Weather Sensitivity of Rice Yield: Evidence from India

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Abstract

This study estimates the weather sensitivity of rice yield in India, using disaggregated (district) level information on rice and high resolution daily weather data over the period 1969-2007. Compared to existing India specific studies on rice which consider only the effects of nighttime (minimum) temperature, the present study takes into account the effects of both nighttime and daytime (maximum) temperatures along with other weather variables on rice yield. The results suggest that both nighttime and daytime temperatures adversely affect rice during different growth phases. The effect of higher nighttime temperature on rice yield was much lower than those estimated by previous studies. Further, the negative impact of higher daytime temperature on rice yield was much larger than the impact due to higher nighttime temperature. The study further estimates that average rice yield would have been 8.4 percent higher had the pre-1960 climatic conditions prevailed during the period of study. This translates into an annual average loss of 4.4 million tons/yr or a cumulative loss of 172 million tons over the 39 year period for India. The paper argues that such significant loss in rice production under climate change conditions in future will have strong implications for the region's food-security and poverty, given that a large number of producers and consumers depend on rice for their livelihood and sustenance.

ACKNOWLEDGMENT

INTRODUCTION

Assessing the influence of historical weather on rice productivity is important in view of the large percentage of current global population depending on the crop for their livelihood and sustenance. About 90 percent of the rice production takes place in the tropical/sub-tropical Asia where more than 60 percent of the world population lives. It is the major staple for more than half of the world's population (FAO, 2013), accounting for approximately 30 percent of the total dietary intake, globally and in South Asia (Lobell et al., 2008). Rice bears high significance for the world's poor population, majority (67 percent) of them living in Asia, in particular South Asia (43 percent) (World Bank, 2013). It accounts for substantial portions in their caloric intake, total food consumption expenditures (> 50 percent), and total household expenditures (> 20 percent). Moreover, a high fraction ($\approx$ 38 percent) of the poor people in South Asia live in areas where rice is a dominant crop (Asia Society and IRRI, 2010).

India being a major rice consumer and producer in South Asia, continues to grapple with stark issues of hunger, malnutrion, poverty and food insecurity, despite the success of green revolution resulting in significant improvements in the productivity of food crops, including rice (Kumar et al., 2013). It accounts for nearly 67 percent of the total rice production of South Asia (FAO, 2013) and 75 percent of the region's poor (World Bank, 2013). Thus, any exogenous or endogenous shock to the rice production system in the Indian sub-continent has significant consequences for the incidence of hunger, malnutrition and food insecurity among the poor living in this region. In sum, the importance of rice in determining global and regional food insecurity and poverty cannot be undermined.

Rice production in the tropics is sensitive to climatic factors (temperature, rainfall, and solar radiation) which affect the crop in

various ways during different stages of its growth (Yoshida, 1978). Further, some stages are more sensitive to climatic factors than others (Wassmann et al., 2009a). Rice, alike other crops, also exhibits non-linear relationships with various weather parameters, particularly temperature (Yoshida, 1981). Existing studies confirm that significant changes have occurred in the climate of this region during the 20th Century (Ramanathan et al., 2001; Ramanathan et al., 2005; Padma Kumari et al., 2007) and that in some regions in the tropics, weather is already approaching critical levels during the susceptible stages of rice growth (Wassmann et al., 2009b). Thus, the observed climatic changes (and attributed weather fluctuations) in the past may have had significant influences on rice productivity in the region.

Assessing the historical weather sensitivity of rice in this region in the context of various non-climatic stresses (e.g., hunger, poverty, malnutrition, etc.) is therefore important (Wassmann and Dobermann, 2007). Such assessment would enable to not only understand the extent of changes in rice production which could be already occurring due to changes in historical climate, but also to identify the rice producing regions vulnerable to weather shocks.

Significant research to assess the weather sensitivity of rice in the tropical/subtropical regions of Asia has been conducted using both process-based experimental crop-simulation models and the statistical models, at different levels of disaggregation. The research focus has been primarily to identify the important climatic factors which affect rice growth and yield, their relative influence during various rice growth stages including the most important stages of growth, and the critical thresholds of these climatic factors during the most susceptible phases. The present study contributes to this rich body of literature by re-examining the weather-rice yield relationship using detailed disaggregated (district-level) data over a long period of time (1969-2007). The study highlights the significant adverse role played by the

increase in maximum temperature on rice yield. The study further argues that the rice production would have been significantly higher in India had the pre-1960s climatic conditions were to prevail during the period 1969-2007.

BACKGROUND

Broadly two approaches are employed in the literature to explore the crop-weather relationship, *viz.*, the agronomic models and the statistical models. Use of statistical models to estimate the functional relationship between climate (weather) and crop yield has gained significant attention in the recent climate change impact assessment literature. The statistical models have come to exist as an alternative approach to the experimental crop-simulation (agronomic) models. The agronomic models are best known for their ability to explore complex crop-environment functional relationship at various crop growth phases under experimental settings. However, these models lack the flexibility to easily adapt to new circumstances, face the challenge of aggregation over broader regions (Baron et al., 2005), and fail to account for farm adaptation possibilities (Mendelsohn, Nordhaus, and Shaw, 1994). On the other hand, using information available at various levels of disaggregation, the statistical models can be readily and flexibly applied at different scales – sub-national, national, and global. As compared to the process-based models, these models perform better when applied at broader than farm-level scales (Lobell and Burke, 2010). Moreover, the cross-sectional models also account for the full range of farm adaptation possibilities owing to changes in the climate (Mendelsoh, Nordhaus, and Shaw, 1996). However, among several limitations associated with these models, omitted variables bias is one. In other words, the accuracy and precision of statistical models depends primarily on their ability to control for unobserved (omitted) factors confounding the true crop-weather relationship due to possible correlations with the weather variables identified in the model (Deschenes and Greenstone, 2007). Nevertheless,

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statistical models associating historical yields with observed weather have become a common approach to explore crop-weather relationships and their potential implications to estimate climate change impact.

Statistical studies on various crop-weather relationship have been conducted at global, regional, national, and sub-national scales (see for example, Lobell and Field, 2007; Lobell, 2007; Lobell et al., 2008; Auffhammer et al., 2006; Barnwal and Kotani, 2013). These models have also evolved over time, differing not only in region, scale, and time-period of their application, but also in the various modeling approaches employed, including the treatment of weather variables in these models (Lobell and Burke, 2010), and in their ability to produce more precise estimates by following the crop science closely (Roberts et al., 2013). For example, earlier statistical studies for various crops were based on simple measures of annual average weather and crop yield relationships (Nicholls, 1997). However, later applications of these models have considered 'growing season' specific direct (Lobell and Asner, 2003; Auffhammer et al., 2006; Lobell, 2007) and derived (transformed) weather measures (Schlenker and Roberts, 2006; Deschenes and Greenstone, 2007) in line with the agronomic literature. Additional weather measures (e.g., T_{min} and T_{max}) instead of T_{avg} considered in the agronomic studies have also been adopted by the statistical studies (Auffhammer et al., 2006; Lobell, 2007; Lobell and Field, 2007; Welch et al., 2010). Further, use of fine-scale spatial and temporal resolution weather information to explore the non-linear crop-weather relation at more disaggregated levels has been a significant advancement in the application of statistical models (Schlenker and Roberts, 2009). Statistical studies have also been applied at the farm level to study crop-weather relationship (Welch et al., 2010). More recent developments in this strand of literature has been to study the effects of climate (weather) at different yield quantiles rather than just on mean yield (see Krishnamurthy, 2012; Barnwal and Kotani, 2013).

Previous studies exploring weather-rice yield relationship for India have shown a decline in historical yield owing to observed changes in the climatic conditions, including the effects of lower rainfall, increasing nighttime temperature, lower radiation and increased weather extremes (see for example Selvaraju, 2003; Krishna Kumar, 2004; Lal et al., 1998; Nagarajan et al., 2010; Yoshida and Parao, 1976; Praba et al., 2004; Krishnamurthy et al., 2009). Emphasis has been laid on the effects of higher nighttime temperature (T_{min}), in view of the increasing trends observed across the globe (Easterling et al., 1997) and for India (Padma Kumari et al., 2007; NATCOM, 2010). However, existing research does not provide sufficient insights into the effects of high nighttime temperature on rice (Wassmann et al., 2009a). On the other hand, the agronomic literature strongly points towards the detrimental effects of high (daytime) temperature and related heat stress on rice yield, with high temperature adversely affecting rice nearly at all stages of development (Wassmann et al., 2009a). Although worldwide and regionally, maximum temperature has not increased as fast as the minimum temperature (Vose et al., 2004), increasing maximum temperature could still have significant and large negative impact on rice yield. This is especially true for regions, including India, where maximum temperature is already approaching critical thresholds for rice development (Wassmann et al., 2009b) and exhibiting greater risks of yield damage due to heat stress (Teixeira et al., 2013). Moreover, since most of the rice cultivation takes place in the rainfed tropics, with tropical climate favouring rice growth (Yoshida, 1978), it is necessary to assess the relative influence of weather (specifically, daytime and nighttime temperature) on rice yield in a tropical climate.

Previous studies exploring weather-rice yield relationship in India have suggested that rice yield has declined due to changes in historical weather characteristics. Using data on rice harvest for 9 Indian states covering large rice growing regions, Auffhammer et al. (2006) found rice harvest to have declined over the period 1972-1998 with changes in

historical climate characteristics attributable to the combined influence of atmospheric brown clouds and greenhouse gas emissions. Controlling for the influence of rainfall, solar radiation and other economic variables, the authors also found higher nighttime temperature during the ripening growth phase of rice had adverse effects on harvest. Using similar state level rice yield data during 1966-2002, Auffhammer et al. (2012) found that warmer nights during the ripening phase and changes in monsoon characteristics (especially weather extremes such as drought) had significant negative effects on rice yield. They conclude that increases in rice yield owing to improvements in farming technology have been partially offset by the observed changes in weather over the period 1966-2002.

The present study employs the statistical modelling approach to empirically estimate the historical weather-rice yield relationship using disaggregated (district) level of information for India during 1969-2007. In particular, the relative sensitivity of rice yield to specific weather measures (minimum and maximum temperatures, rainfall and solar radiation) corresponding to various rice growth phases has been assessed.

METHODOLOGY AND DATA

A common approach to assess the influence of weather on rice yield is the use of multivariate fixed effects panel data regression models. This technique has long been recognized as an important remedy for the omitted variables bias problem from which the cross-sectional statistical models suffer (see Mundlak, 1961). The fixed effects estimators in panel data models rely on variations in weather across time within a spatial unit (e.g., states, districts, counties, etc.) to identify the influence of weather parameters on the outcome of interest (i.e., yield). This technique removes the time-invariant unobserved factors specific to the spatial unit which may confound the true crop-weather relationship and overcomes

the omitted variables bias problem. Past statistical studies assessing the influence of weather on rice yield for US (see Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009) and for India (Guiteras, 2009; Auffhammer et al., 2012; Krishnamurthy, 2012) have primarily relied on this approach. Another approach is the use of first difference estimators usually employed in case of time-series statistical models. Some of the past studies assessing the influence of climate trends on yield of various crops are also based on this approach (see Nicholls, 1997; Lobell and Asner, 2003). However, under certain statistical properties, the fixed effects estimator is more efficient than the first difference estimator (Wooldridge, 2010).

Regression Estimation
The fixed effects model can be specified as per equation (1) below:

$$\ln(y_{it}) = X_{it}\boldsymbol{\beta} + W_{it}\boldsymbol{\gamma} + \alpha_i + \delta_t + \lambda_i t + \varepsilon_{it} \qquad (1)$$

where the dependent variable y_{it} is rice yield in district i and in year t; X_{it} is a vector of (non-weather) farm inputs which includes labour, fertilizer, irrigation and area under High Yield Variety (HYV) rice; W_{it} is the vector of weather variables including temperature, rainfall, and solar radiation. All non-weather farm inputs and weather variables in the X_{it} and W_{it} vectors are expressed in their natural logarithms; α_i are the district fixed effects accounting for the time-invariant district specific unobserved factors; δ_t and $\lambda_i t$ are the time (year) fixed effects and the district specific annual (linear) time trend respectively; ε_{it} are the idiosyncratic error terms. The log-linear model specification implies that the parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ corresponding to the non-weather and weather variables in the model should be interpreted as elasticities of rice yield with the respective variables. The model specification avoids the problem of endogeneity which occurs when rice harvest rather than yield

is modeled as the dependent variable, taking area of rice as an additional regressor (Auffhammer et al., 2012; Mundlak, 2001). Moreover, since yield follows a log-normal distribution, its natural logarithm, following a normal distribution, satisfies important statistical properties necessary for regression estimation.

The vector W_{it} included broadly four weather measures, viz., average maximum temperature (T_{max}) and average minimum temperature (T_{min}), average surface radiation, and total rainfall. Further, each weather measure were defined corresponding to the growing season months of June through September and October through November, which resulted in a total of eight weather variables that were included in the model. The June-September period roughly covered the vegetative and reproductive growth phases, whereas the October-November period represented the ripening phase. The correspondence between growing season months and various rice growth phases are approximate in view of large variations of rice sowing and harvesting dates across states (and possibly districts) as evident from the state-level crop-calendars (ICAR, 2008). Similar approach has been followed in previous studies on rice (see Auffhammer et al., 2012; 2006). Effects of these weather variables corresponding to various rice growth phase on rice yield were estimated after controlling for the farm level inputs such as labour, fertilizer, irrigation and HYV area included in X_{it}. However, with changing weather patterns and resulting shifts in the distribution of weather shocks, the equilibrium response of these farm inputs may also get adjusted over time (see Kelly, Kolstad, and Mitchell, 2005), which could affect the estimated model parameters. Thus, a model specification which muted the influence of the economic (non-weather) variables was estimated. A comparison of the original model with economic variables and the one without economic variables would inform the nature and extent of influence of the non-weather variables on the weather-yield relationship.

District specific unobserved characteristics, which do not change over time, and are correlated with the weather variables (e.g., soil quality) may confound the true effects of weather on rice yield. These unobserved factors were removed by including the district-fixed effects (α_i). Time demeaned and detrended weather and non-weather variables were obtained by using the year fixed effects (δ_t) and annual time trend and $(\lambda_i t)$ to control for additional time-varying sources of variation affecting rice yield. The influence of factors which can vary over state and year (or region and year) as suggested by Deschenes and Greenstone (2007) was not considered under the given model specification.

Recent literature has raised significant concern over the changes in the distributional characteristics (mean, variances, and covariance) of the weather variables over time due to climate change (Mc Carl et al., 2008). Since the study deals with time series data at the district level, it was necessary to test for the stationarity of each of the regressors in X_{it} and W_{it}. The stationarity tests were performed using Im-Pesaran-Shin (2003) panel unit root test. The Im-Pesaran-Shin (2003) unit root test has the advantage of not imposing a common autoregressive parameter restriction on the panels (districts) and is based on a set of Augmented Dickey-Fuller Regressions to estimate the t-statistic first before averaging it across panels. The unit-root tests were carried out under various assumptions on the structure of the panel: (a) fixed N and T; (b) fixed T, but $N \rightarrow \infty$ and (c) both N and T asymptotically sequentially approaching infinity. In view of the significant trends observed for most variables in the model, separate tests were performed with and without time trend taken into account.

Both the Wald statistic (see p. 598; Greene, 2000) and the F-statistic (based on first differenced error) (see p. 319, Wooldridge, 2010) respectively rejected (at $P < 0.01$) the null-hypotheses of residuals (ε_{it})

being homoskedastic and first order serially uncorrelated. For valid inference and hypotheses testing of the estimated model parameters the covariance matrix, thus, standard errors (SEs) must be robust to non-constant error variance across districts, non-zero covariances between districts and within district error correlation over time. The heteroskedasticity and autocorrelation consistent (HAC) robust covariance matrix and SEs were estimated by clustering the residuals at district level (see p. 197, Wooldridge, 2010; p. 1818, Deaton, 1995).

To assess sensitivity of *kharif* rice yield to the relative influence of various weather measures, especially daytime (maximum) temperature and nighttime (minimum) temperature, during key development phases of the crop, two separate models (as specified in equation (1)) were estimated. The first model estimated the relationship between rice yield and minimum temperature (T_{min}) controlling for rainfall and non-weather variables and removing other unobserved factors. The second model included maximum temperature (T_{max}) variable along with T_{min}, and the same set of control variables as the first model. A comparison of both model coefficients and their simulated impacts (discussed below) would determine the relative effects of the two temperature measures – T_{max} and T_{min} – on rice yield.

Simulation of Impact

The estimated coefficients vector for the weather variables ($\widehat{\gamma}$) obtained from equation (1) measures the sensitivity of rice yield to the weather conditions which prevailed during 1969-2007 in India. Existing literature has suggested that significant changes have occurred in the pre-1960 climatic conditions. As mentioned earlier, these changes consists of reductions in monsoonal rainfall and surface radiation (Ramanathan et al., 2005; Padma Kumari et al., 2007), increasing daytime and nighttime temperatures (Padma Kumari et al., 2007; Kothawale et al., 2005) and weather extremes (especially, drought and rainfall extremes) (Dash et al., 2009; Krishnamurthy et al., 2009). In other words, the average

weather conditions in India have 'worsened' in the post-1960 period as compared to the pre-1960 average weather. With climatic factors having significant influence on the growth and yield of rice (Yoshida, 1978) the worsened average weather (climatic) conditions could have had adverse effects on all-India average rice yield during 1969-2007. In order to validate this argument, a statistical simulation exercise was carried out on lines similar to that adopted by Auffhammer et al. (2012). The simulation enabled to understand the extent to which all-India average rice yield would have differed (from the observed yield), if the pre-1960 (1930-60) climate had continued to prevail during 1969-2007, *i.e.*, had changes in the pre-1960 climate not occurred. The impact simulation exercise (with j weather variables) hinges on the following equation:[1]

$$\frac{\tilde{y}_t}{\hat{y}_t} = \left[\prod_j \left(\frac{\tilde{w}_{jt}}{w_{jt}} \right)^{\hat{\gamma}_j} - 1 \right] \times 100 \tag{2}$$

which essentially suggests the comparison of all-India (expected) rice yield across all years during 1969-2007 under two climate scenarios: without climate change and with climate change. Expected yield for a given year (t) during 1969-2007 under the with climate change scenario is simply the predicted yield ($\hat{y}_t$) based on actual weather (w_{jt}) for that year and the estimated parameters ($\hat{\gamma}_j$) from equation (1). However, during 1969-2007 *without climate change scenario* weather ($\tilde{w}_{jt}$) are not observable. As a consequence, the corresponding yield ($\tilde{y}_t$) based on $\tilde{w}_{jt}$ are also not observable. Therefore, statistical simulation exercise was employed to construct counterfactual ('expected') weather, which would have prevailed during 1969-2007, had the climate not changed. The

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[1] A Cobb-Douglas functional form, which is a standard functional specification in the empirical production function estimation literature was considered for the simulation analysis (see Mundlak, 2001; Deaton, 1995).

counterfactual weather $(\widetilde{w}_{jt})$ was assumed to follow a multivariate normal distribution. Under this assumption, Monte Carlo simulations were performed to obtain ten thousand draws for the $\widetilde{w}_{jt}$ for 1969-2007 using the first and second order moments obtained from the pre-1960 (1930-1960) climate. For each year, the simulated weather variables were then averaged across draws to obtain the 'expected' weather which would have prevailed during 1969-2007 had the climate remained the same as before 1960. Using these 'expected' weather values and the estimated parameters $(\hat{\gamma}_j)$ the counterfactual expected yield $(\widetilde{y}_t)$ for each year t during 1969-2007 under the without climate change scenario were obtained.

To calculate the impact due to changes in average weather (climate), first the ratio of the simulated yield $(\widetilde{y}_t)$ to predicted yield $(\hat{y}_t)$ for each year as per equation (2) was calculated. Average of these ratios over the 39 year period during 1969-2007 (say, μ) would suggest the loss/gain in all-India average yield, had the pre-1960 climate continued to prevail during 1969-2007. More specifically, depending on whether $\mu > 1$ or $\mu < 1$ rice yield would have been $(\mu - 1) \times 100$ percent higher/lower due to changes in climate.

Data
Data for regression estimation
Both non-weather and weather data at the Indian district level for 1969-2007 were necessary for the regression analysis of the present study. Details of these variables are reported in Table 1 below.

Table 1: Description of Variables with Source

Variables	Unit	Frequency	Resolution / level of disaggregation	Source
Variables for Regression Estimation				
Yield	Tons/ha	Annual	District	India Agriculture and Climate Dataset (World Bank); ICRISAT.
Irrigated Area	'000 Hectares	Annual	District	-do-
Fertilizer	'000 Tons	Annual	District	-do-
Labour	Number of persons	Annual	District	-do-
HYV	'000 Hectares	Annual	District	-do-
Minimum Temperature	Deg. Celsius	Daily	(1° x 1°) Grid	Srivastava et al. (2009), India Meteorological Department.
Maximum Temperature	Deg. Celsius	Daily	(1° x 1°) Grid	Srivastava et al. (2009), India Meteorological Department.
Rainfall*	mm.	Daily	(1° x 1°) Grid	Rajeevan et al. (2005), India Meteorological Department.
Radiation‡	Wh.m^{-2}	Daily	Met. Station	World Radiation Data Center Online Archive (http://wrdc-mgo.nrel.gov).
Variables for Simulation				
Minimum temperature	Deg. Celsius	Monthly	(0.5^o x 0.5^o) Grid	Mitchel and Jones (2005); India Water Portal
Minimum temperature	Deg. Celsius	Monthly	(0.5^o x 0.5^o) Grid	Mitchel and Jones (2005); India Water Portal
Rainfall	mm.	Monthly	All India	Kothawale et al. (2006), Indian Institute of Tropical Meteorology

Note: All variables used in regression estimation are for time period 1969-2007. Data for simulation are for the period 1930-1960. The economic variables obtained from the World Bank dataset span upto year 1987. For the period 1988-2007 these variables were obtained from ICRISAT. Both World bank and ICRISAT dataset districts were referenced to 1961 census districts. Irrigated Area, Fertilizer and Labour were available for all crops at the district level were prorated using rice's share of total crop area (or Gross Cropped Area) and expressed per hectare. Labour variable consists of number of rural *male* agricultural labourers and cultivators.

* A three year-moving average method was applied to fill the data gaps in the IMD rainfall data.

‡ Daily solar radiation data of the meteorological stations falling within a state were averaged across stations to obtain the state-level monthly average solar radition data. For states with a single or no meteorological station information available, contiguous station data were used to impute the state level average values.

(a) Non-weather data

Information on the non-weather variables were obtained from two comprehensive datasets, viz., (1) India Agriculture and Climate Dataset of the World Bank; and (2) Village Dynamics in South Asia (VDSA) meso-level dataset of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Both datasets provide comprehensive information on Indian agriculture at the district level. Information contained in both datasets have been collected from official (secondary) sources including reports and publications of Ministries under the Government of India and different State Governments, and various other institutions (bodies) which are responsible for the sole dissemination of these information.[2]

The World Bank dataset has been earlier used in several India specific studies to: (a) assess the economic impacts of climate change on Indian agriculture (see Dinar et al., 1998; Kumar and Parikh, 2001; Sanghi and Mendelsohn, 2008; Kumar, 2009; Guiteras, 2009; Kumar, 2011); and (b) evaluate historical performance of other socio-economic aspects in the Indian context with the backdrop influence on agriculture (see for example, Banerjee and Iyer, 2005; Jayachandran, 2006; Pande and Duflo, 2007; Taraz, 2013). The dataset contained agricultural input, output and climatic information for 1956-1987 for 271 districts (as per 1961 Indian Census). In view of its wide use for India specific studies on climate change agricultural impacts and related applications, the World Bank dataset was taken as the base dataset. Thus, data for 271 districts for the period 1969-1987 on inputs including rice area, labour, fertilizer, irrigated area and HYV rice area and output (rice production) were obtained from this dataset. Post-1987 data on these non-weather variables for the 271 Indian districts covered in the World Bank dataset were supplemented by the ICRISAT dataset. These non-weather information from the ICRISAT dataset were available up to year 2007, which was taken as the final year for the present study. Additionally, the

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[2] See Dinar et al. (1998) and ICRISAT (2012) for details of these sources.

non-weather data for 26 districts corresponding to three major agricultural states, viz., Kerala, Assam, and Himachal Pradesh, which were missing from the World Bank dataset, were also obtained from the ICRISAT dataset. Thus, a total of 297 districts which existed as of 1961 Indian Census were taken into account for the present study.

The present study focuses on *kharif* rice, the same being the dominant rice growing season in India.[3] However, the information on rice area and production for the 297 Indian districts, obtained from both datasets, were *annual totals*, i.e., area and production for both *kharif* and *rabi* growing seasons taken together. To obtain district level area and production for *kharif* rice, state-level *proportions* of *kharif* rice area and production for 1969-2007, available from the Ministry of Agriculture, were applied respectively to the district level annual totals of rice area and production. The dependent variable in the regression model, *kharif* rice yield (defined as production per unit area), was obtained by dividing district level *kharif* rice production by *kharif* rice area. Other non-weather variables, *viz.*, labour, fertilizer, and irrigation which were available for all crops grown in a district were apportioned using rice's share of total crop area (Gross Cropped Area) and expressed per hectare to obtain rice specific farm inputs.

(b) Weather data

Weather variables necessary for the regression were obtained from two sources. Information on temperature and rainfall were available from the Indian Meteorological Department (IMD), whereas solar radiation data was available from World Radiation Database. The temperature (maximum and minimum) and rainfall data for the 297 Indian districts included in the study were based on the daily gridded data of $1° \times 1°$ latitude/longitude resolution recently made available by the IMD

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[3] In 2011, *kharif* rice accounted for more than 84 percent of the total rice production in the country (Ministry of Agriculture, Govt. of India, 2012)

(Srivastava et al., 2009; Rajeevan et al., 2005). The daily gridded temperature data for India were available from year 1969 onwards, which determined the initial year for the study. The district level daily weather information was obtained from the daily gridded weather observations using spatial interpolation technique. The district level daily weather information was then averaged over days in a month to get the district level monthly average weather. Daily sum and monthly mean solar radiation data for 1969-2007 were available at the meteorological station level for 13 stations uniformly distributed across different parts of India. The monthly mean solar radiation data were averaged across meteorological stations (falling within a state) to obtain state-level monthly mean solar radiation. For states with one or no meteorological station-level information, contiguous station data were used to impute the state-level average radiation values. These state-level mean monthly radiation values were then uniformly applied for all districts within each state.

To obtain average weather corresponding to the various rice growth phases, the monthly weather measures, viz., average maximum and minimum temperatures, average solar radiation, and total rainfall were averaged across the growing season months of June-September and October-November. The choice of all-India overall *kharif* growing season months (June-November) and growing season months corresponding to the growth phases (June-September and October-November) was based on all-India and state-level *kharif* rice crop calendar of the Crop Science Division, Indian Council of Agricultural Research (ICAR) and existing literature (see Auffhammer et al. 2006; 2012; Lobell, 2007; Lobell et al., 2008).

Data for simulation

All-India aggregated monthly weather information during 1930-1960, representing the pre-1960 climate regime, was necessary for the simulation exercise (see Table 1). District level monthly average maximum and minimum temperature data for the period 1901-2002 were available from the India Water Portal, which was based on the high-resolution ($0.5° \times 0.5°$) monthly weather dataset of the Climate Research Unit (CRU TS 2.1; Mitchell and Jones (2005)). The district level monthly mean temperature data for 1930-1960 were first averaged across growing season months – June-September and October-November -- which were then aggregated using 1969-2007 average of the gross cropped area for each district. All-India aggregated level monthly rainfall data was obtained from the fairly long rainfall time series (1871-2012) available from the Indian Institute of Tropical Meteorology (Kothawale et al., 2006).

RESULTS

Estimation Results

The fixed effects model specification was adopted based on the specification test suggested by Hausman (1978). The stationarity tests for the relevant variables were performed using the Im-Pesaran-Shin (2003) panel unit-root tests. Test results under various assumptions with and without trend included are presented in Table 2. In all cases considered, the null-hypothesis of a unit-root was rejected at 1 percent level of significance suggesting that the series were stationary and can be modeled.

Variables	Fixed N exact t-statistic		Fixed T, asymptotic N				Asymptotic T and N			
	Without Trend	With Trend	Without Trend		With Trend		Without Trend		With Trend	
	t_{bar}	t_{bar}	$Z_{t\text{-tilde-bar}}$	p-value	$Z_{t\text{-tilde-bar}}$	p-value	$W_{t\text{-bar}}$	p-value	$W_{t\text{-bar}}$	p-value
Yield	-4.49***	-5.21***	-44.79	0.000	-53.34	0.000	-49.74	0.000	-60.08	0.000
Jun-Sep: T_{min}	-4.68***	-5.12***	-47.71	0.000	-53.03	0.000	-58.55	0.000	-59.32	0.000
Oct-Nov: T_{min}	-5.03***	-5.41***	-51.90	0.000	-56.08	0.000	-58.27	0.000	-66.73	0.000
Jun-Sep: T_{max}	-5.80***	-6.03***	-58.22	0.000	-60.88	0.000	-82.08	0.000	-79.63	0.000
Oct-Nov: T_{max}	-5.15***	-5.35***	-53.33	0.000	-55.75	0.000	-70.44	0.000	-67.06	0.000
Jun-Sep: *Sol. Rad.*	-5.14***	-5.32***	-53.02	0.000	-55.58	0.000	-64.73	0.000	-66.86	0.000
Oct-Nov: *Sol. Rad.*	-4.21***	-4.52***	-42.74	0.000	-47.40	0.000	-52.74	0.000	-49.43	0.000
Jun-Sep: *Rainfall*	-4.03***	-4.93***	-39.39	0.000	-50.09	0.000	-39.73	0.000	-52.98	0.000
Oct-Nov: *Rainfall*	-5.21***	-5.35***	-53.34	0.000	-55.28	0.000	-68.82	0.000	-64.72	0.000
Labour	-2.13***	-3.27***	-10.01	0.000	-29.03	0.000	-8.29	0.000	-20.73	0.000
Fertilizer	-2.64***	-3.43***	-19.19	0.000	-31.87	0.000	-19.17	0.000	-25.91	0.000
Irrigation	-2.39***	-3.35***	-14.78	0.000	-30.71	0.000	-16.24	0.000	-25.73	0.000
HYV	-3.55***	-3.55***	-32.88	0.000	-30.36	0.000	-40.75	0.000	-29.50	0.000

Note: t-bar calculated under fixed T and N follows a t-distribution and represents average of the panel-level t-statistics obtained through Augmented Dickey-Fuller regressions. Z-ttilde-bar calculated under fixed T and asymptotic N assumption follows a standard normal distribution. The corresponding p-values are reported in the adjacent column. W-tbar are calculated under sequentially asymptotic T and N has an asymptotically standard normal distribution. W-tbar statistics is appropriate under serial correlation, where the ADF regressions were carried out including appropriate number of lags which minimized the Bayesian Information Criterion (BIC). Fixed N critical values without time trend for 1percent, 5percent and 10percent are -1.73, -1.67, -1.64 respectively. Fixed N critical values with trend for 1percent, 5percent and 10percent are -2.36, -2.31, -2.28 respectively.

***   significant at 1 percent.

Table 3 presents the estimated model results. Two models are estimated and compared in terms of their overall impacts on rice yield in order to understand the effects of daytime temperature relative to nighttime temperature in affecting rice yield. The first model follows Auffhammer et al. (2012) and estimates the effect of minimum temperature (T_{min}) on rice yield, while controlling for the influence of other weather variables including rainfall and solar radiation, and the non-weather variables. The second model estimates the relative effects of both minimum (T_{min}) and maximum temperature (T_{max}) with the same control variables as in Model 1.

Table 3: Regression Estimates for Kharif Rice in India: 1969-2007

Dep Var: ln(yield)	With Econ Vars		Without Econ Vars	
	Model 1	**Model 2**	**Model 3**	**Model 4**
T_{min} (Jun-Sep)	0.924**	1.718***	0.460	1.604***
	[0.020]	[0.000]	[0.128]	[0.000]
T_{min} (Oct-Nov)	-0.597***	-0.258*	-0.547***	-0.292**
	[0.000]	[0.098]	[0.000]	[0.024]
T_{max} (Jun-Sep)		-3.198***		-2.703***
		[0.000]		[0.000]
T_{max} (Oct-Nov)		-2.864***		-2.469***
		[0.000]		[0.000]
Sol. Rad. (Jun-Sep)	-0.439***	-0.229***	-0.653***	-0.481***
	[0.000]	[0.010]	[0.000]	[0.000]
Sol. Rad. (Oct-Nov)	-0.408***	-0.227**	-0.627***	-0.457***
	[0.000]	[0.017]	[0.000]	[0.000]
Rainfall (Jun-Sep)	0.134***	0.0915***	0.118***	0.0846***
	[0.000]	[0.000]	[0.000]	[0.000]
Rainfall (Oct-Nov)	0.00137	-0.0169***	-0.00486	-0.0201***
	[0.728]	[0.000]	[0.111]	[0.000]
Labour	-0.0375	-0.0252		
	[0.209]	[0.374]		
Fertilizer	0.0372**	0.0264*		
	[0.027]	[0.095]		
Irrigation	0.0421**	0.0341**		
	[0.016]	[0.026]		
HYV	0.0385***	0.0468***		
	[0.010]	[0.001]		
No of Obs.	8191	8191	10586	10586
R^2	0.769	0.781	0.749	0.759
Adj. R^2	0.760	0.772	0.740	0.751
F	54.60	59.30	54.52	58.59

Note: All models include district and time fixed effects and linear time trend. All variables expressed in natural logarithm. p-value in square brackets in second row correspond to cluster-robust SEs.

* Significant at 10 percent; ** Significant at 5 percent; *** Significant at 1 percent.

As listed in Table 3, column 1, all weather variables except October-November rainfall were statistically significant. Among the economic control variables, all except agricultural labour were significant. Minimum temperature effects seemed to differ across different growth phases: higher T_{min} during the vegetative and reproductive phases improved yield, whereas higher T_{min} during the ripening phase decreased rice yield. This is what is usually reported in the process based models where effect of temperature varies across development phases (Yoshida, 1978; 1981) and shows opposing effects on rice yield. The negative influence of October-November T_{min} during the ripening phase was highly significant ($P < 0.001$) with rice yield falling ≈ 0.6 percent for each 1 percent increase in T_{min}, controlling for other covariates. On the other hand, each 1 percent increase in June-September T_{min} during the vegetative and reproductive phases was associated with an increased yield of 0.92 percent. The June-September rainfall variable corresponding to the vegetative and reproductive phase was positive and significant, suggesting rice yield increases with higher rainfall.

Both solar radiation variables showed statistically significant ($P < 0.001$) inverse association with rice yield. In view of the significant solar dimming trends observed for India (Padma Kumari et al., 2007), such association would suggest that rice yield improved with decreasing radiation. Similar negative relationship was found during the vegetative growth phase of rice in tropical/sub-tropical Asia (Welch et al., 2010). Existing India specific studies also reported negative relation between rice yield and surface radiation. However, the association was found to be insignificant due to the inclusion of more aggregated and hence less accurate radiation variables in the model owing to the unavailability of disaggregated data (see Auffhammer et al., 2006; 2012). Such inverse association which is in contrast to those suggested by the agronomic studies, could be attributed to already high levels of incident solar radiation exceeding the optimum thresholds at different rice growth phases. For example, in a tropical climate solar radiation of

300 Cal.cm^{-2}.day^{-1} ($\approx$ 12.5 MJ.m^{-2}.day^{-1}) is necessary for an optimum yield of 5 t/ha (Yoshida, 1981). Using a quadratic model specification, Welch et al. (2010) found the 'turning point' level of solar radiation after which yield falls $\approx$ 12.8 MJ.m^{-2}.day^{-1} during the vegetative phase (see Table S10, Welch et al. 2010). The overall marginal effect of the solar radiation variable (including the quadratic radiation variables) was negative. During 1969-2007, the All India average of June-September surface radiation was $\approx$ 17.6 MJ.m^{-2}.day^{-1}. Further, experimental evidence based on some crops as opposed to the process based models has suggested that yield could improve with slight fall in total radiation, and increases in diffuse radiation (Stanhill and Cohen, 2001). Moreover, the strong positive association between maximum temperature and solar radiation variables, with maximum temperatures already reaching critical thresholds during the rice growth phases in India (Wassman et al., 2009b) could be another explanation for such inverse association.

Column 2 in Table 3 reports the Model 2 results with maximum temperature (T_{max}) included as an additional regressor into Model 1. Both June-September and October-November T_{max} variables had a highly statistically significant ($P < 0.001$), negative influence on rice yield. That is, higher T_{max} during the vegetative and reproductive stage and the ripening phase decreases rice yield. This is according to the crop models studies where the impact of T_{max} is suggested to have negative influence nearly at all rice growth phases (Wassmann et al., 2009a). The influence of T_{max} during the vegetative and reproductive phase was found to be higher than that during the ripening phase: each 1 percent increase in T_{max} during the vegetative and reproductive phase resulted in approximately 3.2 percent decrease in rice yield as against a 2.9 percent decline in yield during the ripening phase.

Inclusion of T_{max} had significant influence on T_{min}. Although, both T_{min} variables remained statistically significant and retained the signs as

in Model 1, the magnitude of the variables changed significantly. T_{min} during Jun-Sep increased by almost 2 times whereas T_{min} during October-November reduced by more than half with the inclusion of T_{max}. The statistical significance of both T_{min} variables changed: June-September and October-November T_{min} were now significant at $P < 0.001$ and $P < 0.1$ as compared to $P < 0.05$ and $P < 0.001$ in Model 1. This could be due to the positive correlation between maximum and minimum temperature and their opposing effects on rice during the vegetative and reproductive growth phases (Welch et al., 2010).

As expected, addition of T_{max} variables into the model also had influence on the rainfall variables. The June-September rainfall variable was significant ($P < 0.001$) and had positive influence on rice yield. However, the estimated coefficient for June-September rainfall reduced $\approx$ 32 percent in magnitude as compared to Model 1 estimated coefficient for June-September rainfall with the inclusion of T_{max}. That is, the positive influence of rainfall on rice yield reduced when the effects of T_{max} was taken into account. However, October-November rainfall had a significant ($P < 0.001$) and negative influence on rice yield: 1 percent higher rainfall during the ripening phase resulted in 0.02 percent decline in rice yield. Compared to other growth phases, water requirements of rice during the ripening phase is relatively less. Moreover, ripening phase is the most susceptible to excess rainfall. Therefore, additional rainfall over and above the required amount during this phase could be a reason for the yield loss. That is, for given levels of the control variables including T_{max} during October-November, a higher rainfall during the ripening phase could be detrimental to crop yield.

Inclusion of T_{max} variable also influenced the solar radiation variables in the model. In Model 2, both solar radiation variables continued to show similar inverse association with rice yield as in Model 1. However, the estimated radiation variables in Model 2 were approximately half the size of those estimated in Model 1. The influence

of other economic variables (except HYV rice) on rice yield marginally declined with the inclusion of the maximum temperature. This suggests that the sample estimates for the economic variables were upward biased due to the non-inclusion of T_{max}. The HYV of rice developed in the mid-1960s are more heat tolerant. This is reflected by the small increment in the estimated coefficient for HYV rice in Model 2 over that in Model 1.

Both Model 1 and Model 2 were estimated ignoring the influence of non-weather variables and are respectively given in Column 3 and 4, Table 3. Model 3 estimates reflect that the exclusion of the non-weather variables had a significant influence on June-September T_{min} which became insignificant, and almost half the size of that estimated under Model 1. This could be due to low correlation of T_{min} with some non-weather variables ($r <0.1$), exclusion of which could bias the estimates. In other words, the true effect of June-September T_{min} becomes more evident with the inclusion of the economic variables. The negative effects associated with October-November T_{min}, however, remained robust ($P < 0.001$). The June-September rainfall remained significant and did not show much perturbation to the exclusion of the non-weather variables. Both the solar radiation variables continued to be significant and negative with the (absolute) magnitude of these variables increasing ≈ 50 percent with the exclusion of the non-weather variables. One reason is the non-inclusion of T_{max} variables which are correlated with the solar radiation variables during the growth phases. Thus, the exclusion of non-weather variables on the radiation variables would be more clear once the effects of T_{max} has been controlled for as discussed below.

Comparison of Model 4 estimates with Model 2 also reveals some interesting relation between the weather and the non-weather variables. The inclusion of the non-weather variables reflected the true effects associated with both the T_{min} variables: including the non-weather variables increased the positive effects of T_{min} on yield during the vegetative and reproductive state and reduced the negative effects of

T_{min} during the ripening phase. The negative effects of both T_{max} variables however remained robust, and increased in their precision, in terms of lower SEs and P-values, with the inclusion of the non-weather variables. After controlling for the influence of T_{max}, exclusion of the non-weather variables had negligible effect on the solar radiation variables. Similarly, the positive influence of June-September rainfall and the slight negative influence of October-November rainfall on rice yield respectively increased and decreased with the inclusion of the non-weather variables into the model.

Table 4 reports the joint and equality tests of significance of the model parameter. The effect of T_{max} during June-September did not differ significantly from October-November T_{max}, raising concern over the inclusion of both T_{max} variables into the models (Model 2, and Model 4). However, within a growth phase (June-September or October-November) the effects of T_{max} was significantly different from the effects of T_{min}, which gives sufficient reason for the inclusion of T_{max} during both the growth phases. Further, even if the elasticity of T_{max} was not statistically different across both growth phases, the trends underlying the T_{max} variables could be different across growth phases and may result in an overall non-zero impact due to increasing daytime warming. Similarly, both solar radiation variables which did not statistically differ across growth phases were included because within each phase their effect was significantly different from that of the T_{max}.

<div align="center">**Table 4: Joint and Equality Tests of Hypotheses**</div>

Tests of Hypotheses	P-values	
	Model 2	Model 4
Joint tests of significance		
All T_{min} = 0	0.000	0.000
All T_{max} = 0	0.000	0.000
All *Rain* = 0	0.000	0.000
All *Sol. Rad.*= 0	0.001	0.000
All T_{min} = All T_{max} = 0	0.000	0.000
All *T* = All Rain = 0	0.000	0.000
All *T* = All *Rain* = All *Sol. Rad* = 0	0.000	0.000
Jun-Sep: T_{min} = T_{max} = 0	0.000	0.000
Jun-Sep: T_{min} = T_{max} = *Rain* = 0	0.000	0.000
Jun-Sep: T_{min} = T_{max} = *Rain* = *Sol. Rad.* = 0	0.000	0.000
Oct-Nov: T_{min} = T_{max} = 0	0.000	0.000
Oct-Nov: T_{min} = T_{max} = *Rain* = 0	0.000	0.000
Oct-Nov: T_{min} = T_{max} = *Rain* = *Sol. Rad.* = 0	0.000	0.000
All Econ. Vars: Labour, Fertilizer, Irrigation, HYV = 0	0.000	-
All Year Fixed Effects = 0	0.000	0.000
Equality tests across growth phase		
Jun-Sep: T_{min} = Oct-Nov: T_{min}	0.000	0.000
Jun-Sep: T_{max} = Oct-Nov: T_{max}	0.505	0.616
Jun-Sep: Rainfall = Oct-Nov: Rainfall	0.000	0.000
Jun-Sep: Sol. Rad. = Oct-Nov: Sol. Rad.	0.985	0.830
Equality tests within growth phase		
Jun-Sep: T_{min} = Jun-Sep: T_{max}	0.000	0.000
Oct-Nov: T_{min} = Oct-Nov: T_{max}	0.000	0.000
Jun-Sep: T_{max} = Jun-Sep: Sol. Rad.	0.000	0.000
Oct-Nov: T_{max} = Oct-Nov: *Sol. Rad.*	0.000	0.000

$P < 0.10$: Significant at 10 percent
$P < 0.05$: Significant at 5 percent
$P < 0.01$: Significant at 1 percent

Simulation Results

The simulation results corresponding to Model 1 and Model 2 are presented in Table 5 below.

Table 5: Simulation Results

Variables	Model 1				Model 2			
	With Econ Vars		Without Econ Vars		With Econ Vars		Without Econ Vars	
	Individual Effect	Combined Effect	Individual Effect	Combined Effect	Individual Effect	Combined Effect	Individual Effect	Combined Effect
Jun-Sep: T_{min}	0.54	0.54	0.27	0.27	1.02	1.02	0.95	0.95
Oct-Nov: T_{min}	0.58	1.12	0.54	0.81	0.26	1.28	0.28	1.23
Jun-Sep: *Rain*	1.05	2.17	0.91	1.72	0.71	1.99	0.66	1.89
Oct-Nov: *Rain*	0.00	2.18	-0.07	1.65	-0.24	1.75	-0.27	1.62
Jun-Sep: T_{max}	-	-	-	-	1.48	3.23	1.21	2.83
Oct-Nov: T_{max}	-	-	-	-	5.15	8.38	4.42	7.24

Note: All values in percent

Simulations were performed starting with June-September T_{min} and progressively adding other weather variables in order calculate the individual effects and the combined effects of the weather variables. Both individual effects and combined effects corresponding to Model 1 and Model 2 were estimated separately. Model 1 simulation results suggest that during 1969-2007, all-India aggregated *kharif* rice yield would have been 2.18 percent higher had the changes in the pre-1960 climate characteristics not occurred. Reduction in June-September rainfall had the largest individual effect, and reduced rice yield by 1.05 percent. The combined effects of higher T_{min} during all growth phases (June-September and October-November) had reduced rice yield by 1.12 percent during 1969-2007. The impact of higher T_{min} during October-November was slightly higher than that during June-September. Decrease in October-November rainfall had negligible effect on rice yield, perhaps due to little water requirement by rice plant during this phase.

Model 2 simulation results which included T_{max} suggests that during 1969-2007 all-India rice yield would have been $\approx$ 8.4 percent higher had the pre-1960 climate prevailed. Higher October-November T_{max} was the largest individual contributor to the yield loss decreasing rice yield $\approx$ 5.2 percent. Higher T_{max} during June-September was the next big contributor to the yield loss. Combined effects of higher T_{max} during both June-September and October-November suggests that yield would have been 6.7 percent higher had the daytime warming not occurred. Higher T_{min} during both June-September and October-November and lower rainfall during June-September resulted in an additional 2 percent loss. Yield would have been 0.24 percent lower had the pre-1960 October-November rainfall prevailed during 1969-2007. This implies that during the later part of the growing season (ripening phase), when more of heat and sunlight and less of water is necessary for crop maturity, reduction in the rainfall was beneficial.

DISCUSSION AND CONCLUSIONS

The present study empirically assessed the weather sensitivity of rice yield in India using a district level panel data over the period 1969-2007. Using fixed effects multivariate panel regression technique the study estimated the relative influence of various weather parameters. The overall impact of changes in the climate on rice yield were simulated using the estimated model parameters. The study results found significant adverse influence of higher maximum and minimum temperature and reduced rainfall on rice yield during 1969-2007 compared to the pre-1960 climate. Several caveats of the study includes the failure to account for the gradual time-varying unobserved factor which could be potentially be correlated with the weather variables included in the model (Fisher et al., 2012). Further, the methodology applied here does not in any way suggest the likely sensitivity of rice due to the future climatic changes, but is only indicative of the extent of loss which could be already occurring owing to the historical changes in the climate. One of the assumptions of the model while simulating the impact was to hold the influence of non-weather factors fixed. This was primarily owing to the unavailability of the pre-1960 information pertaining to the non-weather variables. However, the non-weather variables could be adjusting to the weather changes occurring over time and therefore, assuming the weather variables to be fixed could lead to mal-adjustment of the non-weather variables to the changes occurring in the weather variables.

The study results show that all-India *kharif* Rice yield would have been $\approx$ 8.4 percent (or cumulative 172 million tons) higher had the pre-1960 climate prevailed during 1969-2007. Daytime (maximum) temperature (T_{max}) was the main source of yield reduction, especially during the later parts of the growing season. The model results confirm with some of the agronomic literature results which suggest detrimental effects of high temperature on rice growth and yield. Further, the results

are also in accordance with the existing statistical studies of global scale climate-crop yield and national cereal yield, which found negative response of rice yield to higher T_{avg} and diurnal temperature range (T_{max}-T_{min}), and more specifically, daytime temperature increase to be more detrimental than increases in nighttime temperature (Lobell, 2007; Lobell and Field, 2007).

The present study's results therefore differ from recent studies on rice which have assessed relative influence of T_{max} and T_{min} during various rice growth phases. These studies have found that T_{min} plays a more important role than T_{max} in affecting rice yield (see Peng et al., 2004; Nagarajan et al., 2010; Welch et al., 2010), and both having significant opposing effects on yield: T_{min} reduces rice yield whereas T_{max} increases yield. The present study found that T_{max} played a bigger role than T_{min} in adversely affecting rice yield in India. The study also finds that T_{max} has negative effects on almost all phases of rice growth, which is in accordance with those suggested in the agronomic studies (Wassmann et al., 2009a; Singh et al., 2010). This could be in view that in several regions in India temperature (especially daytime temperature) is already approaching critical levels during important rice growth phases (Wassmann et al., 2009b).

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