Climate change impact analysis using bias-corrected multiple global climate models on rice and wheat yield

Madhuri Dubey, Ashok Mishra and Rajendra Singh

ABSTRACT

Rice and wheat, two staple food grain crops, play a key role in farmers' income and food security. The response of these crops towards climate change is heterogeneous and uncertain. Therefore, it becomes essential to analyse the impact of climate change on these crops. An investigation was performed to analyse the impact of climate change on rice and wheat yield and to quantify the uncertainties in the yield predictions in West Bengal, India. The climatic projections from eight global climate models were used to simulate the rice and wheat yields in all districts of West Bengal. A quantile mapping method was used to correct systematic biases of daily rainfall, solar radiation and temperature. The corrected data were then used for driving crop environment and resource synthesis models for yield simulations. Results reveal that rice yield is expected to reduce by 7–9% in the 2020s, 8–14% in the 2050s and 8–15% in the 2080s, whereas wheat yield is expected to go down by 18–20% in the 2020s, 20–28% in the 2050s and 18–33% in the 2080s. These reductions signify that rice and wheat yield is more likely to decline under the future climate change condition, which may affect the regional food sustainability.

Key words | CERES, global climate model, quantile mapping method

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HIGHLIGHTS

- GCMs are used to assess the effect of climate change on rice and wheat yield.
- Quantile mapping method is used to correct bias of GCMs outputs.
- DSSAT-CERES for rice and wheat is used for yield prediction.
- Rice and wheat yield is expected to reduce, respectively, up to 15 and 33% by the end of the 21st century in West Bengal.
- Study prompts to develop adaptation for regional food sustainability.

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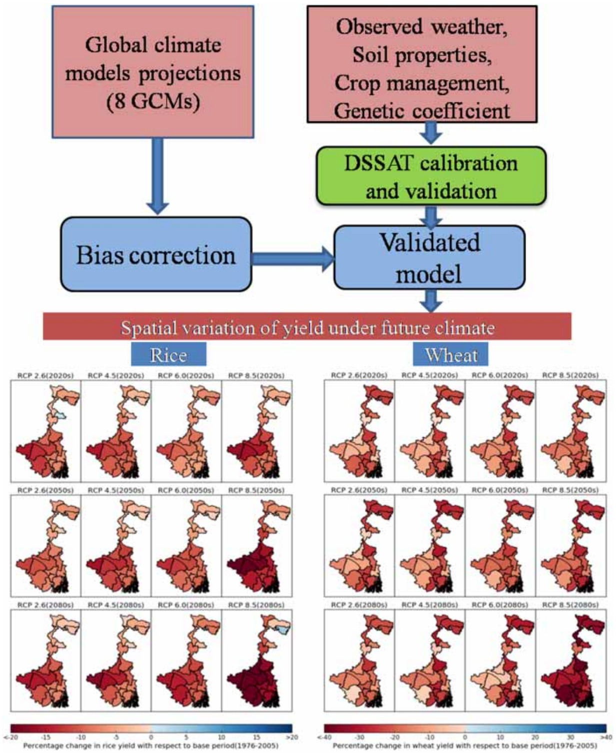
GRAPHICAL ABSTRACT



INTRODUCTION

Global warming is accelerating due to increased atmospheric concentrations of greenhouse gases that depend on natural, direct and indirect anthropogenic activities. This warming leads to changes in magnitude of different weather variables like rainfall, temperature, solar radiation, etc. The global surface temperature has increased in the range of 0.5 to 1.3 °C during 1951 to 2010 and is expected to increase further by 3.7 °C by the end of the century (Stocker *et al.* 2013). As a result, rainfall is likely to change in pattern, frequency and intensity, and will become more intense over the globe in future (Stocker *et al.* 2013). In India, temperatures (minimum and maximum) are projected to increase (Chaturvedi *et al.* 2012), whereas low and medium rainfall events are likely to decrease along with increased frequency of heavy rainfall events by the end of the century (Kundu *et al.* 2014; Pai *et al.* 2015).

Stocker *et al.* (2013) inferred that global surface temperature and rainfall are the most important climatic factors for crop production, and have a substantial effect on agricultural production (Lizumi & Ramankutty 2015). Climate alterations resulting in an increased annual variability of climatic variables have an adverse effect on crop yield around the world (Ceglar & Kajfež-Bogataj 2012; Chun *et al.* 2016; Rao *et al.* 2016). Similarly, rising temperature and uncertain rainfall could decrease water accessibility, crop production, food quality and water use efficiency (Kang *et al.* 2009). Climate change has, thus, the potential to alter crop production in a significant manner. For example, the yields of maize, wheat and other major crops have reduced by 40 MT per year during 1981 to 2002 at the global scale (Lobell & Field 2007).

To analyse the impact of future climate change on crops, it is critical to understand crop behaviour under climate change scenarios. The crop models play an important role as these have the potential to simulate the response of crop growth parameters under various soil, management and climatic conditions (Babel et al. 2011; Banerjee et al. 2016). Among several crop models, the Decision Support System for Agrotechnology Transfer (DSSAT) is one such model being used and tested for the last 30 years by scientists around the world (Fetcher et al. 1991; Alexandrov & Hoogenboom 2001; Baigorria et al. 2007; Babel et al. 2011). It comprises different crop models that are rendered through a single shell. Crop Environment and Resource Synthesis (CERES), Crop Growth (CROPGROW) and other models are available in DSSAT platform for cereals (barley, maize, sorghum, millet, rice and wheat), legumes (dry bean, soybean, peanut and chickpea), root crops (cassava, potato) and other crops (sugarcane, tomato, sunflower and pasture).

Future climate projections, obtained from climate models, are used widely for impact studies because of their ability to represent the climatic variations better as compared to the fixed changes in climate variables. Global climate models (GCMs) are developed to produce projection of climate variables such as precipitation, temperature, wind, etc., based on atmospheric greenhouse gas emissions. GCMs give more accurate facts at large spatial scale that integrate the complicacy of the global system. However, they are unable to catch the characteristics and dynamic of the system at regional scale. A few hypotheses are also formed regarding parameterization and empirical equations in the absence of geophysical process-related information. Consequently, the disparity between observed and simulated climate is referred to as bias, that limits their direct application in crop and hydrological modelling studies. The effect of bias on modelling studies has been widely acknowledged by researchers (Wood et al. 2004; Baigorria et al. 2007; Ghosh & Mujumdar 2009). As direct use of GCM outputs for climate change impact analysis is not capable of predicting the future risks in agriculture, researchers have suggested bias correction of these data before forcing into crop models (Mavromatis & Jones 1999; Challinor et al. 2005, 2017; Glotter et al. 2014).

Uncertainty is also a growing concern in impact studies as it may incapacitate the future estimates (Martre et al. 2015; Guan et al. 2017). There is a significant contribution of climate model in uncertainty involved in climate-crop modelling studies (Kassie et al. 2015; Zhang et al. 2015, 2019). Primary sources of uncertainty in a climate model are model structure and parameter, greenhouse gas emission, misconception about climatic systems and inaccurate assumption of socio-economic-techno and institutional assumptions (Ge et al. 2010). In practice, it is observed that the use of single GCM output in a climate change impact study has higher uncertainty in crop yield prediction (Bachelet et al. 1995; Soora et al. 2013; Shrestha et al. 2016; Rao et al. 2016) that may be reduced by using an ensemble of GCMs (Chaturvedi et al. 2012).

Rice and wheat, two principle food grain crops, are cultivated in a major portion of India and around the world. West Bengal, an important state of India in the context of agriculture, makes a significant contribution to the nation's rice and wheat production. These crops are the source of the basic diet and livelihood of a large population of the state. Thus, to maintain the sustainability of the region under expected climate change, it becomes essential to analyse the impact of climate change on these crops for planning and designing mitigation and adaptation strategies to ensure food security. Keeping this background in view, the objectives of the present study are to set up the Crop Environment and Resource Synthesis (CERES) model for rice and wheat crops using experimental data, and to analyse the impact of climate change on both the crops using bias-corrected GCMs output. Knowledge about all the possible likelihoods of change in crop yield, in future, may assist decision-makers and the farming community to formulate mitigation and adaptation strategies.

MATERIALS AND METHODS

Study area

Field experiments have been conducted at the research farm of Agricultural and Food Engineering Department, Indian Institute of Technology, Kharagpur (22°19′N latitude and 87°19′E longitude) for setting up the CERES models. The climate of Kharagpur is classified as humid and subtropical with an average annual rainfall of about 1,600 mm. The average daily temperature varies between 21 °C in

December/January and 32 °C in May/June. The soil of the farm is red lateritic with sandy loam texture and is taxonomically grouped as 'Haplustalf'. West Bengal, an eastern state of India lying between 21°31′N to 27°14′N latitude and 85°91′E to 89°53′ E longitude (Figure 1) with 19 districts was selected to analyse the climate change impact on rice and wheat yield. The climate of the state lies between tropical wet-dry and humid subtropical from the south to north part of the state. Rice is the most dominant crop in the state followed by potato, jute, sugarcane and wheat.

Data used

Observed and future climate data

Weather variables (rainfall, maximum temperature (T_{max}) and minimum temperature (T_{min})) for the experimental years (2014, 2015, 2016 and 2017) and historical period (1976–2005) at daily scale were collected from the Physics Department of Indian Institute of Technology (IIT), Kharagpur, India. For West Bengal, daily climate data (rainfall, T_{max} and T_{min}) were collected at $1° \times 1°$ spatial scale from India Meteorology Department (IMD), Pune, for the period 1976–2005. Due to the absence of solar radiation data, multi-satellite ensemble data were collected from National Oceanic and Atmospheric Administration (www.noaa.com) and used as measured proxy data after up-scaling to $1° \times 1°$.

Future climate data of daily rainfall, T_{max}, T_{min} and solar radiation were taken from eight GCMs (BCC-CSM1.1 (BC), GFDL-CM3 (GC), IPSL-CM5A-LR (IL), MIROC5 (M5), MIRO-ESM (ME), MIRO-ESM-CHEM (MC), MRI-CGCM3 (MG) and NorESM1-M (NE) for four RCPs (2.6, 4.5, 6.0 and 8.5), belonging to the Coupled Model Intercomparison Project 5 (CMIP5) (cmippcmdi.llnl.gov/cmip5/data_portal.html). These eight GCMs were selected because of consistency in data availability for all four RCP (RCP2.6, 4.5, 6.0 and 8.5) projections. Climate variables were downloaded for historical (1976–2005) and future (2006–2100) period because of climate simulation availability of GCMs' projections as a single freeze (historical) up to 2005 and then from 2006 onward as projected future plausible climate condition by considering four different RCPs (Taylor *et al.* 2012).

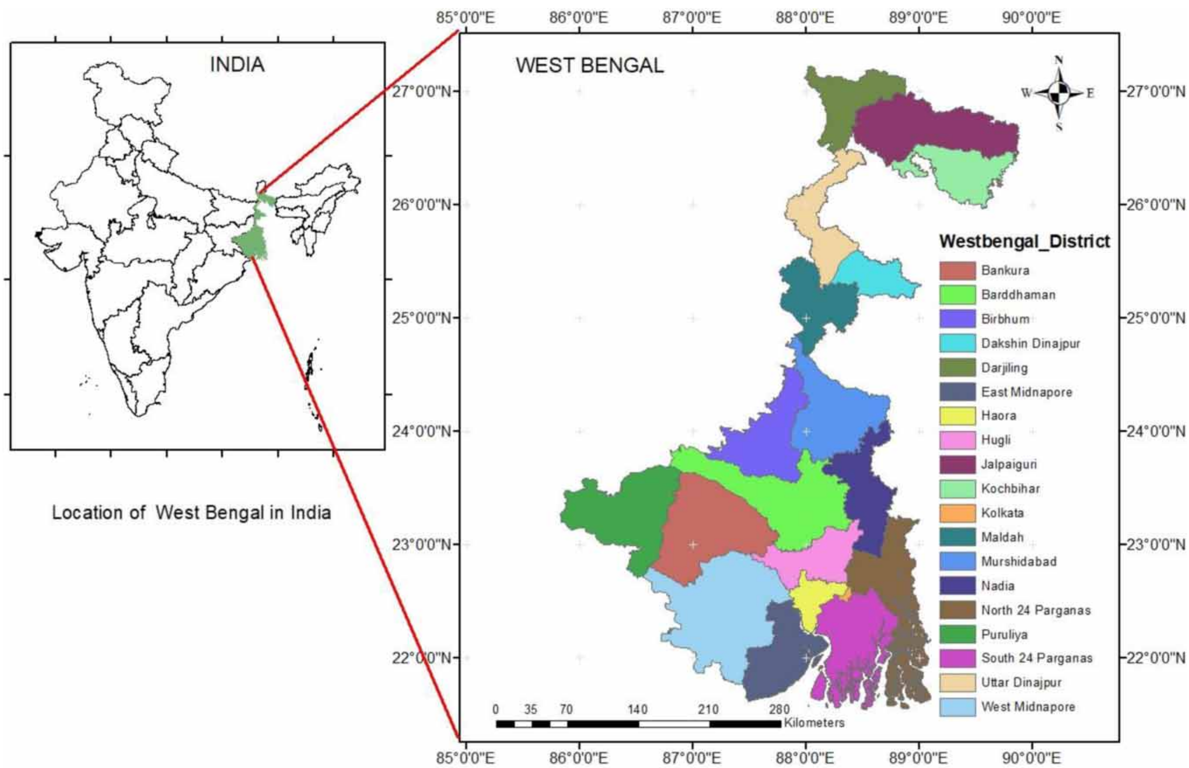


Figure 1 | Index map of the state of West Bengal, India showing spatial extent of its 19 districts.

Crop management and soil data

For calibration and validation of crop models, field observation data were collected during 2014–2017 from the experiments conducted at the Agricultural and Food Engineering Department, IIT Kharagpur farm. The observation data comprise timings for sowing, transplantation, fertilization and irrigation. In this study, IR36 and Sonalika cultivar of rice and wheat, respectively, were used in the experiments. For simulation of rice and wheat yield during the historical period, the recommended dose of fertilizer was applied (FAO 2005; Kaur & Ram 2017). In the case of rice, out of the recommended 120:50:50 kg/ha of N:P:K, the full amount of phosphorus (P) and potassium (K) and one-third the amount of nitrogen (N) were applied at the time of transplanting. The remaining two-thirds of N was top-dressed equally in two halves at tillering and panicle initiation stage. In the case of wheat, from the recommended 100:60:40 kg/ha of N:P:K, the full amount of P and K and one-third amount of N were applied at the time of sowing. The remaining two-thirds of N were applied in two equal parts at crown root initiation and vegetative growth stage. A fixed transplanting date, i.e., 27th June for rice, and a fixed sowing date, i.e., 24th November for wheat, was assumed. The rainfed condition for rice and automated irrigation for wheat were chosen during the model simulation runs. Layer-wise soil information (texture, bulk density, saturated hydraulic conductivity, albedo fraction, runoff curve, organic carbon, etc.) from the Food and Agriculture Organisation available at 5 km × 5 km, was rescaled at $1^\circ \times 1^\circ$ and used in the crop model as input.

Crop model description

CERES model DSSATv4.5 (Jones *et al.* 2003; Hoogenboom *et al.* 2012) for rice and wheat was used for yield simulation of these crops for climate change impact assessment. CERES was chosen because it is an extensively tested and widely used crop model in India (Attri & Rathore 2003; Krishnan *et al.* 2007; Mishra *et al.* 2013a) and across the world (Dubrovsky *et al.* 2000; Baigorria *et al.* 2007; Babel *et al.* 2011). The model simulates crop growth and yield by using weather, soil, soil-plant-atmosphere, and management modules of DSSAT. The CERES model for both rice and wheat was calibrated for two years, i.e., 2014 and 2015, and validated for the next two years, i.e., 2016 and 2017, using weather, soil and crop management data for Kharagpur station. These data were transformed in the DSSAT required format using crop management module, Weatherman module and soil module. Crop management file, an important input file for performing simulation, was created by using field characteristics, soil analysis data, fertilizer application date and amount, irrigation date and quantity, harvesting date and simulation controls. For rice crop, the rainfed condition was adopted and in the case of wheat crop, soil-moisture-based irrigation scheduling was performed by using the temporal soil moisture update. Weatherman was used to create weather files using daily rainfall, T_{max}, T_{min} and solar radiation. Soil module was used to create the soil file for the experimental site using the soil information (texture, bulk density, saturated hydraulic conductivity, albedo fraction, runoff curve and organic carbon) of the area. The observed and simulated anthesis day, maturity day and grain yield for both the crops were compared during calibration and validation. Model performances were evaluated by root mean square error (RMSE) and index of agreement (d) (Willmott 1982) statistics, and are described as below.

Root mean square error (RMSE)

RMSE represents mean absolute difference between observations obtained from experiment and model simulation quantities. It measures the spread of the residual (observed-simulated) around the line of the best fit. In the modelling studies, zero value of RMSE demonstrates ideal representation and minimum value shows better representation of the observed condition.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(S_i - O_i)^2}{n}}$$

Index of agreement (d)

Index of agreement (d) is a descriptive measure of error and represented as the ratio of mean square error and potential error. It is a measure of the degree of model prediction error and varies between 0 and 1. The index value of 1 indicates ideal match and 0 signify disagreement.

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|S_i - O_{avg}\right| + \left|O_i - O_{avg}\right|\right)^2}$$

where S_i and O_i are simulated and observed quantities, respectively, whereas, O_{avg} is the average of observed quantity and n is the number of observations.

GCM data correction

The presence of bias in the GCMs data can misinterpret the modelling results, specifically in regional level impact studies (Feddersen & Andersen 2005; Hansen et al. 2006; Christensen et al. 2008). Hence, in this study, the most widely used technique, i.e., quantile mapping method (QMM), is used for correcting the biases present in GCM outputs (Li et al. 2010; Maraun et al. 2010; Piani et al. 2010). The bias-corrected data for historical and future periods are obtained by mapping the cumulative density functions (CDFs) of GCM data onto the CDFs of observed data (Teutschbein & Seibert 2012). The Gamma, Beta and Gaussian distributions were used for bias correction of GCMs outputs, respectively, rainfall, solar radiation and temperature (Caliao & Zahedi 2000; Watterson & Dix 2003; Ines & Hansen 2006; Wilks 2006; Piani et al. 2010).

Climate change impact assessment and uncertainty analysis

To analyse the climate change impact, the validated crop models were used to simulate rice and wheat yields using bias-corrected GCM outputs for the historical period (1976–2005) and three future periods, i.e., the 2020s (2006–2035), 2050s (2036–2065) and 2080s (2066–2100), and four different climate scenarios (RCP 2.6, 4.5, 6.0 and 8.5) for all ($1° \times 1°$) grids covering West Bengal. The future yield from all GCMs, for three future periods and four RCPs, were compared with the historical (1976–2005) yield at district as well as state level and is presented in terms of per cent change.

The processes involved in developing future climate scenarios (representation of land, ocean and atmospheric features along with atmospheric greenhouse concentrations) contribute to uncertainty in projecting climate change impact. Therefore, uncertainty in the yield prediction (combined climate and crop model) for the future period was captured by showing 95% prediction uncertainty calculated at 2.5 and 97.5 percentiles with the assumption that the data follow a normal distribution.

RESULTS AND DISCUSSION

Calibration and validation of CERES-rice and CERES-wheat

CERES-Rice and CERES-Wheat models are calibrated and validated for Kharagpur station. Tables 1 and 2 present the calibration and validation results for rice and wheat, respectively. As is evident, anthesis and maturity days of both rice and wheat crop are simulated within ±5 days of the observed data, during both calibration and validation periods. Lower RMSE value, i.e., 146 kg/ha and 121 kg/ha were obtained during calibration and validation of the model for rice. In the case of wheat, the model simulated yield with lower RMSE during the calibration and validation period (respectively, 101 kg/ha and 95 kg/ha). Moreover, d also shows that the models perform well during calibration and validation. These results are also in synchronization with previous studies (Satapathy et al. 2014; Mubeen et al. 2019).

Performance of quantile mapping method

Figure 2 presents the monthly variation in rainfall, solar radiation and temperature (maximum and minimum) of eight uncorrected GCM data compared to observed data. The uncorrected GCM outputs showed high variation from the observed data on a monthly scale. It is noticeable that all GCMs underestimate the rainfall except M5, but most of them simulate the changes in the seasonal cycle well. Solar radiation is overestimated by the GCMs, with GCM NE having the highest bias. It is also evident that most of the GCMs either underestimate or overestimate

Table 1 | Calibration and validation results of CERES-rice model

	Calibration				Validation			
	2012		2013		2014		2015	
	OBS	SIM	OBS	SIM	OBS	SIM	OBS	SIM
Anthesis days	58	57	55	59	49	55	52	56
Maturity days	92	95	99	102	99	100	95	98
Grain yield, kg/ha	5,038	5,160	4,186	4,354	4,887	5,018	4,590	4,700
RMSE, kg/ha	146				121			
Index of agreement (d)	0.97				0.85			

Table 2 | Calibration and validation results of CERES-wheat model

	Calibration				Validation			
	2012		2013		2014		2015	
	OBS	SIM	OBS	SIM	OBS	SIM	OBS	SIM
Anthesis days	57	60	55	59	50	54	57	62
Maturity days	98	103	95	100	96	93	95	99
Grain yield, kg/ha	2,685	2,578	2,254	2,341	2,556	2,654	2,723	2,801
RMSE, kg/ha	101				95			
Index of agreement (d)	0.92				0.77			

T_{max} and T_{min}. For the winter season, all GCMs underestimate T_{max}, whereas in the case of the monsoon season, only two GCMs overestimate T_{max} and the rest underestimate T_{max}. In the case of T_{min}, only one GCM in the winter season and two in monsoon season overestimate.

After bias correction of GCM data, monthly variation in climate variables compared to observed data is shown in Figure 3. The monthly mean of corrected data of all GCMs is close to the observed mean, for all climatic variables. Thus, the monthly bias present in all variables needs to be corrected for better and confident use of GCM outputs in simulating the response of rice and wheat crops to climate change.

GCM based yield ensemble results for future period

Yield change at district level

Figure 4 presents changes in rice and wheat yields obtained using the GCM-based yield ensemble, and expressed as percentage change with respect to the historical period, for different districts of West Bengal. The yield of rice crop for all districts, except a few districts under one or two RCP scenarios and time period, is estimated to decrease (Figure 4(a)). The change in rice yield is found to range from +1 to −17% in the 2020s, 0 to −22% in the 2050s and +4 to −24% in the 2080s for all districts under different scenarios. In RCP2.6, yield in some of the districts is seen to decrease until the 2050s and increase again in the 2080s, whereas the trend is reversed in some other districts. In the stabilizing scenario (RCP4.5), most of the districts show a higher reduction in the near future as compared to other time periods as emission in this scenario is expected to increase until the 2050s and then become stabilized with time. Under RCP6.0 and 8.5, most of the districts show yield reduction with time except in a few districts where yield reduction is found to be higher in the 2050s. It is observed that the western districts are highly susceptible to climate change, and show the maximum reduction in yield in all time periods and RCP scenarios. This may be

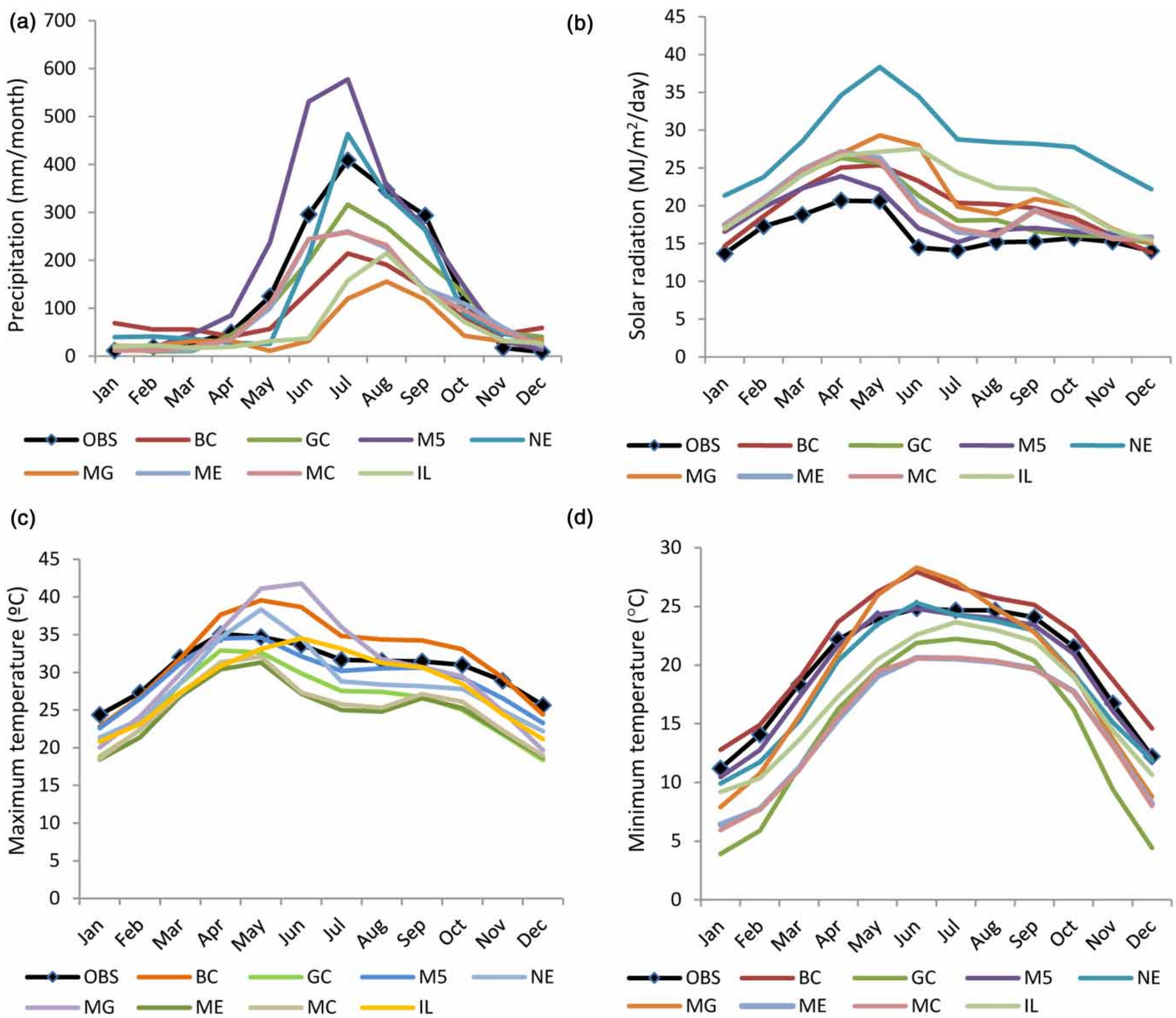


Figure 2 | Comparison between observed and GCM simulated monthly mean data during 1976–2005: (a) rainfall, (b) solar radiation, (c) and (d) maximum and minimum temperatures.

because these districts are expected to witness a higher temperature rise in future as compared to other districts. This could cause the shortening of grain filling duration and may affect the spikelet sterility, and consequent reduction in rice yield (Mishra *et al.* 2013a; Nguyen *et al.* 2014). These results, thus, indicate that there is a possibility of a continuous increase in the negative impact of climate in the future.

Impact of climate change on the wheat yield of 19 districts of West Bengal is shown in Figure 4(b). Overall, the changes in wheat yield are expected to range from −1 to −26% by the 2020s, −3 to −30% by the 2050s and −1 to −59% by the 2080s in all scenarios. In the case of various RCP scenarios, the areal extent of the negative impact of climate change is expected to increase considerably as the number of districts showing higher reduction is greater in the 2080s as compared to the 2020s and 2050s. It is seen from Figure 4(b) that model predictions show the maximum decrease in wheat yield in the north-eastern region of West Bengal in all time periods and all scenarios. This may be due to an increase in temperature during the reproductive stage. Under RCP2.6, 4.5 and 6.0, the majority of districts show higher yield reductions in the 2020s which decrease in the 2050s and increase again in the 2080s. In RCP8.5, all districts, except a few, show a continuous decrease in yield irrespective of time. Asseng *et al.* (2011) also reported yield

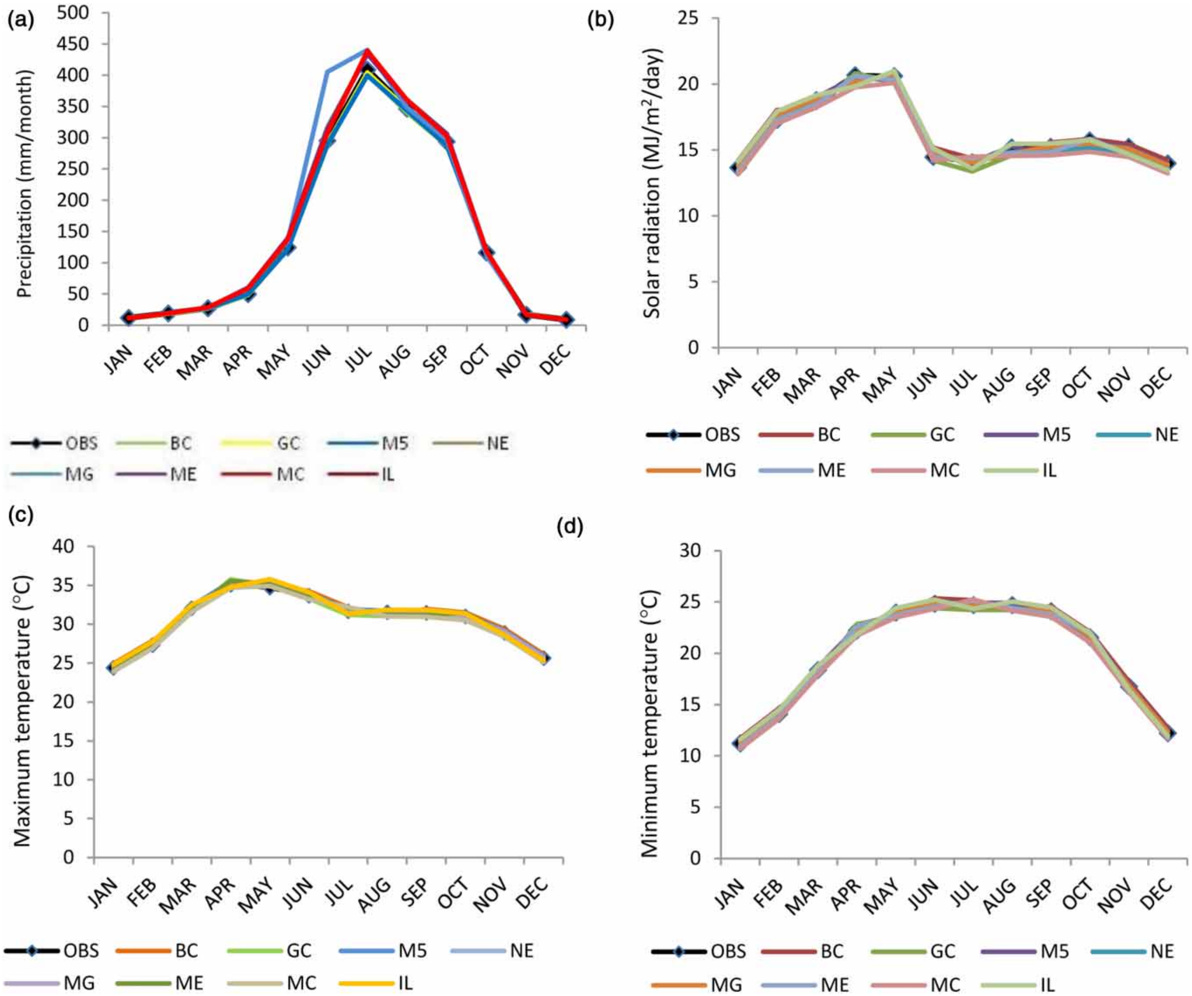


Figure 3 | Comparison between observed and bias-corrected GCM outputs of monthly mean data during 1976–2005: (a) rainfall, (b) solar radiation, (c) and (d) maximum and minimum temperatures.

reduction in wheat crop, attributed to heat stress in the development phase resulting in increased leaf senescence.

Yield change at state level and uncertainty assessment

Figure 5 presents the expected changes in rice and wheat yields in the future time period under all RCPs over West Bengal. The rice yield is expected to decrease up to 8, 9, 10 and 15% by the end of the 21st century under RCP2.6, 4.5, 6.0 and 8.5 scenarios, respectively (Figure 5(a)). Satapathy *et al.* (2014) also reported a similar possibility of a decrease in the rice yield in the future period under A2 and B2 scenarios due to $\geq 0.8\,^{\circ}$C rise in temperature. Similar results were also obtained by Krishnan *et al.* (2007), who concluded that rice yield could decline by 8–22%. Similarly, Babel *et al.* (2011) reported a decrease in rice yield in Thailand ranging up to 18, 28 and 24% due to the increase in CO_2 concentration, temperature and rainfall by the 2020s, 2050s and 2080s.

The future changes in wheat yield (Figure 5(b)) also show a negative impact of climate change, resulting in yield reduction ranging from 18 to 20%, 20 to 28% and 18 to 33% in the 2020s, 2050s and 2080s. The reduction in yield will increase until the 2050s and then decrease under all scenarios except RCP8.5, in which the yield reduction is expected to continue over the century. The probable reason for this

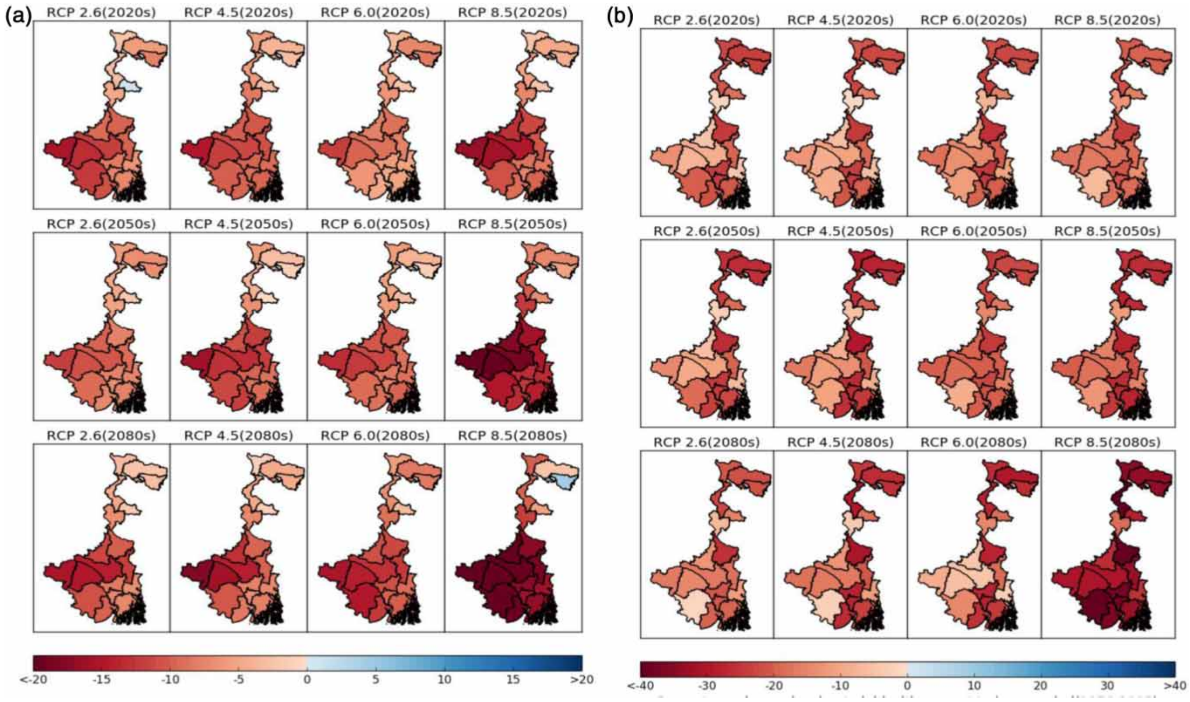


Figure 4 | District-wise change in (a) rice and (b) wheat yields resulting from the GCM ensemble.

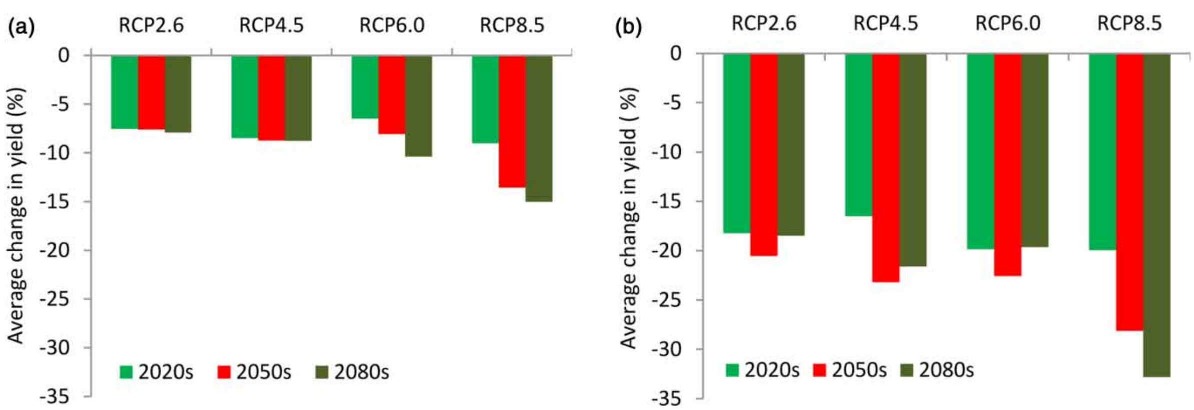


Figure 5 | Expected average changes in (a) rice and (b) wheat yields over West Bengal.

could be that emission in all RCPs except RCP8.5 is expected to either decrease after 2050 (RCP2.6) or become stabilized by 2050 or 2080 (RCP4.5 and RCP6.0). Mishra *et al.* (2013a) also reported similar results. Barlow *et al.* (2015) also concluded that grain number, grain filling period and yield would decline due to increase in seasonal T_{max} and T_{min}.

The uncertainty present in rice and wheat yield predictions for West Bengal is quantified by the 95% prediction uncertainty calculated at the 2.5 and 97.5 percentiles. Figure 6(a) and 6(b) present the uncertainty bands for both rice and wheat, respectively, for three future time periods (the 2020s, 2050s and 2080s) under

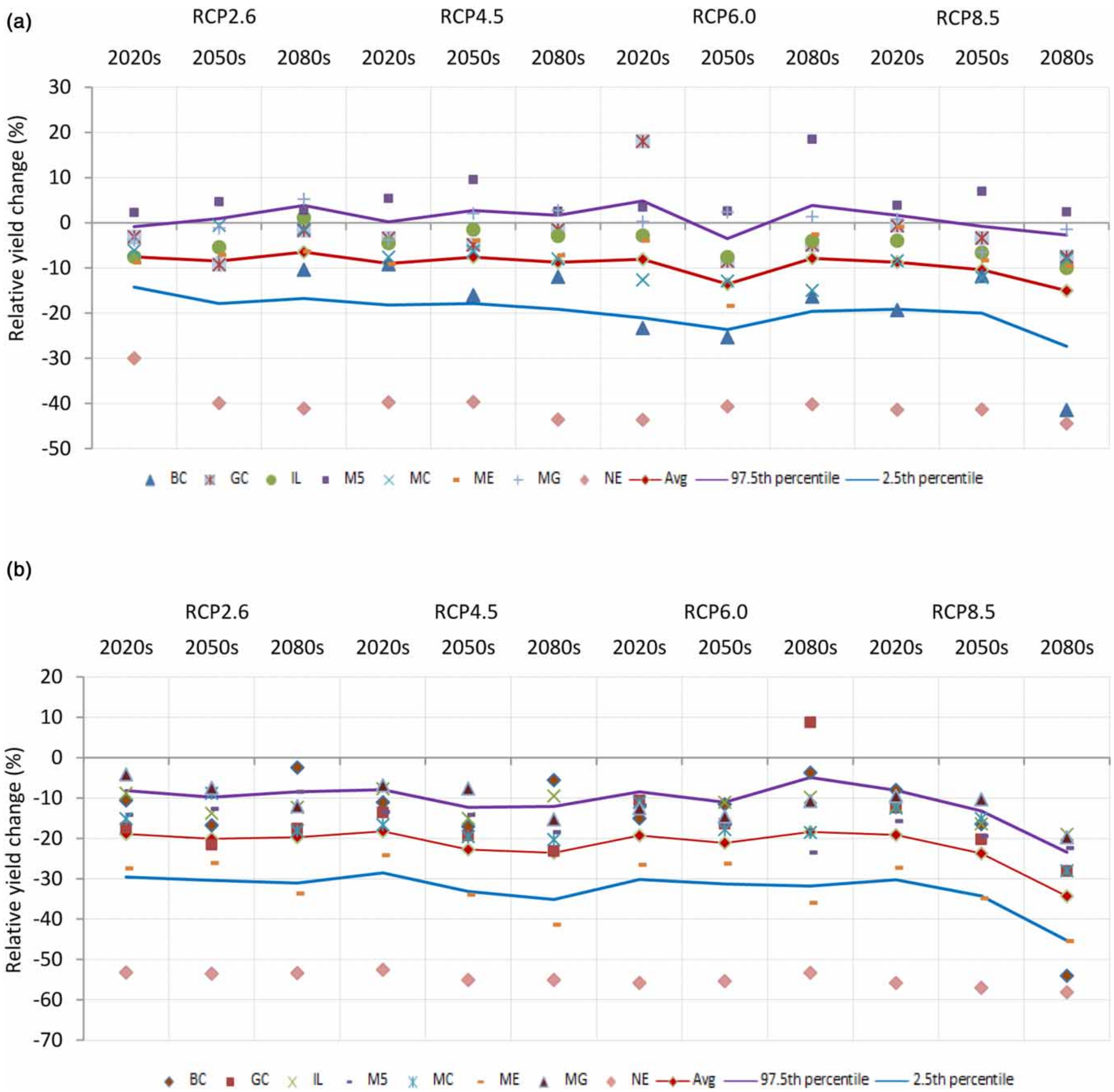


Figure 6 | Predicted yield uncertainty for (a) rice and (b) wheat based on GCM simulation for the 2020s, 2050s and 2080s under four emission scenarios.

four RCP scenarios (RCP2.6, 4.5, 6.0 and 8.5). It is seen that the 95% band is bracketed around 72% of predictions in the case of rice and 64% in the case of wheat, showing a substantial variation in yield predictions. This may, however, be overcome by incorporating greater numbers of GCMs in analysis or by neglecting the data of GCMs resulting in outliers, e.g., M5 and NE in the case of the rice crop and MG and NE in the case of the wheat crop.

Climate change adaptation for rice and wheat crop

Likelihood of yield reduction of both crops increases the requirement of adaptation strategies in the future climate change condition because climate change is predicted to be stronger in the late 21st century (Stocker *et al.* 2013). Various adaptation options for rice and wheat, such as transplanting date, supplemental irrigation, fertilizer management, heat tolerance varieties, modern cultivar, seeding age and planting density have been evaluated in India (Krishnan et al. 2007; Jalota et al. 2014; Banerjee et al. 2016) and different regions of the world (Bai et al. 2016; Chun et al. 2016; Shrestha et al. 2016; Li et al. 2017). Planting date adjustment is one of the important adaptation options which can be easily adapted at farm level to mitigate the adverse impact of climate change (Turral et al. 2011). In addition, adjusting sowing date can also switch vapour flux from evaporation to transpiration within the soil-plant-atmosphere system and enhance water use efficiency (Rockström 2003). Mishra et al. (2013b) used short-term weather forecast in irrigation management as a potential adaptation option for rice crop in North East India with the aim of increasing irrigation efficiency. Singh et al. (2011) stated that storage of crop residue on the soil surface could be advantageous for yield and water use efficiency of rice and wheat by conserving moisture in North West India. These adaptation strategies may be tested and identified for location-specific conditions to maintain the regional food sustainability and security under expected climate change in future.

CONCLUSIONS

The impact of climate change on rice and wheat yield was analysed in different districts and all over the West Bengal state of India. Eight GCMs with four RCP scenarios were used for this purpose. QMM was used for bias correction of GCM projections (precipitation, solar radiation and temperatures). The impact of climate change was analysed by using corrected GCM data as input to the CERES model for rice and wheat for simulating the yield for historical and future periods.

The results indicate that there will be yield-limiting climate in the future as the yields of both rice and wheat are projected to decrease in West Bengal during the 21st century. The uncertainty analysis shows that there are substantial uncertainties present in rice and wheat yield prediction, owing to the uncertainties present in the GCM outputs. The future scenario for rice and wheat yield increases the risk of availability of staple foods which affect the food security of the region. Therefore, it is recommended that climate change adaptation options (change in sowing date and seedling age, cultivar and heat tolerant variety, amount and timing of fertilizer application, irrigation management) must be identified and should be adopted all over the state to sustain the rice and wheat yields in the future. Nevertheless, this study is limited to the use of one cultivar of both rice and wheat crop. Therefore, impact analysis of climate change in different parts of West Bengal using corresponding varieties can be considered as the future scope of this study. This paper also makes clear that along with the aforementioned weather variables (rainfall, T_{max}, T_{min} and solar radiation) the crop yield is also affected by the wind speed and humidity, and therefore, it is prudent to consider these parameters in crop model simulations to get an accurate prediction of crop yield.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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