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Addressing the uncertainties associated in assessing the impacts of climate change on agricultural crop production using model simulations

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Projections of current and future (SRES A2) climates from the three GCMs (ECHAM5, GFDL CM 2.1 and HadCM3) in the Couple Model Intercomparison Project (CMIP3) database assessed by IPCC were selected to study the impacts of climate change on paddy rice yields over India. Model projections are important way to study the potential impacts of future projected climate change on crop production. Such assessments are subjected to a range of uncertainties arising from climate and crop models, initial conditions and emissions. On the basis of uncertainties in the impact assessment, this article summarizes the sources of uncertainty and methods focusing on processing the uncertainties. Peculiar to this exercise is to improve the level of confidence in assessment of climate change impacts on crop production. The EPIC crop simulation model regularly failed to simulate viable crop yields in the north-western states of India due to erroneously low precipitation and high temperatures in the baseline climate. Changes in paddy rice yields varied from -49 to 100 % in the future when unprocessed climate scenarios were used. However, bias corrected climate data exhibited changes in paddy rice from -75 to -15% across major paddy growing states in India. In the elevated CO_2 simulations paddy rice yields are increasing by 15% to 17.

Keywords: Bias Correction; Climate Change Impact; EPIC; General Circulation Models; Paddy Rice yields; Uncertainty

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INTRODUCTION

Global climate change has emerged as an important environmental challenge due to its potential impacts on the biological systems of planet Earth. The average surface temperature of the earth has increased during the twentieth century by about 0.6°C, and the warmest years in the previous century have occurred within the last decade. Atmospheric CO_2 concentration has risen by more than 30% since pre-industrial times, from equilibrium levels of about 280 ppm in 1880, to the current observed levels of 390 ppm. This increase is the direct result of human activities, primarily fossil fuel burning, cements production, and modified land-use patterns (IPCC, 2007). Current anthropogenic CO_2 emissions into the atmosphere are about 8 GT C year−1, with atmospheric levels increasing by almost 0.5% per year. If present emission patterns continue in the future, atmospheric CO_2 will be doubled by the end of the 21st century relatively to previous values (Vaughan, 2015, Dlugokencky, 2015). Simulations with global climate models (GCMs) suggest that the projected increases in CO_2 will modify the global climate, by causing widespread increase of surface air temperatures; by altering precipitation patterns and the global hydrologic cycle; and by increasing the frequency of severe weather events, such as drought spells and flooding (IPCC, 1996). Due to uncertainties in future emissions and concentrations of greenhouse gases, their net warming effect in the atmosphere, and the response of the climate system, estimates of future temperature change are uncertain. The IPCC made the following projections of future warming (IPCC, 2014): The average surface temperature of the Earth is likely to increase by 1.1-6.4°C by the end of the 21st century, relative to 1980-1990, with a best estimate of 1.8-4.0°C. The average rate of warming over each inhabited continent is very likely to be at least twice as large as that experienced during the 20th century.

The Indian summer and winter monsoons constitute the most spectacular manifestation of regional anomalies in the general circulation of atmosphere resulting from land-sea contrasts and geographical features (Parthasarathy et al., 1993, Annamalai and Hamilton, 2006,Kripalani et al., 2007). The All India Summer monsoon (also known as the southwest monsoon (June to September)) is one of the major climate systems on the Earth influencing large portions of Asia. Southwest monsoon onset, interannual variability and its active-break cycle has large implications on various sectors such as agriculture, economic development, industrial production sustainability, planning & policy formulation. A developing country such as India is highly dependent on monsoon rains (especially the summer monsoon which contributes 70% of annual rainfall (Mitra et al., 2002). Despite rapid industrialization and technological advancement in agricultural practices the nation's economy is still highly dependent on spatial and temporal distributions of summer monsoon rainfalls.

Agriculture is the backbone of the Indian economy, as nearly 70% of the population is dependent on agricultural activities for their livelihood. Cereals and pulses are the major sustenance for India's population. Cereals account for 90% of food grains; rice (44%) and wheat (37%) are the main cereals with minor cereals such as maize, sorghum millet etc. (FAO, 2009). Crop production is one of the domains most vulnerable to changing climate (Slingo et al., 2005).

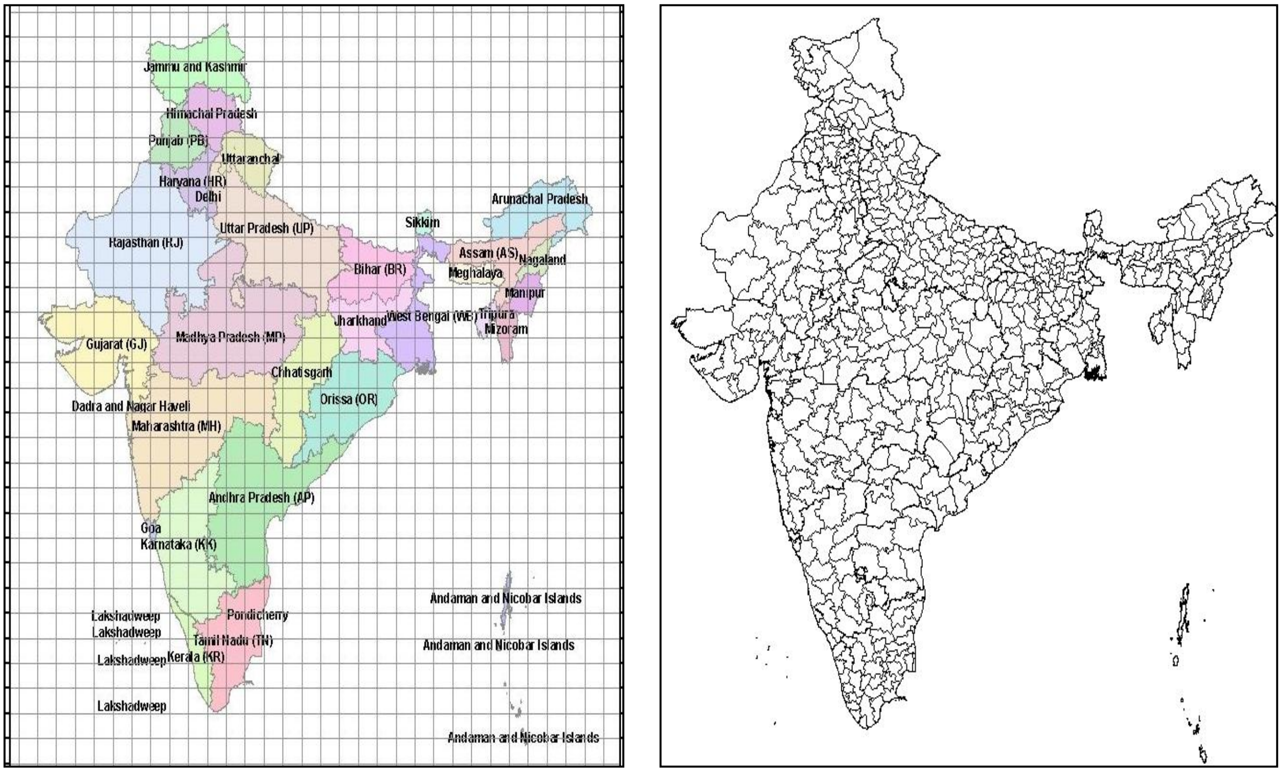
Crop modelling provides a wide range of opportunities to simulate the impacts of different environmental conditions on crop growth, development and yield attributes. Process-based crop simulation models seek to characterize the process of crop growth and development to environmental factors, crop management and genotypic characteristics (e.g., the ''CROPGRO'' model; Boote and Jones 1998, "EPIC" model, Williams, 1995, "GLAM" model, Challinor, et al., 2005). The EPIC crop simulation model is a widely used and tested model for simulation of many agro-ecosystem processes including plant growth, development, yield attributes, weather, soil and agronomic practices.

Climate change scenarios computed with complex atmospheric-ocean coupled models have been extensively deployed to assess the impacts of changing climate for various geographical regions of the world. The current versions of atmospheric-ocean coupled climate models have generally well simulated the features of the current climate at large and continental scales (IPCC, 2007). Coupled climate models are our principal tools for projecting climate change (Houghton et al., 2001). Many researchers (Watterson, 1996; Taylor, 2001; McAvaney, 2001; Piani et al., 2005; Collins et al., 2006; Delworth et al., 2006; Knutti et al., 2006; Shukla et al., 2006; Perkins et al., 2007) have evaluated coupled climate models based on the ability of the climate models to simulate a wide range of diagnostics, including means and variance of key climate variables, past climate and some key phenomenon (e.g. El Niño-Southern Oscillation, monsoons and other specific modes of variability) to provide detailed assessments of the strengths and weakness of major climate models used in the IPCC Third and Fourth Assessment reports. Climate change impacts on crop growth, production are well documented in last few decades due to the potential impacts of climate variability and change. Extensive studies have projected the possible impacts of climate change on crop production using crop models forcing with global and regional climate models (Tao et al., 2003b, 2008b; Parry et al., 2004; Challinor et al., 2005; Xiong et al., 2007). Many studies have assessed crop response to climate change and the possible impacts of future climate change on agricultural production (Rosenzweig et al., 1998; IPCC, 2007). This working paper focus on the potential uncertainty in climate change projections and applying reasonable empirical methods in minimising the uncertainty.

This study examines comprehensive assessments of impacts that better represent the uncertainties associated with climate model projections in addressing potential impacts of climate change scenarios from 3 GCMs on crop productivity over India. The current study focuses on single greenhouse gas emission scenario (A2 SRES) in the future (2080s).

MATERIALS AND METHODS

There are two main components of the research: firstly, we evaluate the GCMs baseline to estimate the associated uncertainty. Secondly, we quantified the impact of climate change on crop production using bias corrected GCMs climate projections.



a b

Figure 1: Maps displaying one degree grid points (a) over Indian states and district locations in India

Study area

The study is conducted in India especially major paddy rice growing states. India is divided into states and union territories that are comprised of a number of districts (Figure 1). The districts are further divided into blocks. The area of Indian states ranges from 3655 km^2 in Goa to 342885 km^2 in Rajasthan; the area of districts varies from 916.66 km^2 to 47822 km^2. Annual reported crop yields at state level were obtained from the Indian Statistics Department (ISD) from 1950 to 2005. Cropping seasons in India are classified into two seasons based on the monsoon; *Kharif* (summer season) is from July to October and *Rabi* (winter season) from October to March.

Crop data

Fifteen states across India were selected based on their agricultural economic contributions towards the total Gross Domestic Product (GDP) of India. At each state, crop yield, production, area and fertilizer application data for paddy rice, groundnut and maize during the period 1969-2002 were collected from the Ministry of Statistics and Programme Implementation (http://www.mospi.gov.in) and Datanet India Pvt. Ltd. (http://www.indiastat.com). Per hectare fertilizer data was calculated by dividing total fertilizer used with total crop area sown in each state. Due to data limitations, it is assumed that fertilizer application is homogenous for all the grid points within the state. The crop management details such as sowing, transplanting, tillage operations and harvest dates were obtained from the Indian Meteorological Department's (IMD) published crop calendars and the state agricultural universities. Crop calendars are prepared based on long-term crop (planting and harvest dates) and climate observations. IMD crop calendars IMD-AGRIMET (2008) are used to determine optimum start and end dates of growth cycles and potential crop combinations under comprehensive consideration of climate and crop growth conditions such as optimal and minimum temperature for plant growth, potential heat unit, growth period, and rain-fed condition. Temperature criteria such as minimum crop temperature, optimal temperature, and potential heat units from planting to physiological maturity have been adopted from EPIC parameter files (Kiniry et al., 1995).

Climate and soil data

The elevation, slope and soil parameters are collected in raster and shape file format (ArcGIS 9x). Soil data for depth, layers, texture (percentage of sand and silt), soil pH, organic carbon content, soil moisture and calcium carbonate were obtained from the National Bureau of Soil Survey & Land Use Planning (NBSS&LUP 2011), Nagpur, India, which represents these soil parameters on a 1:250000 scale. Soil water content at wilting point (WP) and field capacity (FC) were estimated from soil texture in EPIC using the Rawls method (Rawls et al., 1983).

The daily weather inputs used in driving the EPIC crop model are maximum and minimum temperatures and rainfall. The daily 1x1 degree gridded climate datasets of rainfall (1951-2004) and temperatures (1969-2004) were obtained from IMD. Rajeevan et al. (2006) developed the 1-degree gridded rainfall dataset for the Indian region, consisting of 2140 rain gauge stations with 90% data availability during the period 1951-2004. The interpolation method was as proposed by Shepard (1968) based on weights calculated from the distance between the station and the grid point.

Sources of uncertainty

Model simulations are important tools in understand the potential impacts of climate change on agriculture in current and future climates. To understand the possible impacts of climate change on crop production researchers usually couple mechanistic crop models with climate model projections. However, when such analysis is carried-out the uncertainty in the climate model projects along with uncertainties within the crop models cascade and limits our level of confidence in addressing the possible future impacts. Climate model projections for the future are based on one or more emission driven scenarios, the results obtained are relate to certain emission scenario. There are large technical uncertainties associated in estimating the emission scenarios. IPCC narrated emission scenarios are based on the estimates of greenhouse gas (GHG) emissions, future technology, energy usage, population dynamics, economic growth and decisions governments will make relating to GHG emissions.

Crop model

Physiological crop simulation models are applied in a wide range of studies such as seasonal yield forecasting, climate change impacts on crop production and crop management. Depending upon the scientific discipline, there are different types of Crop Simulation Models (hereafter CSMs), ranging from very simple to extremely advance models that include thousands of equations (Hoogenboom, 2000). Different crop models exist across the globe, the crop models that are extensively used in many parts of the world are: DSSAT (Decision Support System for Agro-technology Transfer) modelling system, EPIC (Environmental Policy Integrated Climate) APSIM (Agricultural Production System Simulator) CropSyst, WOFOST (World Food Studies), GLAM (General Large Area Model for Annual Crops) and CENTURY. These crop simulation models require large input data to simulate the crop-climate dynamic, these models vary from each other with respect to their applications and they have their own strengths and limitations. The Environmental Policy Integrated Climate (EPIC) crop simulation model was selected for the study after considering the model with other crop simulation models like DSSAT, APSIM, CropSyst, Century, CropWat and GLAM. DSSAT does not provide a unified model to simulate different crops, instead, it brings together a number of models for specific crops (ISBNAT, 1989), and requires input of genetic coefficients for the crop varieties. Obtaining genetic coefficients for paddy rice, groundnut and maize crops grown in India was difficult as the varieties vary from district to district and in between crop growing states. APSIM, CropWat, CropSyst, WOFOST and GLAM are not suitable for rice simulation because rice parameters are not well calibrated or not included (Keating, et al., 2003, Confalonieri and Bocchi 2005). WOFOST model is sophisticated in describing crop physiology, thus need more detail input data (Monteith, 1996). The Century model is focused on element and material cycles. It is more specifically designed for soil processes such as organic matter, decomposition, nitrification and de-nitrification (Zhang et al., 2002).

Both annual and perennial crops can be modelled with the EPIC crop simulation model. Crops grow from sowing date to harvest date or until the accumulated heat units equal the potential heat units. Heat unit accumulation governs the phenological development of the crop (Williams, 1995).

Climate simulations and CO_2

To explore the sensitivity of CO_2 on modelled yields, two sets of simulations were developed. The current CO_2 atmospheric concentration is 390 ppm. With the current emissions pattern the future, atmospheric CO_2 will be doubled by the end of 21st century. The direct effect of increasing CO_2 concentration on plant growth is of particular interest because of the possibility of increasing crop yields in the future.

Climate model

The coupled models of atmosphere and ocean provide realistic features of the present climate (IPCC 2001). However, there are many concerns in climate projections and many uncertainties on a regional scale. The selections of these models are based on the previous studies of Annamalai et al.,2006 and Sujata et al., 2007.

Based on the above studies three coupled models have been selected for the current study. They are GFDL 2.1, ECHAM and HadCM3. In both the studies GFDL 2.1 ECHAM and HadCM3 performed well in simulating current spatial precipitation pattern over India, hence their selection.

Probability Density Functions (PDFs) were computed for three parameters - precipitation, maximum and minimum temperatures, to assess the uncertainty associated with the coupled climate model projections. Climate model projections were evaluated using PDFs, one of the major advantages of evaluating climate models projections using PDFs is that if the model is able to reproduce the entire PDF, this illustrates the strength of the model in simulating rare extremes and hence gives us more confidence in their projections of future climates.

A simple skill score test was performed to look at the distribution of events in GCMS and observed PDFs. This skill score test measures the similarity between two PDFs across the entire range of bins. It is a simple and robust test that measures the common area between the two PDFs curves (Perkins et al, 2007), and is expressed as

$$S_{score} = \sum_{1}^{n} min\,(f_{obs}\ , f_{sim})$$

Where, S_{score} is the sum of n bins used to calculate the PDFs, and f_{obs}, f_{sim} are the rainfall or temperature frequencies for a given bin in the observations and simulations respectively. Values of S_{score} equal to 1 indicate a high skill score in simulating the distribution. GCM-modelled rainfall is spatially highly variable; performing a skill score based at state level produced very low.

Uncertainty processing methods for impact assessment

The delta method is very simple and widely applied in impact assessment studies (Hijmans et al., 2005). A common application of the delta method will apply monthly changes in temperature and precipitation from aGCM, calculated at the grid scale, to the corresponding observed set of stations or gridded data sets that are the inputs to a crop simulation model. Climate model output is used to determine future change in climate with respect to the model‟s present-day climate, typically a difference for temperature and a percentage change for precipitation. Then, these changes are applied to observed historical climate data (IMD) for input to an impacts model. The delta method assumes that future model biases for both mean and variability will be the same as those in present day simulations. The meteorological variables from the GCMs were used to calculate the changes in temperatures and precipitation (A2 - baseline). The changes in mean monthly climate variables both maximum and minimum temperatures and relative changes in precipitation were computed and the changes in variables are perturbed to the corresponding observed historical variables (Mote and Salathe, 2010). For this study, we have considered IMD gridded dataset and three GCMs simulations of current and future climate. The changes in mean climate (A2 – baseline), calculated for each climate model and calendar month, the changes are applied at daily time scales for the corresponding IMD grid cell, as follows:

$$T_{New} = T_{Obs} + T_{\Delta}$$

Where, $T_{\Delta}$is the mean difference in the GCM simulated temperature from future period to historical period, for each GCM grid cell and perturbations are added to T_{obs}.

The changes in precipitation are computed as given below:

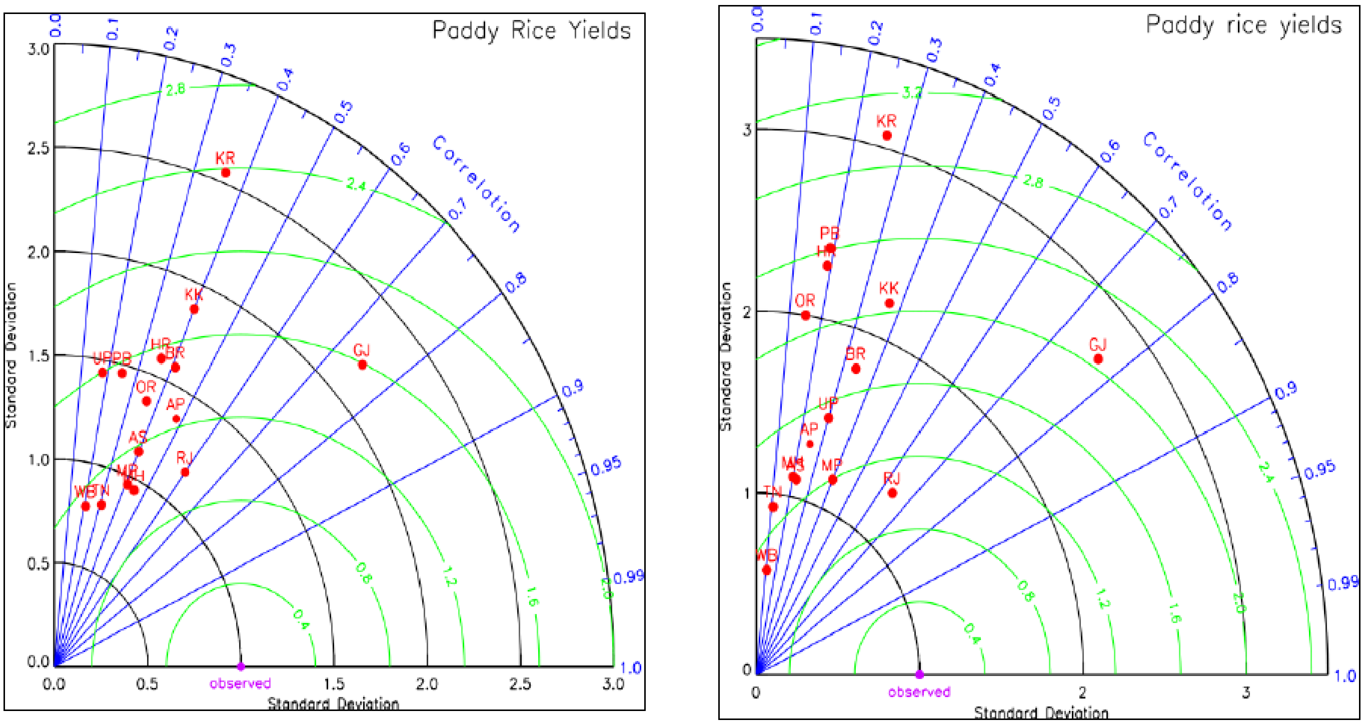
$$P_{New} = P_{Obs} * P_{\Delta}$$

Where, P_{Δ} is the ratio of the GCM simulated mean precipitation from the future (2081-2100) relative to the 20th century (1961-1990) simulations, for each GCMs grid cell. P_{obs} is the observed IMD daily precipitation and the P_{new} is the perturbed changes in IMD precipitation. Multiplicative perturbation is used for precipitation to avoid potential sign problems.

RESULTS

EPIC model validation

The objective of this analysis is to test the performance of EPIC crop model in simulating the historical paddy rice, groundnut and maize yields. Validation of simulated yields is carried out at state level by forcing EPIC to simulate at a resolution of 1x1 degree grid boxes for the years 1969-2002. Validation was performed using *Kharif* (June-October) season simulated paddy rice yields. Crop yields were detrended by fitting a linear regression, to remove the widely known technological trend. Two simulations were carried out across the paddy growing states in India. (1) EPIC-forced to simulate for all the grid points that fall in the state (EPIC_GRID) and (2) the area averaged of IMD data (temperatures and rainfall) for all the grid boxes with in the state are computed to drive the crop model (EPIC_STATE). For evaluating the crop simulation model in the study area various statistics (Goodness of fit) were computed such as mean, standard deviation, coefficient of variation, correlation and root mean square error. Based on the statistical values of both observed and simulated crop yields the performance



EPIC_GRID **EPIC_STATE**

Figure 2: Taylor diagram displaying statistical comparison of observed paddy rice yields with the EPIC simulated paddy rice yields estimates at different paddy rice growing states over India (Blue line indicates the strength of correlation and green line represents RMSE.)

where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India

of the EPIC crop model was evaluated. For a hassle free interpretation of the results Taylor diagrams (Figure 2) were plotted to summarize how close the simulated crop yields were at each crop and its growing states. Paddy rice is extensively cultivated in fifteen Indian states; paddy rice yield simulated using the EPIC at each grid point is aggregated to state level and compared with the observed yields. Some examples of closeness between reported and simulated paddy rice yields are displayed in Figure 3. Observed yields are detrended in a conventional manner using a simple linear regression model to remove the technology influence on crop production, leaving the residuals to indicate the year-to-year variations in yields due to weather. The EPIC simulated crop yields are much higher than the observed yields prior to 2000 and are nearly equal to observed yields after 2000. Simulated yields show better agreement with detrended yields than with observed yields. The EPIC simulated yields (EPIC_STATE) are higher than observed and EPIC simulated yields at each grid point (EPIC_GRID) due to averaging the temperatures, rainfall and soil in the state, in both the simulations the results varied as a function of seasonal climate variations and soil water holding characteristics. Differences between the simulated (EPIC_GRID) and measured yields were within ± 20% of observed detrended yields for paddy rice and ground. While, maize showed a difference of ± 25%. The observed yield was satisfactorily simulated by the EPIC simulation model for major crop growing states in India as presented in Table 1.

Climate model uncertainties

Evaluating the relative skills of coupled models in simulating the broad features of present climatology such as large-scale tropical precipitation pattern in winter (DJF) and summer (JJAS) seasons are the concerns of both climate and impact assessment researchers. Before assessing the impacts of the projected climate change scenarios, the climate models performance skill in the region is to be evaluated as a primary footstep. The observed (IMD) mean summer monsoon rainfall (JJAS) for the period 1951-2004 is 1003 mm with a standard

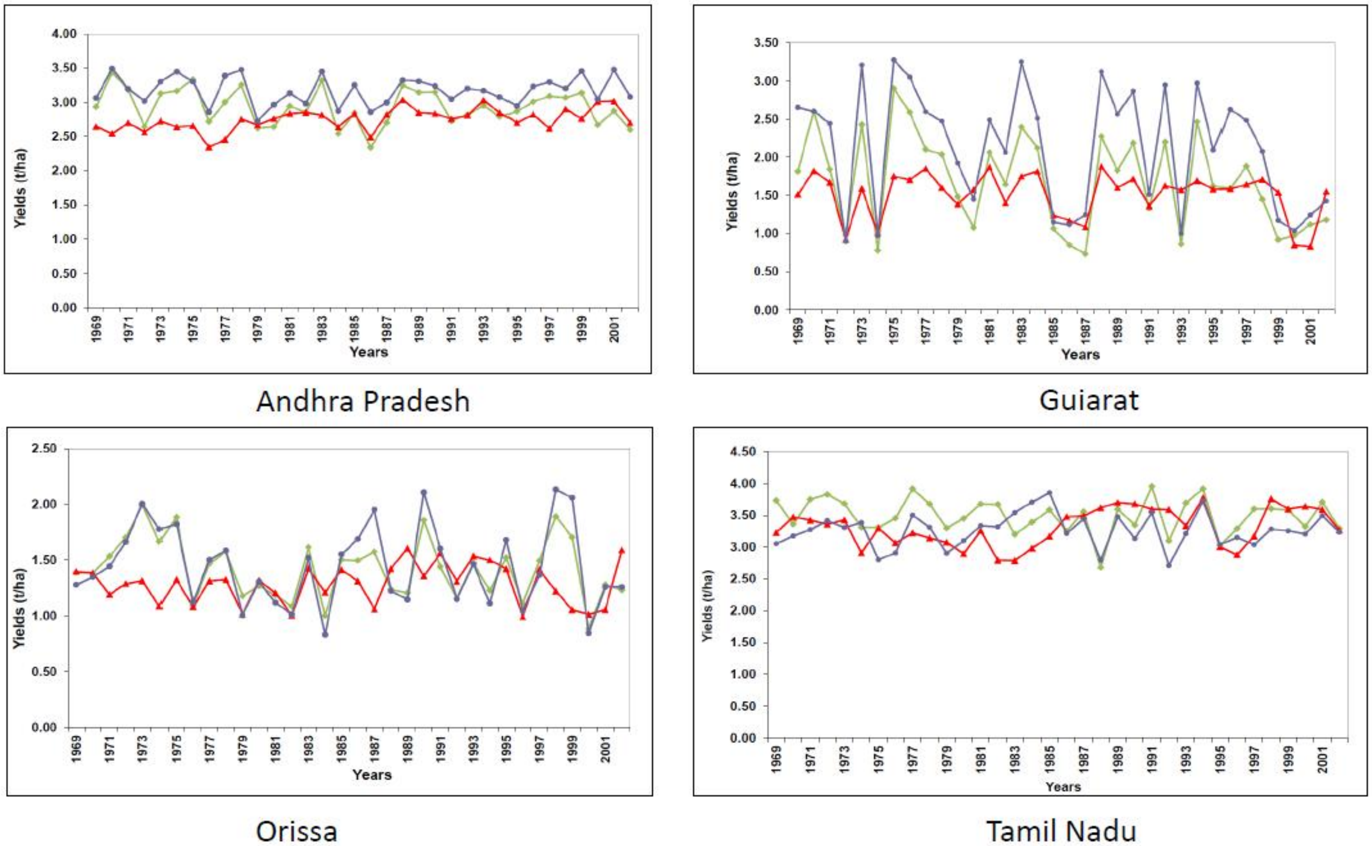


Figure 3 : Comparison of detrended observed (red line) and EPIC modelled paddy riced yields during the period 1969 -2002).Green and blue lines represents EPIC simulated paddy rice yields EPIC_GRID) EPIC_STATE respectively.

deviation of 122 mm. While GFDL simulated mean summer monsoon rainfall over India (1961-1990) is 1076 mm with a standard deviation of 232 mm. ECHAM modelled mean summer monsoon rainfall over India is 808 mm with a standard deviation of 165 mm. While, HadCM3 climate model is underestimating the summer monsoon rainfall over India, the mean summer monsoon rainfall (1961-1990) is 694 mm with a standard deviation of 161 mm. Probability Density Functions (PDFs) were computed for three parameters, precipitation, maximum and minimum temperatures to assess the uncertainty associated with the coupled climate model projections. The strength of climate model in simulating the entire PDF is more skilful test than the annual/seasonal mean and standard deviation. The selection of variables is based on the inputs required for crop model, and the importance of the variables in crop growth and development. The comparisons of observed and simulated precipitation PDFs are presented in Figure 4. The daily values below 2.5 mm are omitted to remove non-rainy days from comparison following IMD standards. GCMs modelled rainfall is spatially highly variable; performing a skill score based at state level produced very low skill scores (Table 2) due to the aggregation of grids at state level. Hence, the skill score test was performed at country level by taking the area average precipitation from both the GCMs and IMD datasets. The skill score obtained at country level for three GCMs are: 0.80 (GFDL), 0.98 (ECHAM) and 0.96 (HadCM3).

Overall, the climate models simulated mean surface temperature are in good agreement with IMD observations as presented in Table 3. Overall performance of the climate model varies from variable to variable in the region, all the three climate models shows a poor skill in simulating the monsoon precipitation over the Indian-sub continent. The GFDL skill score for precipitation was found to be better than the other two climate models. However, the GFDL has underestimated surface temperatures in most parts of India. ECHAM and HadCM3 showed poor skill in reproducing the current precipitation conditions over India, but both the models performance in reproducing current surface temperature was satisfactory.

Impressions of climate change on agricultural crop yields

Assessment of climate change induced future yield

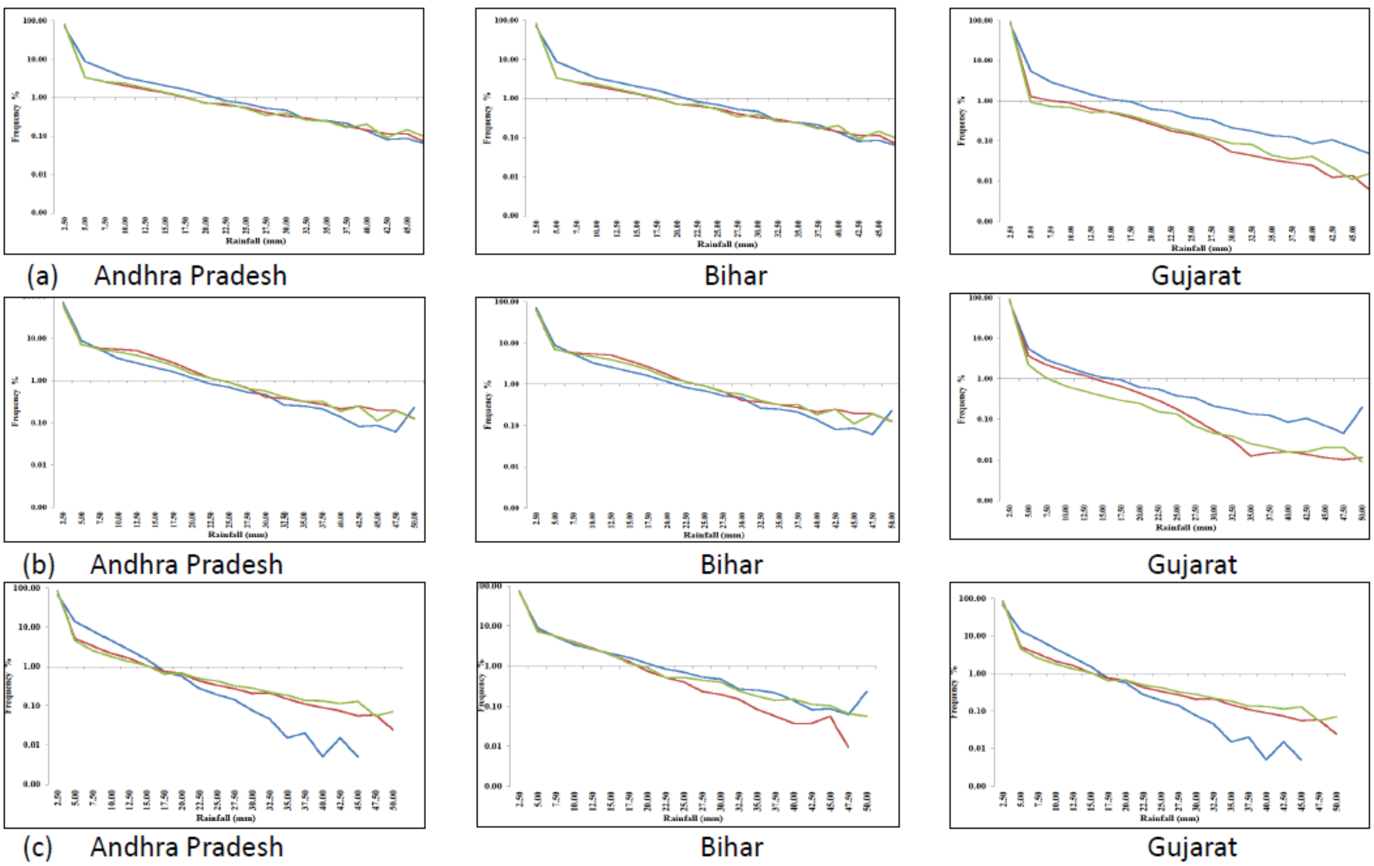


Figure 4: (a) Probability density functions of ECHAM5 modelled (Baseline: red, SRES A2: green) and observed (IMD: blue) rainfall, **(b)** Probability density functions of GFDL modelled (Baseline: red, SRES A2: green) and observed (IMD: blue) rainfall, **(c)** Probability density functions of HadCM3 modelled (Baseline: red, SRES A2: green) and observed (IMD: blue) rainfall

variations is addressed by forcing EPIC with climate model simulated climate for the baseline (1961-1990) and SRES A2 (2071-2100). IMD forced EPIC paddy rice yields in the region ranges from 0.96 to 3.99 t/ha, in contrast the observed detrended yields ranges from 1.11 to 3.49 t/ha. The paddy rice yields simulated with EPIC crop model, driven with ECHAM5 baseline (1961-1990) ranges from 0.77 to 2.76 t/ha. Paddy rice yields simulated with ECHAM5 baseline climate are much lower than the observed and IMD simulated yields in the region due to poor precipitation amounts simulated by the climate model in the region.For instance, simulated paddy rice yields at Gujarat (GJ), Haryana (HR), Uttar Pradesh (UP) and West Bengal (WB) are far below the observed and IMD simulated yields (Figure 5). The climate model underestimates precipitation amounts in these states, at Gujarat the observed mean summer monsoon (JJAS) rainfall amount is 700 mm, while the ECHAM5 simulated rainfall amount is 200 mm.

Simulated average paddy rice yields for the baseline (GFDL) ranges from 0.76 to 2.75 t/ha. The GFDL forced EPIC paddy rice yields in the region are very low at states such as Assam (AS), Gujarat (GJ), Haryana (HR), Punjab (PB), Tamil Nadu (TN) and Uttar Pradesh (UP). The GFDL climate model underestimates the surface temperatures in the above states. At Assam, the modelled precipitation is nearly representing the observed precipitation amounts with high year-to-year variability. The average recorded maximum and minimum temperatures at Assam were 32° and 20°C respectively, while the GFDL modelled day and night temperatures are 17.5° and 10°C. Due to lower temperatures simulated in the baseline climate at Assam, potential heat units required to complete the growth stages are not attained.

EPIC simulated paddy rice yields driven with HadCM3 modelled baseline climate for India were very low compared to IMD forced EPIC yields. Paddy crop suffered substantial water and temperature stress during the growing period, because of the poor representation of the observed climatology. The crop model failed to simulate viable yields at Bihar, Gujarat, Haryana and Punjab sates. At Bihar state the climate model underestimates surface temperatures, very low temperatures were modelled for the baseline simulation

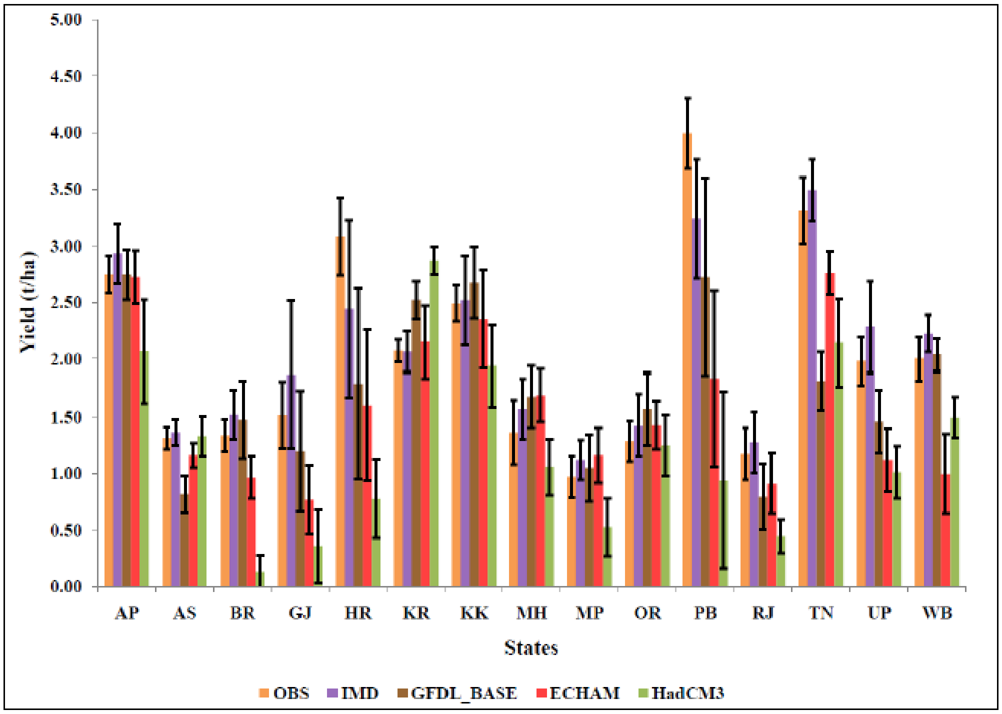


Figure 5: Comparison of mean and associated inter-annual variability (error bars) in simulated paddy rice yields driven using AOGCMs baseline climate with observed *where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India*

Table 1: The mean, standard deviation (SD), coefficient of variation (CV %), correlation coefficient (r) ($p \leq 0.05$) and root mean square error (RMSE) (degrees of freedom 31) of detrended observed and simulated paddy rice yields

Detrended yields (t/ha)				EPIC_GRID (t/ha)					EPIC_STATE (t/ha)				
	Mean	SD	CV%	Mean	SD	CV%	R	RMSE	Mean	SD	CV%	r	RMSE
AP	2.75	0.16	5.89	2.84	0.22	7.78	0.48	0.22	3.17	0.21	6.52	0.25	0.48
AS	1.31	0.10	7.39	1.38	0.11	8.01	0.40	0.13	1.39	0.11	6.52	0.22	0.17
BR	1.34	0.14	10.65	1.49	0.22	15.11	0.41	0.26	1.57	0.25	15.69	0.34	0.33
GJ	1.51	0.29	19.44	1.87	0.65	34.68	0.75	0.58	2.13	0.79	36.92	0.77	0.85
HR	3.09	0.34	11.12	2.80	0.55	19.51	0.36	0.60	2.59	0.78	29.95	0.19	0.94
KR	2.49	0.15	6.19	2.52	0.39	15.59	0.36	0.36	2.71	0.46	17.11	0.26	0.49
KK	2.08	0.10	4.83	2.09	0.19	9.02	0.40	0.17	2.21	0.22	9.76	0.37	0.30
MP	0.97	0.18	18.65	1.12	0.17	15.55	0.41	0.24	1.03	0.21	20.37	0.40	0.22
MH	1.36	0.28	20.78	1.51	0.27	17.90	0.45	0.32	1.47	0.31	21.00	0.20	0.38
OR	1.29	0.18	14.10	1.39	0.25	17.87	0.36	0.26	1.44	0.36	25.04	0.15	0.41
PB	3.99	0.31	7.77	3.38	0.45	13.40	0.25	0.78	3.04	0.74	24.43	0.19	1.28
RJ	1.17	0.23	19.70	1.27	0.27	21.19	0.60	0.25	1.10	0.30	27.33	0.64	0.24
TN	3.31	0.29	8.80	3.52	0.24	6.76	0.31	0.37	3.26	0.27	8.20	0.11	0.39
UP	1.98	0.21	10.57	2.27	0.30	13.33	0.18	0.43	1.59	0.31	19.24	0.30	0.50
WB	2.01	0.19	9.46	2.14	0.15	7.01	0.21	0.25	2.31	0.11	4.96	0.11	0.38

Table 1: PDF based skill score for precipitation for each climate model averaged over each state in India

State	GFDL	ECHAM	HadCM3
AP	0.19	0.20	0.18
AS	0.40	0.38	0.33
BR	0.22	0.18	0.18
GJ	0.06	0.02	0.04
HR	0.08	0.07	0.07
KK	0.18	0.20	0.17
KR	0.28	0.30	0.23
MH	0.16	0.18	0.14
MP	0.14	0.15	0.12
OR	0.21	0.23	0.21
PB	0.16	0.06	0.07
RJ	0.07	0.05	0.03
TN	0.17	0.16	0.13
UP	0.17	0.15	0.16
WB	0.22	0.19	0.26

Table 2: PDF based skill score for mean temperature for each climate model averaged over each state in India

State	GFDL	ECHAM	HadCM3
AP	0.75	0.87	0.68
AS	0.36	0.69	0.32
BR	0.61	0.65	0.31
GJ	0.83	0.72	0.80
HR	0.23	0.53	0.17
KK	0.82	0.69	0.46
KR	0.50	0.30	0.20
MH	0.89	0.74	0.89
MP	0.87	0.79	0.84
OR	0.86	0.77	0.66
PB	0.79	0.56	0.75
RJ	0.80	0.66	0.82
TN	0.82	0.66	0.86
UP	0.75	0.64	0.57
WB	0.86	0.59	0.65

where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India

and as a result the crop model simulated severe temperature stress and most of the crop plants were

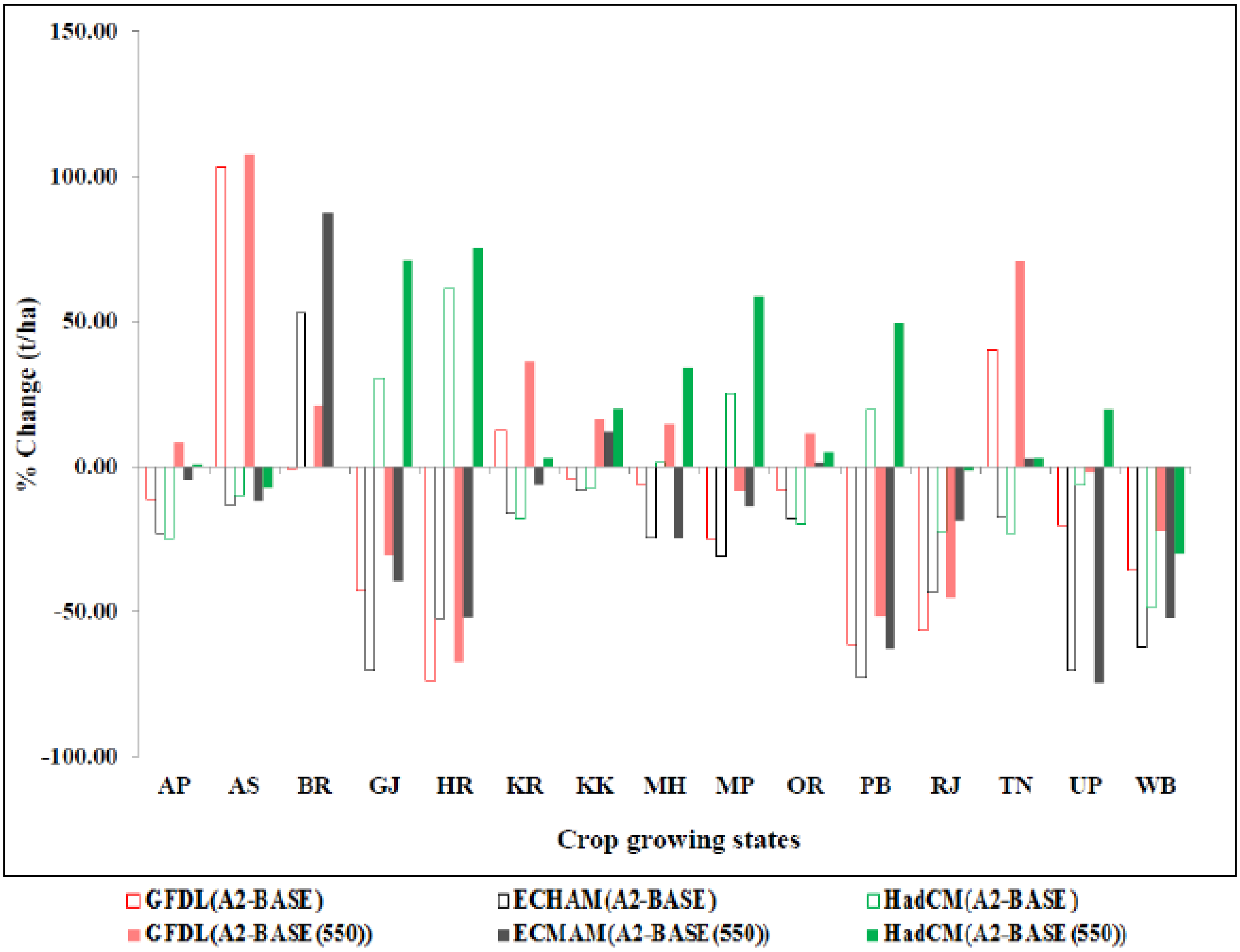


Figure 6: Changes (%) in paddy rice yield with and without CO_2 fertilization in the SRES A2 climate change scenario (compared with the baseline simulated paddy yields)
where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India

damaged due to low temperatures. At Haryana the simulated average seasonal rainfall is 200 mm, Gujarat and Punjab the mean seasonal rainfall modelled is below 130 mm, paddy rice crop suffered from heavy water stress due to the poor rainfall simulated in these locations.

Paddy rice yields decreased dramatically in the future up to -74 %, as displayed in Figure 6. GFDL future projections show a decrease in paddy rice yield in all the states except for AS and TN states. In these states the baseline climate is poorly represented as explained earlier. EPIC modelled paddy rice yields with ECHAM5 showed that paddy rice yields in the future are substantially decreasing except for BR state. ECHAM5 modelled rainfall amounts at Bihar for the baseline scenario is very low compared to the IMD, in the climate change scenario the precipitation amounts are increasing with a marginal increase in temperatures hence paddy rice yields are increasing at Bihar state.

Paddy rice yields are increasing in future projected climate scenarios of HadCM3 in few states, such as Bihar (374%), Gujarat (30%), Haryana (61%), Madhya Pradesh (25%) and Punjab (20%). In other states, crop yields are decreasing from -49 to -6%. At Bihar state, the baseline

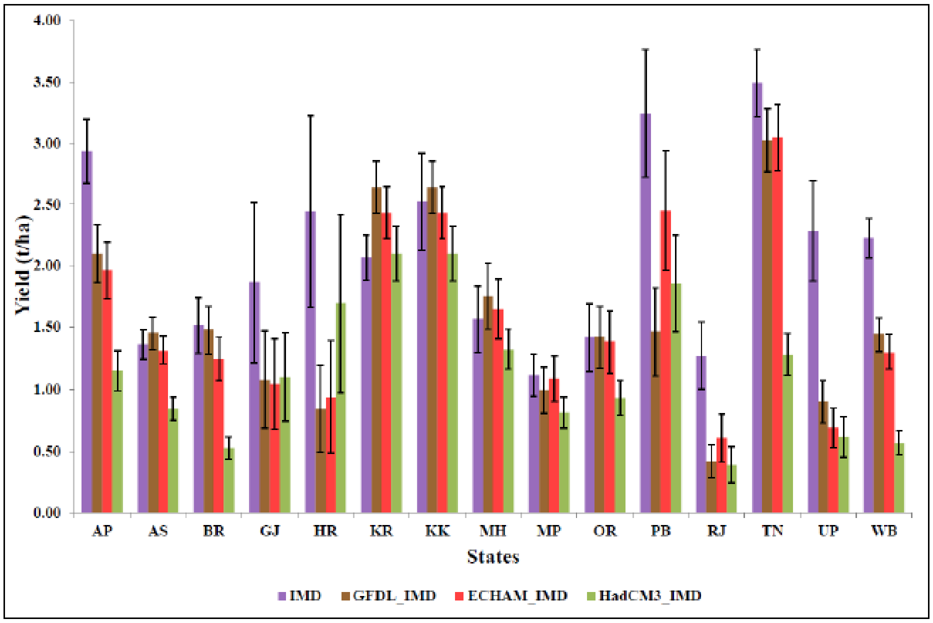


Figure 7: Projected changes in simulated paddy rice yields modelled using three GCMs perturbed climate change scenario (Delta method) over India
where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India

temperatures were very low and as a result, the crop plants were damaged due to frost. In future projected climate scenarios extreme minimum temperature are becoming less frequent and as a result crop yields are increasing as compared to baseline but still below observed yields. HadCM3 modelled low average seasonal precipitation amounts in the baseline scenario (105 mm) at Gujarat, in the future the precipitation amounts are increasing by 100% (237 mm) as compared to the baseline. The observed total average seasonal precipitation at Gujarat is 719 mm; the climate model fails to reproduce the observed precipitation conditions in this state in both the baseline and SRES A2 scenarios. Similarly, at Haryana, Madhya Pradesh and Punjab states simulated future precipitation amounts are considerably increasing compared to the baseline and hence the crop yields are increasing.

When the atmospheric CO_2 concentration is increased to 550 ppm in the EPIC crop simulation model to consider the possible fertilization effect on paddy rice yield for the SRES A2 climate change scenario, it is expected that yields would increase in most parts of India. Only few states show an increase in yields in future projected climate change scenario (A2 550 ppm - Baseline 350 ppm). Most of the paddy rice yields are increasing relative to the lower CO_2 levels in the baseline simulation. A clear direct influence of elevated CO_2 can be measured at states where poor baseline yields were simulated due to the poor estimation of baseline climate in the region. With the CO_2 fertilization effect, paddy rice yield would increase by +20% as compared to without CO_2 fertilization effect.

Uncertainty processing methods

It is noted that the selected GCMs performance in reproducing current climate precipitation was very poor in both spatial and temporal aspects. The GCMs are either underestimating or overestimating the all-India summer monsoon rainfall amounts. ECHAM5 and HadCM3 coupled models were measured to underestimate the precipitation amounts in most parts of India. GFDL is overestimating precipitation amounts. However, underestimating the surface temperatures at the regional scale. Crop simulation models are highly sensitive to the changes in climate input as this data is the key driving factor for the simulated crop yields.

Agricultural impact studies using GCMs simulations as inputs need to define realistic changes in future projected temperatures and precipitation. Unbiased and nearly realistic changes in temperatures and precipitation could be achieved with downscaling.

The simulated crop yields using the perturbed climate are gradually decreasing in the three climate models projected high emission scenario (SRES A2) due to rise in temperatures. HadCM3 showed highest decrease in simulated crop yields followed by ECHAM and GFDL as displayed in Figure 7 and Figure 8. The HadCM3

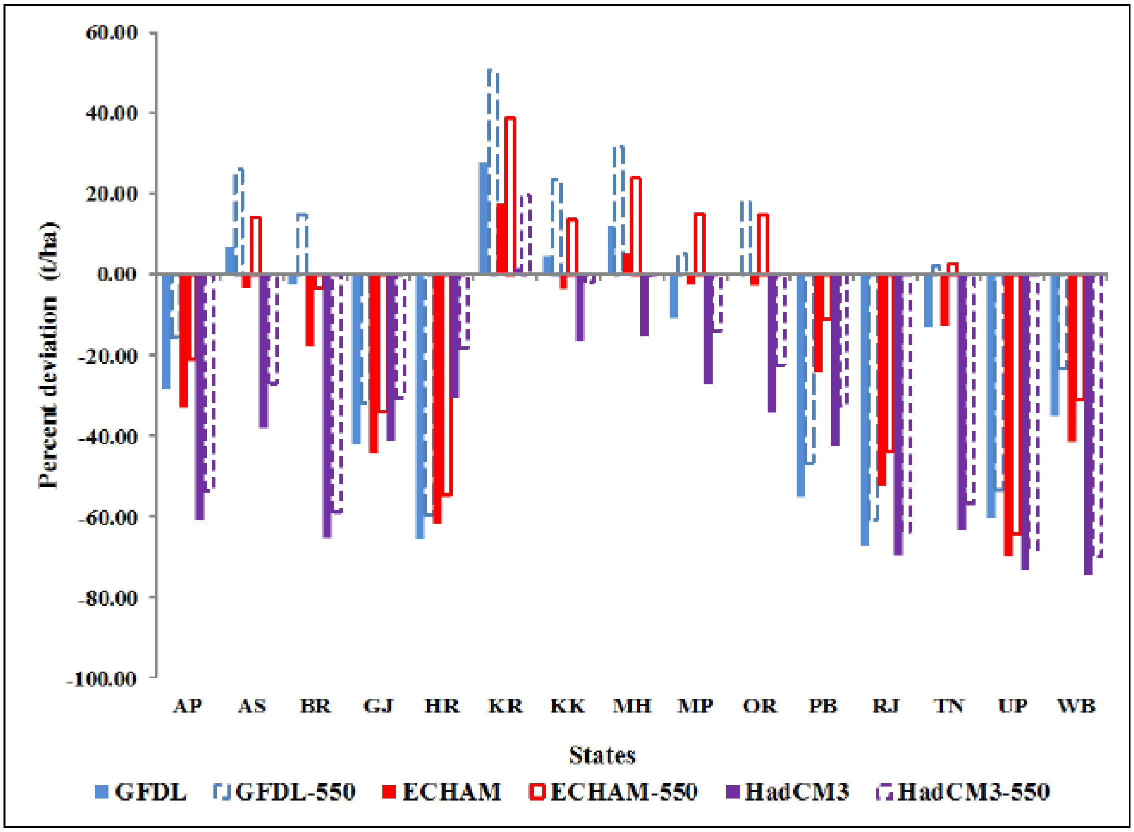


Figure 8: Projected changes in paddy rice yields with and without CO_2 fertilization simulated with the EPIC crop simulation model using perturbed future changes in temperature and precipitation modelled with three GCMs

where, AP: Andhra Pradesh, AS: Assam, BR: Bihar, HR: Haryana, KR: Kerala, KK: Karnataka, MH: Maharashtra, MP: Madhya Pradesh, OR: Orissa, PB: Punjab, RJ: Rajasthan, TN: Tamil Nadu, UP Uttar Pradesh and WB: West Bengal are the major paddy rice growing states in India

modelled maximum temperature in the region is projected to increase from +3°C to +6°C and minimum temperature are increasing by +4°C to +6.5°C.

Temperatures are increasing in all months but the highest increase is measured during the *Kharif* crop reproductive phase i.e., in October and November months. The projected future rainfall is increasing during the monsoon season but it is decreasing during the reproductive phase. The perturbed HadCM3 climate change scenario driven EPIC simulated paddy rice yields in the region are decreasing from -75% to -15%. An increase of 1.44% in paddy rice yields is measured at Kerala state, but the state has only two HadCM3 grid points and the grid points has a landmass around 30% remaining area is under ocean. Most of the HadCM3 grid points over Kerala state fall under ocean and as a result the diurnal temperature range is very small (less than 2°C). The inter-annual variability in HadCM3 perturbed observed climate simulated paddy rice yields is similar to the year-to-year variability in paddy rice yields simulated using IMD observed climate. North Indian states such as Bihar, Gujarat, Punjab, Rajasthan and Uttar Pradesh and Tamil Nadu in the south coast and West Bengal in the east coast show a decrease of 50% or more in HadCM3 perturbed simulated paddy rice yields. At Bihar, Gujarat, Punjab, Rajasthan and Uttar Pradesh the temperatures, both maximum and minimum temperatures were increasing from +4.5° to +7°C and the highest increase is measured during post summer monsoon season i.e., from October to January.

In the elevated CO_2 simulations paddy rice yields are increasing by 15% to 17%. Due to the Rubisco activity in C3 plants in elevated CO_2, simulates higher photosynthetic carbon grain and net primary production and at the same time increases the nitrogen and water use efficiency. As a result, higher grain yields are obtained in the elevated CO_2 simulations using the EPIC crop simulation model.

CONCLUSIONS

The statistical evaluations have indicated that the EPIC simulation model has satisfactorily simulated the corresponding historical crop yields at regional scale. In terms of model validation, better simulation performance (see goodness of fit) is noticed. This indicates, the crop model has the ability to model paddy rice yields across wide range of environments over India. The analysis has highlighted three major points. First, the aggregate production impacts of possible future climate change to 21st century on paddy rice major crop growing states are comparatively modest in the southern states to sever in the north western states of India. A 40% and above decrease in crop yields by the end of 21st century is certainly a serious issue especially in the Northern states like, Gujarat, Haryana Punjab, Rajasthan, Uttar Pradesh. Impacts can certainly be compensated with plant breeding and technological interventions up to certain extend (Pardey and Beintema, 2001).

Second, the aggregated results at state level hide enormous uncertainty due to poor representation of baseline climate. Downscaled and bias correct the baseline and future climate projections has improved the results and builds confidence in addressing possible potential impacts of climate change on agricultural production. In some areas, increased yields may allow intensification of agriculture and concomitant increase in rural wealth. However, in areas where a yield reduction is expected to be sever, considerable disruption to rural life may occur. Third, results indicate that with increase in surface temperatures along with inter-annual variability of precipitation crop yields are decreasing severely, poses treat to small holder farmers in the region.

In general, the results indicate that the uncertainty in the GCMs projected future climate change scenario during the growing season represent a greater source of uncertainty. The findings show that the future precipitation changes will be far greater relative to year-to-year variability. While, the surface temperatures are dramatically increasing up to 6.5°C by the end of the century. Impact of temperature uncertainties, and in particular the uncertainties in crop response to temperature, should receive increased attention.

In the future, actual yield changes will reflect the combined influence of the (generally negative) effects of warming and the potentially positive effects of management, technology, and elevated atmospheric CO_2. The effects of elevated atmospheric CO_2 on perennial crops are not well known, as few experiments have been conducted (Bindi et al., 2001 and Idso and Kimball, 2001). The projections presented in this study may be used to guide future adaptation efforts, for instance by concentrating efforts on developing heat tolerant varieties. Therefore, long-term losses may largely be avoidable with strategic crop adaptation measures.

The reliability of impacts of climate change on agricultural crops increases with the accuracy of simulated baseline yields. The poor simulated crop yield in a baseline scenario reduces confidence in assessing the impacts of future projected climate change on crop yields. In order to improve reliability, bias correction method should be applied to assess the impacts of climate change on crops. The results from the analysis conclude that instead of forcing the crop models with the raw climate model projections, climate data need to be processed to remove the associated bias in simulated climate for better impacts assessment.

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