Table S5, Supplementary Table S6 and Supplementary Table S7. In addition, the summary statistics for the average across the six Loop survey provinces by growing phase (in the WS) are provided in Supplementary Table S4. Note that Supplementary Table S4 shows that both *tmin* and *tmax* are predicted to increase in the future. Under most of the "emission scenario-GCM-growing phase" combinations examined, the magnitudes of the changes in *tmin* and *tmax* are similar (which validates the original "warming scenario" examined above). However, specifically under the"A1B-CNCM3-Vegetative Phase" combination and the"A2-CNCM3-Vegetative Phase" combination, the incremental increase in *tmin* is double that of the increase in *tmax*, which typically leads to relatively different climate predictions under CNCM3 model (as compared to the other two GCMs).

The percentage change in rice yields due to the projected temperature changes are presented in Figure S4 and Figure S6 for the fully specified model (Model 5), and the detailed yield effects for all models are presented in Supplementary Table S8. In general, our results suggest that MV4 rice yields are still the ones that are more tolerant to projected warming temperatures for most of the GCM-emission-scenario combinations examined (with the exception of the results from the CNCM3 projection model). Results from this analysis also suggest that Early MVs exhibit better tolerance to projected warming temperatures (as compared to the TVs). These climate projection results are consistent with the earlier analysis from the warming scenario examined (Table 3).

So far, we have focused on the differential warming impacts across different varietal groups using both the warming scenario and climate projection models. Precipitation

[13]Note that GCMs are powerful computer programs that use physical processes to replicate, as accurately as possible, the functioning of the global climate system (Comer et al. (2007). The BCM2 model was established by the Bjerknes Centre for Climate Research. On the other hand the CNCM3 GCM was developed by the Météo-France (Centre National de Recherches Météorologiques). Lastly, the MPEH5 was developed by the Max Planck Institute for Meteorology. These three GCMs are considered the most effective at simulating climate for the Philippines (Tolentino et al. (2016)).

On the other hand, the A1B and A2 are two emissions scenarios used in the regional climate projections of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4), and were generated by the Geophysical Fluid Dynamics Laboratory (GFDL) model. The A1 family of scenarios assumes a more integrated world and A1B is based on a balanced technological emphasis on all energy sources. The A2 scenarios, on the other hand, assumes a more divided world.

effects have not been discussed. In Figure S7, we also show the marginal rice yield response due to a 1 standard deviation increase in growing season cumulative precipitation *prec* (evaluated at the mean of *prec*). Increases in *prec* (at the mean) tend to reduce yields of all three varietal groups. Among the three varietal groups, the estimated reduction in MV4 yield is the smallest. These estimates indicate that MV4 is the rice varietal group that is more tolerant to increases in cumulative precipitation. Although, it should be noted that the Early MVs also exhibit resilience to increases in cumulative precipitation (as compared to the TVs).

5 Robustness Checks

As a robustness check, we also estimate similar models as described in Equations (1) and (2), but instead of *tmin* and *tmax*, as the two main temperature variables considered, we instead utilize average temperature (*tavg*) and the diurnal temperature range (*dtr*). Cumulative precipitation *prec* is still included in this robustness check specification (with both linear and quadratic terms). We still follow the approach from the previous section where we examine four parsimonious models (Models 1-4) and build-up to a fifth full model specification.[14]

The estimated marginal yield effects of *tavg* and *dtr* for various warming scenarios and model specifications are presented in Table 4 (and regression results for the specifications are in Supplementary Table S9 in the Appendix). In addition, the marginal effects of 1°C increasein *tavg* are graphically shown in Figure 4. Our results indicate that increases in *tavg* negatively impact rice yields. However, the magnitudes of the marginal effects for *tavg* is smaller than the ones in the previous section for *tmin* and *tmax*. In addition, a good number of these marginal effects are statistically insignificant, which is consistent with previous studies (Welch et al. (2010)). This is because for most varietal groups in nearly all specifications, *tmin* and *tmax* have opposing rice yield impacts. Thus, the opposing temperature impacts may partly cancel each other out. On the other hand, the marginal effect of *dtr* is positive (See Table 4 (middle panel) and Supplementary Figure S8). Note that an increasing *dtr* means that *tmax* is increasing faster than *tmin*, while a decreasing *dtr* means that *tmin* is growing faster than *tmax*. Thus, the positive marginal

[14] One subtle difference to note in the baseline model here (Model 1) is that the interactions considered are only for: (a) *tavg* in the reproductive phase, and (b) *dtr* in the vegetative phase. As in the previous section, this choice was made since preliminary runs of specifications without interactions indicate that the estimated coefficients associated with reproductive phase *tavg* and vegetative phase *dtr* are the highest (among the *tavg* and *dtr* coefficients for all three growing phases separately).

effect for *dtr* supports the notion that increasing *tmin* has a negative impact on rice yields (i.e., consistent with our main specification results in the previous section).

Under all five model specifications, the percentage negative yield impact of *tavg* is the highest for TVs and the lowest for MV4. This result is consistent with the conclusion we made based on the models above involving *tmin* and *tmax*, which provides further evidence as to the effectiveness of the breeding work done to develop MV4. In addition, Figure S9 shows the marginal yield impacts of *prec* at the mean for the model using *tavg* and *dtr*, which also shows the robustness of the precipitation mitigation effect of MV4 from the earlier regression runs.

Another robustness check is running separate regressions by varietal groups. The dataset was divided into three subsamples by varietal groups. We constructed a model specification including linear terms for *tmin* and *tmax*, linear and quadratic terms for *prec*, and applied this specification to each varietal group subsample. The estimated impacts of a +1°C warming scenario and a 1 standard deviation increase in *prec* for each varietal group subsample are seen in Supplementary Table S10 and the parameter estimates are reported in Supplementary Table S11. In addition, we graphically show the impact of a +1°C warming scenario based on the separate regression runs in Supplementary Figure S10, while the impact of a 1 standard deviation increase in *prec* is provided graphically in Supplementary Figure S11. Note that in Supplementary Figure S10, we only plot the confidence interval for early MVs and MV4 because of the large confidence interval for the TV group (which is likely due to the small sample size), and this do not easily fit the scale of the figure. Even though the significance of estimated marginal effects largely decline in these subsample runs due to the small sample sizes (especially for TVs), the mitigation effect observed for MV4 is still present.

Since the roll-out and use of the different varieties occurred sequentially through time (i.e., TVs in earlier years, followed by the release of Early MVs, and then Recent MVs in more recent years), one other approach to check the robustness of results is by running a specification with no varietal group dummy interactions with weather, but instead interacting the weather variables (by growing phase) with the time trend. Parameter estimates from this alternative specification is reported in Supplementary Table S12.[15] In

[15]Specifically, results from Model 3 and Model 4 in Supplementary Table S12 are the ones that coincide with the specification and results described here. We also present results from another two specifications (Model 1 and Model 2) where there are no varietal group interactions with weather and no time trend interactions with weather. This is the case where one has no data on varietal groups and it is assumed that the marginal effect of warming is constant. In this case, the estimated marginal impact of 1°C warming scenario is -15.4% from Model 1 and -9.9% from Model 2. Hence, in this naive specification, we do not

this specification, varietal development is embedded in the time trend (along with other rice technologies evolving over time). Hence, if varietal development is a main driver of rice technological change, then we would expect a pattern where the adverse effect of warming would be larger in earlier years (where TV is predominant) and it would then slowly decrease over time as more MVs are released. More recent years will have smaller negative warming effects than earlier years given the release of MV4s. This pattern is indeed verified and shown in Supplementary Figure S12, which supports robustness of our earlier results.

The last robustness check we conducted is to examine a specification with both: (a) varietal group interactions with weather, and (b) time trend interactions with weather. Compared to the specification in the previous paragraph, this last specification separates out the warming effect of varietal groups from the warming effect due to other technologies. Parameter estimates from this specification are reported in Supplementary Table S13 and Table S14 and the pertinent marginal effects are presented in Supplementary Figure S13. Results from this last robustness check is still consistent with the main pattern of results from the previous analysis, where the adverse warming effect is smaller for MV4 relative to the earlier MVs and the TVs.

6 Conclusions

The main objective of this study is to investigate whether modern rice varieties (MVs) mitigate the adverse yield impacts of climate change, especially the more recent MV4 varieties specifically bred to be more tolerant to abiotic stresses. By merging Philippine farm-level survey data (from 1966-2016) with monthly, municipality-level climate data, we are able to estimate fixed effect econometric models with "weather-varietal group" interactions and assess whether there is heterogeneity in the warming effects across different rice varietal groups. Results from the analysis indicate that modern rice varieties mitigate the detrimental effects of warming on rice yields, and there is evidence that rice varieties in the MV4 varietal group indeed tend to be more resilient to a warming climate relative to the earlier rice MVs. Although early modern varieties were not specifically developed to address climate change and abiotic stresses, we find that they in fact partially mitigate the negative yield effects of warming. The presence of some climate change mitigation ef-

adequately capture the heterogeneity in the warming effects (e.g., the larger warming effects on TVs) and further highlights the importance of having varietal data when exploring climate change impacts in agriculture.

fects for these early modern rice varieties can be considered a "spillover" benefit from rice breeding efforts that was not specifically targeted to improve resilience to climate change. Moreover, the stronger climate change mitigation effects for MV4 provides evidence that there are indeed direct yield benefits from rice-breeding efforts to improve tolerance to abiotic stresses.

Findings from our study suggest that public rice breeding efforts to develop rice varieties with "high temperature tolerance traits" is essential to maintenance of past rice yield gains, especially in a future with global warming. This implies that future public investments in breeding for abiotic stress tolerance is important for ensuring food security and in reducing climate-change-induced production risks faced by rice farmers in developing countries. Even though we provide some evidence on the success of recent breeding efforts to increase resilience to abiotic stress, our results for rice producers in the Central Luzon region of the Philippines still show that rice yields will be negatively affected by future climate change even when using MV4. Hence, there should be continued research investments in rice breeding at international centers (i.e., like IRRI) and national breeding institutions (i.e., such as PhilRice in the Philippines and BRRI in Bangladesh) if rice yield growth is expected to continue in the future and meet the food demand of a population getting close to 10 billion by 2050. Specific focus on funding research projects to develop "climate-change-tolerant" rice varieties should be one of the priorities of funding agencies and donor institutions interested in global food security and poverty alleviation in developing countries (e.g., Bill and Melinda Gates Foundation, USAID, etc.).

For rice farmers, our results indicate that rice variety selection is an important adaptation strategy to climate change. However, adoption of new rice varieties often demands more knowledge, better management, and higher cost. Therefore, policies and programs that provide more education and outreach programs is needed to help producers understand the relationships between climate (as well as other production environment conditions) and the yield and quality impacts of planting different rice varieties. Providing small initial subsidies for rice farmers to try out new climate-change-tolerant varieties may be one policy option that developing country governments can explore (i.e., if they want to encourage adoption of these varieties). Lastly, providing extension support to provide information about complementary climate change adaptation strategies (other than simply adopting more tolerant varieties) would also better arm producers with tools to face a production environment with higher temperatures and more frequent extreme weather events.

Even though the present study provides important inferences about the likely heterogeneous effects of warming across different rice varietal groups, it is important to recognize some limitations in the study. First, the sample size of our survey data is still relatively small and this constrained us to only focus on climate change effects for irrigated rice farmers in the WS. It may not be appropriate to extrapolate our data to rainfed rice farmers planting in the dry season. Nevertheless, since climate change is likely to cause more damage to rice grown in the dry season, it is reasonable to say that our estimated results can be considered as a lower bound of the warming impacts across rice varietal groups. Second, the relatively small survey sample also made us focus on developing more parsimonious models, rather than developing more flexible models that are less parsimonious. We leave these kinds of efforts for future work. Third, the weather data used in the study was only at the municipal level (rather than at the farmer level or lower levels of aggregation). Future studies may consider collecting individual farm-level weather data to improve inferences going forward. In addition, collecting individual information about other weather variables like radiation and vapor pressure deficit (VPD) may also be important in better understanding rice yield effects under climate change in the future (Krishnan and Rao (2005), Welch et al. (2010), Gourdji et al. (2013)). Lastly, conducting the analysis in this study for other countries with more variable weather may also be beneficial in the future.

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Table 1: Descriptive statistics for the economic variables

Variable	Units/Definition	Mean	St Dev	Min	Max
Yield	kg/ha	3893.4	1560.5	306.7	11250
Land Tenure	1=owner; 0=other	.42	.49	0	1
Farm size	ha	1.32	.97	.03	9
Nitrogen Fert.	kg/ha	82.73	53.78	0	483.91
Labor	man-days/ha	70.19	28.82	0	257.75
Age of Head	no. of yrs.	52.79	13.71	22	94
Educ. of Head	no. of yrs.	7.23	3.35	0	16

Table 2: Descriptive statistics for the weather variables

Phase	Variable	Unit	Mean	St Dev	Min	Max
Vegetative	tmin	Deg. C	22.85	0.61	19.91	24.05
	tmax	Deg. C	30.50	0.83	27.56	32.00
	tavg	Deg. C	26.66	0.67	24.16	28.00
	dtr	Deg. C	7.64	0.74	5.14	9.45
Reproductive	tmin	Deg. C	22.63	0.74	20.15	24.31
	tmax	Deg. C	30.40	0.79	27.78	32.45
	tavg	Deg. C	26.48	0.68	24.03	28.07
	dtr	Deg. C	7.76	0.75	5.00	9.50
Ripening	tmin	Deg. C	22.49	0.82	19.83	24.34
	tmax	Deg. C	30.56	0.84	27.62	32.65
	tavg	Deg. C	26.44	0.73	24.02	28.13
	dtr	Deg. C	8.07	0.87	6.00	10.51
Growing Season	Cum. Precip.	mm	1386.77	358.20	692.84	3038.72

Notes: The table above displays the descriptive statistics of weather variables used in the regressions. The first four rows are the growing season averages of the daily minimum, maximum, and mean temperatures, as well as the diurnal temperature range for the vegetative phase. The second four rows are the weather variables for the reproductive phase and the third four rows shows the weather variables for the ripening phase. The last row is cumulative precipitation for the entire growing season.

Table 3: Marginal percentage yield impact of weather variables for different warming scenarios and varietal groups

Variables	Model 1 vtmin×V, ritmax×V		Model 2 3 tmin×V, 3tmax×V		Model 3 add prec, precsq		Model 4 add prec×V, precsq×V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tmin&tmax: tv	-0.20	0.092	-0.16	0.210	-0.28	0.023	-0.27	0.034	-0.23	0.088
tmin&tmax: early mv	-0.08	0.116	-0.11	0.049	-0.21	0.000	-0.23	0.000	-0.17	0.006
tmin&tmax: mv4	-0.07	0.165	-0.10	0.068	-0.19	0.005	-0.19	0.002	-0.14	0.043
1°C increase in tmin:										
tmin: tv	-0.18	0.284	-0.37	0.086	-0.54	0.012	-0.68	0.003	-0.62	0.01
tmin: early mv	-0.12	0.023	-0.11	0.040	-0.24	0.000	-0.25	0.000	-0.20	0.00
tmin: mv4	-0.09	0.224	-0.19	0.083	-0.33	0.020	-0.33	0.004	-0.28	0.02
1°C increase in tmax:										
tmax: tv	-0.02	0.905	0.21	0.419	0.25	0.313	0.41	0.129	0.39	0.20
tmax: early mv	0.04	0.388	0.00	1.000	0.03	0.610	0.02	0.639	0.03	0.55
tmax: mv4	0.01	0.774	0.09	0.243	0.15	0.130	0.14	0.056	0.14	0.06
1 standard deviation increase in cumulative precipitation										
prec: tv							-0.19	0.213	-0.24	0.156
prec: early mv							-0.17	0.000	-0.15	0.000
prec: mv4							-0.09	0.106	-0.04	0.473
Adj R-square	0.298		0.299		0.329		0.333		0.372	

Notes: (1) The table displays coefficients and p-values of marginal yield effect of +1°C warming scenarios and 1 standard deviation of increase in *prec* from 5 farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where *tmin* and *tmax* of each growing phase and the interactions between *tmin* in the vegetative phase (*vtmin*) and *tmax* in the ripening phase (*ritmax*) and dummies for rice varietal groups are included in the specification. Model 2 includes the *tmin* and *tmax* variables in all the growing phases(e.g., the vegetative(*vtmin* and *vtmax*), reproductive(*retmin* and *retmax*), and the ripening (*ritmin* and *ritmax*) phases and their interactions with dummies for rice varietal groups. Model 3 adds on cumulative precipitation in the growing season (*prec*) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of *prec* and squared *prec* with varietal grouping dummy variables to Model 3. Model 5 is the specification including all the "economic variables" in addition to the variables in Model 4. (3) The first column indicates what weather variables are the marginal effects based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1°C increase in both *tmin* and *tmax* for the TV, early MV and MV4 varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1°C increase in *tmin* for the TV, early MV and MV4. The rows of the third panel refer to the marginal effect of a 1°C increase in *tmax* for the TV, early MV and MV4. Lastly, the rows of the fourth panel indicates the marginal effect of a 1 standard deviation of increase in *prec* for the TV, early MV and MV4.

Table 4: Marginal percentage yield impact of weather variables: Alternative specification using mean temperatures & DTR

Variables	Model 1 retavg*V, vdtr*V		Model 2 3 tavg*V, 3 dtr*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tavg: tv	-0.13	0.280	-0.05	0.696	-0.16	0.214	-0.16	0.226	-0.12	0.358
tavg: early mv	-0.07	0.113	-0.06	0.178	-0.14	0.004	-0.16	0.001	-0.11	0.021
tavg: mv4	-0.06	0.120	-0.05	0.265	-0.12	0.016	-0.12	0.012	-0.10	0.057
1°C increase in diurnal temperature variation :										
dtr: tv	0.25	0.212	0.22	0.366	0.32	0.170	0.46	0.042	0.44	0.061
dtr: early mv	0.03	0.422	0.03	0.474	0.10	0.057	0.10	0.065	0.08	0.147
dtr: mv4	0.12	0.033	0.16	0.018	0.19	0.042	0.17	0.047	0.16	0.066
1 standard deviation of increase in cumulative precipitation:										
prec: tv							-0.2308	0.020	-0.25	0.027
prec: early mv							-0.1586	0.000	-0.14	0.000
prec: mv4							-0.0518	0.293	0.00	0.946
Adj R-square	0.298		0.297		0.322		0.328		0.368	

Notes: (1) The table displays coefficients and p-values of the marginal yield effect of +1°C increase in *tavg* and *dtr* for all phases in the growing season and 1 standard deviation increase in *prec*, based on the 5 farm fixed-effect models estimated. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where *tavg* and *dtr* for the three growing phases and the interactions between *tavg* in the reproductive phase (*retavg*) and *dtr* in the ripening phase (*ridtr*) and dummies for rice varietal groups are included in the specification. Model 2 includes the *tavg* and *dtr* variables in all the growing phases(e.g., the vegetative(*vtavg* and *vdtr*), reproductive(*retavg* and *redtr*), and the ripening (*ritavg* and *ridtr*) phases and their interactions with the rice varietal group dummies. Model 3 adds on cumulative precipitation for the growing season (*prec*) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of *prec* and squared *prec* with the varietal grouping dummy variables to Model 3. Model 5 is the full specification including all the "economic variables" in addition to the variables in Model 4. (3) The first column indicates what weather variables are the marginal effects based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1°C increase in *tavg* for the TV, early MV and MV4 varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1°C increase in *dtr* for the TV, early MV and MV4. Lastly, the rows of the third panel indicates the marginal effect of a 1 standard deviation of increase in *prec* for the TV, early MV and MV4.

Figure 1: The Study Area: Central Luzon Loop Survey

Source: "Changes in rice farming in the Philippines: Insights from five decades of a household-level survey" (http://irri.org/resources/publications/books/changes-in-rice-farming-in-the-philippines-insights-from-five-decades-of-a-household-level-survey)

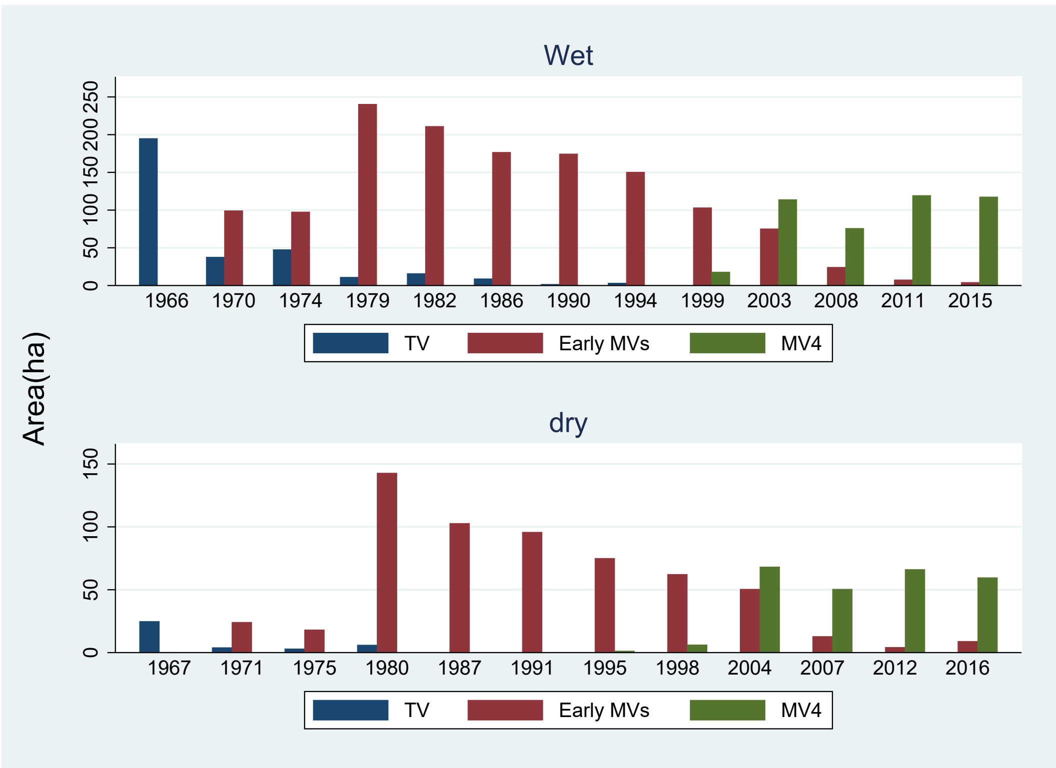


Figure 2: Adoption area of rice by varietal group and survey year

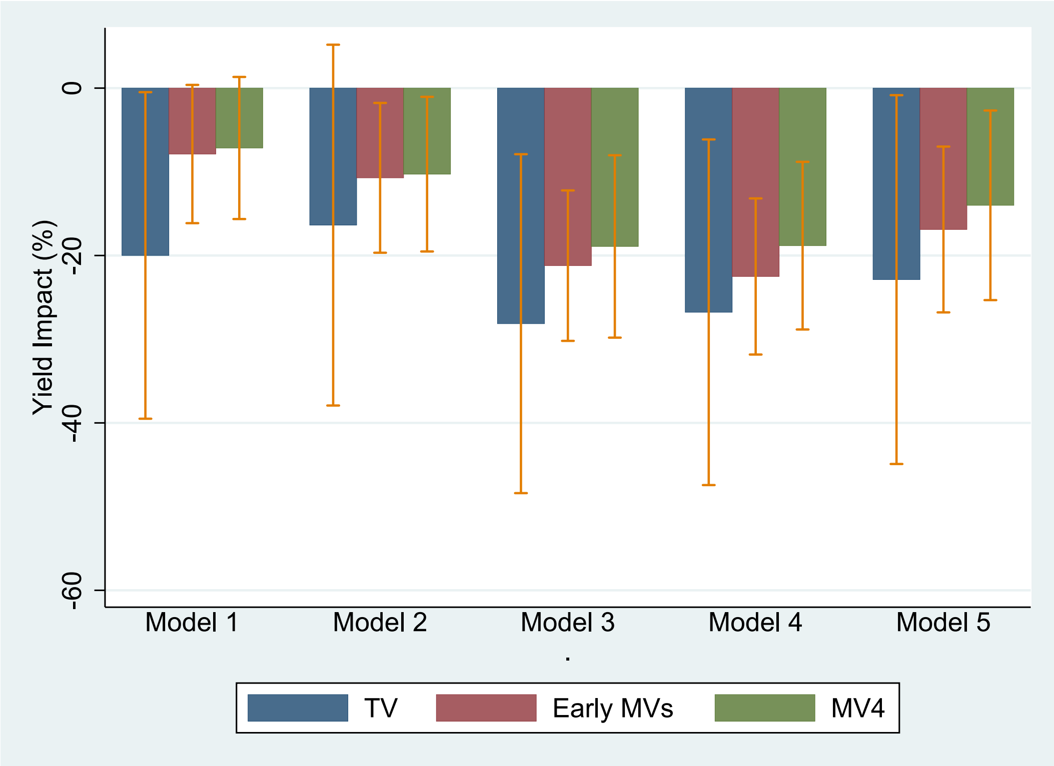


Figure 3: Predicted impacts of the +1°C warming scenario on three rice varietal groups for 5 model specifications. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval

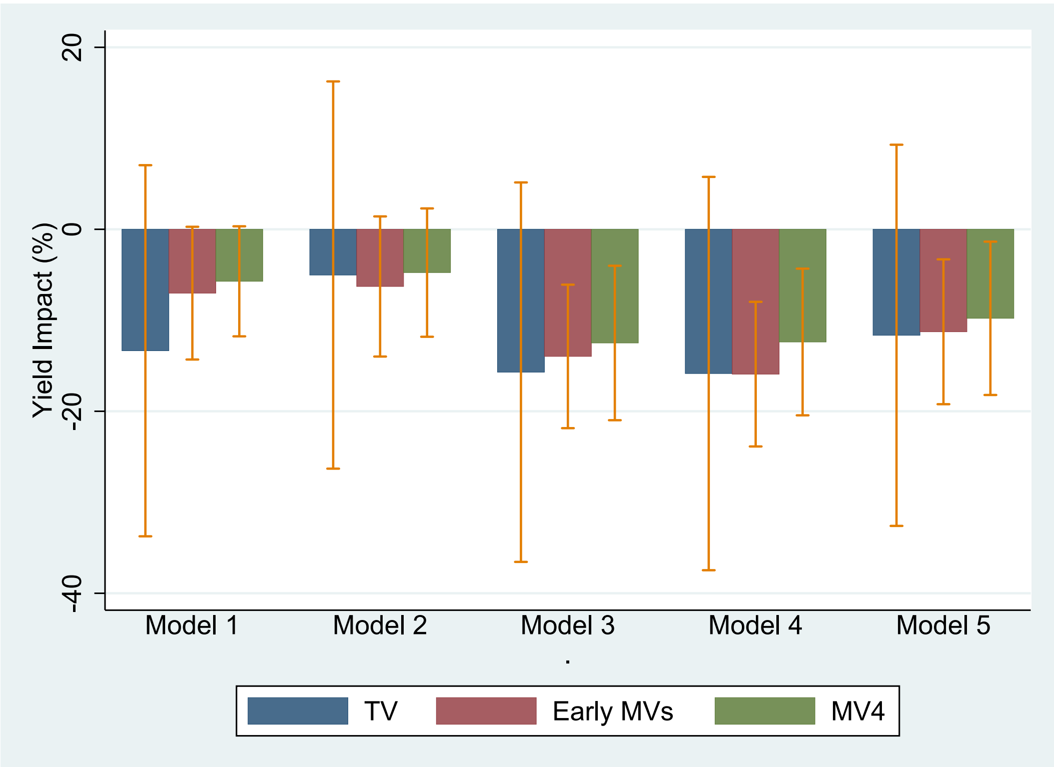


Figure 4: Predicted impacts of a +1°C increase in *tavg* on three rice varietal groups for 5 model specifications. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

Appendix

Table S1: Regression results for the five main model specifications in Table 3

	(1) Model 1 vtmin*V,ritmax*V	(2) Model 2 add 3 tmin*V,3 tmax*V	(3) Model 3 add prec,precsq	(4) Model 4 add prec*V,precsq*V	(5) Model 5 add econ var
vtmin	-0.175	-0.096	-0.269	-0.281	-0.313
	(0.173)	(0.296)	(0.285)	(0.374)	(0.413)
retmin	-0.083**	-0.518	-0.500	-0.453	-0.256
	(0.041)	(0.330)	(0.331)	(0.383)	(0.389)
ritmin	0.074	0.245	0.233	0.058	-0.045
	(0.057)	(0.225)	(0.238)	(0.322)	(0.319)
vtmax	0.011	0.093	0.282*	0.351*	0.457**
	(0.021)	(0.164)	(0.165)	(0.179)	(0.183)
retmax	-0.067	0.158	0.107	0.143	-0.012
	(0.048)	(0.260)	(0.261)	(0.255)	(0.254)
ritmax	0.039	-0.046	-0.135	-0.086	-0.058
	(0.127)	(0.107)	(0.100)	(0.142)	(0.146)
prec			-0.001***	-0.003	-0.004
			(0.000)	(0.003)	(0.003)
prec × prec			0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)
mv1mv2mv3 × vtmin	0.067	0.020	0.031	0.046	0.105
	(0.172)	(0.323)	(0.296)	(0.377)	(0.418)
mv1mv2mv3 × retmin		0.451	0.387	0.340	0.164
		(0.341)	(0.345)	(0.396)	(0.400)
mv1mv2mv3 × ritmin		-0.208	-0.121	0.040	0.146
		(0.230)	(0.241)	(0.325)	(0.327)
mv1mv2mv3 × vtmax		-0.108	-0.206	-0.274	-0.375**
		(0.168)	(0.163)	(0.177)	(0.181)
mv1mv2mv3 × retmax6		-0.241	-0.229	-0.263	-0.112
		(0.249)	(0.253)	(0.247)	(0.245)
mv1mv2mv3 × ritmax	0.055	0.143	0.207**	0.154	0.132
	(0.124)	(0.102)	(0.101)	(0.140)	(0.142)
mv4 × vtmin	0.098	-0.174	-0.019	-0.034	0.023
	(0.176)	(0.335)	(0.338)	(0.391)	(0.434)
mv4 × retmin		0.518	0.433	0.381	0.191
		(0.353)	(0.357)	(0.406)	(0.414)
mv4 × ritmin		-0.168	-0.213	0.001	0.124
		(0.233)	(0.248)	(0.332)	(0.334)
mv4 × vtmax		-0.024	-0.159	-0.246	-0.347*
		(0.167)	(0.169)	(0.179)	(0.182)
mv4 × retmax		-0.158	-0.088	-0.095	0.057
		(0.275)	(0.283)	(0.277)	(0.261)
mv4 × ritmax	0.030	0.066	0.139	0.073	0.040
	(0.145)	(0.121)	(0.111)	(0.153)	(0.155)
mv1mv2mv3 × prec				0.002	0.003
				(0.003)	(0.003)
mv1mv2mv3 × prec × prec				-0.000	-0.000
				(0.000)	(0.000)
mv4 × prec				0.003	0.004
				(0.003)	(0.003)
mv4 × prec × prec				-0.000	-0.000
				(0.000)	(0.000)
Observations	1160	1160	1160	1160	1158
Adj R-squared	0.298	0.299	0.330	0.333	0.372
Number of Farmers	180	180	180	180	180

Notes: (1) Dependent variable in all regressions is the natural log of rice yield. (2) *vtmin*, *retmin*, and *ritmin*, respectively, are the monthly average of the minimum temperatures for the vegetative, reproductive and ripening phase; *vtmax*, *retmax*, and *ritmax*, respectively, are the monthly average of the maximum temperatures for the vegetative, reproductive and ripening phase. The variable *prec* is the cumulative precipitation for the entire growing season. (3) Units for *tmin* and *tmax* is °C and for *prec* it is in mm.

Table S2: Marginal percentage yield impacts of "1 standard deviation" warming scenarios

Variables	Model 1 vtmin*V, ritmax*V		Model 2 3 tmin*V, 3tmax*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1 standard deviaton increase in both tmin & tmax										
tmin&tmax: tv	-0.12	0.149	-0.08	0.468	-0.14	0.192	-0.13	0.297	-0.10	0.482
tmin&tmax: early mv	-0.03	0.408	-0.06	0.149	-0.11	0.007	-0.12	0.004	-0.08	0.059
tmin&tmax: mv4	-0.03	0.368	-0.03	0.409	-0.09	0.019	-0.09	0.027	-0.05	0.227
1 standard deviaton increase in tmin										
tmin: tv	-0.11	0.315	-0.25	0.078	-0.35	0.012	-0.46	0.002	-0.42	0.01
tmin: early mv	-0.07	0.044	-0.07	0.049	-0.14	0.000	-0.15	0.000	-0.11	0.01
tmin: mv4	-0.05	0.283	-0.10	0.127	-0.21	0.019	-0.20	0.008	-0.16	0.03
1 standard deviaton increase in tmax										
tmax: tv	-0.01	0.926	0.16	0.423	0.20	0.310	0.33	0.128	0.32	0.19
tmax: early mv	0.04	0.325	0.00	0.916	0.03	0.515	0.03	0.545	0.03	0.45
tmax: mv4	0.01	0.704	0.08	0.230	0.12	0.120	0.11	0.054	0.11	0.05
Adj R-square	0.298		0.299		0.329		0.333		0.372	

Notes: (1) The table displays coefficients and p-values of marginal yield effect of warming scenarios where both *tmin* and *tmax* in each growing phase increases by 1 standard deviation. The results are estimated based on 5 farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where *tmin* and *tmax* of each growing phase and the interactions between *tmin* in the vegetative phase (*vtmin*) and *tmax* in the ripening phase (*ritmax*) and dummies for rice varietal groups are included in the specification. Model 2 includes the *tmin* and *tmax* variables in all the growing phases(e.g., the vegetative(*vtmin* and *vtmax*), reproductive(*retmin* and *retmax*), and the ripening (*ritmin* and *ritmax*) phases and their interactions with dummies for each rice varietal group. Model 3 adds on the cumulative precipitation for the growing season (*prec*) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of *prec* and squared *prec* with the varietal grouping dummy variables to Model 3. Model 5 is the specification including all the "economic variables" in addition to the variables in Model 4. (3) The first column indicates what weather variables are the marginal effects based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1 standard deviation increase in both *tmin* and *tmax* in each growing phase for the TV, early MV, and MV4 varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1 standard deviation increase in *tmin* in each growing phase for TV, early MV, and MV4. Lastly,the rows of the third panel refers to the marginal effect of a 1 standard deviation increase in *tmax* in each growing phase for the TV, early MV, and MV4.

Table S3: Correlations between maximum and minimum temperatures by growing phase

Phase	Variable	tmin
Vegetative	tmax	0.4045(0.0000)
Reproductive	tmax	0.4582(0.0000)
Ripening	tmax	0.4534(0.0000)

Note: The table displays correlations between minimum and maximum temperature for 32 municipalities (34 municipalities in 2015) across 13 survey years. Number of observations = 418. P-values are in parentheses

Table S4: Predicted change in *tmin* and *tmax* between 1971-2000 and 2011-2041 averaged over all provinces, by WS growing-phase

		Vegetative		Reproductive		Ripening	
		mean	sd	mean	sd	mean	sd
tmin							
A1B	bcm2	0.28	0.030	0.33	0.054	0.39	0.028
	cncm3	0.34	0.056	0.43	0.158	0.66	0.065
	mpeh5	0.33	0.040	0.35	0.065	0.40	0.042
A2	bcm2	0.28	0.032	0.33	0.052	0.39	0.034
	cncm3	0.29	0.030	0.37	0.097	0.48	0.059
	mpeh5	0.32	0.031	0.35	0.069	0.46	0.065
tmax							
A1B	bcm2	0.38	0.037	0.43	0.048	0.49	0.038
	cncm3	0.17	0.111	0.38	0.313	0.74	0.097
	mpeh5	0.32	0.030	0.34	0.048	0.34	0.048
A2	bcm2	0.27	0.038	0.30	0.014	0.31	0.032
	cncm3	0.15	0.072	0.30	0.222	0.53	0.047
	mpeh5	0.38	0.059	0.40	0.045	0.34	0.065

Table S5: Predicted change in *tmin* between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(2011-2040)				CNCM3(2011-2040)				MPEH5(2011-2040)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B (business-as-usual scenario)												
La Union	0.5	0.5	0.3	0.4	0.9	0.9	0.5	0.7	0.7	0.9	0.3	0.4
Pangasinan	0.5	0.4	0.2	0.4	0.7	0.5	0.3	0.6	0.4	0.6	0.3	0.4
Nueva Ecija	0.5	0.3	0.3	0.4	0.7	0.5	0.3	0.7	0.5	0.6	0.3	0.4
Pampanga	0.5	0.4	0.2	0.4	0.7	0.4	0.2	0.6	0.5	0.6	0.4	0.4
Bulacan	0.6	0.4	0.3	0.4	0.8	0.6	0.4	0.7	0.6	0.7	0.4	0.5
Tarlac	0.5	0.3	0.2	0.3	0.6	0.4	0.3	0.5	0.4	0.5	0.4	0.3
A2 (differentiated world scenario)												
La Union	0.6	0.7	0.3	0.4	0.6	0.7	0.3	0.5	0.7	0.7	0.3	0.5
Pangasinan	0.5	0.5	0.2	0.4	0.5	0.4	0.2	0.5	0.6	0.5	0.3	0.4
Nueva Ecija	0.5	0.5	0.3	0.4	0.5	0.4	0.3	0.5	0.6	0.6	0.3	0.5
Pampanga	0.5	0.5	0.2	0.3	0.6	0.4	0.2	0.4	0.6	0.5	0.3	0.4
Bulacan	0.6	0.6	0.3	0.4	0.6	0.5	0.3	0.5	0.7	0.7	0.4	0.5
Tarlac	0.4	0.4	0.2	0.3	0.5	0.3	0.2	0.3	0.5	0.5	0.3	0.3

Notes: The climate projection dataset were generated and completed under a cooperation project between the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA-DOST), the Food and Agriculture Organization of the United Nations (FAO) and FAO-AMICAF Philippines. Climate projections are based on the statistical downscaling of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2). DJF, December to February; MAM, March to May; JJA, June to August; SON, September to November.

Table S6: Predicted change in $tmax$ between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(∘C)				CNCM3(∘C)				MPEH5(∘C)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B (business-as-usual scenario)												
La Union	0.2	0.5	0.5	0.6	0.5	0.4	0.1	0.7	0.1	0.4	0.2	0.4
Pangasinan	0.4	0.5	0.3	0.5	0.6	0.5	0.1	0.8	0.2	0.4	0.3	0.4
Nueva Ecija	0.4	0.6	0.4	0.5	0.6	0.6	0.1	0.7	0.2	0.4	0.3	0.3
Pampanga	0.5	0.6	0.3	0.4	0.7	0.6	0.2	0.8	0.3	0.5	0.3	0.4
Bulacan	0.4	0.5	0.4	0.4	0.5	0.5	0.1	0.6	0.2	0.3	0.3	0.3
Tarlac	0.4	0.7	0.3	0.5	0.8	0.7	0.1	1	0.2	0.6	0.4	0.4
A2 (differentiated world scenario)												
La Union	0.4	0.7	0.4	0.2	0.3	0.5	0	0.6	0.6	0.4	0.1	0.3
Pangasinan	0.5	0.7	0.2	0.3	0.4	0.5	0.1	0.6	0.5	0.4	0.3	0.4
Nueva Ecija	0.5	0.8	0.3	0.3	0.4	0.5	0.1	0.5	0.4	0.4	0.4	0.3
Pampanga	0.5	0.8	0.2	0.3	0.5	0.5	0.1	0.5	0.6	0.4	0.4	0.4
Bulacan	0.4	0.7	0.3	0.3	0.3	0.5	0.1	0.5	0.5	0.3	0.3	0.3
Tarlac	0.6	0.9	0.2	0.4	0.6	0.6	0.2	0.6	0.6	0.4	0.5	0.5

Table S7: Predicted change in cumulative precipitation (*prec*) between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(∘C)				CNCM3(∘C)				MPEH5(∘C)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B (business-as-usual scenario)												
La Union	-20.7%	-23.6%	0.2%	10.5%	8.2%	10.5%	9.3%	35.5%	27.1%	24.8%	12.2%	17.6%
Pangasinan	8.4%	-4.2%	-1.5%	4.3%	39.1%	22.9%	20.0%	30.0%	36.0%	57.9%	15.4%	22.1%
Nueva Ecija	8.0%	-1.4%	-2.2%	10.1%	24.6%	32.0%	11.4%	19.7%	26.0%	58.5%	13.0%	14.2%
Pampanga	24.5%	3.1%	-0.2%	8.4%	59.0%	20.4%	22.3%	17.7%	46.0%	60.7%	14.9%	12.9%
Bulacan	-1.7%	-6.5%	-4.0%	8.3%	17.6%	10.2%	12.4%	16.2%	20.2%	35.6%	13.9%	18.6%
Tarlac	27.5%	3.3%	-2.1%	14.7%	49.1%	19.7%	21.1%	20.9%	51.1%	64.8%	15.9%	17.0%
A2 (differentiated world scenario)												
La Union	-7.2%	-17.6%	-4.3%	28.2%	9.1%	5.3%	5.6%	8.1%	30.7%	41.4%	10.3%	28.6%
Pangasinan	19.6%	-11.2%	-2.8%	11.7%	29.4%	2.6%	11.4%	10.9%	24.3%	35.4%	9.4%	28.1%
Nueva Ecija	17.9%	-8.0%	-4.6%	14.2%	13.9%	12.8%	9.2%	6.0%	19.2%	36.7%	8.2%	24.3%
Pampanga	26.4%	-12.6%	2.0%	11.8%	37.7%	9.1%	11.3%	6.0%	33.1%	32.9%	3.9%	24.5%
Bulacan	2.8%	-12.8%	-3.4%	12.6%	14.8%	6.1%	7.1%	1.2%	13.0%	31.6%	9.2%	28.0%
Tarlac	32.9%	-12.3%	-2.0%	15.5%	32.9%	6.0%	10.6%	11.8%	41.7%	33.2%	4.8%	26.5%

Table S8: Predictions of log rice yield (kg/ha) change for TVs,Early MVs and MV4 across CGM-estimation scenario combinations

	Model 1 vtmin*V, vtmax*V		Model 2 3 tmin*V, 3tmax*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
tv_a1b_bcm2	-0.05	0.236	-0.02	0.718	-0.06	0.325	-0.05	0.478	-0.05	0.562
tv_a1b_cncm3	-0.04	0.530	-0.05	0.529	-0.17	0.069	-0.20	0.137	-0.22	0.135
tv_a1b_mpeh5	-0.06	0.113	-0.05	0.283	-0.09	0.040	-0.10	0.049	-0.09	0.088
tv_a2_bcm2	-0.05	0.130	-0.04	0.282	-0.08	0.045	-0.09	0.062	-0.09	0.112
tv_a2_cncm3	-0.04	0.352	-0.06	0.258	-0.15	0.013	-0.17	0.047	-0.17	0.061
tv_a2_mpeh5	-0.06	0.138	-0.02	0.774	-0.05	0.406	-0.06	0.388	-0.06	0.417
mv1mv2mv3_a1b_bcm2	-0.01	0.702	0.00	0.983	-0.04	0.257	-0.06	0.137	-0.05	0.173
mv1mv2mv3_a1b_cncm3	0.02	0.470	0.07	0.317	0.00	0.973	-0.06	0.574	-0.07	0.498
mv1mv2mv3_a1b_mpeh5	-0.02	0.193	-0.02	0.373	-0.06	0.015	-0.07	0.009	-0.06	0.022
mv1mv2mv3_a2_bcm2	-0.02	0.290	-0.01	0.805	-0.04	0.150	-0.06	0.083	-0.06	0.104
mv1mv2mv3_a2_cncm3	0.00	0.819	0.03	0.442	-0.02	0.664	-0.06	0.354	-0.06	0.338
mv1mv2mv3_a2_mpeh5	-0.02	0.309	-0.01	0.442	-0.04	0.238	-0.07	0.129	-0.07	0.140
mv4_a1b_bcm2	-0.01	0.580	0.01	0.770	-0.02	0.602	-0.04	0.326	-0.03	0.343
mv4_a1b_cncm3	0.01	0.659	0.04	0.613	-0.01	0.868	-0.07	0.507	-0.09	0.392
mv4_a1b_mpeh5	-0.02	0.261	-0.02	0.458	-0.05	0.069	-0.06	0.038	-0.05	0.075
mv4_a2_bcm2	-0.02	0.344	0.00	0.907	-0.03	0.288	-0.05	0.172	-0.05	0.185
mv4_a2_cncm3	0.00	0.959	0.01	0.819	-0.03	0.546	-0.07	0.318	-0.07	0.262
mv4_a2_mpeh5	-0.02	0.356	0.01	0.876	-0.02	0.550	-0.04	0.323	-0.04	0.325

Notes: Table shows the predicted changes in the natural log of yield of three varietal groups under various global climate models and emission scenarios between 1971-2000 and 2011-2041. Projections on seasonal temperature increase and rainfall change are provided by PAGASA. The first panel shows the predicted changes in average yield of TV under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2).The second panel shows the predicted changes in average yield of MV1-MV3 under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2). The second panel shows the predicted changes in average yield of MV4 under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2).

Table S9: Regression results for the alternative model specifications in Table 4

	(1) Model 1 retavg*V,vdt*V	(2) Model 2 add 3 tavg*V,3 dtr*V	(3) Model 3 add prec,precsq	(4) Model 4 add prec*V,precsq*V	(5) Model 5 add econ var
vtavg	-0.035	0.286	0.247	0.323	0.368
	(0.058)	(0.227)	(0.240)	(0.265)	(0.265)
retavg	-0.208	-0.179	-0.223	-0.151	-0.119
	(0.147)	(0.375)	(0.354)	(0.388)	(0.372)
ritavg	0.109	-0.156	-0.181	-0.330	-0.365
	(0.073)	(0.354)	(0.374)	(0.415)	(0.412)
vdtr	0.226	-0.026	0.166	0.206	0.288
	(0.194)	(0.270)	(0.265)	(0.248)	(0.234)
redtr	-0.005	0.312	0.247	0.203	0.055
	(0.029)	(0.382)	(0.386)	(0.365)	(0.346)
ridtr	0.025	-0.069	-0.088	0.046	0.100
	(0.036)	(0.179)	(0.183)	(0.212)	(0.208)
prec			-0.001***	-0.004**	-0.004**
			(0.000)	(0.002)	(0.002)
prec × prec			0.000	0.000**	0.000**
			(0.000)	(0.000)	(0.000)
mv1mv2mv3 × vtavg		-0.290	-0.286	-0.337	-0.370
		(0.247)	(0.259)	(0.282)	(0.280)
mv1mv2mv3 × retavg	0.063	0.009	-0.016	-0.116	-0.112
	(0.114)	(0.402)	(0.378)	(0.411)	(0.393)
mv1mv2mv3 × ritavg		0.269	0.319	0.452	0.486
		(0.373)	(0.388)	(0.428)	(0.424)
mv1mv2mv3 × vdtr	-0.215	0.020	-0.070	-0.126	-0.210
	(0.194)	(0.277)	(0.268)	(0.253)	(0.239)
mv1mv2mv3 × redtr		-0.321	-0.254	-0.209	-0.073
		(0.383)	(0.387)	(0.367)	(0.346)
mv1mv2mv3 × ridtr		0.117	0.105	-0.019	-0.076
		(0.179)	(0.182)	(0.212)	(0.212)
mv4 × vtavg		-0.372	-0.347	-0.438	-0.484*
		(0.234)	(0.251)	(0.270)	(0.276)
mv4 × retavg	0.076	0.037	0.054	-0.002	0.004
	(0.127)	(0.381)	(0.363)	(0.392)	(0.377)
mv4 × ritavg		0.337	0.325	0.475	0.499
		(0.356)	(0.377)	(0.417)	(0.419)
mv4 × vdtr	-0.126	0.145	0.016	-0.050	-0.123
	(0.190)	(0.274)	(0.276)	(0.250)	(0.239)
mv4 × redtr		-0.318	-0.227	-0.158	-0.014
		(0.386)	(0.393)	(0.375)	(0.351)
mv4 × ridtr		0.037	0.079	-0.080	-0.148
		(0.180)	(0.185)	(0.216)	(0.215)
mv1mv2mv3 × prec				0.003*	0.003*
				(0.002)	(0.002)
mv1mv2mv3 × prec × prec				-0.000*	-0.000*
				(0.000)	(0.000)
mv4 × prec				0.004**	0.004**
				(0.002)	(0.002)
mv4 × prec × prec				-0.000*	-0.000**
				(0.000)	(0.000)
Observations	1160	1160	1160	1160	1158
Adj R-square	0.298	0.297	0.322	0.328	0.368
Number of Farmers	180	180	180	180	180

Notes: (1) All regressions use the natural log of yield as the dependent variable. (2) *vtavg*, *retavg*, and *ritavg* respectively are the average of daily mean temperature in the vegetative, reproductive and ripening phase; *vdtr*, *redtr*, and *ridtr* respectively are the average of daily diurnal temperature ranges for the vegetative, reproductive and ripening phase. The variable *prec* is cumulative precipitation for the entire growing season. (3) Unit for *tavg* and *dtr* is °C. Unit for *prec* is mm.

Table S10: Marginal yield impacts from the separate regressions by varietal group

	TV		Early MV4s		MV4	
Method	Estimates	P-value	Estimates	P-value	Estimates	P-value
tmin(+1 °C)	-1.04	0.540	-0.31	0.000	-0.13	0.320
tmax(+1 °C)	0.42	0.786	0.03	0.667	0.09	0.339
prec(1 sd)	-0.52	0.208	-0.16	0.000	0.00	0.985
tmin+tmax(+1 °C warming scenario)	-0.62	0.791	-0.28	0.004	-0.05	0.577

Notes: The table displays estimated change in the natural log of rice yields caused by 1 °C increase in *tmin*, *tmax*, both *tmin* and *tmax* and 1 standard deviation of increase in *prec*, by running regressions for varietal groups separately. Columns 2 and 3 are the marginal effects and P-value for the TV subsample, respectively. Columns 4 and 5 are the marginal effects and P-value for the MV1-MV3 subsample, respectively. Columns 6 and 7 are the marginal effects and P-value for the MV4 subsample, respectively.

Table S11: Regression results from the separate regressions by varietal groups

	TV	MV1MV2MV3	MV4
vtmin	0.054	-0.239***	-0.323***
	(2.230)	(0.083)	(0.106)
retmin	-0.687	-0.108**	-0.013
	(1.994)	(0.052)	(0.113)
ritmin	-0.403	0.040	0.204***
	(1.470)	(0.065)	(0.074)
vtmax	0.160	0.061	0.114
	(1.030)	(0.037)	(0.074)
retmax	0.804	-0.084	-0.103
	(1.120)	(0.055)	(0.082)
ritmax	-0.547	0.053	0.075
	(0.669)	(0.043)	(0.068)
prec	-0.006	-0.001*	-0.000
	(0.008)	(0.000)	(0.001)
prec × prec	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Observations	99	765	298
Adj R-squared	-0.114	0.318	0.400
Number of Farmers	69	154	97

Notes: (1) All regressions use the natural log of yield as the dependent variable. As explanatory variables,we use linear terms for *tmin* and *tmax* for each growing phase, and linear and quadratic terms for *prec*. (2) The first column indicates the weather variables the marginal effects are based on. Note that *vtmin*,*retmin*,and *ritmin*, respectively, are the average of daily maximum temperature in the vegetative, reproductive and ripening phase; *vtmax*, *retmax*, and *ritmax*, respectively, are the average of daily maximum temperature in the vegetative, reproductive and ripening phase. Note that *prec* is cumulative precipitation for the entire growing season.(3) Column 2 is on the subsample for TV, column 3 is on the subsample for MV1-MV3 and column 4 is the results for the MV4 subsample. (4) Unit for *tmin* and *tmax* is °C. Unit for *prec* is mm.

Table S12: Regression results for the model specifications without interactions between the varietal grouping dummies and the weather variables

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
year	0.002	0.000	-0.141	-0.164
	(0.003)	(0.003)	(0.076)	(0.075)
mv1mv2mv3	0.326***	0.273**	0.365***	0.318**
	(0.106)	(0.107)	(0.126)	(0.130)
mv4	0.350***	0.312**	0.438***	0.410***
	(0.123)	(0.122)	(0.137)	(0.139)
vtmin6	-0.234***	-0.205***	26.151**	30.305***
	(0.084)	(0.072)	(10.213)	(9.490)
retmin6	-0.104***	-0.092**	-8.862	-7.174
	(0.038)	(0.035)	(6.470)	(6.665)
ritmin6	0.106**	0.118***	-2.476	-5.869
	(0.052)	(0.045)	(6.751)	(7.039)
vtmax6	0.082***	0.097***	-7.372	-7.437
	(0.026)	(0.025)	(4.977)	(4.746)
retmax6	-0.072	-0.093	-18.034**	-21.485***
	(0.055)	(0.061)	(7.154)	(7.399)
ritmax6	0.067*	0.076**	5.356	6.685
	(0.034)	(0.037)	(4.197)	(4.096)
prec	-0.001**	-0.001**	-0.003	-0.042
	(0.000)	(0.000)	(0.048)	(0.048)
prec × prec	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
year × vtmin6			-0.013**	-0.015***
			(0.005)	(0.005)
year × retmin6			0.004	0.004
			(0.003)	(0.003)
year × ritmin6			0.001	0.003
			(0.003)	(0.004)
year × vtmax6			0.004	0.004
			(0.002)	(0.002)
year × retmax6			0.009**	0.011***
			(0.004)	(0.004)
year × ritmax6			-0.003	-0.003
			(0.002)	(0.002)
year × prec			0.000	0.000
			(0.000)	(0.000)
year × prec × prec			0.000	-0.000
			(0.000)	(0.000)
Constant	7.680	9.724	295.249*	339.590**
	(5.721)	(5.971)	(153.017)	(150.750)
Observations	1160	1158	1160	1158
Adj R-squared	0.325	0.361	0.344	0.386
Number of Farmers	180	180	180	180
Other Factors Included	N	Y	N	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is the natural log of rice yield. The independent variables of Model 1 include the maximum and minimum temperature for each growing phase, growing season cumulative precipitation, linear time trend and varietal grouping dummies. Model 2 includes the independent variables of Model 1 and the economic variables described by Table 1. Model 3 includes the interactions between time trend and weather variables in addition to the variables of Model 1. Model 4 includes the independent variables of Model 3 and the economic variables described by Table 1.

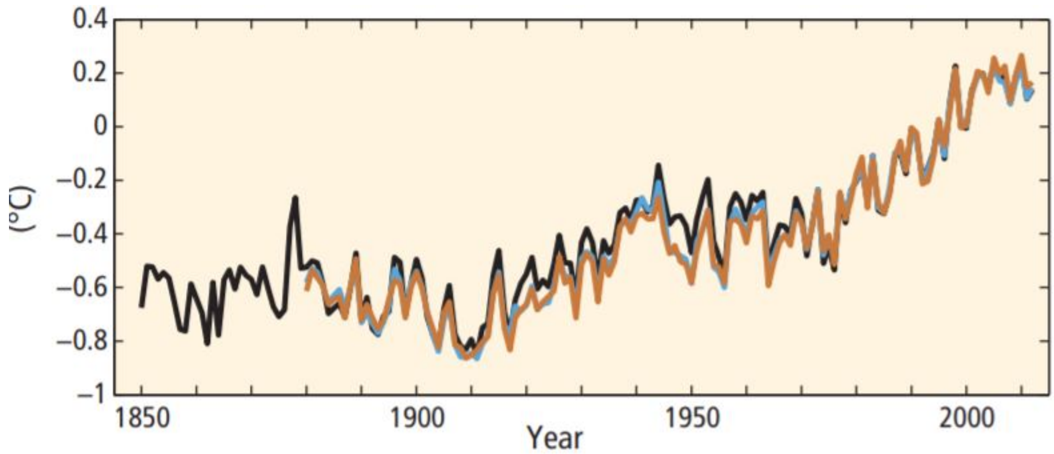
Table S13: Regression results for the model specifications with both varietal group interactions with weather and time trend interactions with weather.(Table 1)

	(1) Model 1	(2) Model 2
year	-0.125	-0.155*
	(0.096)	(0.087)
vtmin6	53.928***	56.905***
	(16.338)	(15.240)
retmin6	-10.189	-7.496
	(10.611)	(11.733)
ritmin6	-12.299	-16.639
	(10.852)	(10.666)
vtmax6	-7.213	-7.543
	(7.343)	(7.843)
retmax6	-38.120***	-40.274***
	(11.102)	(12.393)
ritmax6	14.928**	14.951**
	(7.354)	(7.280)
prec	-0.031	-0.050
	(0.071)	(0.075)
prec × prec	-0.000	-0.000
	(0.000)	(0.000)
year × vtmin6	-0.027***	-0.029***
	(0.008)	(0.008)
year × retmin6	0.005	0.004
	(0.005)	(0.006)
year × ritmin6	0.006	0.008
	(0.005)	(0.005)
year × vtmax6	0.004	0.004
	(0.004)	(0.004)
year × retmax6	0.019***	0.020***
	(0.006)	(0.006)
year × ritmax6	-0.008**	-0.008**
	(0.004)	(0.004)
year × prec	0.000	0.000
	(0.000)	(0.000)
year × prec × prec	0.000	0.000
	(0.000)	(0.000)
Observations	1160	1158
Adj R-squared	0.357	0.397
Number of Farmers	180	180
Other Factors Included	N	Y

Table S14: Regression results for the model specifications with both varietal group interactions with weather and time trend interactions with weather.(Table 2)

	(1) lnyield	(2) lnyield
mv1mv2mv3 × vtmin6	0.516	0.574
	(0.390)	(0.432)
mv1mv2mv3 × retmin6	0.108	-0.033
	(0.378)	(0.376)
mv1mv2mv3 × ritmin6	0.033	0.091
	(0.310)	(0.306)
mv1mv2mv3 × vtmax6	-0.161	-0.231
	(0.164)	(0.172)
mv1mv2mv3 × retmax6	-0.596**	-0.484*
	(0.259)	(0.276)
mv1mv2mv3 × ritmax6	0.163	0.150
	(0.168)	(0.163)
mv4 × vtmin6	0.951*	1.021**
	(0.481)	(0.513)
mv4 × retmin6	0.014	-0.116
	(0.423)	(0.425)
mv4 × ritmin6	-0.127	-0.096
	(0.345)	(0.330)
mv4 × vtmax6	-0.194	-0.262
	(0.189)	(0.201)
mv4 × retmax6	-0.838***	-0.732**
	(0.318)	(0.335)
mv4 × ritmax6	0.314	0.285
	(0.208)	(0.205)
mv1mv2mv3 × prec	0.002	0.002
	(0.003)	(0.003)
mv1mv2mv3 × prec × prec	-0.000	-0.000
	(0.000)	(0.000)
mv4 × prec	0.002	0.002
	(0.003)	(0.003)
mv4 × prec × prec	-0.000	-0.000
	(0.000)	(0.000)
Observations	1160	1158
Adj R-squared	0.357	0.397
Number of Farmers	180	180
Other Factors Included	N	Y

Notes: Dependent variable is the natural log of rice yield. Independent variables include both varietal group interactions with weather and time trend interactions with weather. Model 2 includes the independent variables of Model 1 and the economic variables described by Table 1.



Source: *IPCC AR5*

Figure S1: Annually and globally averaged combined land and ocean surface temperature anomalies relative to the average over the period 1986 to 2005. Colours indicate different data sets.

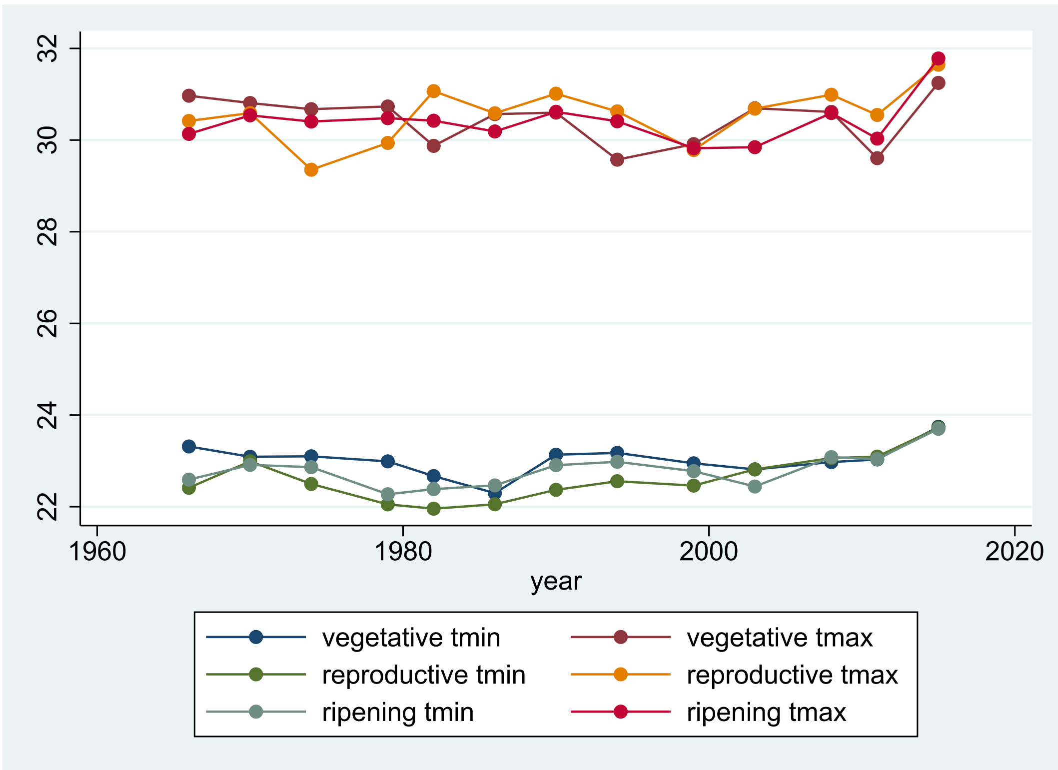


Figure S2: Average minimum temperature and maximum temperature trends across survey years for the study area.

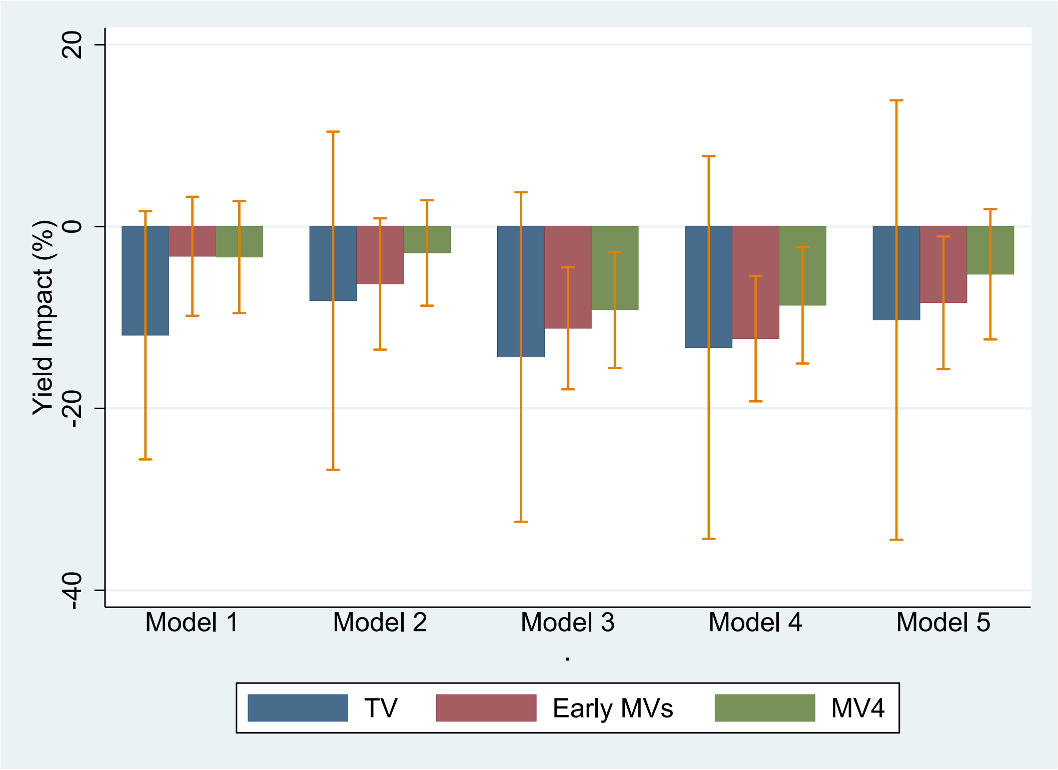


Figure S3: The 1 standard deviation warming impact on three rice varietal groups estimated by the 5 models based on Equation 1 and Equation 2. Impacts are reported as the percentage change in yield.

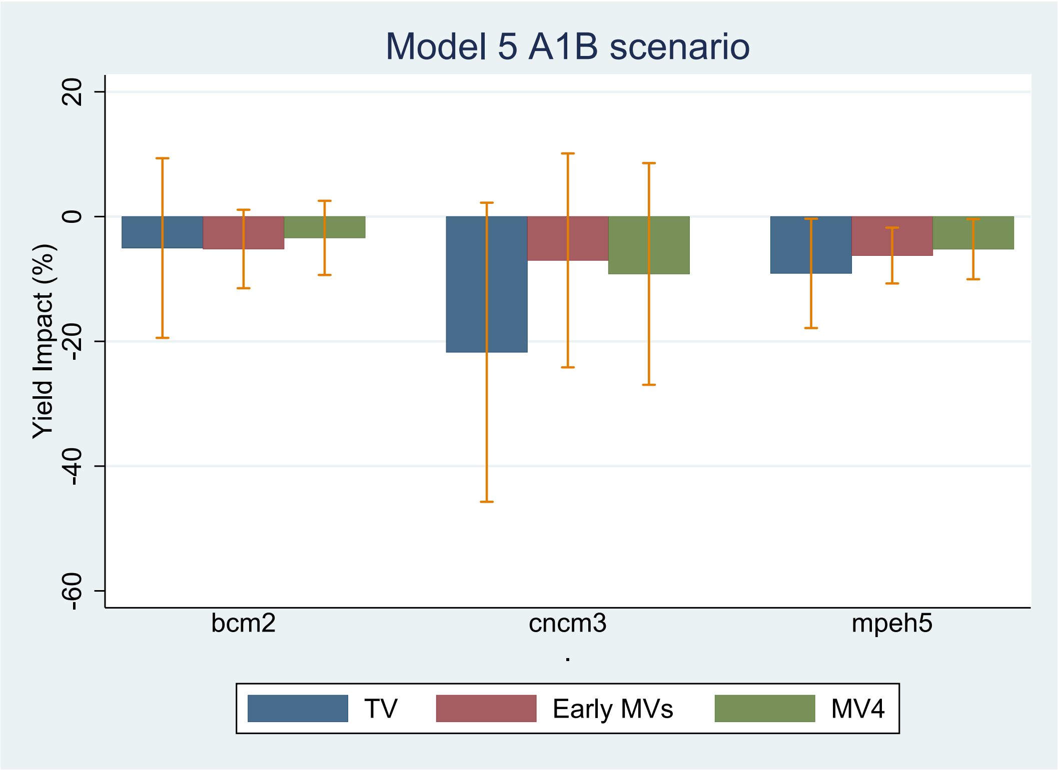


Figure S4: Predicted warming impacts under the A1B scenario and Model 5. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

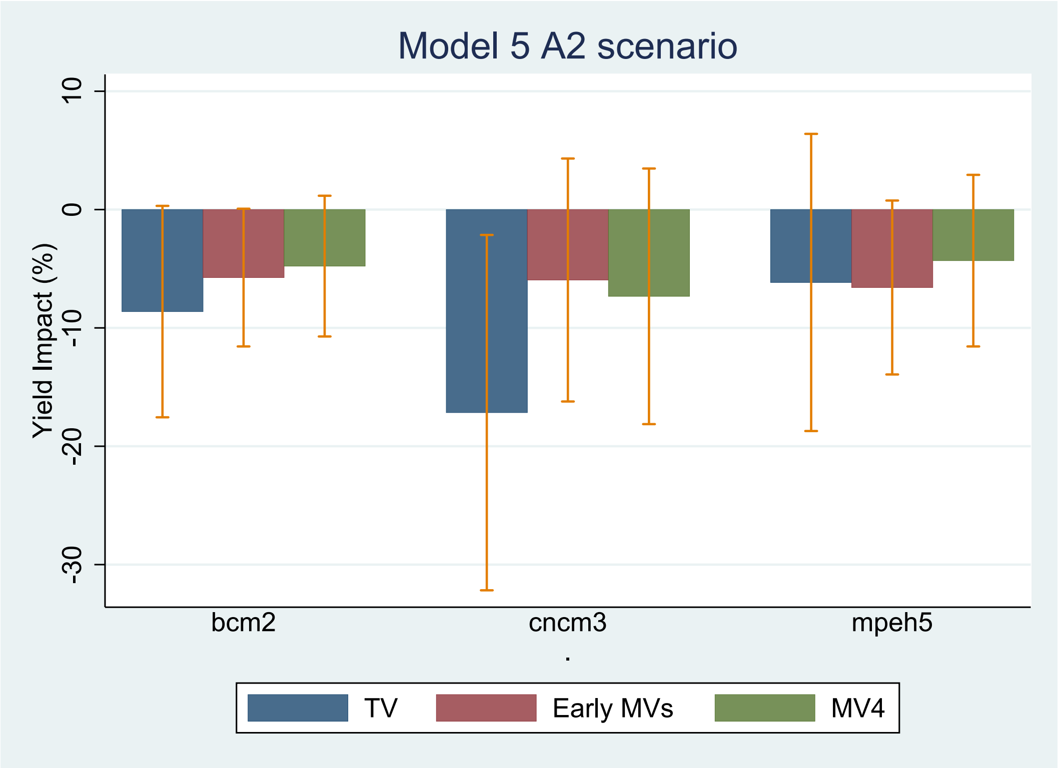


Figure S5: Predicted warming impacts under the Scenario A2 and Model 5. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

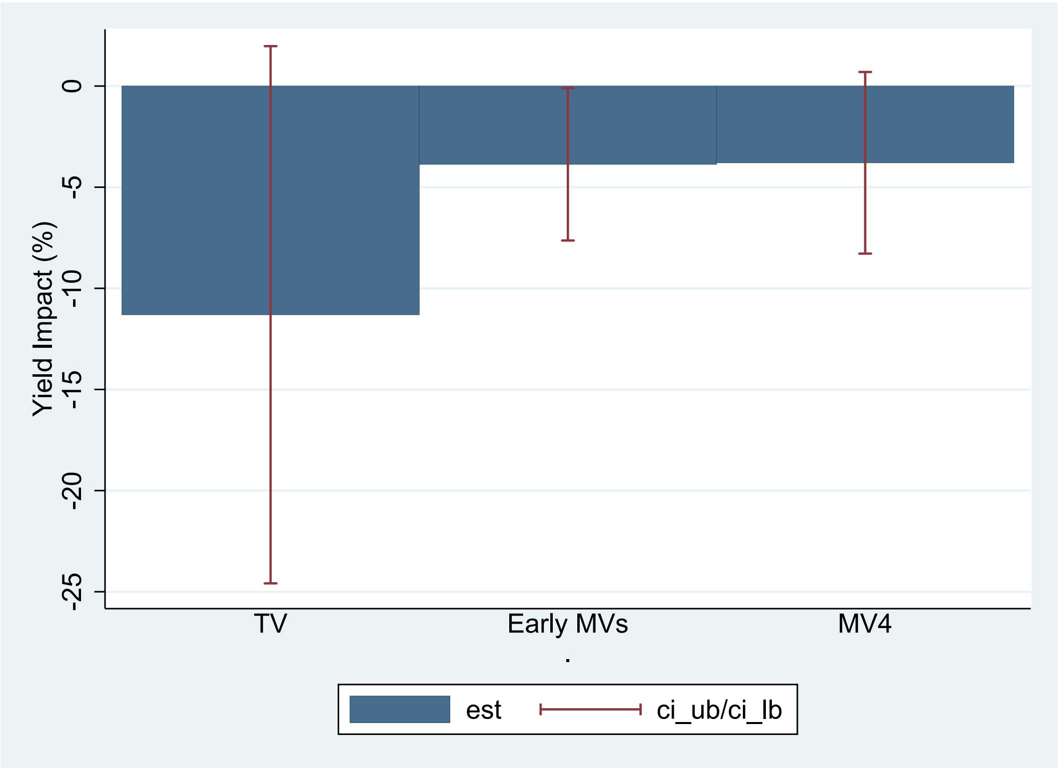


Figure S6: Predicted changes in yields of three varietal groups at the average predicted temperature changes of the six GCM-emission-scenarios. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

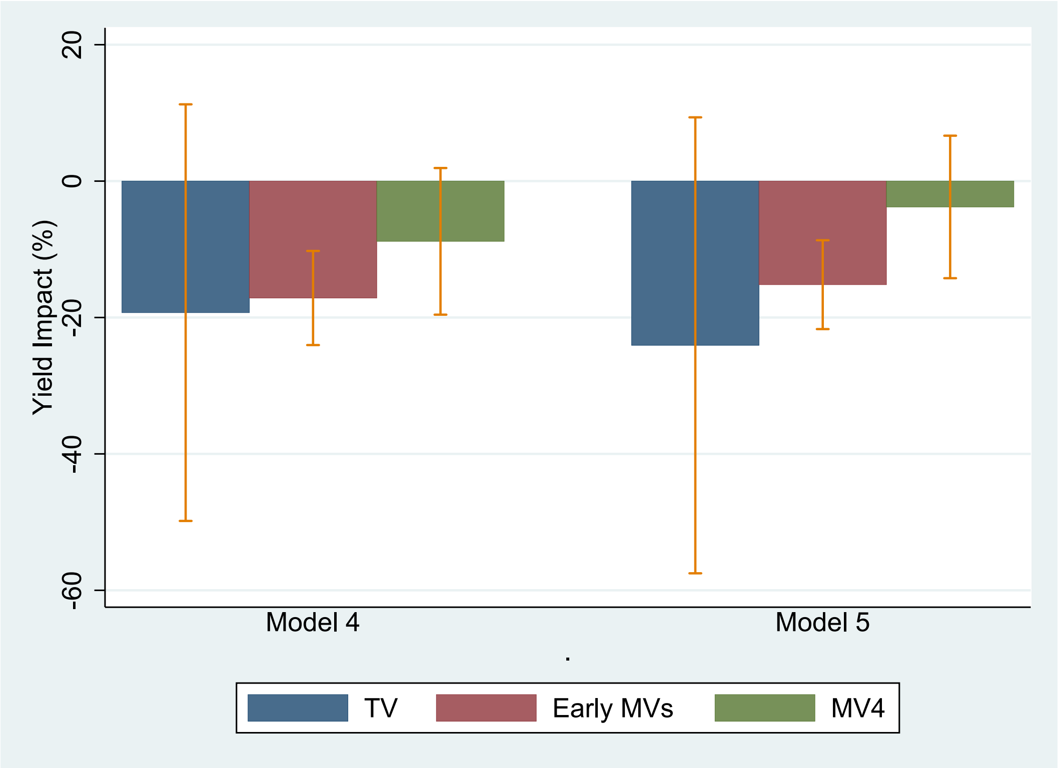


Figure S7: Marginal effects of a 1 standard deviation increase in *prec* for Model 4 and Model 5. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

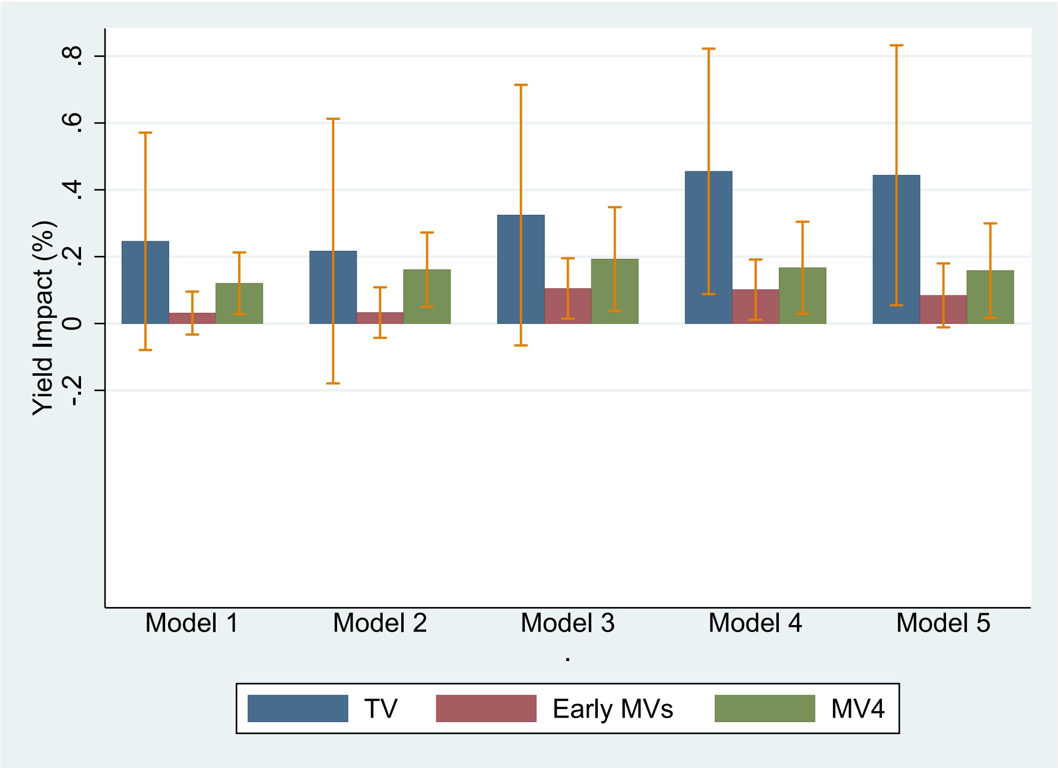


Figure S8: Predicted impacts of +1°C increase in *dtr* on three rice varietal groups for 2 model specifications. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

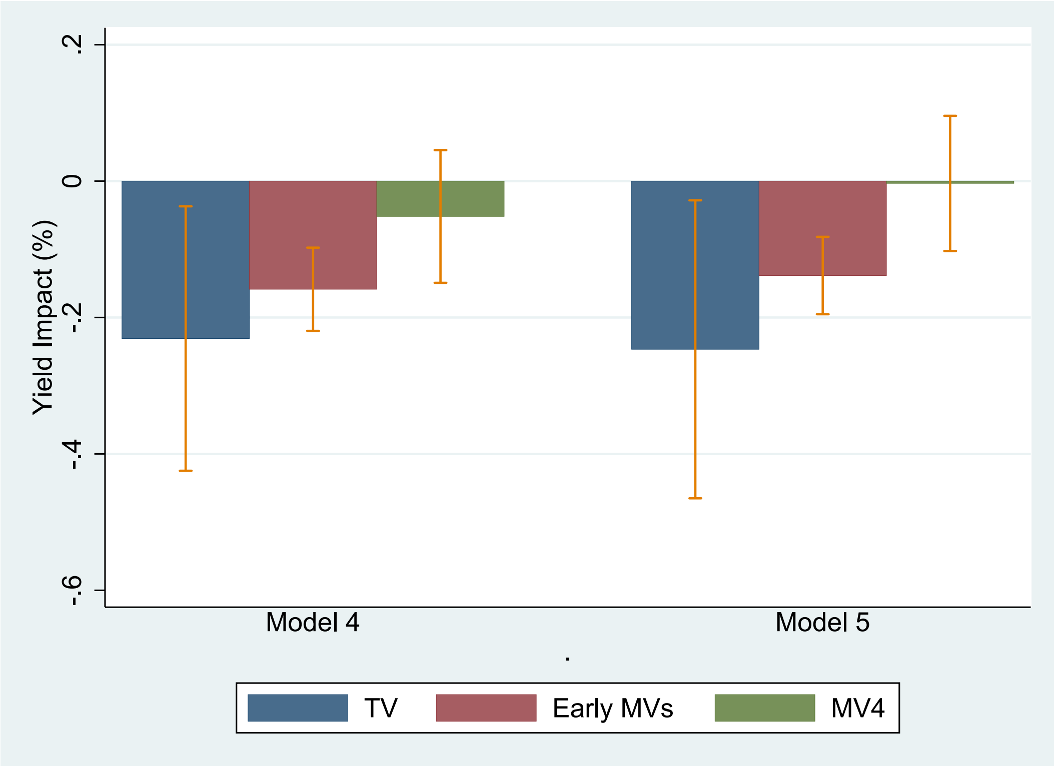


Figure S9: Marginal effects of a 1 standard deviation increase in *prec* for Model 4 and Model 5 which use *tavg* and *dtr* in the specification. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

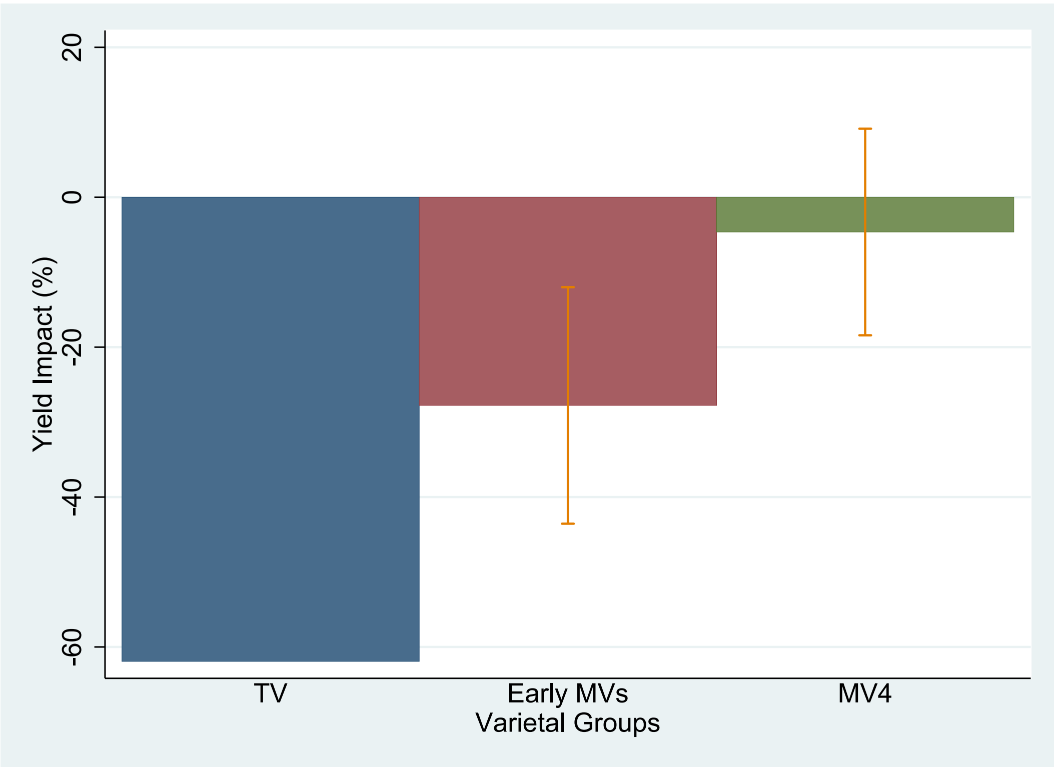


Figure S10: The +1°C warming impacts on three rice varietal groups estimated by running separate regressions by varietal groups. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

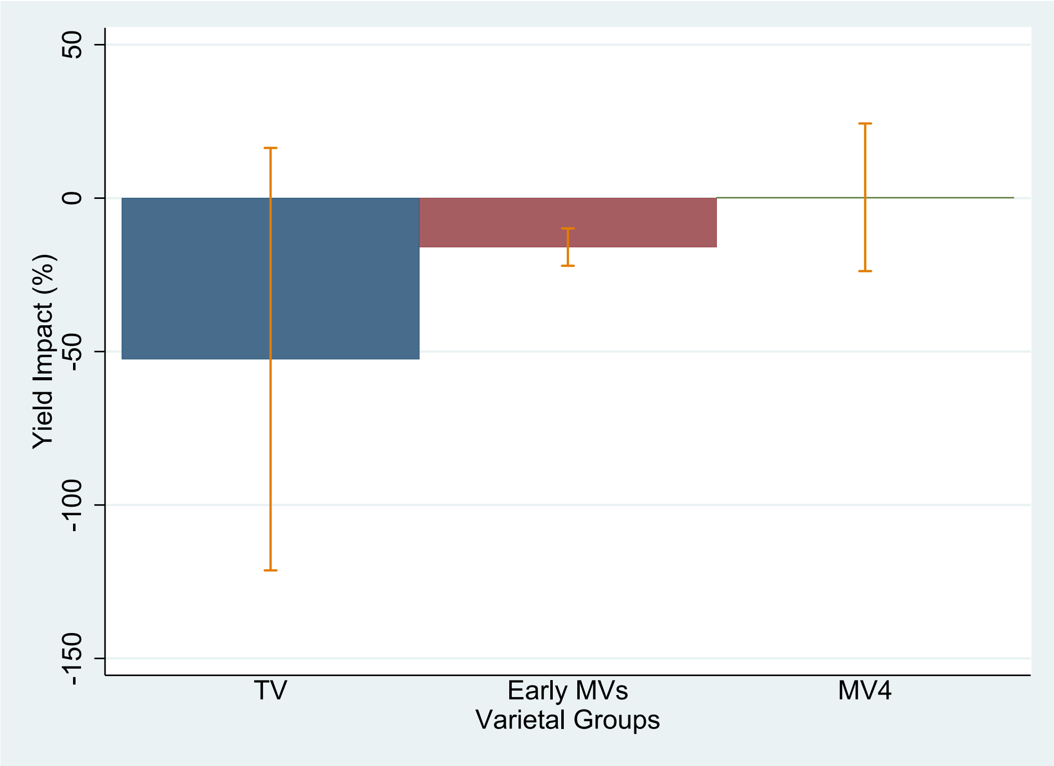


Figure S11: The marginal impact of a 1 standard deviation increase in *prec* on three rice varietal groups estimated by running separate regressions by varietal groups . Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

Figure S12: The marginal impact of +1°C warming scenario across years estimated from Model 3 and Model 4 described by Table S12. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.

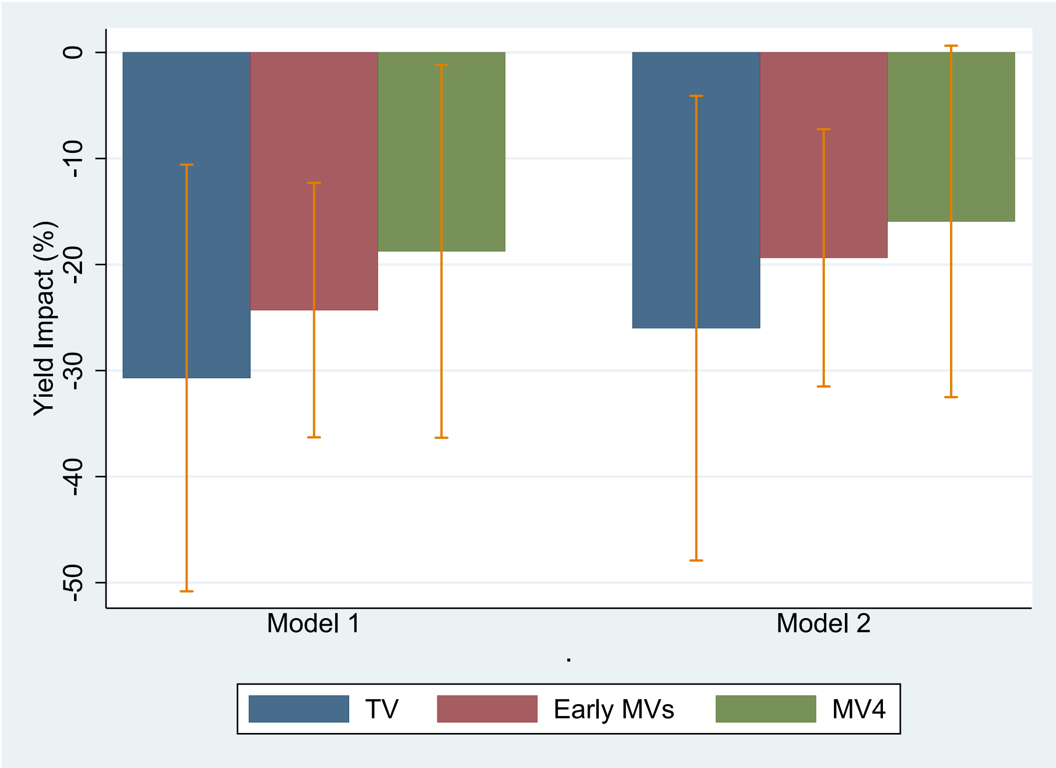


Figure S13: The average marginal impact of +1°C warming scenario across years estimated from the models with varietal group interactions with weather, and time trend interactions with weather. Impacts are reported as the percentage change in yield. Bars show 90% confidence interval.