WORKING PAPER 162/2017

Does Weather Sensitivity of Rice Yield Vary Across Regions? Evidence from Eastern and Southern India

Anubhab Pattanayak

and

K. S. Kavi Kumar

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

March 2017

Does Weather Sensitivity of Rice Yield Vary Across Regions? Evidence from Eastern and Southern India

Anubhab Pattanayak
Lecturer, Madras School of Economics
anubhab.pattanayak@gmail.com

and

K. S. Kavi Kumar
Professor, Madras School of Economics
kavi@mse.ac.in

WORKING PAPER 162/2017

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

March 2017

Phone: 2230 0304/2230 0307/2235 2157
Fax : 2235 4847/2235 2155
Email : info@mse.ac.in
Website: www.mse.ac.in

Price : Rs. 35

Does Weather Sensitivity of Rice Yield Vary Across Regions?
Evidence from Eastern and Southern India

Anubhab Pattanayak and K. S. Kavi Kumar

Abstract

With the objective of assessing climatic impacts at the regional (i.e., sub-national) level, past studies employing statistical models have largely followed the approach of uniformly applying the climate response function estimated at the aggregate (national) level to extrapolate/interpolate the impacts for the region(s) of interest. Although impact estimates based on this approach could loosely indicate the magnitude of regional impacts (or at the least the direction of such impacts), they may exhibit significant overestimation or underestimation of the true regional impacts. Thus, following this approach could be misleading and will be inappropriate if the objective is effective adaptation planning and policy implementation at the regional level to withstand future climate change impacts.

The present study is an extension of this literature and examines the above issue through an assessment of regional weather sensitivity of rice crop in the Indian context. Using disaggregated (district) level weather and non-weather data during 1969-2007 and region-specific rice growing season information, the crop-yield response functions for two dominant rice growing regions (East and South) are estimated. The study finds significant adverse effects of higher daytime temperature during all phases of crop growth on rice yield for both regions. However, the effects of higher nighttime temperature and rainfall across growth phases tend to differ across regions. The paper then examines whether an aggregate (all-India) response function represents well the regional impacts on rice yield due to a hypothetical scenario of pre-1960 climatic conditions prevailing during the period of study. Accordingly, comparison is made between regional impacts simulated using the all-India yield response function and impacts simulated using the region-specific yield response functions. The analysis suggests that regional impacts are overestimated when simulated using an all-India yield response function instead of using the region-specific yield response function. Regional impacts simulation results indicate that the average yield loss for the Southern and the

Eastern regions due to past changes in climate has been to the tune of ~8 per cent and ~5 per cent respectively. Regional distribution of impacts shows that majority of districts in each region, especially in the East, suffered yield losses due to climate change in the past. The study highlights the need to conduct regional crop-weather sensitivity assessment using region-specific characteristics to understand regional vulnerability to climatic and non-climatic stressors and for region-level adaptation planning to tackle climate change.

Key words: *Rice; India; Climate Change; Regional Impacts; Poverty*
JEL Codes: *Q10; Q54; R50; I30;*

Acknowledgement

The authors would like to thank Dr. Brinda Viswanathan for her valuable comments on the paper at different stages of its development. An earlier version of this paper was presented at the Madras School of Economics Seminar Retreat in the Central University of Tamil Nadu (CUTN), Thiruvarur during February 26-27, 2014. The authors would like to thank the seminar participants for their comments and suggestions. The authors would also like to thank Dr. Chandra Kiran Krishnamurthy for sharing the weather data.

Anubhab Pattanayak
K. S. Kavi Kumar

INTRODUCTION

In the production of any given crop, it is natural to find few regions being more dominant as compared to others. For rice crop in India, the South and the East are the two most dominant regions, accounting for nearly two-third (~63 per cent) of total rice production of the country. Examining the weather sensitivity of rice for these dominant regions is important since any abiotic shocks to these regions could be detrimental for the total national output of the crop, leading to imminent distributional effects. While national level estimates of climate change impact (on any crop) essentially indicate the extent of damage or loss at the aggregate level, it is important to understand whether these national level estimates are good enough indicators of impacts observed at the regional level. The main objective of this paper is to examine this issue.

With the objective of assessing climatic impacts at the regional (*i.e.*, sub-national) level, existing studies employing statistical models have largely followed the approach of uniformly applying the climate response function[1] estimated at the aggregate (national) level to extrapolate/interpolate the impacts for the region(s) of interest. Although impact estimates based on this approach could loosely indicate the magnitude of regional impacts (or at the least the direction of such impacts), they may exhibit significant overestimation or underestimation of the *true* regional impacts. Thus, following this approach could be misleading and will be inappropriate if the objective is effective adaptation planning and policy implementation at the sub-national (regional) level to withstand future climatic impacts. Moreover, such an approach could overshadow the true *within* region distribution of impacts.

A number of factors may lead to the overestimation/ underestimation of regional impacts. Population growth, share of

[1] Climate (weather) response function is the empirically estimated relation between the climatic (weather) parameters and the outcome of interest, say, net farm income or crop yield, etc.

population in different economic activities including those in climate sensitive sectors, the existing and evolving practices in these economic activities, price sensitivities to weather or climatic shocks, changing technology, etc. are some of the factors that would determine the climate sensitivity of the outcome of interest in a region. In essence, all those factors that determine or affect the climate sensitivity estimates of the outcome variable are responsible for such overestimation or underestimation of impacts. The level of development of a region or country is one such factor that determines its climate sensitivity. Following this approach, Mendelsohn *et. al.* (2001) estimate climate change impacts (on agriculture) for India based on the climate response function for the United States. The study finds that using the climate response function of a developed country (the US) to estimate impacts for a developing country (India) could lead to underestimation of impacts for the latter.[2]

For examining the magnitude of potential impacts for the Asian continent as a whole, Mendelsohn (2014) adheres to a similar approach. The study attempts to examine the range of potential impacts across 29 Asian countries based on the impacts response function for China estimated by Wang *et. al.* (2009). The representativeness of China in the Asian continent in terms of its geographical size could appear as though providing a reasonable approximation to the overall impacts for Asia. However, it is also one of the more developed regions of the continent. Hence, assuming that the rest of Asia would follow similar impacts as China or extrapolating China's response function to estimate impacts for

[2] In the context of Ricardian models which allow for the possibility of adaptation, the difference in the estimated impacts between India and US reflects the huge untapped adaptive capacity. Vanschoenwinkel and Passel (2015) present a similar analysis for eastern and western Europe and suggest that if eastern Europe – the less developed region – were to adopt the response function of western Europe it could avoid a significant impacts which it may face with climate change. However, conflicting evidence exists when examining the weather sensitivity of economic production (GDP) or growth in economic production across developed and developing countries. Burke et. al. (2015) find that the nature of non-linearity in the relation between economic production and weather remain similar for developed and developing regions across the world.

other Asian countries will be misleading and inappropriate for formulating national level policies and planning to tackle climate change in these countries.[3] This suggests that a less developed country could exhibit higher climate sensitivity compared to a more developed country and *vice versa*. Therefore, using the climate response function of the latter to estimate the impacts of the former may lead to significant underestimation of impacts for the latter.[4]

In the Indian context, a number of studies employing cross-sectional Ricardian models have followed a similar approach to assess either regional or sub-national distribution of impacts (see for example, Kumar and Parikh, 2001a; Kumar, 2011; Sanghi and Mendelsohn, 2008). More recently, Dasgupta *et. al.* (2013) applying a panel model to state-level data have adhered to this approach wherein an assessment of climate change impacts on food-grain production for all-India as well as at the regional (state) level is carried out. Sub-national and/or regional impacts assessed through these models may have overstated or understated the true regional impacts.

The above argument of possible overestimation or underestimation of impacts could be extended, and such bias is equally valid in the context of crop-weather sensitivity assessment using statistical approach at the sub-national level. Factors such as crop growing season (including planting and harvesting dates), length of growing season, cropping system practice (single or multiple), crop diversity and cropping intensity, prevalence of specific genotypes, and other factors relating to farm management etc., tend to be key

---

[3] Future climate change will require cooperation between countries within a broad geographic region (e.g., a given continent), if not across all countries. The motivation and basis for such cooperation will come from the knowledge of precise magnitude of impacts across countries within such regions. Without the availability of such knowledge, cooperation may not be forthcoming and may lead to significant turbulence in geopolitical efforts to tackle climate change.

[4] Similarly, climate sensitivity of the agricultural outcome (net farm income or yield) could be different across the country between rainfed (dryland) regions and irrigated regions. Schlenker *et. al.* (2005) highlight this issue.

characteristics for any region growing a particular crop (for rice crop see Duncan *et. al.*, 2014; Panigrahy *et. al.*, 2011; Krishnan *et. al.*, 2005). These along with other socio-economic characteristics typical to a region determine the climate or weather sensitivity of a given crop in that region. The present study examines this issue for two rice growing regions in India by focusing on the crop growing season as a crucial determinant of crop-weather sensitivity.

Crop-specific impacts assessment at the sub-national (regional) level has received relatively less attention in the literature. Existing empirical literature has largely focused on estimating the yield response function at the aggregate (e.g., national) level. The weather sensitivity estimates obtained from such aggregate response functions were then uniformly applied across regions to calculate regional impacts on the crop. However, national level weather sensitivity estimates are broad enough to downplay the influence of region-specific climatic and farm-management characteristics (indicated above; e.g., planting dates) on the weather-crop relationship. As a consequence of using the national-level yield response function, the true regional impacts on the crop could be overestimated or underestimated. In view of such possibilities, it is important to assess whether the sensitivity estimates obtained from national-level yield response functions are appropriate for calculation of sub-national impacts.

To examine the reliability of aggregate-level crop yield response function based impacts projections in the US context, Schlenker and Roberts (2009) carry out a policy experiment. First the impacts across a given set of geographic locations (counties) are projected based on the aggregate yield response function. Then impacts are projected for the *same* set of counties based on the yield response function estimated from only the Southern counties. The study finds that the range of impacts are similar whether one follows an 'all-US' yield response function or the sub-nationally identified (southern counties based) yield response function. This indicates that the southern region captures well the national-level impacts.

This validation exercise by Schlenker and Roberts (2009) is different in principle from the above discussion. The study by Schlenker and Roberts (2009) projects the impacts for all counties in US based on yield response function identified from a sub-section of this broader geography. To the extent that this sub-regional characteristics coincide with the aggregate (or dominate in the aggregate level estimation), impacts projections based on either yield response functions are going to be similar. However, the above discussion points to the projection of impacts for a sub-region based on an aggregate, nation-level response function. In principle, the extent of overestimation/underestimation is likely to be *greater* when broader geography-level predictions are made based on sub-national response function than the other way around.

Using panel models, Deschenes and Greenstone (2007) estimate the sub-national (US state) level impacts of climate change on net farm income (or revenue). The study identifies the response function for each of the 48 states by exploiting the year-to-year random weather fluctuations observed at US county-level within each state. A similar approach is followed by Guiteras (2009) for the case of India where the author estimates regional (East, South, North, Northwest) impacts on crop productivity.[5]

Although much of the impact assessment literature has remained largely confined to studying climate change impacts at the aggregate (national) level, with increasing availability of disaggregated data, the literature has gradually moved in the direction of examining regional and sub-national impacts. Assessments of true impacts at these sub-national

[5] The dependent variable is a monetary measure of average crop productivity of six major crops, *viz*., rice, wheat, jowar (sorghum), bajra (millet), maize and sugar. The number as well as constituent entities within each region defined by Guiteras (2009) are different from that used in this paper.

geographic scales will require estimation of *region-specific* response functions.

LITERATURE REVIEW – CLIMATE CHANGE IMPACTS ON RICE IN INDIAN SUB-NATIONAL REGIONS

Past trends as well as future projections in the climatic parameters tend to significantly differ across regions (Dash *et. al.*, 2007; Cline, 2007; Rathore *et. al.*, 2013). An important goal of conducting a region-level impact assessment within a country for rice crop is to understand the distribution of impacts due to climate change at the sub-national level. While informing the relative vulnerability of sub-national geographies, analysis of distributional impacts could potentially facilitate regional as well as local-level adaptation planning to insure against future climate change induced risks. Assessing the regional weather-sensitivity of rice assumes specific importance since most of the rice is currently cultivated in regions where temperatures are above the levels that are optimal for plant growth (Krishnan *et. al.*, 2011). Hence, any further increase in the mean temperatures during various crop growing seasons in any of these regions may result in significant reduction in crop productivity.

Moreover, in specific sub-regions of India temperatures are already approaching critical levels during the most susceptible stages of rice growth (e.g., during April and August in South India, March-June in East India) (Wassmann et. al., 2009). There is strong evidence that many regions (especially the Northern region) have been facing low to very high heat stress intensity for rainfed rice (Texeira et. al., 2013). Such evidence only suggests that heat stress related damages to the crop could become significant with future climate change. Increasing variability in regional rainfall, extremes, as well as continuing trends in radiation could be the other regional level abiotic factors likely to be pronounced with climate change. Further, adverse impacts on rice crop due to climate change in the most dominant rice growing regions could have further ramifications on the regional poverty trends especially where incidence of poverty are at significantly high levels.

Focusing specifically on rice and the two dominant rice growing regions in India, the paper attempts to address the following question: to what extent the all-India estimates capture the relative vulnerability of districts within the Southern or the Eastern regions, representing the true region-level impacts? To be able to address this question, the past studies that employ the aggregate (national) level response functions to calculate the region-level impacts must be brought under discussion and critical appraisal.

India specific literature assessing crop impacts at the regional level that employs region-specific yield response function is limited but slowly emerging. It must be highlighted that the exact definition of region is context-specific and depends on the underlying objective. For instance, if the objective is to assess climate change impacts on a given crop across agro-climatic zones, each of these zones then become the study regions. Similarly, if the objective is to examine the impacts on a crop for rainfed areas, all regions where rainfed cultivation is carried out would constitute the region for the study. The crop-simulation studies and statistical studies employed to assess climate change impacts on rice crop in India are discussed below.

Crop-simulation Studies

Crop simulation models remain one of the most widely used tools to assess climate change impacts on rice in India. Crop model experiments studying the influence of climatic parameters are carried out in controlled environment tend to be site/location specific. These models are then be calibrated to other locations or regions.[6] While there exists broad agreement among these studies in respect of overall climate change

[6] A number of issues exist pertaining to calibration of these models to different locations and broader geography (see for example Hansen and Jones, 2000; Baron *et. al.*, 2005).

impacts on the crop across regions, for specific regions there could be difference in the assessed impacts.

The high productive North-West India (Punjab and Haryana) and the Indo-Gangetic Planes (Uttar Pradesh, Bihar and West Bengal) remains one of the most important regions for the crop simulation studies. Most of these crop simulation studies examining the climatic influence on rice in this region find that rice yield is vulnerable to higher nighttime temperature, and lower radiation. (Lal *et. al.*,1998; Pathak *et. al.*, 2003). While the effect of doubling of ambient CO_2 levels renders significant positive influence on rice productivity, under moderate to high water stress scenarios these positive effects get cancelled with 1°C and 1.5°C increase in daytime and nighttime temperature. In such scenario, rice yield could decline upto 24 per cent below present yield levels (Lal *et. al.*, 1998).

Kumar and Parikh (2001b) examine climate change impacts on rice yield using crop-simulation models at various locations representing the northern, eastern, southern and western regions across the country. The study finds that, climate change by 2060 (without CO_2 fertilization effects) could reduce rainfed (irrigated) rice yield across various regions in the range of 16 to 43 per cent (20 to 50 per cent). However, with CO_2 fertilization, climate change induced yield changes could be in the range of +2 to – 24 per cent and -5 to -34 per cent for rainfed and irrigated rice respectively. The model projects that the Northern region is likely to suffer significantly high impacts compared to the eastern, western and southern sites that tend to exhibit similar impact magnitudes.

Using CERES-rice and ORYZA1N crop-simulation models, Aggarwal and Mall (2002) project the climate change impacts on rice for different regions across India. The study finds that at current levels of CO_2, increased temperature of 1 to 2°C could result in 3-17 per cent decrease in yield across different regions. More specifically, the study finds low impacts on rice yield for the Eastern and the Western regions, moderate for Northern region and severe for the South. An interesting finding of the study is that range of temperature changes that would outweigh the beneficial effects of 450ppm of CO_2 (a likely scenario by mid-21st Century) tends to differ across regions – 1.9 to 2.0°C for North and Eastern India and 0.9-1.0°C in South and Western regions. Further, at current CO_2 concentration level and improved management with 1-4°C increase in temperature led to 5-30 per cent decrease in yield across regions.

Using crop and weather information from 10 different locations in Eastern India, Krishnan *et. al.* (2007) examine the impact of increased CO_2 and temperature on rice yield for the region. The Info Crop and the ORYZA models used in the study project average declines in the crop yield across 3 climate scenarios to tune of 9 to 21 per cent and 7.6 to 15.9 per cent respectively. At the current CO_2 concentration level, the changes in yield for uniform 1°C rise in temperature predicted by the two models range between 6.7 to 7.2 per cent. However, for a given CO_2 concentration level (400ppm; touched in the year 2015) the fixed (uniform) increase in temperature between +1°C to +5°C led the crop yield losses to vary between 2.9 per cent to 40.3 per cent.

In another study across the Western Ghats, Coastal and the North-Eastern regions, Kumar *et. al.* (2011) assesses the potential impacts of climate change on irrigated as well as rainfed rice. The study finds that majority of the Western Ghats region under irrigated rice is likely to witness ~4 per cent yield loss by the 2030s. Rainfed rice in this region could reduce up to ~10 per cent. In the coastal areas, yield losses by 2030s could go up to ~10 per cent with potentially increasing yield in coastal rainfed rice growing areas. In the North-East region, rainfed rice is most vulnerable with range of impacts falling between -35 per cent to +5 per cent.[7]

Kumar *et. al.* (2013) use the InfoCrop-rice model to examine the climatic impacts on regional (irrigated and rainfed) rice productivity for the 2020s, 2050s and the 2080s of the 21st Century. The study finds that the yield of rainfed rice in India is likely to be reduced the ~6 per cent in the 2020s scenario. However, the reduced yield projections for the other future scenarios are much smaller (<2.5 per cent). The study suggests that for potential adaptation of rainfed rice improved management and increasing nutrient supply could be necessary. The model projections suggest that rainfed rice in the southern states of Andhra Pradesh and Tamil Nadu is likely to benefit due to climate change whereas rainfed rice in Maharashtra, Chhattisgarh, Odisha, and Assam are expected to reduce 8-10 per cent yield in the 2020 scenario.[8]

Similarly, Banerjee *et. al.* (2016) for West Bengal (Eastern India) project that yield reductions of wet-season (*kharif*) rice could be as high as 20.0 per cent and 27.8 per cent by the years 2025 and 2050 respectively.

More recently, for Central India (Madhya Pradesh), Mall *et. al.* (2016) find that climate change (RCP 4.5 scenario of the AR5, IPCC) by the 2050s is likely to reduce potential and irrigated rice yield by ~6-14 per cent across different agro-climatic zones. On the other hand, rainfed rice yield in the region is likely to reduce ~15 to ~45 per cent by the 2050s with the range of impacts for rainfed rice growing regions expected to be wider than the irrigated rice growing regions.

---

[7] These estimates for rice are also discussed in INCCA (2010).

[8] Irrigated rice yield in these southern states of Tamil Nadu and Andhra Pradesh however are likely to be ~10 per cent and ~5 per cent lower in the 2080s scenario. This appears in contrast to the regional distribution of impacts suggested in Aggarwal and Mall (2002), suggesting inconclusiveness of the crop-modeling approach in projecting regional impacts.

These studies point towards the differential nature of regional impacts due to climate change. Further, they indicate towards the differential nature of adaptation (CO_2 fertilization or irrigation) that could prevail or be needed in future. In fact such inference could also be drawn for any given region. Krishnan *et. al.* (2007) find that same sowing dates at two different locations (Cuttack in Odisha and Jorhat in Assam) within a given region (East) could lead to differential impacts of climate change on crop yield.

Statistical Studies

In recent years, an increasing number of studies have assessed sub-national or regional impacts of climate change on crop yield using the statistical approach. Krishnamurthy (2012) assessed the influence of climate on rice and wheat for India using district level data for a 30-year period. Employing a quantile regression fixed effects (QR-FE) panel models, the study examines the effects of climate change across regions (North, South, East, West, and Central) and across conditional yield quantiles. The study finds Northern and Eastern India to benefit from climate change and most of the losses are attributatable to the South.

Following a closely related fixed effects quantile regression approach, Barnwal and Kotani (2013) assess the weather sensitivity of rice yield for both *Kharif* and *Rabi* rice growing seasons for the most important rice growing region in Southern India – the state of Andhra Pradesh. The study finds that the effects of climatic (weahter) variables vary not only across different yield quantiles, but also across different agro-climatic zones within the state.

Saravanakumar (2015) employs a panel model to examine the impacts of climate change on rice, sorghum and maize yield for Tamil Nadu – another important rice growing state in South India. The study finds sensitivity of rice yield to temperature and rainfall parameters with inherent non-linear effects. The study projects end-of-century impacts for rice yield and suggests that yield could decline ~10 per cent relative to the baseline yield (1971-2009).

Focusing on a number of river-basins, Palanisami *et. al.* (2014) study the sensitivity of different crops including rice to climatic parameters. Based on a Just-Pope production function estimation and using panel data, the study finds that climate change is likely to reduce *Kharif* rice yield in the Godavari basin region by 7.6 per cent by mid-century and 30.5 per cent by the end of the century. The corresponding estimates for the *Rabi* rice yield are likely to be 5.7 per cent and 26.3 per cent by mid- and end-of-century, respectively.

Similarly, *Kharif* rice in the Krishna river basin is likely to be 0.7 per cent and 17.1 per cent lower compared to the baseline levels by mid- and end-of-century. This region however is likely to suffer significantly high impacts for *Rabi* rice where productivity could reduce by 34.8 and 45.3 per cent respectively for these two future time periods. For the Cauvery river basin, *Kharif* rice is projected to decline by 13.2 per cent and 24.1 per cent for the two future time periods in the present century.

With this background, the present paper undertakes an assessment of the regional (sub-national) weather sensitivity of rice yield for two dominant rice growing regions in India, *viz*., East and South. The specific analysis of the present study involves: (a) estimation of the regional weather sensitivity of rice yield for the East and the South regions using region-specific information on rice growing seasons; (b) calculating and comparing regional impacts on rice due to changes in historical weather using both All-India and the region-specific yield response functions; and (c) assessing the within-region distribution of impacts. The methodology and data employed to carry out these analyses are discussed below.

METHODOLOGY AND DATA

The main objective of the paper is to assess the weather sensitivity of rice yield for the two dominant rice growing regions in India – the East and the South. Statistical panel regression approach is employed for both regions to examine the region-specific sensitivity of the crop to weather variation. Monte Carlo simulations are carried out to simulate the impacts for each region.

Econometric Estimation

For estimating the regional sensitivities, the following fixed-effects panel regression specification is used.[9]

$$\ln(y_{it}) = \boldsymbol{X}_{it}\boldsymbol{\beta}^{\boldsymbol{R}} + \boldsymbol{W}_{it}\boldsymbol{\gamma}^{\boldsymbol{R}} + \alpha_i + \delta_t + \lambda_i t + \varepsilon_{it} \qquad (1)$$

where the dependent variable y_{it} is rice yield in district *i* and in year *t*; $\boldsymbol{X}_{it}$ is a vector of (non-weather) farm inputs which includes labour, fertilizer, irrigation and area under High Yield Variety (HYV) rice; $\boldsymbol{W}_{it}$ is the vector of weather variables including temperature, rainfall, and solar radiation. All non-weather farm inputs and weather variables in the $\boldsymbol{X}_{it}$ and $\boldsymbol{W}_{it}$ vectors are expressed in their natural logarithm.

The corresponding non-weather and weather vectors of parameters of the region-specific model are denoted by $\boldsymbol{\beta}^{\boldsymbol{R}}$ and $\boldsymbol{\gamma}^{\boldsymbol{R}}$. For all exogenous variables, district-by-year variations pertaining to the entire dataset (not just specific to the region of interest) are exploited to estimate these parameters.[10] Specifically, region-specific non-weather parameter $\boldsymbol{\beta}^{\boldsymbol{R}}$ is defined as $\boldsymbol{\beta} + \boldsymbol{\delta}D$, where D is an indicator taking value

[9] The choice of a fixed effects specification is based on the Hausman test.

[10] Such econometric strategy providing a much larger variation for the exogenous parameters of the model is key to more consistent and precise estimation of the model parameters. Moreover, given the fixed effects nature of the regression model adopted here involving a large number of exogenous parameter estimation, following this approach also saves the degrees of freedom underlying such estimation.

1 if the specific observation correspond to the region of interest (say, East or South) and 0 otherwise. Here, $\boldsymbol{\beta}$ is the parameter estimate of the given variables for rest of the observation that are not part of the region (say, rest of India) and $\boldsymbol{\delta}$ is the *difference* between the effects of the exogenous variable(s) on yield between the specific region (say, South) and the rest of India. Region-specific weather parameters are estimated in the same way (Wooldridge, 2010).

The dependent variable and the independent variables of the model are expressed in logarithms, leading to a log-log specification of the model. Hence, the estimated parameter corresponding to any given variable represents elasticity of rice yield with respect to that variable. The district fixed effects are denoted by α_i representing time invariant characteristics. Time fixed effects and the linear time trends are captured by the terms δ_t and $\lambda_i t$ respectively to represent the short-run and long-run effects. The model specification avoids the problem of endogeneity and allows estimations to be carried out on the basis of normality assumption as suggested in the literature (see for example, Auffhammer *et. al.*, 2012; Lobell *et. al.*, 2011; Mundlak, 2001).

Choice of Regional Weather Variables

The choice of regional weather variables is a pre-requisite for regional crop-weather sensitivity assessment exercise. Key region-specific characteristics tend to influence the choice of regional weather variables and thereby the sensitivity of the crop to weather (climatic) factors. Therefore, region-specific characteristics need to be given special attention to while estimating regional crop yield sensitivity to weather (*i.e.*, regional yield response function).

Variation in growing season window is an important region-specific characteristic that determines the regional sensitivity of the crop. For water-intensive and largely rainfed crops such as rice, the onset of monsoon marks the starting point of the growing season. Given that rice in India is grown over a range of agro-climatic environments, the onset of South-West monsoon tends to vary significantly somewhere between late April (in Kerala) to end of July across the country. Moreover, some regions (e.g., South) depend on both South-West and North-East monsoonal rainfall compared to other regions (e.g., East) which exhibit only South-West monsoon rainfall dependency. Multiple-cropping seasons could be another reason for such variations in the growing season window.[11] Similarly, a number of region-specific socio-cultural factors (customs) mark the starting of the growing season.[12]

The region-specific growing season window encompassing several of these factors could get underrepresented through the use of an aggregated fixed growing season window. For instance, an average growing season window for all-India such as June through November months for *Kharifi* rice could be uniformly applied to assess the crop's sensitivity for any given region. However, in such a situation, the assessed regional weather-sensitivity of the crop would be biased to the extent such fixed, national-level, average growing season window would misrepresent the actual region-specific growing season window. It is therefore necessary to take into account the region-specific growing season windows for the purpose of estimating regional weather sensitivity of the crop. Towards this goal, state-specific rice sowing and harvesting months information for both South and East are analyzed.

Considerably less heterogeneity is found amongst the Eastern states (consisting of Assam, Bihar, Odisha and West Bengal) in the *Kharif* season rice growing window. For this region, sowing starts as early as

---

[11] In states such as Tamil Nadu, there are as high as 6-8 rice growing seasons throughout the year. See http://www.rkmp.co.in/sites/default/files/ris/rice-state-wise/Status per cent20Paper per cent20on per cent20Rice per cent 20 in per cent20Tamilnadu.pdf

[12] Festivals such as the *Akshaya Tritiya* in the Eastern states of Assam, West Bengal and Odisha and *Eruvaku Purnima* in Andhra Pradesh are examples of pre-sowing rituals that tends to mark the beginning of cultivation of main rice growing season (Sharma, 2010). Historically, these festivals have coincided with the onset of South-West monsoon.

end of April (in West Bengal) and goes up till the end of June.[13] The harvesting season for these states tends to lie between the months of November and December. For South India (consisting of Andhra Pradesh, Karnataka, Kerala and Tamil Nadu), significant heterogeneity is observed in the *Kharif* growing season window. This is specifically attributable to multiple rice growing seasons observed in Tamil Nadu. The sowing month in this region starts as early as May (in Andhra Pradesh) and goes up to September (in Kerala) and harvesting begins by November and goes up to January.

For arriving at the regional average growing season window three considerations were taken into account: (a) the *Kharif* sowing/harvesting month that represented the majority of the states in the given region; (b) the production share of the respective states; and (c) the general nature of the variety (short, medium or long) of rice grown in each region. The regional production share of each state was used as weight to determine the regional average sowing and harvesting months, which in turn yielded the average regional window for *Kharif* rice. It is generally observed that irrigated rice growing regions allow for multiple-rice-growing seasons which in turn require short- to medium-duration variety of rice to be grown. The opposite is true for rainfed regions. Based on these criteria, the growing season windows used in the analysis are July-October for the Southern region and May-September months for Eastern region.[14]

Given this growing window, intra-season weather parameters (temperature, rainfall and radiation) are constructed following the crop

[13] Department of Rice Development, Patna (Website: http://drdpat.bih.nic.in/; Accessed on 29 March, 2016).

[14] Applying criteria (a) and (b), the South average sowing month is obtained as July. Criteria (c) informs that mostly short- to medium- maturity variety is grown in the highly irrigated South. This along with criteria (a) and (b) are applied to the harvesting months to arrive at the average harvesting month of October for the region. The same approach, with the recognition of medium- to long- duration varieties grown in the East leads to determination of the average harvesting window for this region.

phenology literature. For East (South), May-July (July-August) is taken to represent the vegetative and reproductive phases and August-September (September-October) is taken to represent the ripening phase of the crop.

Robustness-Check via Mean-Variance Comparison Tests

It is important to assess whether the region-specific yield response functions are better predictors of regional yield as compared to an all-India yield response function. For this a mean-variance comparison test is undertaken. The mean-comparison test is simply a two-sample *t*-test of the difference between the sample means for any given variable. The variable in the present context is the absolute deviation between *actual* yield (y_i) and the *predicted* yield ($\widehat{y_i}$) for each district *i*, that is, $D_i = |y_i - \widehat{y_i}|$.

Absolute deviations for each district using predictions from the all-India (AI) specification can be written as $D_i^{AI} = \left|y_i - \hat{y}_i^{AI}\right|$. Similarly, the absolute deviation using predictions from the regional specification would be $D_i^R = |y_i - \hat{y}_i^R|$. If the *average* (across districts) of the absolute deviation based on predicted yield from AI specification (say, $\mu^{AI} = \frac{1}{N}\sum_{i=1}^{N} D_i^{AI}$) is *higher* than the absolute deviation based on regional predicted yield (say, $\mu^R = \frac{1}{N}\sum_{i=1}^{N} D_i^R$), that is, $\mu^{AI} - \mu^R > 0$, then it can be inferred that the regional specification provides a better measure of assessing yield sensitivity at the regional level, compared to an all-India specification. A lower average absolute deviation would imply better (precise) prediction.

The variance comparison test follows the same reasoning, except that here it needs to be tested whether ${\sigma_i^{AI}}\big/{\sigma_i^R} > 1$, where σ_i^{AI} and σ_i^R are the variance of the absolute deviation of actual yield from the predicted yield obtained from AI specification and regional specification, respectively. Lower variation in these deviations would simply mean higher consistency of the predicted yields of the adopted specification.

Combining the two tests, if both the average of absolute deviation *and* its variance based on regional specification yield prediction turns out to be lower than those based on the AI specification yield predictions, estimates of the region-specific yield response functions would be considered more robust. The same conclusion will hold true if only the average absolute deviation of the former type is lower than the latter, while exhibiting no difference between their respective variance.

Simulation of Impacts

Monte Carlo simulations are used to calculate the impacts. Equation (2) is used for carrying out the simulations:

$$\frac{\tilde{y}_{it}}{\hat{y}_{it}} = \left[\prod_j \left(\frac{\widetilde{w}_{ijt}}{w_{ijt}}\right)^{\hat{\gamma}_j^R} - 1\right] \times 100 \qquad (2)$$

The simulations are carried out at the district level as indicated with the subscript *i*. Impact is defined as the per centage deviation of predicted yield ($\hat{y}_{it}$) from the counterfactual yield ($\tilde{y}_{it}$). Predicted yield is a function of the actual (realized) weather across districts during 1969-2007. Counterfactual yield is a function of simulated weather – that is, weather that would have been realized during 1969-2007 had the past (1930-1960) climate prevailed.[15] Thus, the counterfactual weather observations are simulated based on the distributional characteristics (mean, variance and covariance) of the climate which prevailed during 1930-1960. District-wise simulations are based on Mean and Covariance matrices of the (1930-1960) weather parameters that allow for intra-

[15] Equation (2) is employed to simulate the counterfactual yield during 1969-2007 with the average yield observed during the same period. Since the effect of non-weather factors is the same for observed and counterfactual yield during this period, their inclusion under specification of equation (2) becomes redundant.

seasonal (within and across rice growth phases) correlation between different weather variables.[16]

Equation (2) is used for two types of impacts simulations: the first category of simulated impacts are based on parameters ($\hat{\gamma}_j^R$) obtained from an all-India yield response function and the second category of simulated impacts are based on those obtained from the region-specific yield response functions. The all-India yield response function is obtained from Pattanayak and Kumar (2014).

Data

For the purpose of regression estimation, district-level weather and non-weather data during 1969-2007 are required. The period of analysis is essentially determined by the availability of various weather and non-weather information. For simulation of climate change impacts district-wise weather information during 1930-1960 is necessary. The various data required for the aforementioned analyses along with their sources are summarized in Table 1.

---

[16] Auffhammer *et. al.*, (2012) indicate that interaction between two weather variables (especially, temperature and rainfall) could be having significant effects on crop yield and assuming the covariances between weather variables to be zero could be downplaying the role of such interaction effects. This requires the off-diagonal elements of the covariance matrix to be non-zero.

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^o x 1^o) Grid	Srivastava et. al. (2009), India Meteorological Department.
Maximum Temperature	Deg. Celsius	Daily	(1^o x 1^o) Grid	Srivastava et. al. (2009), India Meteorological Department.
Rainfall*	mm.	Daily	(1^o x 1^o) 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 single or no meteorological station information available, contiguous station data were used to impute the state level average values.

(a) Weather Data

Three key weather variables, *viz*., temperature, rainfall and solar radiation are taken into account for assessment of the weather sensitivity of rice crop. Temperature and rainfall information are obtained from the India Meteorological Department (IMD). Solar radiation data is obtained from World Radiation Database (WRD). Daily maximum and minimum temperature and rainfall information are available as gridded ($1°\times1°$ latitude/longitude) weather data products from the IMD (Srivastava et. al., 2009; Rajeevan et. al., 2005). The daily gridded temperature data for India are available from year 1969 onwards, which thereby becomes the initial year for the study. Districts are the unit of analysis given that non-weather information is comprehensively available at this level of the administrative unit. Hence, the gridded weather data are transformed into district-level weather information using spatial interpolation technique. The district level daily weather information are 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 are available at the meteorological station level for 13 stations uniformly distributed across different parts of India. Given that the spatial coverage of such data is rather limited, spatial interpolation technique applied to obtain district-level mean monthly solar radiation information may produce significantly biased disaggregated-level information. However, such bias could be reduced by interpolating this information at the state level. Thus, monthly mean solar radiation data are 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. The state-level mean monthly radiation values are 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*., monthly average maximum and minimum temperatures, monthly average solar radiation, and monthly total rainfall are aggregated across the growing season months of June-September and October-November. The choice of all-India and regional *kharif* growing season months and intra-seasonal growing season months corresponding to the growth phases are based on all-India and state-level *kharif* rice crop calendar of the Crop Science Division, Indian Council of Agricultural Research (ICAR, 2008) and existing literature (see Auffhammer et. al. 2006; 2012; Lobell, 2007; Lobell et. al., 2008; Welch et. al., 2010). [17]

For calculation of impacts weather variables which are incorporated in the regression estimation needs to be simulated to obtain the counterfactual weather over the study period. Towards this goal, the distributional characteristics (represented through the mean and covariance matrices) of the past (1930-1960) climate corresponding to each district are required. Indian district-wise information of past weather (1901-2002) are obtained from Mitchell et. al. (2005) which is available from India Water Portal.[18]

---

[17] Given the disaggregated (district) level data, district-wise crop growing season months should be used to arrive at the regional average window. However, the ICAR data for Individual states is the best possible publically available information. The validity of this data is made with other available sources including the growing season calendar available from the Directorate of Rice Development, Patna and past statistical studies and summary of spatial database based on remote sensing data (Manjunath and Panigrahy, 2010).

[18] Weather data to be used for simulation for most of the districts in Kerala and Himachal Pradesh were unavailable from India Water Portal. To overcome this issue, temperature variable for all other districts are obtained by spatial averaging approach. Under this approach, the temperature in any given month in a particular year for a district in Kerala is imputed value of the average temperature which prevailed in the rest of the Southern region – average temperature which prevailed in that month and year over Andhra Pradesh, Karnataka and Tamil Nadu. Adopting such an approach could however lead to significant bias in the estimates specific to the state and therefore, such estimates are to be interpreted with caution. Similar issue was reported for several districts of Himachal Pradesh.

(b) Non-weather Data

District-level non-weather information are obtained from two datasets: (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). Official (secondary) sources including reports and publications of the Ministries under the Government of India (GoI), different State Governments, and various other institutions (bodies) that are responsible for the sole dissemination of these data form the informational basis of both datasets.[19] The World Bank dataset contains agricultural input, output and climatic information for 1956-1987 for 271 districts (as per 1961 Indian Census) and has been used previously in several India specific studies to assess the impacts of climate change on Indian agriculture (see Dinar et. al., 1998; Kumar and Parikh, 2001a; Sanghi and Mendelsohn, 2008; Kumar, 2009; Guiteras, 2009; Kumar, 2011). In view of this, the World Bank dataset is taken as the base dataset for analysis of the paper. Accordingly, 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. However, the World Bank dataset not only excludes some important rice growing states (Assam, Himachal Pradesh and Kerala), but also does not include information corresponding to the more recent years. To overcome this limitation, the World Bank dataset was supplemented by the ICRISAT dataset which contains post-1987 information. The non-weather information from the ICRISAT (2012) dataset available up to the year 2007 determined the final year for the analysis. With the addition of 26 districts corresponding to the above three states, a total of 297 districts that existed as of 1961 Indian Census are taken into account for the present study.

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

RESULTS

Various diagnostic checks were carried out prior to model estimation.[20] The panel-unit root tests suggested by Im, Pesaran and Shin (2003) under various assumptions shows that the region-specific variables follow I(0) process suggesting stationarity . That is, any temporal correlation between the model variables may not be deemed spurious. The Hausman (1978) test rejects the null hypothesis suggesting evidence against the random effects assumption.[21] As in case of all-India estimates, heteroskedasticity and autocorrelation were detected in the model error structure. Accordingly the Heteroskedasticity and Autocorrelation (HAC) robust standard errors need to be estimated through clustering at the district-level.

Climate Response Function for Rice

The region-specific regression estimation results are presented in Table 2. Based on the regional crop calendar information for the *kharif* season, the East- and South-specific yield response functions are estimated using panel fixed effects regression.[22] Estimation results for the non-weather variables are not included in the discussion of results, considering that the objective is to simulate the impacts at the regional level which takes into account only the weather variables.

South-specific Climate Response Function

For South, both minimum and maximum temperatures are statistically significant in influencing rice yield. The adverse effects of maximum temperature ($T_{\max}$) on yield appear across all rice growth phases.

[20] The results of the Panel Unit Root tests are available from the authors upon request.

[21] The Hausman test essentially examines whether the individual heterogeneity (or individual effects) are uncorrelated with the model regressors or not. The Null hypothesis is H_0: Cov(α_i , $\mathbf{x}_{it}$) = 0 (Wooldridge, 2010).

[22] The Model 2 specification for both regions *includes* the daytime temperature effects, compared to a specification (Model 1) that excludes daytime temperature effects. As discussed in case of the all-India specification in Pattanayak and Kumar (2014), since Model 2 happens to be a better specification than Model 1, for both regions only Model 2 is estimated.

However, yield shows opposing sensitivities to increase in minimum temperature (T_{min}) across phases: higher T_{min} during the vegetative and reproductive phases (July-August) reduces yield ($P < 0.1$), but higher T_{min} during the ripening phase (September-October) increases rice yield.[23] The positive effects of higher nighttime temperature during the ripening phase however remain statistically insignificant ($P < 0.11$). On the contrary, the higher daytime temperature during all growth phases has negative and significant ($P < 0.1$) influence on *kharif* rice yield in South. This reflects that rice yield tend to exhibit differing sensitivity to daytime and nighttime temperatures.

Other weather variables of the model, such as solar radiation and rainfall also suggest opposing sensitivity during various growth phases. Higher radiation during the vegetative and reproductive stages increases rice yield ($P < 0.1$). Given the existing evidence of a declining trend of radiation (Padma Kumari *et. al.*, 2007), this would suggest that for South, lower radiation has contributed to reduced rice yield during the period 1969-2007. Radiation effects on yield during the ripening phase is negative but are statistically insignificant.

[23] Nighttime temperature over the past Century showing an increasing trend over the peninsula in South India could be one of the reasons leading to a negative and significant impact of higher T_{min} during July-August months on yield (Dash *et. al.*, 2007). Studies assessing weather sensitivity of rice yield in tropical/sub-tropical Asia also tend to support that higher T_{min} during the initial period of rice growth could also reduce yield (see, for example, Welch *et. al.*, 2010).

Table 2: Region-Specific Regression Estimates for *Kharif* Rice

South-specific weather Vars.	South (Model 2)	East-specific weather vars.	East (Model 2)
Jul–Aug: T_{min}	-1.257*	May–Jul: T_{min}	1.602***
	[0.071]		[0.002]
Sep–Oct: T_{min}	0.879	Aug–Sep: T_{min}	0.275
	[0.107]		[0.636]
Jul–Aug: T_{max}	-0.906*	May–Jul: T_{max}	-0.688*
	[0.079]		[0.055]
Sep–Oct: T_{max}	-1.270***	Aug–Sep: T_{max}	-1.830***
	[0.001]		[0.000]
Jul–Aug: *Sol. Rad.*	0.258*	May–Jul: *Sol. Rad.*	-0.267*
	[0.063]		[0.073]
Sep–Oct: *Sol. Rad.*	-0.014	Aug–Sep: *Sol. Rad.*	-0.272***
	[0.913]		[0.007]
Jul–Aug: *Rainfall*	-0.036***	May–Jul: *Rainfall*	0.047**
	[0.009]		[0.021]
Sep–Oct: *Rainfall*	0.098***	Aug–Sep: *Rainfall*	-0.016
	[0.000]		[0.443]
No. of Obs.	8414		8418
R^2	0.791		0.783
Adj R^2	0.782		0.774
F	51.56		53.97

Note: Dependent variable is logarithm of rice yield. Both models include non-weather variables (Labour, Fertilizer, Irrigation and HYV area), district and time fixed effects and linear time trends. All continuous variables expressed in natural logarithm. *p*-value in square brackets in second row correspond to cluster-robust SEs.
* Significant at 10 %; ** Significant at 5 %; *** Significant at 1 %
Source: Author's own calculations

The effects of rainfall tend to vary across rice growth phases. Higher total rainfall during the months of July-August has a yield reducing effect whereas increased rainfall during the ripening phase increases yield. However, the yield reducing effects tends to be smaller compared to the positive effects so that the net effects of rainfall are positive ($P < 0.001$).

Tests of joint significance of the weather variables are carried out for both regions as suggested in Pattanayak and Kumar (2014) for the all-Inida specification.[24] These effects measure the joint statistical significance of each weather variable across all growth phases. Evidently, the overall effect of nighttime temperature is significant. In other words, higher nighttime temperature leads to yield decline in Southern India. Similarly, the joint significance tests of daytime temperature, solar radiation and rainfall are significant ($P < 0.001$).

Equality tests of various weather parameters across growth phases as well as within a growth phase are also carried out. The effects of higher nighttime temperature and rainfall tend to differ across rice growth phases – the null hypothesis of equality is rejected at 5 per cent level of significance. However, there appears insignificant difference between the effects of higher daytime temperature as well as solar radiation across growth phases. This raises the concern of including each variable corresponding to all the developmental phases in regression modeling. However, equality tests *within* a given growth phase suggests that the effects of higher daytime temperature, nighttime temperature and solar radiation tend to differ from one another, justifying the inclusion of each of the variables across growth phases.

East-specific Climate Response Function

For the Eastern region, both nighttime and daytime temperature influence rice yield, and their effects vary across *growth* phases. The negative effects of higher daytime temperature are significantly pronounced. Rice yield sensitivity to higher daytime temperature on yield varies across rice growth phases: 1 per cent increase in daytime temperature during the ripening phase has a significant negative influence on yield, resulting in 1.83 per cent decline in yield. However, the same during the vegetative and reproductive stages lowers yield by 0.69 per cent. On the other hand, higher nighttime temperature has a positive influence on yield: for every 1 per cent increase in average

[24] The results of the Joint- and Equality-tests are available from the authors upon request.

nighttime temperature during May-July months, rice yield increases by 1.6 per cent. Thus, maximum and minimum temperatures tend to exert opposing effects on rice yield in Eastern region.

In contrast to the South, where rice cultivation is mostly irrigation dependent, the Eastern region depends primarily on the South-West Monsoon (during June-September) for cultivation of the crop.[25] With the required amount of water necessary during the vegetative and reproductive stages for crop growth being met through rainfall, higher rainfall during these phases enables crop development. This is evident through the positive and significant ($P < 0.05$) relation between rainfall and yield during this phase: 1 per cent increase in rainfall during the vegetative and reproductive phase leads to 0.05 per cent increase in yield. As discussed earlier, during the later part of the growth phases when water requirement of the crop is low, higher rainfall could affect yield (Huda *et. al.*, 1975). This phenomenon is captured through the negative effects of higher rainfall during the ripening (August-September) period. However, this turns out to be statistically insignificant.

Surface radiation across all crop growth phases leads to yield reduction. The negative effects are statistically significant ($P < 0.01$), in line with the effects of both daytime and nighttime temperatures, in view of high correlation between solar radiation and temperature variables (especially, maximum temperature).[26] The inverse relation between yield and radiation, however, translates to an increased yield in view of the historically observed declining trend of solar radiation in the East.

[25] In 2011-12, the regional (weighted) average of share of rice area that is irrigated for the Eastern region is 38.2 per cent (*Source*: Agricultural Statistics at a Glance, 2015, Ministry of Agriculture, Govt. of India). That is, nearly 62 per cent of the regional rice cultivated is rainfed.

[26] Similar negative effects of radiation have been discussed in other studies in tropical Asia and India (see Auffhammer *et. al.*, 2012; Welch *et. al.*, 2010). Various factors leading to adverse effects of radiation on yield have been discussed in Pattanayak and Kumar (2014).

As in case of South, joint tests of significance of model parameters and tests of their equality – both within and across growth phases are carried out for the estimated East-specific yield response function. The null-hypothesis testing the joint significance of each of the weather variable is rejected (*P* < 0.001). Tests of equality of weather variables across growth phases suggest that the effects of minimum temperature (and solar radiation) do not differ. However, within a given growth phase, the effects of minimum temperature or solar radiation tend to differ from those resulting from daytime temperature.

Mean Variance Comparison Tests Results

The justification for using region-specific yield response function to assess the regional weather sensitivity of rice as against using all-India yield response function can be examined through the *mean/variance-comparison test* for each region.

The two-sample paired and unpaired *t*-test results are carried out for both regions, under the assumption of equal variance. For South, the test rejects (*P* < 0.1) the null hypothesis ($H_0: \mu^{AI} = \mu^{South}$) in favour of the one-sided alternative ($H_a: \mu^{AI} > \mu^{South}$). This suggests that mean absolute deviation of South-specification-based-predicted-yield from actual (mean) yield for the region is *lower* than the mean absolute deviation of the AI specification based predicted yield from the actual yield.

The two-sample variance-ratio test for the Southern region also rejects (*P* < 0.1) the null hypothesis ($H_0: \frac{\sigma_i^{AI}}{\sigma_i^{S}} = 1$) in favour of the one-sided alternative $H_a: \frac{\sigma_i^{AI}}{\sigma_i^{S}} > 1$. Both mean and variance-comparison tests for South thus imply that the South-specification more precisely and consistently estimates the weather sensitivity of rice yield in South than the AI-specification.

For the Eastern region, although the mean absolute deviation of East-specification-based-predicted-yield from actual (mean) yield for the region is lower than that based on AI-specification, the difference is insignificant under the *null* hypothesis. Thus, for East one fails to reject the null hypothesis of equality of means. In other words, in terms of model precision, the East-specification fares at best as well as the AI-specification.

The variance-comparison test for Eastern region however rejects ($P < 0.1$) the null hypothesis ($H_0: \frac{\sigma_i^{AI}}{\sigma_i^{E}} = 1$) in favour of the one-sided alternative $H_a: \frac{\sigma_i^{AI}}{\sigma_i^{E}} > 1$. That is, given that both AI-specification and East-specification are of equal precision, more consistent estimates are obtained from the East-specification compared to the AI-specification.

Simulation of Impacts

Impact simulation results are carried out across all the 297 districts in the dataset using the all-India (AI) yield response functions obtained from Model 1 and Model 2 (see Pattanayak and Kumar, 2014). These results are presented in Table 3 below. The Model 1 specification for all-India *excludes* the daytime temperature effects on rice yield whereas Model 2 specification for all-India *includes* the daytime temperature effects.

The results suggest that there is significant variation in the impacts of historical climate change on rice yield across regions and across states within region. On average, some states have benefited while some other states have suffered losses due to changes in climatic parameters in the 1969-2007 period compared to the pre-1960 period. Moreover, within each region, the impacts appear to be non-uniform.

A comparison of the simulations from both all-India specifications based on Model 1 and Model 2 can be made. Daytime temperature effects included in Model 2 specification outweighs the positive effects observed for many states in Model 1. In fact, for several of these states the absolute magnitude of the impacts turns out to be much higher under Model 2 than those under Model 1.

Table 3: Simulation of Impacts Using all-India Specifications

Region	State Name	Model 1	Model 2
East	Assam	-7.3	26.7
	Bihar	-5.9	4.2
	Odisha	-5.2	26.0
	West Bengal	0.03	19.6
South	Andhra Pradesh	-3.1	11.2
	Karnataka	3.3	32.0
	Kerala	-8.5	-23.1
	Tamil Nadu	-8.4	40.2
West	Gujarat	22.5	33.5
	Rajasthan	21.8	-5.3
North	Haryana	-4.6	-22.8
	Himachal Pradesh	-13.6	19.7
	Punjab	1.8	-20.2
	Uttar Pradesh	-1.0	-12.6
Central	Madhya Pradesh	0.4	6.1
	Maharashtra	-3.5	-2.7

Note: 1. All values in per cent. All values are weighted averages of simulated impacts across districts, where the weights are the (1969-2007) average production share of each district in a given state.

2. Positive value suggests that rice yield would have been x per cent higher had the pre-1960 climate prevailed during 1969-2007. Similarly, negative values suggest that rice yield would have been y per cent lower had the pre-1960 climate prevailed during 1969-2007.

For several regions inclusion of daytime temperature effects in Model 2 results in *higher adverse effects* due to historical changes in climate on the productivity of rice compared to Model 1 specification. These negative effects are most visible in the Eastern region as well as in Southern region (with the exception of Kerala).[27] Similar effects are

[27] Combined effect of higher CO_2 concentration as well as increase in rainfall has the potential to outweigh the negative effects on yield due to increased temperature. Saseendran *et. al.* (2000) examining the impact of climate change on rice productivity in Kerala shows that climate change

observed for the West and the Central regions.[28] However, the Northern part of the country tends to benefit from the inclusion of the daytime temperature effects. The result could be primarily due to increasing nighttime temperature trends and decreasing daytime temperature trends observed in the North (except Himachal Pradesh) during the *Kharif* (June-November) season (Rathore *et. al.*, 2013).[29]

Overall, from Model 2 based simulated impacts, it is evident that the Northern Region appears to have benefited from the past climatic changes than the Eastern or the Southern regions. This result is consistent with the existing literature that points to the disproportionate nature of climatic impacts across geography, whereby low latitude countries could suffer greater impacts than their higher latitude counterparts (Mendelsohn *et. al.*, 2006).

Distribution of Impacts

Distribution of Impacts using all-India Yield Response Functions

Distribution of impacts across districts using all-India (AI) specifications as estimated in both Model 1 and Model 2 shows significant variations across regions (see Figure 1).[30]

---

impacts is likely to *increase* rice yield up to 12 per cent in Kerala, when the effects of higher CO_2 and rainfall are taken into account over and above the effects of increased temperature. However, a decline of 6 per cent in yield is projected when temperature effects alone are included in the crop-simulation exercise. The possibility of simulation data construction issues discussed earlier could be another factor leading to such exceptions within a given region.

[28] The case of Rajasthan in the West appears more in line with general trends observed in the Northern region.

[29] Hence, given the above observed trends and the estimated sensitivity parameters (see Pattanayak and Kumar, 2014), the inference that benefits of reduced daytime temperature tend to outweigh the negative effects associated with increased nighttime temperature in North India (except in Himachal Pradesh) would follow. With significantly increasing daytime temperature trend and decreasing nighttime temperature trends (Rathore *et. al*., 2013), the case of Himachal Pradesh is the opposite.

[30] The notion of impacts, by definition, allows for the possibility of having some gainers and some losers. Here, the analysis focuses on the districts that have been adversely affected due to past climatic changes. Towards this end, districts that have *benefited* from past climatic changes are referred to as 'gainers'. After grouping the gainers together, further classification of districts is based on per centile values of *adverse* impact facing districts. See Figure 1 footnote for details of the classification.

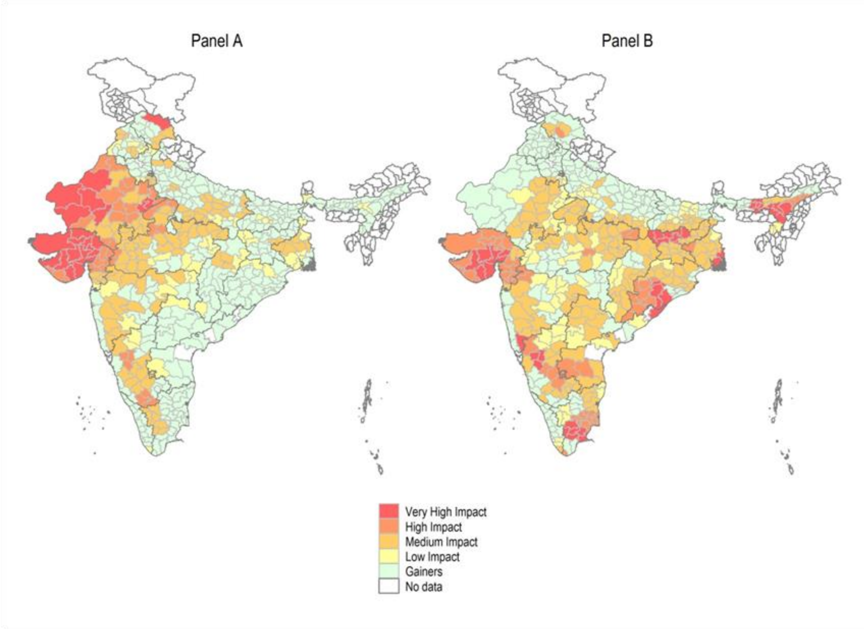


Figure 1: Distribution of Impacts Using All-India Specification

Notes: Panel A and B respectively portray the maps of simulated impacts from all-India specifications Model 1 and Model 2 in Pattanayak and Kumar (2014). "Gainers" are districts whose rice yield would have been lower had the "old" (1930-1960) climate prevailed during the period of study (1969-2007). Districts suffering negative impacts are classified based on impact per centiles as follows: Low Impacts (< 25th Per centile); Medium Impact (≥ 25th Per centile and < 75th Per centile); High Impact (≥75th Per centile and < 90th Per centile); Very High Impact (≥ 90th Per centile).

As evident from Panel A, majority of the impacts simulated from Model 1 are observed to the left of the Standard Meridian of India (82 ° 30'). In this region, the impacts are concentrated in the West (Gujarat and Rajasthan), Northern part of Central India and the districts in the Western Ghats region which spans across the Central and the Southern regions. To the right of the Standard Meridian of India, few districts in the East tend to exhibit negative impacts. On the other hand, with the exception of some districts in Punjab, Himachal Pradesh and Uttar Pradesh, most of the Northern districts have witnessed increased rice yield due to past changes in climate.

Panel B shows that the most of the Northern districts (except some districts in Himachal Pradesh) have witnessed positive impacts. These are similar to those obtained under Model 1, except that the magnitude of the beneficial effects of past climatic changes simulated using Model 2 specification are much more pronounced than those simulated using Model 1 specification. Most of the Eastern and the Southern districts however have experienced yield losses due to changes in climate.

Distribution of Impacts using Region-specific Yield Response Functions

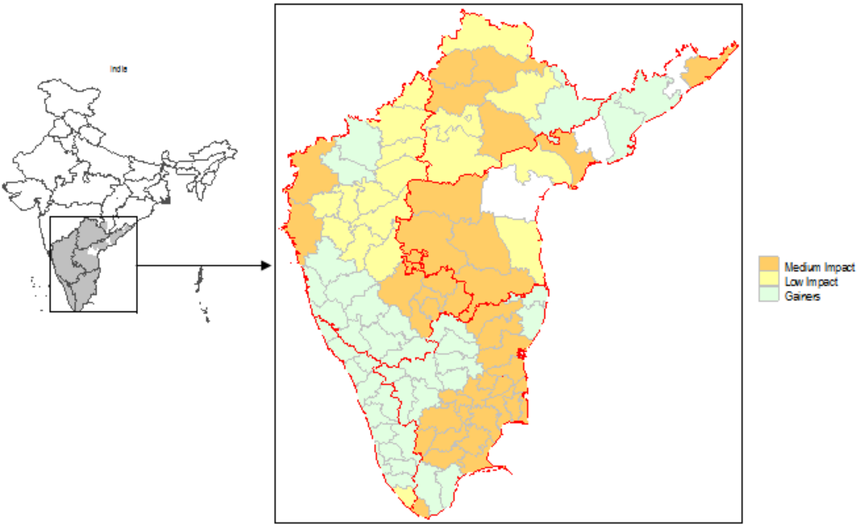
Comparison between predicted and actual yield based on the all-India and the region-specific response functions suggests that the region-specific response function based predicted (average) yield is closer to the actual (observed) yield. Based upon this inference, it is necessary to examine the distribution of impacts at the regional level using the region-specific yield response function.

The district-wise impact simulation results for the South using South-specific yield response function is presented first, followed by the distribution in the East based on the East-specific yield response function. These district-wise simulated impacts are then averaged to study the aggregate state-level impacts within each region.

- ***Distribution of Impacts for South using South-specific Yield Response Function***

The district-wise simulated impacts for the South using the South-specific response function are presented in Figure 2.

Figure 2: District-wise Impacts for Southern India using South Specification (Model 2)



Notes: see Figure 1 notes for the impacts classification.

Districts in the South faced low to medium impacts.[31] Most of the gainers are districts concentrated in the South-West of the region. This comprises of all districts of Kerala (except Trivandrum), districts in the south-west of Karnataka, and most of the districts in the north-west and west of Tamil Nadu.

[31] For the purpose of comparison, threshold values of the per centile distribution of impacts based on the all-India (AI) specification are maintained towards classification of regional impacts (see Figure 3.2 footnote). Following this fixed classification approach, it can be seen that while the impacts based on the AI specification shows some districts facing high and very high impacts, the distribution based on South-specific response function does not have districts facing at most medium impacts. This implies an overestimation of impacts for South using the AI specification compared to using South-specific response function.

Districts facing *any* adverse impacts (either Low or Medium) are largely spread across the Deccan Plateau and the Eastern Ghat regions of the South. The southern part of both these geographic regions in the South has most of the districts facing medium impacts. Districts facing medium impact are present in the southern part of Andhra Pradesh, Northern, and East-Central Tamil Nadu including some districts in the Cauvery river basin. The district-wise impacts for South, aggregated to the state level are presented in Table 4. Model 2 simulations include the non-weather variables whereas Model 4 simulations do not. Both model simulated district-wise impacts are averaged with and without using weights.

Table 4: Distribution of Impacts for South using South Response Functions

State	Model 2 (WITH ECON.VARS.)		Model 4 (W/O ECON.VARS.)	
	Unweighted	Weighted	Unweighted	Weighted
Andhra Pradesh	7.9	6.9	8.7	7.5
Karnataka	4.7	7.8	4.2	7.2
Kerala	-14.6	-18.5	-15.4	-19.6
Tamil Nadu	13.5	14.7	13.3	14.7
South Average	7.8	8.0	8.0	8.2

Notes: Model 2 and Model 4 are response functions for South estimated *with* and *without* economic variables, respectively. All values in per cent.

District-wise production contributions to the total state-level rice production (1969-2007) are used as weights for calculating the weighted average impacts at the state level. The state-wise production contributions to the total regional rice production (1969-2007) are the weights used for arriving at the weighted average impacts at the regional level.

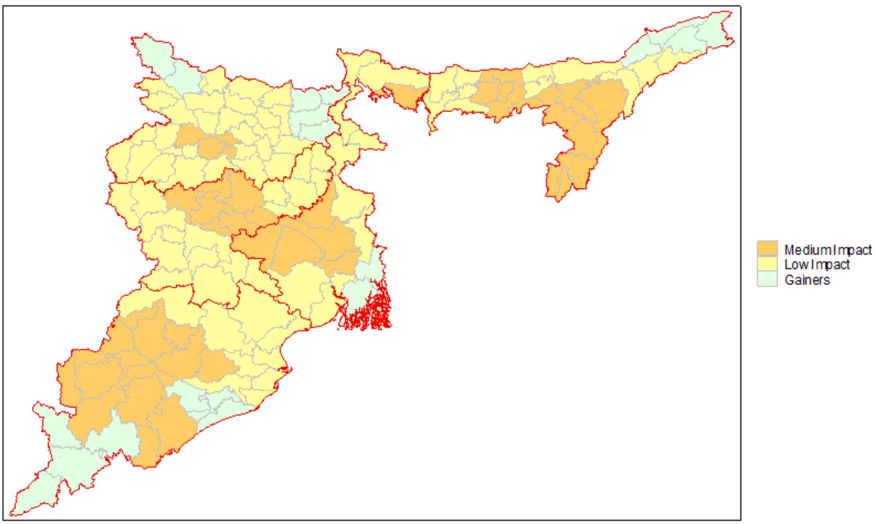
The (weighted) Model 2 results suggest that South would have witnessed ~8 per cent higher yield, if the pre-1960 climate (old climate) had prevailed during 1969-2007. Except Kerala, all the other Southern

Indian states have lost yield due to climate change. The maximum yield loss is for Tamil Nadu (~ 15 per cent) and the minimum loss is for Andhra Pradesh. The (weighted) model 4 estimates also fall in the similar range, suggesting consistency of the estimates across different model specification.

- ***Distribution of Impacts for East using East-specific Yield Response Function***

District-wise simulation of impacts for Eastern India using east-specific response function (Figure 3) suggests that most (~90 per cent) of the districts in the Eastern region faced either low or medium impacts due to past changes in climate. No districts faced high or very high impacts as predicted using the AI specification.

Figure 3: District-Wise Impacts (1969-2007) For Eastern India Using East Specification (Model 2)



Notes: see Figure 1 notes for the impacts classification.

The state of Bihar in its present form (*i.e.*, excluding Jharkhand) was the least affected in the sense that most of the districts faced low impacts. Most of the medium impacts were concentrated in the West-Central to South-Eastern parts of Odisha, Western and Central regions of West Bengal, and Southern parts of Assam.

The district-wise estimates aggregated to the state and regional levels are presented in Table 5.

Table 5: Distribution of Impacts for East using East Response Functions

State	Model2 (With Econ.Vars.)		Model4 (W/O Econ.Vars.)	
	Unweighted	Weighted	Unweighted	Weighted
Assam	5.6	5.4	6.6	6.4
Bihar	3.5	2.8	4.9	4.1
Odisha	5.7	5.9	7.2	7.5
West Bengal	5.8	6.3	6.7	7.5
East Average	5.2	5.3	6.4	6.6

Notes: Model 2 and Model 4 are response functions for East estimated *with* and *without* economic variables, respectively. All values in per cent.

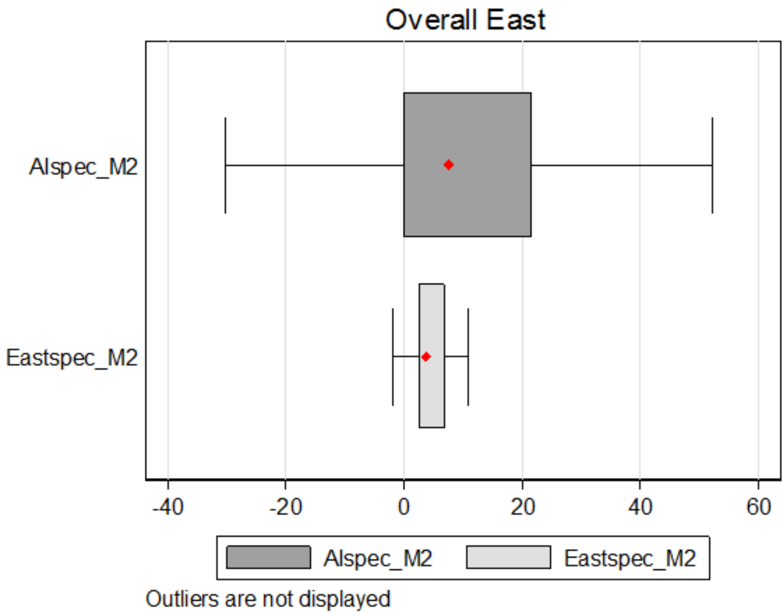
The results suggest that all states have faced adverse impacts. Eastern India on average has suffered ~5 per cent yield loss due to climate change of the past. The maximum impact has been in the state of West Bengal, which is also the most dominant rice producing state in the region.[32] The state of Odisha, which has historically high records of poverty, appears to rank second in the region in terms of yield loss experienced.

Regional (East) impacts simulated using the AI specification are compared with those simulated using the East-specific response function suggests in Figure 4. It is apparent that climate change impacts on rice

[32] West Bengal accounts for ~42 per cent of regional production share.

yield for East are overestimated with the AI specification compared to that with the East-specific response function – the range of simulated impacts as median impact is greater under the AI specification.

Figure 4: Regional Distribution of Impacts (per cent) for East using AI and East Specifications (1969-2007) (Model 2)



Notes: Red dots show the median impacts for each model specification. Horizontal axis represents impacts (in per cent)

DISCUSSION AND CONCLUSION

This study presents a regional level assessment of climate change impacts on rice crop in India. The study focuses on the dominant Eastern and Southern rice growing regions to assess the regional weather sensitivity of rice yield. The analyses presented in this paper suggest that assessment of climate change impacts at the regional level requires region-specific estimates of crop yield sensitivity to weather using disaggregated level of information on crop and weather. Using the aggregated (national) level yield response function, however, systematically overestimates the regional impacts – yield losses estimated for South and East using national yield response function are 21.6 and 15.4 per cent respectively as against 8 and 5 per cent simulated using the region-specific yield response functions. Consequently, the impacts-based rankings of adversely affected geographies (states) tend to be different for the all-India response function and the region-specific response function. Further, distribution of districts across various impacts categories (e.g., Low, Medium, High etc.) under the two response functions are likely to be different having implications towards climate change adaptation planning. Limited ability of the aggregate-level response function to capture region-specific characteristics such as region-specific growing season window of the crop (and thereby the region-specific average behaviour of farmers) could be seen as an important reasons for such overestimation.

The retrospective impacts calculations based on the simulation analysis of the study suggest that Southern (Eastern) region has suffered yield losses to the tune of 8 per cent (5 per cent) during 1969-2007 due to past changes in climate in each region. Regional distribution of impacts across districts for the Southern and Eastern regions suggests that majority of districts within each region (59 per cent in South and 90 per cent in East) have suffered yield losses due to past changes in climate. The results suggest that in the Eastern region, the major rice producing states like West Bengal and Odisha have suffered significantly high losses. In the South, Tamil Nadu (the 2nd large producer of rice in the region) suffered the maximum. These findings could have significant implications for the poor, especially in the East that has high incidence of poverty.

REFERENCES

Aggarwal, P. K. and R. K. Mall (2002), "Climate Change and Rice Yields in Diverse Agro-Environments of India. II. Effect of Uncertainties in Scenarios and Crop Models on Impact Assessment", *Climatic Change*, 52(3), 331–343. http://doi.org/10.1023/A:1013714506779

Auffhammer, M., V. Ramanathan and J. R. Vincent (2006), "Integrated Model Shows That Atmospheric Brown Clouds and Greenhouse Gases Have Reduced Rice Harvests in India" *Proceedings of the National Academy of Sciences of the United States of America*, 103(52), 19668–19672. http://doi.org/10.1073/pnas.0609584104

Auffhammer, M., V. Ramanathan and J. R. Vincent (2012), "Climate Change, the Monsoon, and Rice Yield in India", *Climatic Change*, 111(2), 411–424. http://doi.org/10.1007/s10584-011-0208-4

Banerjee, S., S. Das, A. Mukherjee, A. Mukherjee and B. Saikia (2016), "Adaptation Strategies to Combat Climate Change Effect on Rice and Mustard in Eastern India", *Mitigation and Adaptation Strategies for Global Change*, 21(2), 249–261. http://doi.org/10.1007/s11027-014-9595-y

Barnwal, P., and K. Kotani (2013), "Climatic Impacts across Agricultural Crop Yield Distributions: An Application of Quantile Regression on Rice Crops in Andhra Pradesh, India", *Ecological Economics*, 87, 95–109. http://doi.org/10.1016/j.ecolecon.2012.11.024

Baron, C., B. Sultan, M. Balme, B. Sarr, S. Traore, T. Lebel, S. Janicot, and M. Dingkuhn (2005), "From GCM Grid Cell to Agricultural Plot: Scale Issues Affecting Modelling of Climate Impact", *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1463), 2095–2108. http://doi.org/10.1098/rstb.2005.1741

Cline, W. R. (2007), *Global Warming and Agriculture: Impact Estimates by Country*. Center for Global Development, Peterson Institute for International Economics, Washington, DC.

Dasgupta, P., D. Bhattacharjee and A. Kumari (2013), "Socio-economic analysis of climate change impacts on foodgrain production in Indian states", *Environmental Development*, 8, 5–21. http://doi.org/10.1016/j.envdev.2013.06.002

Dash, S. K., R. K. Jenamani, S. R. Kalsi and S. K. Panda (2007), "Some Evidence of Climate Change in Twentieth-Century India", *Climatic Change*, 85(3-4), 299–321. http://doi.org/10.1007/s10584-007-9305-9

Deschênes, O. and M. Greenstone (2007), "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather", *American Economic Review*, 97(1), 354–385. http://doi.org/10.1257/aer.97.1.354

Dinar, A., R. Mendelsohn, R. Evenson, J. Parikh, A. Sanghi, K. S. Kavi Kumar, J. McKinsey and S. Lonergan (1998), "*Measuring the Impact of Climate Change on Indian Agriculture*", The World Bank. http://doi.org/10.1596/0-8213-4192-8

Duncan, J. M. A., J. Dash and P. M. Atkinson (2014), "Spatio-temporal Dynamics in the Phenology of Croplands across the Indo-Gangetic Plains", *Advances in Space Research*, 54(4), 710–725. http://doi.org/10.1016/j.asr.2014.05.003

Guiteras, R. P. (2009), "The Impact of Climate Change on Indian Agriculture", *Unpublished Manuscript.*

Hansen, J. W. and J. W. Jones (2000), "Scaling-up Crop Models for Climate Variability Applications", *Agricultural Systems*, 65(1), 43–72. http://doi.org/10.1016/S0308-521X(00)00025-1

Hausman, J. A. (1978), "Specification Tests in Econometrics", *Econometrica*, 46(6), 1251-1271.

Huda, A. K. S., B. P. Ghildyal, V. S. Tomar and R. C. Jain (1975), "Contribution of Climatic Variables in Predicting Rice Yield", *Agricultural Meteorology*, 15(1), 71–86. http://doi.org/10.1016/0002-1571(75)90019-9

ICRISAT (2012), "District Level Data Documentation: 19 States of India (Apportioned Database) Documentation of Files: 1966-67 to 2007-08", *Village Dynamics in South Asia (VDSA)*, ICRISAT-ICAR-IRRI Collaborative Research Project.

Im, K. S., M. H. Pesaran and Y. Shin (2003), "Testing for Unit roots in Heterogeneous Panels", *Journal of Econometrics*, 115(1), 53–74. http://doi.org/10.1016/S0304-4076(03)00092-7

Indian Council of Agricultural Research (2008), "Crop Calendar of Major Crops", Crop Science Division, Indian Council of Agricultural Research, New Delhi. http://eands.dacnet.nic.in/At_Glance_2008/28-Appendix per cent201V.xls (Accessed on August 18, 2013).

Indian Network for Climate Change Assessment (INCCA) (2010), *Climate Change and India: A 4×4 Assessment – A Sectoral and Regional Analysis for 2030s*, Ministry of Environment and Forests, Government of India.

Krishnamurthy, C. K. B. (2012), "The Distributional Impacts of Climate Change on Indian Agriculture : A Quantile Regression Approach", Working Paper No. 69, Madras School of Economics.

Krishnan, P. and A. V. Surya Rao (2005), "Effects of Genotype and Environment on Seed Yield and Quality of Rice", *The Journal of Agricultural Science*, 143(October), 283. http://doi.org/10.1017/S0021859605005496

Krishnan, P., D. K. Swain, B. Chandra Bhaskar, S. K. Nayak and R. N. Dash (2007), "Impact of Elevated CO2 and Temperature on Rice Yield and Methods of Adaptation as Evaluated by Crop Simulation Studies", *Agriculture, Ecosystems and Environment*, *122*(2), 233–242. http://doi.org/10.1016/j.agee.2007.01.019

Krishnan, P., B. Ramakrishnan, K. R. Reddy and V. R. Reddy (2011), "High-Temperature Effects on Rice Growth, Yield, and Grain Quality", In *Advances in Agronomy* (1st ed., Vol. 111, pp. 87–206), Elsevier Inc.

Kumar, K. S. Kavi (2009), "Climate Sensitivity of Indian Agriculture", Working Paper No. 43, Madras School of Economics.

Kumar, K. S. Kavi (2011), "Climate Sensitivity of Indian Agriculture: Do Spatial Effects Matter?", *Cambridge Journal of Regions, Economy and Society*, 4(2), 221-235.

Kumar, K. S. Kavi. and J. Parikh (2001a), "Indian Agriculture and Climate Sensitivity. *Global Environmental Change*", 11(2), 147–154. http://doi.org/10.1016/S0959-3780(01)00004-8

Kumar, K. S. Kavi. and J. Parikh (2001b), "Socio-economic Impacts of Climate Change on Indian Agriculture", *International Review for Environmental Strategies*, 2(2), 277–293.

Kumar, S. N., P. K. Aggarwal, S. Rani, S. Jain, R. Saxena and N. Chauhan (2011), "Impact of Climate Change on Crop Productivity in Western Ghats, Coastal and Northeastern Regions of India", *Current Science*, 101(3), 332–341.

Kumar, S. N., P. K. Aggarwal, R. Saxena, S. Rani, S. Jain and N. Chauhan (2013), "An Assessment of Regional Vulnerability of Rice to Climate Change in India", *Climatic Change*, 118(3-4), 683–699. http://doi.org/10.1007/s10584-013-0698-3

Lal, M., K. K. Singh, L. S. Rathore, G. Srinivasan and S. A. Saseendran (1998), "Vulnerability of Rice and Wheat Yields in NW India to Future Changes in Climate", *Agricultural and Forest Meteorology*, 89(2), 101–114. http://doi.org/10.1016/S0168-1923(97)00064-6

Lobell, D. B. (2007), "Changes in Diurnal Temperature Range and National Cereal Yields", *Agricultural and Forest Meteorology*, 145(3-4), 229–238. http://doi.org/10.1016/j.agrformet.2007.05.002

Lobell, D. B., W. Schlenker and J. Costa-Roberts (2011), "Climate Trends and Global Crop Production Since 1980", *Science*, 333(6042), 616–620. http://doi.org/10.1126/science.1204531

Lobell, D. B., M. B. Burke, C. Tebaldi, M. D. Mastrandrea, W. P. Falcon, and R. L. Naylor (2008), "Prioritizing Climate Change Adaptation Needs for Food Security in 2030", *Science*, 319(5863), 607–610. http://doi.org/10.1126/science.1152339

Mall, R. K., G. Sonkar, N. K. Sharma and N. Singh (2016), "Impacts of Climate Change on Agriculture Sector in Madhya Pradesh: An Assessment Report" State Knowledge Management Centre on Climate Change (SKMCC), EPCO, Government of Madhya Pradesh.

Manjunath, K. R. and S. Panigrahy (2009) "Spatial Database Generation of the Rice-Cropping Pattern of India using Satellite Remote Sensing Data", *ISPRS Archives XXXVIII-8/W3 Workshop Proceedings: Impact of Climate Change on Agriculture*.

Mendelsohn, R. (2014), "The Impact of Climate Change on Agriculture in Asia. *Journal of Integrative Agriculture*", 13(4), 660–665. http://doi.org/10.1016/ S2095-3119(13)60701-7

Mendelsohn, R., A. Dinar and A. Sanghi (2001), "The Effect of Development on the Climate Sensitivity of Agriculture", *Environment and Development Economics* null (01): 85–101.

Mendelsohn, R., A. Dinar and L. Williams (2006), "The Distributional Impact of Climate Change on Rich and Poor Countries", *Environment and Development Economics*, 11(02), 159. http://doi.org/10.1017/S1355770X05002755

Mitchell, T. D. and P. D. Jones (2005), "An Improved Method of Constructing a Database of Monthly Climate Observations and Associated High-Resolution Grids", *International Journal of Climatology*, 25(6), 693–712. http://doi.org/ 10.1002/joc.1181 Mundlak, Y. (2001), "Production and Supply", *Handbook of Agricultural Economics*, 1, 3-85.

Padma Kumari, B., A. L. Londhe, S. Daniel and D. B. Jadhav (2007), "Observational Evidence of Solar Dimming: Offsetting Surface Warming over India", *Geophysical Research Letters*, 34(21), 1–5. http://doi.org/10.1029/2007 GL031133

Palanisamy, K., C. R. Ranganathan, U. S. Nagothu and K. R. Kakumanu (2014), *Climate Change and Agriculture in India: Studies from Selected River Basins*, Routledge India.

Panigrahy, S., S. S. Ray, K. R. Manjunath, P. S. Pandey, S. K. Sharma, A. Sood, M. Yadav, P. C. Gupta, N. Kundu and J. S. Parihar (2011), "A Spatial Database of Cropping System and its Characteristics to Aid Climate Change Impact Assessment Studies", *Journal of the Indian Society of Remote Sensing*, 39(3), 355–364. http://doi.org/10.1007/s12524-011-0093-3

Pathak, H., J. K. Ladha, P. K. Aggarwal, S. Peng, S. Das, Y. Singh, B. Singh, S. K. Kamra, B. Mishra, A. S. R. A. S. Sastri, H. P. Aggarwal, D. K. Das and R. K. Gupta (2003), "Trends of Climatic Potential and On-Farm Yields of Rice and Wheat in the Indo-Gangetic Plains", *Field Crops Research*, 80(3), 223–234. http://doi.org/10.1016/S0378-4290(02)00194-6

Pattanayak, A. and K. S. Kavi Kumar (2014), "Weather Sensitivity of Rice Yield: Evidence from India", *Climate Change Economics*, 5(04), 1450011.

Rajeevan, M., J. Bhate, J. D. Kale and B. Lal (2005), "Development of a High Resolution Daily Gridded Rainfall Data for the Indian Region", *Met. Monograph Climatology*, 22/2005, National Climate Center, India Meteorological Department, Pune.

Rathore, L. S., S. D. Attri and A. K. Jaswal. (2013), "State Level Climate Change Trends in India", *Metorological Monograph*, No. ESSO/IMD/EMRC/02/2013, India Meteorological Department, Ministry of Earth Sciences, Government of India.

Saravanakumar, V. (2015), "Impact of Climate Change on Yield of Major Food Crops in Tamil Nadu, India", SANDEE Working Paper No. 91-15, South Asian Network for Development and Environmental Economics (SANDEE), Kathmandu, Nepal.

Sanghi, A. and R. Mendelsohn (2008), "The Impacts of Global Warming on Farmers in Brazil and India", *Global Environmental Change* 18 (4): 655–65. doi:10.1016/j.gloenvcha.2008.06.008.

Schlenker, W., W. M. Hanemann and A. C. Fisher (2005), "Will US Agriculture really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach", *The American Economic Review*, 95(1989), 395–406. http://doi.org/10.1126/science.151.3712.867-a

Schlenker, W. and M. J. Roberts (2009), "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change", *Proceedings of the National Academy of Sciences of the United States of America*, 106(37), 15594–15598. http://doi.org/10.1073/pnas.0906865106

Sharma, S. D. (2010), Rice: Origin, Antiquity and History, CRC Press: Taylor and Francis Group.

Srivastava, A. K., M. Rajeevan and S. R. Kshirsagar (2009), "Development of a High Resolution Daily Gridded Temperature Data Set (1969–2005) for the Indian Region", *Atmospheric Science Letters*, 10(4), 249-254.

Teixeira, E. I., G. Fischer, H. van Velthuizen, C. Walter and F. Ewert (2013), "Global hot-spots of heat stress on agricultural crops due to climate change", *Agricultural and Forest Meteorology*, 170, 206–215. http://doi.org/10.1016/j.agrformet.2011.09.002

Vanschoenwinkel, J. and S. van Passel (2015), "Do Western and Eastern Europe have the same agricultural climate response?:The importance of a large adaptive capacity", Unpublished Manuscript.

Wang, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle and L. Zhang (2009), "The impact of climate change on China's agriculture", *Agricultural Economics*, 40(3), 323–337. http://doi.org/10.1111/j.1574-0862.2009. 00379.x

Wassmann, R., S. V. K. Jagadish, K. Sumfleth, H. Pathak, G. Howell, A. Ismail, R. Serraj, E. Redona, R. K. Singh and S. Heuer (2009), "Chapter 3 Regional Vulnerability of Climate Change Impacts on Asian Rice Production and Scope for Adaptation", Advances in Agronomy (Vol. 102), 91-133.

Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., and Dawe, D. (2010), "Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures", *Proceedings of the National Academy of Sciences of the United States of America*, 107(33), 14562–14567.

Wooldridge, J. M. (2010), *Econometric analysis of cross section and panel data*. The MIT Press: Cambridge, Mass.

MSE Monographs

* Monograph 24/2013
  Estimation and Forecast of Wood Demand and Supply in Tamilandu
  K.S. Kavi Kumar, Brinda Viswanathan and Zareena Begum I

* Monograph 25/2013
  Enumeration of Crafts Persons in India
  Brinda Viswanathan

* Monograph 26/2013
  Medical Tourism in India: Progress, Opportunities and Challenges
  K.R.Shanmugam

* Monograph 27/2014
  Appraisal of Priority Sector Lending by Commercial Banks in India
  C. Bhujanga Rao

* Monograph 28/2014
  Fiscal Instruments for Climate Friendly Industrial Development in Tamil Nadu
  D.K. Srivastava, K.R. Shanmugam, K.S. Kavi Kumar and Madhuri Saripalle

* Monograph 29/2014
  Prevalence of Undernutrition and Evidence on Interventions: Challenges for India
  Brinda Viswanathan

* Monograph 30/2014
  Counting The Poor: Measurement And Other Issues
  C. Rangarajan and S. Mahendra Dev

* Monograph 31/2015
  Technology and Economy for National Development: Technology Leads to Nonlinear Growth
  Dr. A. P. J. Abdul Kalam, Former President of India

* Monograph 32/2015
  India and the International Financial System
  Raghuram Rajan

* Monograph 33/2015
  Fourteenth Finance Commission: Continuity, Change and Way Forward
  Y.V. Reddy

* Monograph 34/2015
  Farm Production Diversity, Household Dietary Diversity and Women's BMI: A Study of Rural Indian Farm Households
  Brinda Viswanathan

* Monograph 35/2016
  Valuation of Coastal and Marine Ecosystem Services in India: Macro Assessment
  K. S. Kavi Kumar, Lavanya Ravikanth Anneboina, Ramachandra Bhatta, P. Naren, Megha Nath, Abhijit Sharan, Pranab Mukhopadhyay, Santadas Ghosh, Vanessa da Costa, Sulochana Pednekar

MSE Working Papers
Recent Issues

* Working Paper 153/2016
  Asymmetric Impact of Relative Price Shocks in Presence of Trend Inflation
  Sartaj Rasool Rather

* Working Paper 154/2016
  Triggers And Barriers for ‘Exclusion’ to ‘Inclusion’ in the Financial Sector: A Country-Wise Scrutiny
  Keshav Sood and Shrabani Mukherjee

* Working Paper 155/2017
  Evaluation Index System (EIS) for the Ecological- Economic- Social Performances of Ousteri Wetland Across Puducherry and Tamil Nadu
  Zareena Begum Irfan, Venkatachalam. L, Jayakumar and Satarupa Rakshit

* Working Paper 156/2017
  Examining The Land Use Change Of The Ousteri Wetland Using The Land Use Dynamic Degree Mode
  Zareena Begum Irfan, Venkatachalam. L, Jayakumar and Satarupa Rakshit

* Working Paper 157/2017
  Child Work and Schooling in Rural North India What Does Time Use Data Say About Tradeoffs and Drivers of Human Capital Investment?
  Sudha Narayanan and Sowmya Dhanaraj

* Working Paper 158/2017
  Trade, Financial Flows and Stock Market Interdependence: Evidence from Asian Markets
  Sowmya Dhanaraj, Arun Kumar Gopalaswamy and M. Suresh Babu

* Working Paper 159/2017
  Export Performance, Innovation, And Productivity In Indian Manufacturing Firms
  Santosh K. Sahu, Sunder Ramaswamy and Abishek Choutagunta

* Working Paper 160/2017
  An Alternative Argument of Green Solow Model in Developing Economy Context
  Santosh K. Sahu, Arjun Shatrunjay

* Working Paper 161/2017
  Technical Efficiency of Agricultural Production in India: Evidence from REDS Survey
  Santosh K. Sahu, Arjun Shatrunjay

---

* Working papers are downloadable from MSE website http://www.mse.ac.in
$ Restricted circulation