Assessment of rice yield gap under a changing climate in India

Subhankar Debnath, Ashok Mishra, D. R. Mailapalli, N. S. Raghuwanshi and V. Sridhar

ABSTRACT

Climate change evokes future food security concerns and needs for sustainable intensification of agriculture. The explicit knowledge about crop yield gap at country level may help in identifying management strategies for sustainable agricultural production to meet future food demand. In this study, we assessed the rice yield gap under projected climate change scenario in India at 0.25° × 0.25° spatial resolution by using the Decision Support System for Agrotechnology Transfer (DSSAT) model. The simulated spatial yield results show that mean actual yield under rainfed conditions (Y_a) will reduce from 2.13 t/ha in historical period 1981–2005 to 1.67 t/ha during the 2030s (2016–2040) and 2040s (2026–2050), respectively, under the RCP 8.5 scenario. On the other hand, mean rainfed yield gap shows no change (≈1.49 t/ha) in the future. Temporal analysis of yield indicates that Y_a is expected to decrease in the considerably large portion of the study area (30–60%) under expected future climate conditions. As a result, yield gap is expected to either stagnate or increase in 50.6 and 48.7% of the study area during the two future periods, respectively. The research outcome indicates the need for identifying plausible best management strategies to reduce the yield gap under expected future climate conditions for sustainable rice production in India.

Key words | climate change, DSSAT, India, rice, yield gap

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HIGHLIGHTS

- The study assessed rice yield gap in India by using the DSSAT model.
- Equidistant quantile mapping technique is used for bias correction of RCM outputs.
- Rice yield is expected to decrease in 30–60% of the study area in future.
- Mean rainfed yield gap of 1.49 t/ha is expected in future.
- The RegCM4 model performed well to simulate rice yield than other models.

INTRODUCTION

Crop production and food security are the two major concerns as inherent climatic variations and ever-increasing food demand are expected to affect the global community in an adverse manner (Bodirsky *et al.* 2015). Food demand is expected to increase by 60% to feed the growing global population by 2050 (Alexandratos & Bruinsma 2012). About 770 million people, or close to 10% of the world population, were exposed to severe food insecurity in 2017 (Ten Berge *et al.* 2019). In India, approximately 350 million people are undernourished (Sridhar 2008) and nearly 47 million children are chronically undernourished (United Nations – India 2020). With these assessments, the Government of India introduced the National Food Security Act in 2013, to provide subsidized food grains to approximately

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two-thirds of the country's population, which demands 33.6 million tonnes of rice per year for its public food distribution system (Debnath *et al.* 2018a). Rice, one of the major crops in India, is grown in approximately 40–43% of the food grain cropped area (Bhambure & Kerkar 2016) in which 52% of the total rice planting area is under rainfed conditions (Das & Baruah 2008). The rainfed agriculture of India is one of the most vulnerable sectors to climate change due to limited availability of land and water resources. Therefore, the food security scenario of India may worsen if climatic change has a negative impact on the rice yield.

An extensive review of previous studies (Nagarajan *et al.* 2010; Mishra *et al.* 2013; Shrestha *et al.* 2014; Kang & Sridhar 2017; Shrestha & Shrestha 2017; Singh *et al.* 2017; Arunrat *et al.* 2018; Kang & Sridhar 2018; Kang *et al.* 2019) indicates that climate changes, i.e. changes in seasonal temperature and rainfall, are likely to cause drought leading to a significant decrease in world food production, especially in developing countries. Bhattacharya & Panda (2013) analyzed the effect of climate change on rice yield by using an AquaCrop model at Kharagpur, India. The climate of the study area was classified as sub-humid, subtropical. The study reported that the yield will decrease with increases in average monthly temperature due to heat stress, and increase with increases in average monthly rainfall in the subtropical region. Mishra *et al.* (2013) studied the spatial variability of climate change impacts on rice yield using regional climate models (RCMs) and reported a significant gap between the actual (i.e. estimated from field observations) and potential yield (i.e. yield of a cultivar or hybrid when grown under favourable conditions without growth limitation from water, nutrients, pests or diseases (Lobell *et al.* 2009)) because of cyclic stress and changes in the management inputs. They also suggested that uncertainty issues in future climate change impact studies should be addressed by using outputs from more number of RCMs. Srivastava *et al.* (2017) investigated the impact of climatic variables on the yield gap and found that spatial and temporal variability in the yield gap was positively correlated with solar radiation. Samiappan *et al.* (2018) studied the impact of projected climate changes on the northeast monsoon on rice yield during rabi season (September–December) in Tamil Nadu, India. They estimated an increased rice yield of 10–12 and 5–33% during 2021–2050 and 2081–2100, respectively in response to an increase in projected monsoon rainfall and surface temperature.

To meet the increasing food demand of an ever-growing population, a 2–2.5% increase of rice yield per annum until 2020 is required to meet future food security (Singh *et al.* 2017). In the past, a few studies (Foley *et al.* 2011; Smith 2013) have been devoted to address the issue of yield improvement and suggested 'close the yield gap' as one of the promising options (van Ittersum *et al.* 2013), which is the difference between water limited potential yield (Y_w) (van Ittersum *et al.* 2013) and actual yield under rainfed conditions (Y_a). Yield gap analysis can provide a basis for identifying the best management strategies to improve the rainfed rice yield by reducing the gap from the potential yield. In recent years, a number of studies (Boling *et al.* 2011; Foley *et al.* 2011; Mueller *et al.* 2012; Alam *et al.* 2013; Espe *et al.* 2016; Stuart *et al.* 2016) highlighted the possibilities of increasing rice yields in many areas across the world by reducing the yield gap in rice-based farming systems. Licker *et al.* (2010) studied the global pattern of rice yield gap and highlighted that approximately 40% more rice yield could be obtained if the top 95% of the crops' harvested areas met their current climatic potential. Mueller *et al.* (2012) found that a large production increase (45–70% for most crops) could be possible by closing the yield gap to 100% of attainable yield. Debnath *et al.* (2018b) quantified the yield gap of a rice cropping system by using a decision support system for an agrotechnology transfer (DSSAT) model and found that an attainable average yield gap of 0.33 t/ha in rainfed conditions existed in the agricultural lands of the Lower Gangetic Plains in India.

It is seen that most of the yield gap studies are confined to management aspects such as different levels of nitrogen (N) treatments (Boling *et al.* 2011; Nhamo *et al.* 2014), combination of best management practices along with N management options in the farmers' crop management practices (Alam *et al.* 2013), different date of transplanting (Debnath *et al.* 2018b), and different water management strategies (Mueller *et al.* 2012; Debnath *et al.* 2018b). Only a few studies (Licker *et al.* 2010; Mishra *et al.* 2013) have discussed the impacts of climate change on the inconsistencies in rice yield gap assessments. Licker *et al.* (2010) presented spatial datasets of both the potential yields and yield gap patterns for 18 crops around the year

2000. The study highlighted the regions where yields may potentially be raised. Mishra *et al.* (2013) examined the impact of climate change on rice yield at three different locations in the Indian Ganga Basin. The study found a significant gap between the actual and potential yield which may be attributed to the cyclic stress and changes in the management inputs.

On the other hand, previous studies on the effect of climatic variations on rice yield gap in India are mostly concentrated on location-specific applications (Aggarwal *et al.* 2008; Singh *et al.* 2016). However, these location-specific data about certain weather variables and distributed soil properties are unable to reproduce the crop yield gap characteristics due to uncertainties in representing the localized conditions on a regional scale. Hence, implementation of spatially distributed fine resolution weather and soil information may result in improved accuracies in regional crop yield gap assessment. Therefore, the variation in yield gaps caused by climate change is not well understood because of very limited study. An analysis of the impact of climate change on the rice yield gap at a large number of spatially distributed locations in India is crucial to understand the magnitudes and causes of yield gaps of rice cropping systems and to formulate plans and policies for adapting the agricultural system against the changing climate.

In the present study, therefore, we assessed rice yield gap under a projected climate change scenario in major rice-growing states in India at $0.25 \times 0.25°$ spatial resolution with diversity in climate and soils. The objectives of the study are: (i) to analyze temporal and spatial variability of rice yield gap under historical (1981–2005) and future climatic conditions (2030s (2016–2040) and 2040s (2026–2050)); and (ii) to compare the performances of different RCMs on rice yield gap assessment in India.

MATERIALS AND METHODS

Study area

Though rice is grown in India throughout the country, except for the arid eastern parts, 17 major rice-growing states were selected as the study area (Figure 1), based on average annual rice production. The average observed rice

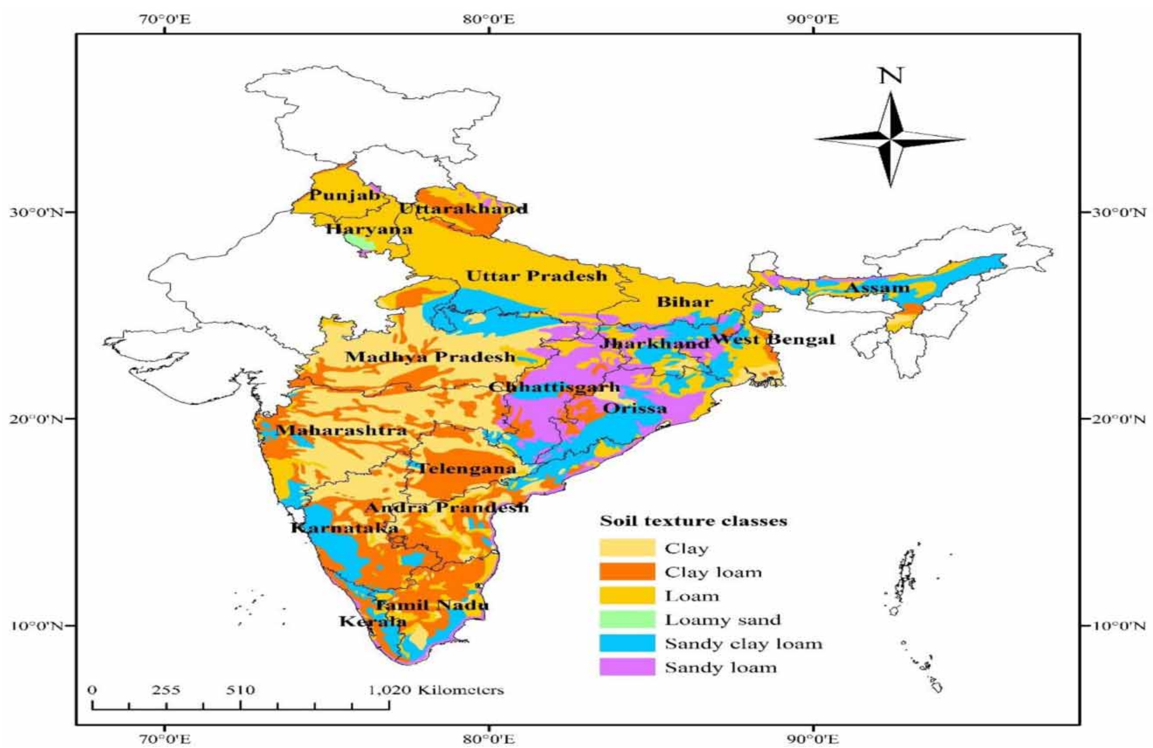

Figure 1 | Index map of the study area showing the selected rice-growing states and soil types.

yield for the study area varies from 1.42 (Madhya Pradesh) to 3.87 t/ha (Punjab) with an average yield of 2.43 t/ha (Table 1). Depending upon variation in landscape and climate in the rice-growing regions of India, a large number of unique paddy cultivation methods are being practiced based on farming type (irrigated, rainfed and deepwater), crop management (single crop and multi-crop), and seasons (kharif and rabi). Kharif rice accounts for over 85% of the total rice production in the country.

Data collection

Climate data

The required daily observed weather data (maximum and minimum temperature ($T_{\max}$ and $T_{\min}$) at $1\times1^{\circ}$ resolution and rainfall at $0.25\times0.25^{\circ}$ resolution) for the period of 1981–2015 were collected from the India Meteorological Department (IMD). Daily solar radiation (R_s) data were collected from the National Centers for Environmental Prediction (NCEP) at $0.3\times0.3^{\circ}$ resolution and used as proxy observed data. The observed $T_{\max}$, $T_{\min}$ and R_s were downscaled to $0.25\times0.25^{\circ}$ resolution by using the bilinear interpolation method. Daily weather sequences ($T_{\max}$, $T_{\min}$, R_s and rainfall) from three different RCMs, namely HadGEM3-RA, RegCM4, and YSU_RSM, were downloaded from CORDEX East Asia website (http://cordex-ea.climate.go.kr/cordex/) at $0.44\times0.44^{\circ}$ spatial resolution for the period of 1981–2050. These three RCMs have consistency in data availability without any missing information unlike two other RCMs (SNU-MM5 and SNU-WRF) which are also available from the CORDEX East Asia website. All three RCMs used initial and boundary conditions of the HadGEM2-AO Global Climate Model (GCM) to develop the long-term future plausible climate scenarios at a 0.44° (~50 km) grid scale covering India in its entirety. These RCMs data have been used in many previous studies (Lee *et al.* 2014; Oh *et al.* 2014). The RCMs simulate outputs as future weather information from 2006 onwards, however, observed weather information is available up to 2015 for the study area. Therefore, the study period was considered as: the historical period (1981–2005), transition period (2006–2015) and future periods (the 2030s (2016–2040) and 2040s (2026–2050)) with two representative concentration pathways (RCPs) scenarios (RCP 4.5 and RCP 8.5) to evaluate climate change impacts on rice yield gap.

Table 1 | Average observed kharif season rice yield of major rice growing states of India during 2010–2015 (*source*: Ministry of Agriculture and Farmers Welfare, Government of India, www.indiastat.com)

State	Average yield (t/ha)	Maximum yield (t/ha)	Minimum yield (t/ha)
Andhra Pradesh (AP)	2.56	3.04	2.21
Assam (AS)	1.84	1.92	1.69
Bihar (BR)	1.83	2.27	1.06
Chhattisgarh (CH)	1.74	1.94	1.60
Haryana (HR)	3.09	3.27	2.79
Jharkhand (JH)	3.09	3.27	2.79
Karnataka (KT)	2.62	2.72	2.55
Kerala (KR)	2.54	2.72	2.38
Madhya Pradesh (MP)	1.42	1.68	1.11
Maharashtra (MH)	1.87	1.97	1.77
Odisha (OD)	1.63	1.89	1.34
Punjab (PN)	3.87	4.00	3.74
Tamil Nadu (TN)	3.11	3.82	2.65
Telangana (TG)	3.11	3.82	2.65
Uttar Pradesh (UP)	2.29	2.46	2.07
Uttarakhand (UK)	2.15	2.26	2.06
West Bengal (WB)	2.55	2.61	2.49
India	2.43	4.00	1.06

Soil data

The soil properties of the study area, namely thickness of soil layer, the texture of the soil, saturated hydraulic conductivity, bulk density, albedo fraction, runoff curve number and organic content, were collected from the FAO soil database (India Datasets for SWAT2012 2020). The properties of these soils are available at 1×1 km grid scale and were therefore rescaled to $0.25\times0.25^{\circ}$ grid to have all information in the same spatial resolution. The study area is characterized by six soil classes with loam as the most dominant soil type (Figure 1). The soil hydraulic properties, namely water holding capacity, permanent wilting point, and moisture at saturation, were estimated by using ROSETTA software (Schaap *et al.* 2001).

Historical rice yield information

The historical rice yield information was collected from the Ministry of Agriculture and Farmers Welfare, Government of India for the period 1986–2015. These yields are generated through the analysis of crop cutting experiments (CCEs) conducted under scientifically designed general crop estimation surveys. Field Operation Divisions of the National Sample Survey Organization provides technical guidance to the states for conducting crop estimation surveys for estimating the rice yield. The CCEs consist of identification, and marking of experimental plots of specific size and shape in a selected field on the principle of random sampling, harvesting and threshing the crop, and recording of the yield information. These yield statistics do not describe the number of farmers, transplanting dates and other site-specific information considered for composing it. These yields are the average yield of all rice varieties grown in the state. Generally, 80–120 experiments are selected in a major crop growing district (the area under the crop in the district either exceeds 80,000 ha or lies between 40,000 and 80,000 ha and exceeded the average area per district in the state) and about 44 or 46 experiments are planned in a minor district. A time series of collected state-wise kharif season rice yield was considered as observed rainfed rice yields and was used to calibrate and validate the DSSAT model in this study.

Bias correction of RCMs' output

Although RCMs are regarded as the best tools available for the projection of future climate (Jones *et al.* 2004; Rajib *et al.* 2011), there are biases in the RCMs output. Limited understanding of the atmosphere and simplified representation of its process in RCMs are regarded as the main cause of RCM bias (Li *et al.* 2010). In this study, the used RCMs outputs ($T_{\max}$, $T_{\min}$, R_s and rainfall) are bias corrected on monthly scale, after rescaling to $0.25 \times 0.25°$ resolution, by using a modified version of the quantile mapping technique known as equidistant quantile mapping (EDQM) (Li *et al.* 2010). This technique is more superior than other correction methods as it takes into account the non-stationarity of data, i.e. it considers the difference between the CDFs for the future and historic periods. Li *et al.* (2010) found that the equidistance quantile-matching method is more efficient in reducing biases than the traditional CDF mapping method for changing climates, especially for the tails of the distribution. The basic procedure of the technique is outlined below.

First, cumulative distributions are fitted separately to the historical observed and RCM outputs. For rainfall, the threshold value is identified in the RCM output for adjusting wet-day frequency of rainfall time series before distribution fitting. The fitted distributions are Gaussian distribution for $T_{\max}$ and $T_{\min}$, Beta distribution for R_s and Gamma distribution for rainfall as given below:

$$f_1(x|\mu, \sigma^2) = x^{\propto-1}.\frac{1}{\sqrt{2\pi\sigma^2}}.e^{\frac{-(x-\mu)^2}{2\sigma^2}}; \quad x \epsilon R \text{ (Gaussian distribution)} \tag{1}$$

$$f_1(x|\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)}.\frac{(x-a)^{\alpha-1}(b-x)^{\beta-1}}{(b-a)^{\alpha+\beta-1}}; \quad a \le x \le b;\ \alpha, \beta > 0 \text{ (Beta distribution)} \tag{2}$$

$$f_1(x|\alpha, \beta) = x^{\alpha-1}.\frac{1}{\beta^{\alpha}.\Gamma(\alpha)}.e^{\frac{-x}{\beta}}; \quad x \ge x_{threshold};\ \propto, \beta > 0 \text{ (Gamma distribution)} \tag{3}$$

where μ is the mean, σ is the standard deviation, α and β are the shape and scale parameters, and a and b are the lower and upper bounds of the distribution.

The distribution parameters are determined by using maximum likelihood estimations. Then the cumulative distribution of the daily RCM output of historical period ($F_{i,hist}(x)$) is mapped onto the cumulative distribution of the observations ($F_{i,obs}(x)$). The bias-corrected historical RCM outputs ($X'_{i,hist}$) on day i can be calculated as:

$$X'_{i,hist} = F^{-1}_{i,obs}\left(F_{i,hist}(x_i)\right) \tag{4}$$

The whole procedure is followed separately for each month in order to correct the errors in the seasonal cycle.

For the future climatic projection of RCMs output, climate shifting factor (d) is calculated which takes into account changes in variability between historical and future RCM output simulations:

$$d_i(x_{i,fut}) = F^{-1}_{i,fut}\,(F_{i,fut}(x_{i,fut})) - F^{-1}_{i,hist}\,(F_{i,fut}(x_{i,fut})) \tag{5}$$

The bias corrected future RCM outputs (X'_{ifut}) on day i can be calculated as:

$$X'_{i,fut} = F^{-1}_{i,obs}\,(F_{i,fut}(x_{i,fut})) + \; d_i(x_{i,fut}) \tag{6}$$

Trend estimation of climate data

Mann–Kendall test

The Mann–Kendall test (Mann 1945; Kendall 1948) is a popular rank-based method for detecting the trend in hydro-climatological variables. In this study, it is applied to estimate the trend of seasonal (monsoon season – June–September) climate data ($T_{\max}$, $T_{\min}$ and rainfall) for the historical period (1981–2005) and projected periods (2006–2050) under RCP 4.5 and RCP 8.5 scenarios at 95% confidence level. The Mann–Kendall (MK) test statistic is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(X_j - X_i) \tag{7}$$

where n is the length of the data set, X_i and X_j represent data points in time series i and j, respectively ($i < j$):

$$sgn(X_j - X_i) = \begin{cases} +1 \;\; if\ (X_j - X_i) > 0 \\ 0, \;\; if\ (X_j - X_i) = 0 \\ -1\ if\ (X_j - X_i) < 0 \end{cases} \tag{8}$$

It has been reported that for $n \geq 10$, statistic S is normally distributed with:

$$E(S) = 0 \tag{9}$$

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)}{18} \tag{10}$$

where $E(S)$ is the mean, $V(S)$ is the variance of S, m is the number of tied groups, and t_i is the size of the ith tied group. The standard normal test statistics Z is given by:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{V(S)}}, & if\ S > 0 \\ 0, & if\ S = 0 \\ \dfrac{S+1}{\sqrt{V(S)}} & if\ S < 0 \end{cases} \tag{11}$$

If the value of $|Z|$ is greater than critical value 1.96 at 5% significance level, the null hypothesis for 'no trend in time series' is rejected and a significant trend exists. The positive value of the Z statistic indicates an increasing trend and vice-versa.

Modified Mann–Kendall test

In the Mann–Kendall test, it is assumed that the data are random and independent. However, the existence of positive autocorrelation in the data increases the probability of detecting trends when actually it does not exist, and vice-versa. Therefore, a modified Mann–Kendall test (Hamed & Rao 1998) is conducted in this study for detecting trends in autocorrelated time series by considering the effect of autocorrelation on the variance of the Mann–Kendall trend test statistic. To apply the modified Mann–Kendall test the following procedures are performed.

First, all the time series data are examined for possible lag-1 autocorrelation (r_1) by using the following relationship given by Box *et al.* (1994):

$$r_k = \frac{C_k}{C_o} \tag{12}$$

$$C_k = \frac{1}{n}\sum_{i=1}^{n-k} (x_i - \bar{x})(x_{i+k} - \overline{x}) \tag{13}$$

$$C_o = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{14}$$

where r_k is the kth lag autocorrelation.

The upper and lower critical values of autocorrelation function can be obtained from Anderson's test (Anderson 1942) as follows:

$$(r_k)_{upper} = -\left(\frac{1}{n-k}\right) + Z_{1-\frac{\alpha}{2}}\left(\frac{\sqrt{n-k-1}}{n-k}\right) \tag{15}$$

$$(r_k)_{lower} = -\left(\frac{1}{n-k}\right) - Z_{1-\frac{\alpha}{2}}\left(\frac{\sqrt{n-k-1}}{n-k}\right) \tag{16}$$

where $z_{1-\alpha/2}$ is the two-tailed standard variate at the α significance level. If r_k falls within the critical values, data is assumed to be serially independent.

In case the data is found to have lag-1 autocorrelation, modified variance $V(S)^*$ is calculated by taking the variance correction factor $\left(\frac{n}{n_s}\right)$ into account as follows:

$$V(S)^* = V(S) \times \frac{n}{n_s} \tag{17}$$

$$\frac{n}{n_s} = 1 + \frac{n}{n(n-1)(n-2)} \sum_{k=1}^{n-1} (n-k)(n-k-1)(n-k-2) r_k \tag{18}$$

It is noted that only significant values of r_k are used to calculate the correction factor.

Theil–Sen's slope test

Theil–Sens's slope (β) test (Theil 1950; Sen 1968) is used to determine the magnitude of the slope of climate variables. The β is defined as:

$$\beta = median\left(\frac{X_j - X_i}{j - i}\right) \tag{19}$$

where X_i and X_j represent data points in time series i and j, respectively ($i < j$). A positive value of β indicates an increasing trend and vice versa.

Management practice

In the present study, rice crop cultivar IR36 was chosen as the representative of all cultivars grown in India for analysing the effect of climate variability and expected change in weather variables on the rice yield gap. For the simulation analysis, rainfed rice crop with a fixed transplanting date of 15th July of each year is assumed as monsoon season begins over the study area by that time. The transplanting dates have been fixed to exclude the impact of growing season on rice yields. Nitrogen (N) fertilizer is scheduled at a rate of 120 kg/ha in three splits: 50% of total N-fertilizer as basal dose (i.e. at the time of transplanting), 25% at 20 days after transplanting (DAT) and the remaining 25% at 40 DAT (Mishra *et al.* 2013; Debnath *et al.* 2018b), whereas the recommended levels of 50 kg/ha phosphorus (P_2O_5) and 60 kg/ha potash (K_2O) are scheduled as basal dose in the study area (Debnath *et al.* 2018b). The harvest date is decided as per the maturity of the crop simulated by the DSSAT model.

Database preparation for implementing the DSSAT model

The database of gridded climate and soil data are prepared by using open source database software (MySQL version 6.1) and the high-level programming language, Python (Python version 3.4.3). A python programming code is developed to: (i) extract weather and soil information of a particular grid from the database, (ii) prepare weather input file (.WTH) and soil input file (.SOL) for that particular grid, (iii) prepare crop management input file (.SNX), (iv) run the DSSAT model to simulate the rice yield by linking all these files, and finally (v) arrange the output files of the model run (.OSU, .OOV and warning.OUT). The same process is performed for all grids covering the study area one by one for a given period. The flowchart of various steps involved in database preparation and model simulation are shown in Figure 2.

DSSAT model calibration and validation

The CERES-Rice model, embedded in DSSAT v4.5 (Jones *et al.* 2003; Hoogenboom *et al.* 2009), is used in this study. It simulates crop yield by considering impacts of weather, genotype, soil properties and management practice on crop growth, development, soil water and nitrogen balance on a daily basis as a function of soil-plant-atmosphere dynamics. The model requires daily weather information (T_{max}, T_{min}, R_s and rainfall), soil properties (soil texture, permanent wilting point, field capacity, saturation moisture content), cultivar information (i.e. cultivar's genotype coefficients) and input management information (timing of sowing/ transplanting, quantity and timing of irrigation and fertilizer application and harvesting) to simulate the rice yield. Generally, the DSSAT model needs to be calibrated once for each rice variety as genotype coefficients are not location specific. However, the model has been

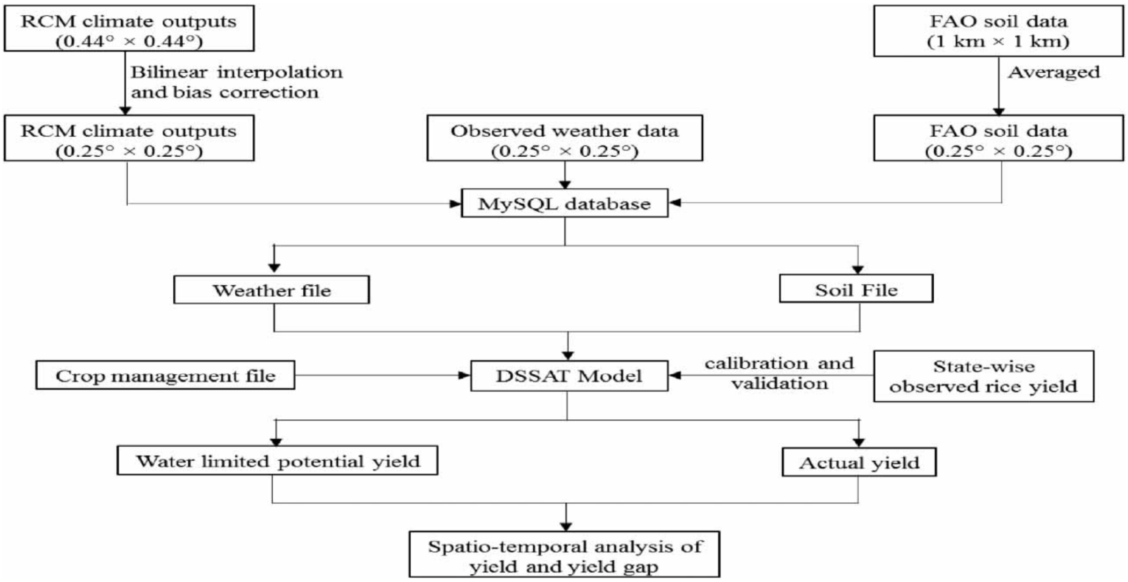

Figure 2 | Flowchart to simulate rice yield and yield gap assessment by using the DSSAT model and RCMs.

calibrated for identifying the genotype coefficients of IR36 rice cultivar for each rice-growing state of India to capture the average rice yield and other growth parameters of a state as the observed rice yield information are the average of all cultivars grown in a particular rice growing state. There are a number of dominant cultivars in each state which are reported by government (Rice Varieties 2020). The rice yield information of individual cultivars is not reported by any state agency or reliable source. Therefore, it is difficult to calibrate the DSSAT model for each cultivar without the observed yield information. The model was calibrated for the duration of 1986–2000 and validated for the 2001–2015 period in each rice growing state. The calibration parameters considered in the model were the date of flowering (71 ± 3 days after transplanting as found from three years field experiments (2015–2017)), date of maturity (120 days crop maturity period for IR36 rice variety) and state-wise observed rice yield. Genotype coefficient calculator, GENCALC (Hunt *et al.* 1993), available within the DSSAT model framework, was used to determine genotype coefficients of IR36 cultivar for each state during calibration by running the crop model iteratively with input data and base values of the genotype coefficients, comparing the model output with observed data, and then altering the value of genotype coefficients until the minimum difference between simulated and observed values were found (Debnath *et al.* 2018b). The model is used to simulate rice yield in $0.25 \times 0.25°$ grids covering the states and the average simulated yield of each state is calculated to compare the model performance in this study. The model performance is evaluated graphically and by using three performance indices, namely root-mean-square error (RMSE), the coefficient of determination (R^2), and index of agreement (D-index):

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}\right]^{0.5} \tag{20}$$

$$R^2 = \left[1 - \frac{\sum(P_i - O_i)^2}{\sum(O_i - \bar{O})^2}\right] \tag{21}$$

$$D - \mathrm{index} = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}[|P_i - \bar{O}| + |O_i - \bar{O}|]^2}\right] \tag{22}$$

where P_i and O_i are model simulated and observed yield, $\bar{O}$ is the mean of observed yield and n is the number of observations.

These three performance indices give the characteristics of model in terms of mean and variance produced by model simulation with observed data. Also, there is EasyGrapher software (Yang & Huffman 2004) embedded in DSSAT v4.5 which helps the user to calculate these indices. During calibration and validation runs of the model, it is easier to check the model performance by using the software. Therefore, these specific indices were used in the study to assess model performances.

Estimation of rice yield and yield gap

In this study, the calibrated and validated DSSAT model is used to simulate water limited potential yield (Y_w) (i.e. maximum possible yield under rainfed conditions without growth limitations from nutrient, pests or diseases) and actual yield under rainfed conditions (Y_a) by using crop management information, described earlier, in all grids ($0.25 \times 0.25°$) covering the majoring rice-growing states for the historical period (1981–2005), transition period (2006–2015) and future periods (2030 and 2040s). Both observed weather information from IMD and outputs of RCMs were used in the yield simulations. The performance of RCM model outputs to simulate yield by using the DSSAT model was evaluated by using previously mentioned performance indices along with pair t-test at 5% significance level. Finally, the yield gap (Y_g) is calculated as the difference between Y_w and Y_a of the cultivar under rainfed conditions:

$$Y_g = (Y_w - Y_a) \tag{23}$$

RESULTS

Climate change analysis

Table 2 shows the seasonal average (June–September) $T_{\max}$, $T_{\min}$, R_s, and rainfall of each rice growing state of India during the historical period (1981–2005), and change in the transition period (2006–2015) and future periods (2030 and 2040s). The weather data from IMD was considered for the historical period whereas the data of RCP 8.5 scenario of RegCM4 model was considered for the transition period as well as future periods (2030 and 2040s) in the study. The seasonal averaged $T_{\max}$ is expected to increase in the future in all the rice-growing states (ranges from 0.6

Table 2 | Seasonal (June–September) change in average temperatures (maximum and minimum), solar radiation, and rainfall in the study area

	Historical period				Change in transition period				Change in 2030s				Change in 2040s			
States	$T_{\max}$	$T_{\min}$	R_s	Rain	$T_{\max}$	$T_{\min}$	R_s	Rain	$T_{\max}$	$T_{\min}$	R_s	Rain	$T_{\max}$	$T_{\min}$	R_s	Rain
Andra Prandesh	33.2	24.5	17.7	517	0.1	–0.1	0.3	43	1.0	1.1	–0.1	607	1.1	1.1	0.0	602
Assam	30.9	23.7	16.4	1,411	0.7	0.2	0.5	–135	0.8	0.8	–0.1	443	0.8	0.8	0.0	456
Bihar	33.2	25.0	17.5	1,066	0.6	0.4	0.1	–133	0.6	0.7	–0.1	436	0.7	0.7	0.0	442
Chhattisgarh	32.3	24.0	17.5	1,141	0.1	0.0	0.1	–5	0.7	0.9	–0.2	161	0.9	0.9	–0.1	160
Haryana	35.3	25.1	19.3	460	0.0	0.2	–0.1	–8	1.5	1.7	–0.1	121	1.6	1.7	0.0	118
Jharkhand	32.6	24.4	17.4	1,064	0.4	0.4	0.0	–44	0.7	0.9	–0.1	176	0.8	0.9	0.0	178
Karnataka	28.6	21.1	16.3	1,625	0.2	0.2	0.0	137	0.9	1.1	–0.2	549	1.0	1.1	–0.2	535
Kerala	29.4	21.2	17.2	732	0.1	0.0	0.0	79	1.0	1.2	–0.2	609	1.1	1.2	–0.1	600
Madhya Pradesh	31.3	22.9	17.5	943	0.1	0.1	–0.1	34	0.9	1.1	–0.2	485	1.0	1.1	–0.1	480
Maharashtra	32.9	23.9	18.1	928	0.0	0.2	–0.2	–26	1.0	1.2	–0.1	197	1.1	1.3	0.0	196
Orissa	32.2	24.4	17.0	1,114	0.3	0.0	0.2	123	0.7	0.8	–0.2	191	0.8	0.8	–0.1	192
Punjab	34.9	24.2	19.7	490	0.1	0.1	0.0	34	1.5	1.7	–0.1	213	1.7	1.8	0.1	210
Tamil Nadu	32.6	23.8	17.8	776	0.2	0.1	0.3	2	0.9	1.1	–0.1	484	1.1	1.2	0.0	477
Telengana	33.1	23.8	18.2	316	0.2	0.2	0.0	77	1.1	1.2	–0.1	578	1.1	1.2	–0.1	564
Uttar Pradesh	29.8	21.2	17.8	1,064	0.2	0.3	–0.2	15	1.3	1.5	–0.1	42	1.5	1.5	0.0	43
Uttaranchal	34.3	25.2	18.2	804	0.1	0.3	–0.1	–112	0.9	1.2	–0.1	297	1.0	1.2	0.0	297
West Bengal	32.1	24.7	16.6	1,499	0.3	0.5	–0.2	–107	0.7	0.8	–0.1	256	0.8	0.9	–0.1	265

Note: $T_{\max}$ and $T_{\min}$ are in °C; R_s is in MJ m^{-2} day^{-1} and rainfall is in mm.

to 1.7 °C) with respect to the historical period. However, the difference between seasonal averaged T_{max} of the historical period to that of the transition period is very low. Similar to T_{max}, T_{min} is also expected to increase throughout the study area with an average of 1.12 and 1.14 °C during two future periods (2030 and 2040s, respectively). Among all the states, the maximum increment in both T_{max} and T_{min} are expected to occur in Punjab whereas the minimum may be observed in Bihar during future periods. The mean of seasonal averaged R_s in the study area is expected to remain almost the same throughout the study periods. The mean of seasonal rainfall is decreased during the transition period; however, it is expected to be increased by ~342 mm during both the future periods. The maximum increment of rainfall is expected to be realised in Kerala (during the 2030s) and Andhra Pradesh (2040s) whereas it may be minimum in Uttar Pradesh.

The trend of seasonal climate variables was analyzed by Mann–Kendall test and Theil–Sen's Slope estimator (Figure 3, Table 3). The results of Z-statistic and Sen's slope reveal that all the states may have a significantly increasing trend in seasonal T_{max} and T_{min} at the 5% significance level in future periods except Bihar, Jharkhand, Orissa and Telangana during the 2030s, and Jharkhand, Orissa and West Bengal during the 2040s. The trend analysis results indicate that seasonal R_s is expected to decrease in

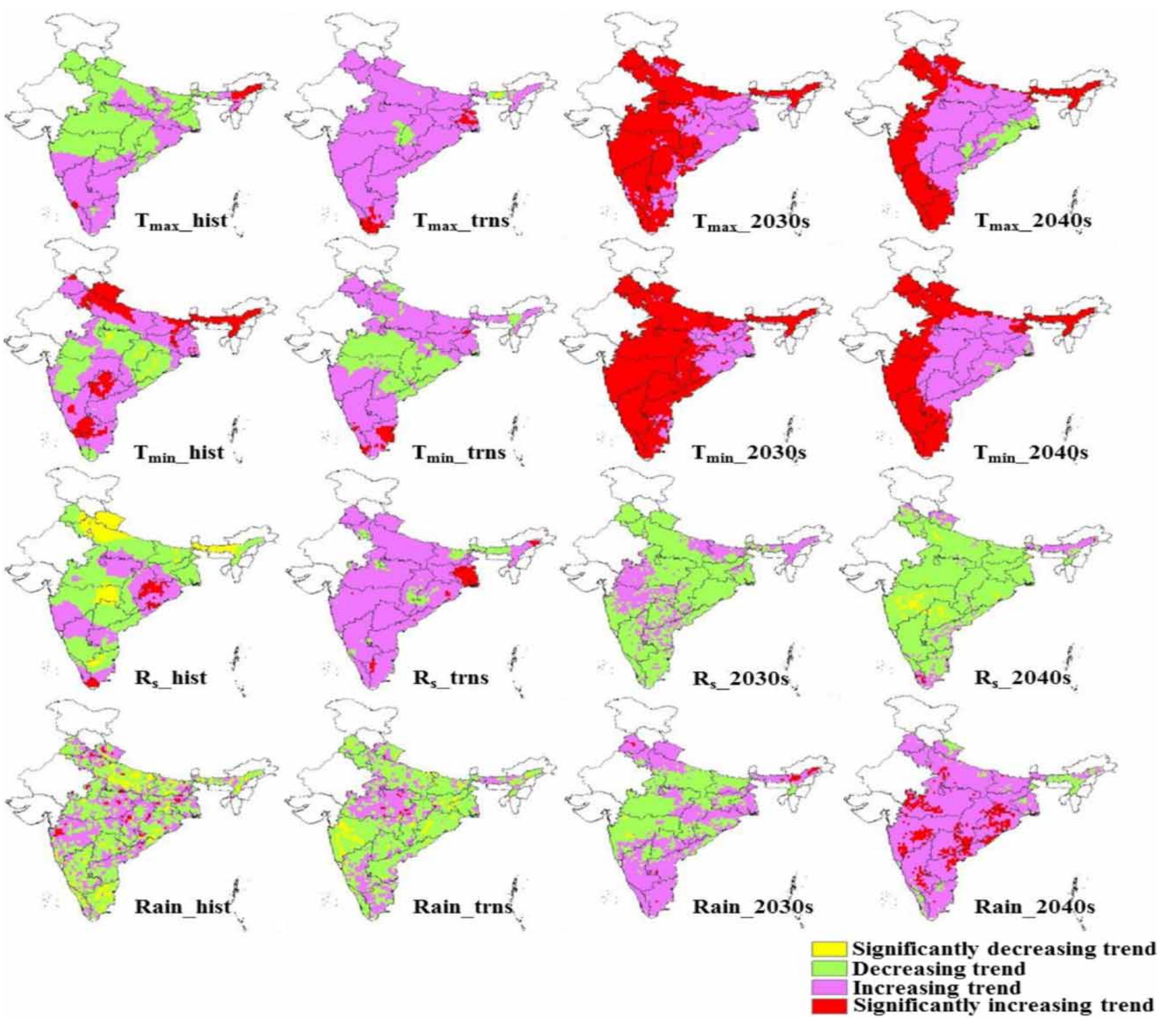

Figure 3 | Trend analysis of climate variables based on Z statistic of Mann–Kendall test and modified Mann–Kendall test in the study area (hist: historical period (1981–2005); trns: transition period (2006–2015); 2030s: (2016–2040) and 2040s: (2026–2050)).

Table 3 | Sen's slope of seasonally (June–September) averaged maximum and minimum temperatures, solar radiation, and rainfall in the study area

	T_{max} (°C)				T_{min} (°C)				R_s (MJ m^{-2} day^{-1})				Rain (mm)			
States	**hist**	**trns**	**2030s**	**2040s**	**hist**	**trns**	**2030s**	**2040s**	**hist**	**trns**	**2030s**	**2040s**	**hist**	**trns**	**2030s**	**2040s**
Andra Prandesh	0.01	0.10	0.04	0.05	0.00	0.01	0.03	0.03	0.00	0.05	0.02	0.02	0.00	−13.84	5.40	5.75
Assam	0.02	0.02	0.06	0.06	0.04	0.03	0.05	0.05	−0.03	0.02	0.01	0.01	−5.11	−2.96	11.55	11.52
Bihar	0.00	0.09	0.04	0.04	0.03	0.06	0.02	0.02	−0.03	0.02	0.01	0.01	−5.98	−33.16	−7.99	−7.08
Chhattisgarh	0.00	0.06	0.04	0.04	−0.01	0.01	0.02	0.03	0.00	0.03	0.02	0.02	−1.16	−14.17	−4.48	−4.39
Haryana	−0.01	0.04	0.06	0.06	0.02	0.05	0.04	0.04	−0.03	0.02	0.01	0.01	0.31	−12.40	4.69	4.66
Jharkhand	0.00	0.12	0.03	0.03	0.01	0.07	0.02	0.02	−0.01	0.06	0.02	0.02	1.21	−38.94	−0.56	0.20
Karnataka	0.01	0.13	0.04	0.05	0.01	0.07	0.03	0.03	0.01	0.04	0.01	0.01	−16.35	−28.77	8.93	10.28
Kerala	0.01	0.09	0.04	0.05	0.02	0.06	0.03	0.03	0.00	0.03	0.02	0.02	−6.15	−7.90	3.90	4.80
Madhya Pradesh	−0.01	0.10	0.06	0.06	0.00	0.01	0.03	0.03	−0.01	0.10	0.03	0.03	2.12	−48.34	−6.94	−7.13
Maharashtra	−0.01	0.08	0.07	0.07	−0.01	−0.02	0.04	0.04	−0.01	0.09	0.03	0.03	−0.41	16.43	−6.27	−6.19
Orissa	0.01	0.08	0.03	0.03	−0.03	−0.03	0.02	0.02	0.03	0.03	0.01	0.01	−1.45	−47.30	−2.14	−1.72
Punjab	−0.01	0.03	0.05	0.06	0.01	0.02	0.04	0.04	−0.02	0.07	0.01	0.01	−0.88	−13.40	15.56	15.33
Tamil Nadu	0.00	0.15	0.05	0.05	0.02	0.01	0.03	0.03	−0.02	0.09	0.02	0.02	−3.24	−12.45	−0.06	0.00
Telengana	0.01	0.10	0.03	0.04	0.01	0.06	0.02	0.03	−0.01	0.04	0.01	0.01	−7.42	3.99	5.26	6.17
Uttar Pradesh	−0.02	0.09	0.05	0.05	0.04	0.00	0.04	0.04	−0.06	0.07	0.01	0.01	4.77	−0.94	7.67	6.88
Uttaranchal	−0.01	0.11	0.06	0.06	0.01	0.04	0.03	0.03	−0.02	0.06	0.02	0.02	−7.92	−11.16	1.44	0.82
West Bengal	−0.01	0.11	0.03	0.03	0.03	0.01	0.02	0.02	−0.04	0.09	0.01	0.01	−3.42	−10.15	4.02	3.43

all the states except Assam, whereas seasonal rainfall may have a non-significant increasing trend throughout the study area in the 2040s.

Evaluation of DSSAT model

Comparison of the observed and simulated rice yield, for both calibration and validation periods, shows a close correspondence across all grids of the study area (Figure 4). It was found that the model simulated rice yields within 15% of the observed yields during both calibration and validation of the model, except where the observed yields were lower than 1.5 t/ha, indicating its inability to simulate crop growth when there is extreme stress. Comparison between pooled data (from all rice-growing states) of observed yield and model simulated yield indicates that RMSE of grain yield were 0.52 and 0.48 t/ha, R^2 values of grain yield were 0.68 and 0.62 and the D-index for grain yield were 0.86 and 0.88, respectively, during the calibration and validation periods. The state-wise model performance results indicated that RMSE values during both the calibration and validation were less than 0.70 t/ha in almost all the states which represent an acceptable model fit for this study.

Spatial patterns of mean and trend in Y_w, Y_a and Y_g during historical period (1981–2005)

The DSSAT model was used to dynamically simulate Y_w and Y_a in each grid of the study area by providing required soil and weather information for the historical period (1981–2005). The observed weather information from IMD, along with the projected weather information from three RCMs, was used in the model simulation. The spatial analysis of mean Y_w and Y_a by using observed weather data indicated that Y_w ranges from 1.66 to 7.5 t/ha with an average of 3.62 t/ha whereas the mean Y_a ranges from 0.60 to 4.99 t/ha with an average of 2.13 t/ha in the study area. As a result, the Y_g varies from 0.35 to 4.78 t/ha with an average of 1.49 t/ha in the study area. The temporal analysis of Y_w showed that Y_w increased at a rate of 10–120 kg/ha/year in 44.6% of the study area, however it had a decreasing trend in 30.8% of the study area as well. The results suggest that Y_w became stagnated in 24.6% of the area during 1981–2005. Similar to Y_w, the temporal analysis of Y_a showed that Y_a was also increased in 46.8% of the study area at a rate of 10–90 kg/ha/year, however it was stagnated and decreased in 29.9 and 23.3% of the study area, respectively. As a result, the temporal pattern of Y_g shows that the yield gap was decreased, stagnated and increased in 39.5, 22.9 and 37.6% of the study area, respectively. State-wise mean Y_w, Y_a and Y_g during the historical period are shown in Table 4. Among the rice-growing states, relatively higher mean Y_w was estimated to be in Chhattisgarh (5.82 t/ha) because of favorable environmental conditions (Table 2) along with a better distribution of rainfall during June–September. However, maximum mean Y_g (3.91 t/ha) was also estimated for Chhattisgarh due to the smaller mean value of Y_a. The minimum values of Y_w and Y_g were

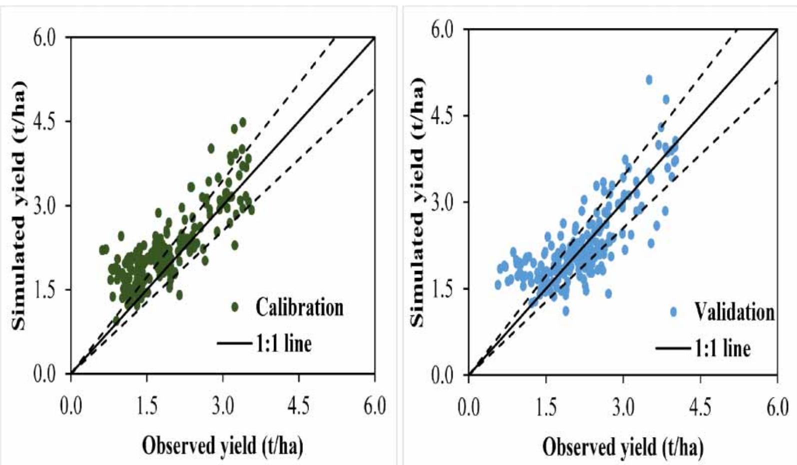

Figure 4 | Observed and simulated rice yield for model calibration (1986–2000) and validation (2001–2015).

Table 4 | State-wise mean water limited rice yield (Y_w), actual yield (Y_a) and yield gap (Y_g) in major rice growing states of India

Climate scenario and data source	Historical period (1981–05) (observed data of IMD)			Transition period (2006–15) (RCP 8.5 of RegCM4 model)			Future period (2016–2040) (RCP 8.5 of RegCM4 model)			Future period (2026–2050) (RCP 8.5 of RegCM4 model)		
States	Y_w (t/ha)	Y_a (t/ha)	Y_g (t/ha)	Y_w (t/ha)	Y_a (t/ha)	Y_g (t/ha)	Y_w (t/ha)	Y_a (t/ha)	Y_g (t/ha)	Y_w (t/ha)	Y_a (t/ha)	Y_g (t/ha)
Andra Prandesh	3.56	2.33	1.23	3.56	2.30	1.26	2.92	1.81	1.11	2.86	1.75	1.11
Assam	2.57	1.44	1.13	2.54	1.43	1.11	2.06	1.05	1.01	1.99	1.03	0.96
Bihar	2.75	1.50	1.25	2.69	1.65	1.04	2.36	1.01	1.35	2.31	0.98	1.33
Chhattisgarh	5.82	1.91	3.91	5.91	1.95	3.96	5.29	1.67	3.62	5.13	1.58	3.55
Haryana	4.07	2.97	1.10	4.21	3.07	1.14	3.48	2.01	1.47	3.26	2.00	1.26
Jharkhand	4.18	1.91	2.27	4.16	1.98	2.18	3.67	1.38	2.29	3.61	1.31	2.30
Karnataka	5.39	1.97	3.42	5.22	1.87	3.35	4.27	1.18	3.09	4.12	1.08	3.04
Kerala	3.92	2.51	1.41	4.08	2.54	1.54	3.57	1.97	1.60	3.48	1.92	1.56
Madhya Pradesh	2.73	1.94	0.79	2.84	2.01	0.83	2.41	1.62	0.79	2.33	1.60	0.73
Maharashtra	2.58	1.81	0.77	2.58	1.86	0.72	2.14	1.51	0.63	2.11	1.51	0.60
Orissa	2.52	1.67	0.85	2.59	1.62	0.97	2.16	1.38	0.78	2.16	1.34	0.82
Punjab	5.34	3.85	1.49	5.48	3.85	1.63	4.70	2.95	1.75	4.48	2.84	1.64
Tamil Nadu	5.00	2.75	2.25	4.99	2.88	2.11	4.36	2.35	2.01	4.23	2.30	1.93
Telengana	4.70	3.05	1.65	4.63	3.04	1.59	3.78	2.47	1.31	3.67	2.45	1.22
Uttar Pradesh	3.07	1.95	1.12	3.08	1.94	1.14	2.46	1.56	0.90	2.37	1.48	0.89
Uttaranchal	3.90	2.12	1.78	3.91	2.21	1.70	3.33	1.40	1.93	3.24	1.34	1.90
West Bengal	3.75	1.99	1.76	3.70	2.03	1.67	3.20	1.57	1.63	3.15	1.54	1.61

analyzed for Orissa (2.52 t/ha) and Maharashtra (0.77 t/ha), respectively.

The spatial pattern of mean and trend in Y_w, Y_a, and Y_g by using projected weather information of RCMs are shown in Figures 5 and 6, respectively, during the historical period (1981–2005). The performance of RCMs to simulate Y_w and Y_a was analyzed by comparing model outputs (i.e. Y_w and Y_a) using observed weather information with model outputs using projected weather information of RCMs. It is seen that the RegCM4 model performed better than the other RCMs during the historical period, having RMSE of 0.26 and 0.32 t/ha, R^2 of 0.95 and 0.87 and D-index of 0.99 and 0.93 for Y_w and Y_a, respectively (Table 4).

Spatial patterns of mean and trend in Y_w, Y_a and Y_g during the transition period (2006–2015)

Though the time period of 2006–2015 was considered as the future in the simulation of RCM models, in observation, we have this period unfolded and that is why it was decided to test the models' applicability in the transition period. During the period (2006–2015), Y_w and Y_a were simulated for each grid by using observed weather information along with projected weather information of two climate scenarios (RCP 4.5 and RCP 8.5) based on three RCM outputs. Figures 7 and 8 show the spatial patterns of mean and trend in Y_w, Y_a and Y_g during the transition period. The simulated spatial yield results show that the mean of Y_w, Y_a and Y_g were found to be 3.65, 2.17 and 1.48 t/ha, respectively, by using observed weather information. It is noted that the simulated mean Y_w and Y_a are found to increase minimally (0.03 and 0.04 t/ha, respectively) during the transition period as compared to the historical period, however, Y_g remains almost the same. The trend analysis of Y_w and Y_a indicate that Y_w is decreased, stagnated and increased, respectively, in 37.7, 12.4 and 49.9% of the study area, whereas Y_a decreased, stagnated and increased, respectively, in 38.7, 8.3 and 53.0% of the study area during the transition period. As a result, Y_g is decreased, stagnated and increased by 45.5, 7.2, 47.3% of the study area, respectively.

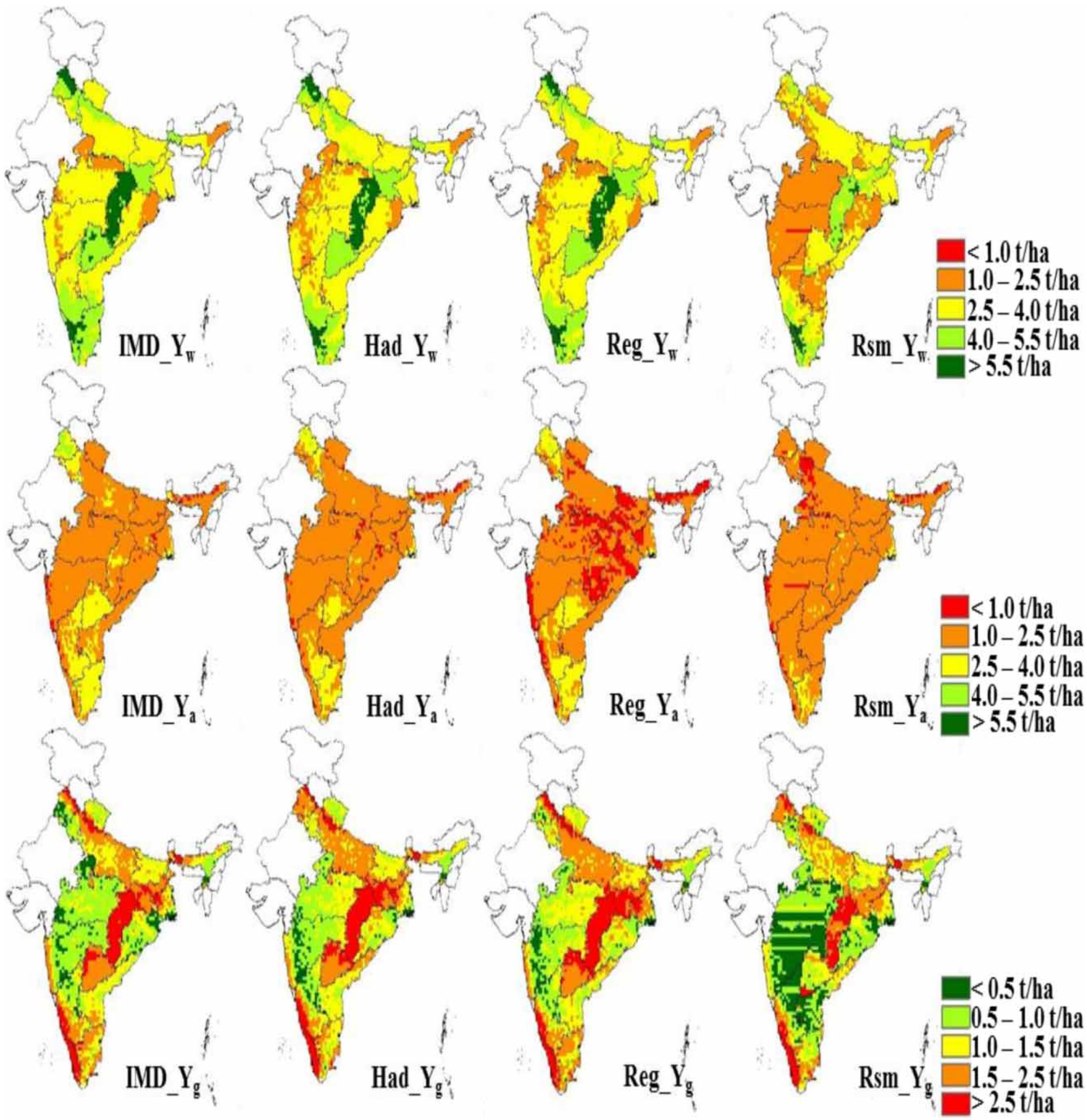

Figure 5 | Spatial variations of mean simulated water limited potential yield (Y_w), actual yield (Y_a) and yield gap (Y_g) based on RCM output for the historical period (1981–2005) (Had: HadGEM3-RA model, Reg: RegCM4 model, Rsm: YSU_RSM model, Y_w: water limited potential yield, Y_a: actual yield under rainfed conditions and Y_g: rainfed yield gap).

Similar to the historical period, the performance of RCMs was also evaluated by comparing the DSSAT model outputs (i.e. Y_w and Y_a) by using observed weather information with that of RCMs projections during the transition period. It is seen that the climate scenario RCP 8.5 of both the HadGEM3-RA and RegCM4 models performed well to simulate Y_w in the study area whereas the climate scenario RCP 8.5 of the RegCM4 model performed better than the other RCM scenarios to simulate Y_a in the study area (Table 5). As the RegCM4 model performed well in both historical and transition periods and there is no statistically significant difference (t-test at $\alpha = 5\%$) between yields by using observed weather information and outputs of the RegCM4 model, the RCP 8.5 scenario of RegCM4 model was chosen for analysing the future climate change impact on rice yield gap in the study area.

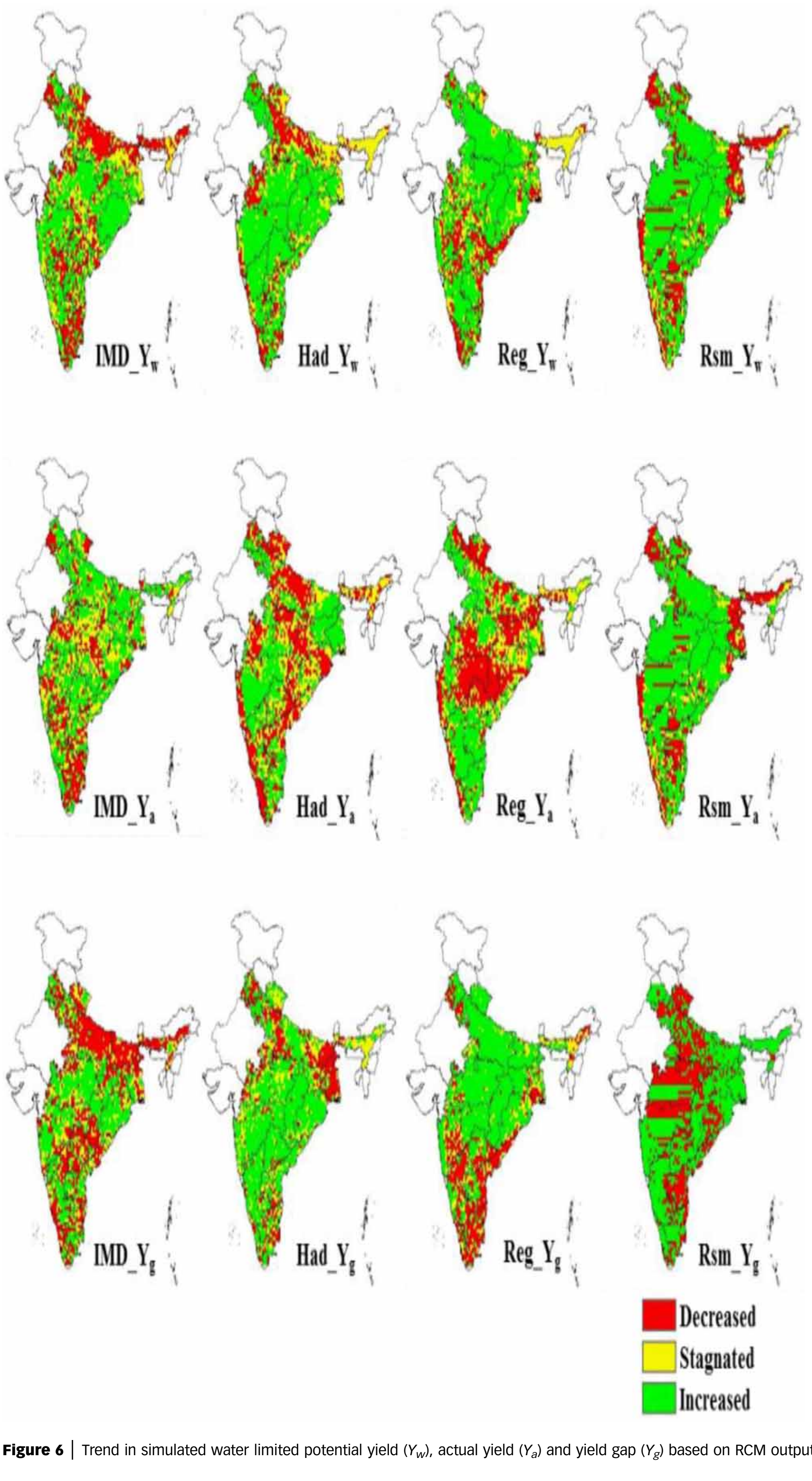

Figure 6 | Trend in simulated water limited potential yield (Y_w), actual yield (Y_a) and yield gap (Y_g) based on RCM output for the historical period (1981–2005).

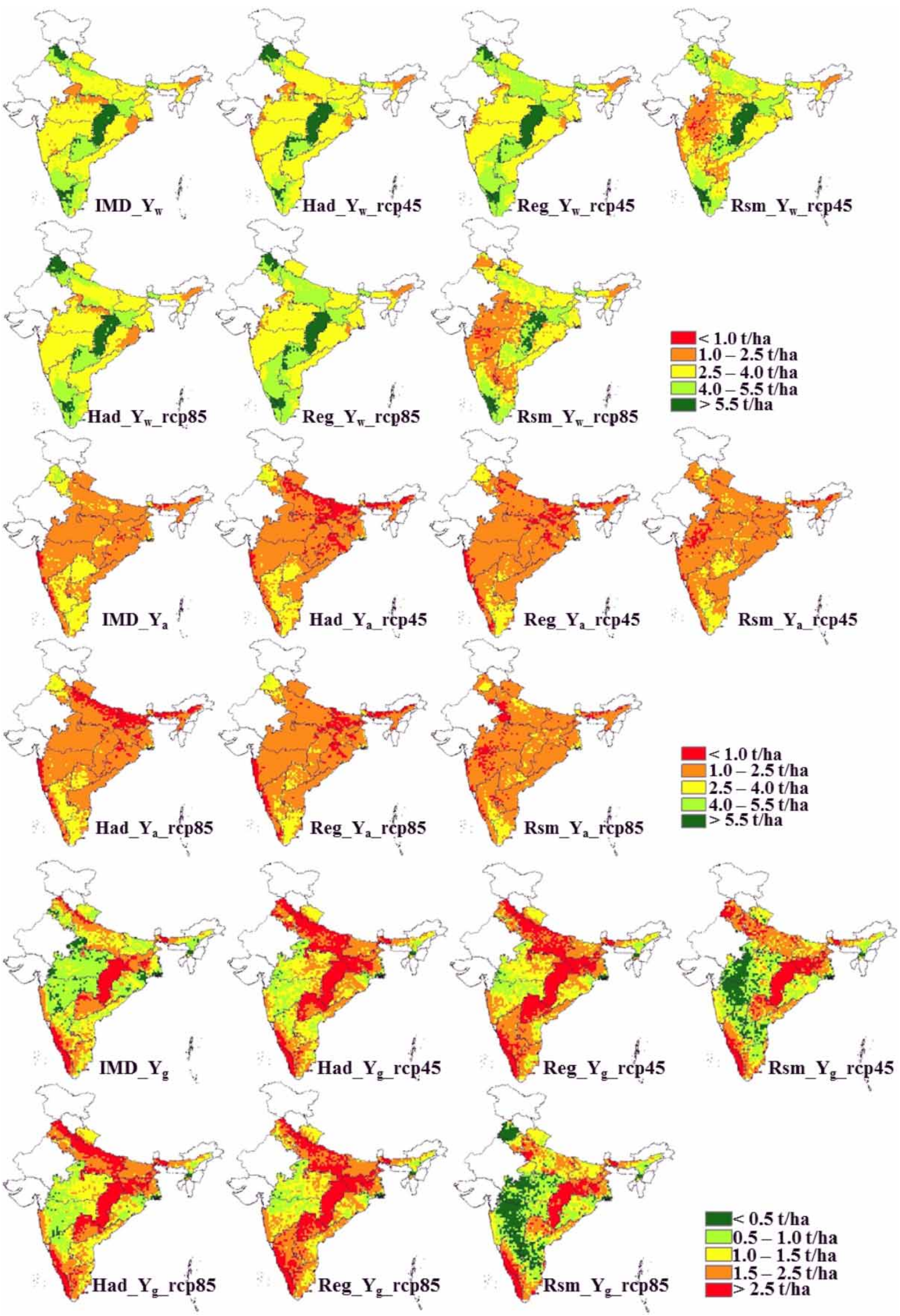

Figure 7 | Spatial variations of average simulated water limited potential yield (Y_w), actual yield (Y_a) and yield gap (Y_g) based on RCM output for the transition period (2006–2015).

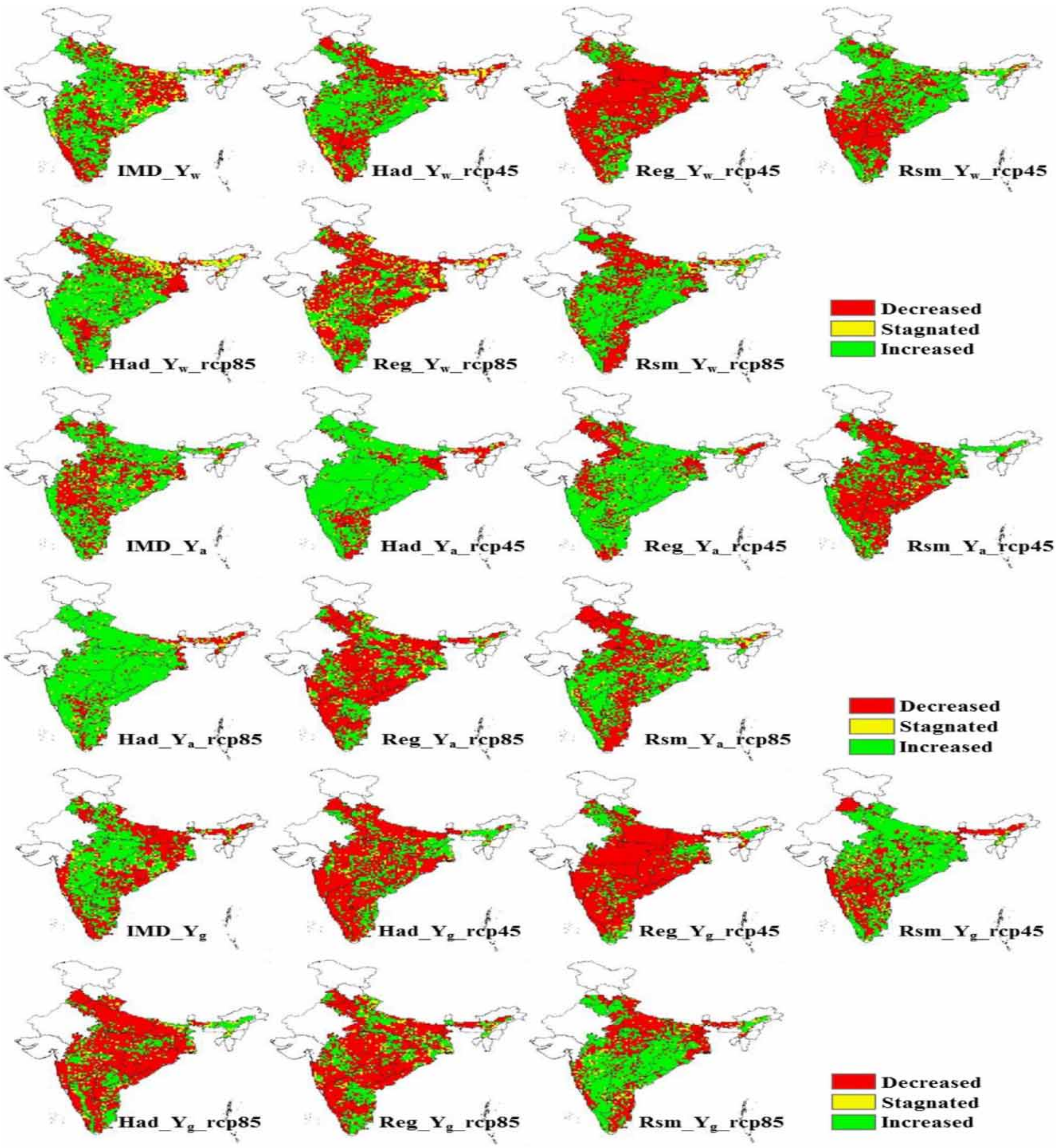

Figure 8 | Temporal variations of average simulated water limited potential yield, actual yield and yield gap based on RCM output for the transition period (2006–2015).

Spatial patterns of mean and trend in Y_w, Y_a and Y_g during future periods (2030 and 2040s)

The climate change impact on rice yield gap in the future period was assessed by using the RCP 8.5 scenario of the RegCM4 model. Figure 9 shows the spatial pattern of mean Y_w and Y_a of the study area in the 2030 and 2040s. It is seen that the mean Y_w may get reduced from 3.62 t/ha (historical period) to 3.11 and 3.02 t/ha during the 2030 and 2040s, respectively. Similar to Y_w, the average Y_a of the study area may also get reduced from 2.13 (historical period) to 1.67 and 1.62 t/ha during the 2030 and 2040s, respectively. As both Y_w and Y_a are simulated to be reduced during future periods, the average Y_g of the study area

Table 5 | Evaluation of selected RCM models for simulation of rice yields by using the DSSAT model

		Y_w			Y_a		
Time period	**RCM models**	**RMSE (t/ha)**	**R^2**	**D-index**	**RMSE (t/ha)**	**R^2**	**D-index**
Historical period (1981–2005)	HadGEM3-RA	0.29	0.94	0.98	0.31	0.85	0.93
	RegCM4	0.26	0.95	0.99	0.32	0.87	0.93
	YSU-RSM	1.03	0.60	0.78	0.62	0.36	0.69
Transition period (2006–2015)	HadGEM3-RA (RCP 4.5)	0.37	0.90	0.97	0.63	0.60	0.78
	HadGEM3-RA (RCP 8.5)	0.34	0.91	0.97	0.58	0.58	0.81
	RegCM4 (RCP 4.5)	0.41	0.89	0.97	0.60	0.63	0.79
	RegCM4 (RCP 8.5)	0.44	0.88	0.96	0.55	0.65	0.82
	YSU-RSM (RCP 4.5)	0.84	0.64	0.87	0.58	0.44	0.77
	YSU-RSM (RCP 8.5)	1.08	0.50	0.79	0.66	0.31	0.68

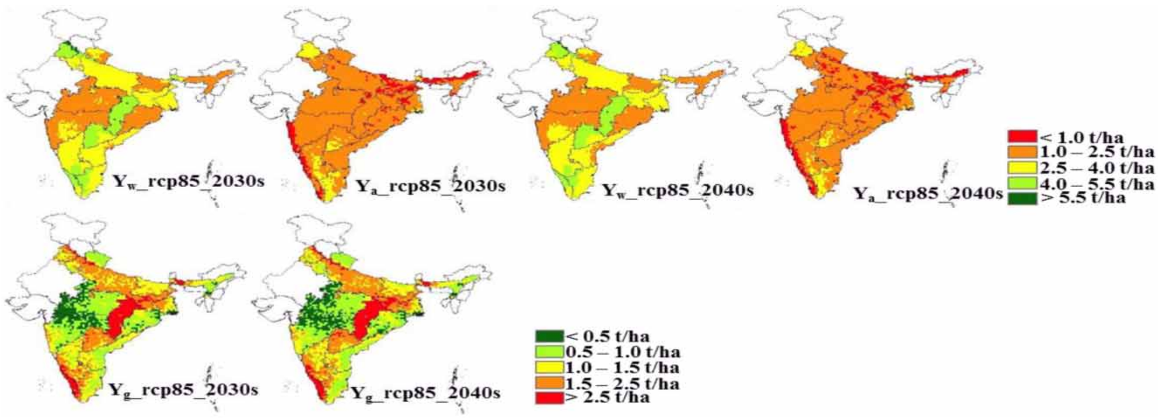

Figure 9 | Spatial variations of average simulated water limited potential yield (Y_w), actual yield (Y_a) and yield gap (Y_g) based on RegCM4 model output for future periods (2030 and 2040s).

remains almost the same (1.49, 1.44 and 1.40 t/ha during the historical period, 2030s and 2040s, respectively). The trend analysis of simulated yield results shows a decreasing Y_w in 58.2 and 62.8%, stagnated Y_w in 30.8 and 27.2% and an increasing Y_w in 11.0 and 10.0% of the study area during the 2030 and 2040s, respectively (Figure 10). The results also show that Y_a is expected to get either stagnated or decreased in a considerably large portion of the study area (78–82%) under expected future climate conditions. As a result, Y_g is expected to decrease, stagnate and increase in 49.4, 29.7 and 20.9% of the study area, respectively, during the 2030s. The projected climate for the 2040s showed a considerably smaller change in temporal pattern of Y_g (decreased, stagnated and increased in 51.3, 26.5 and 22.2%, respectively) as compared to the climate of the 2030s. Similar to the historical period, both maximum Y_w and Y_g in Chhattisgarh and maximum Y_a in Punjab are expected to occur during future periods (Table 4). Among rice-growing states, a maximum reduction of mean Y_w (≈1.1 t/ha) is expected to occur in Karnataka whereas both maximum reduction of Y_a and highest increment of Y_g are expected to be found in Haryana.

DISCUSSION

The study has attempted to establish the seasonal trend in $T_{\max}$, $T_{\min}$, R_s and rainfall at 17 major rice growing states in India during the historical period (1981–2005), transition period (2006–2015) and future periods (2030 and 2040s). It is seen that seasonal $T_{\max}$ and $T_{\min}$ and rainfall are expected to increase in the future whereas R_s may remain the same

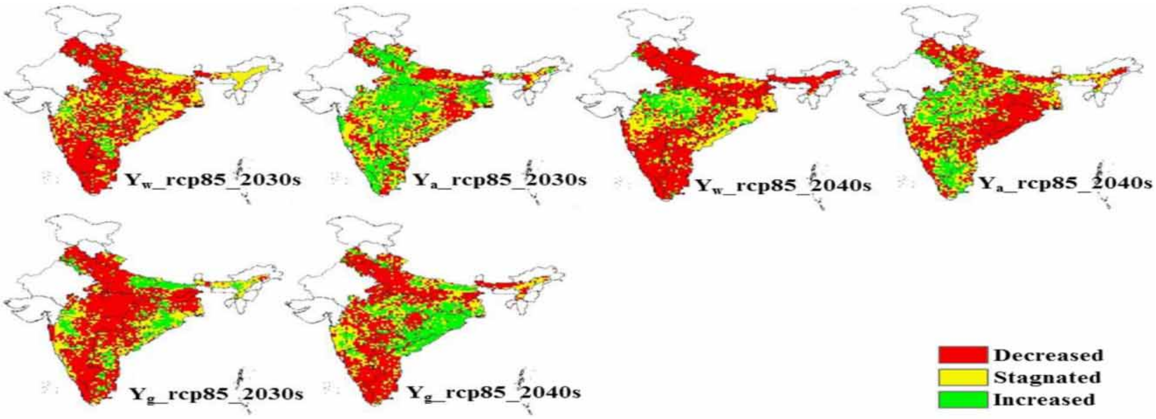

Figure 10 | Temporal variations of average simulated water limited potential yield (Y_W), actual yield (Y_a) and yield gap (Y_g) based on RegCM4 model output for future periods (2030 and 2040s).

throughout the study period. These results are well supported by the findings of Birthal *et al.* (2014) who also showed a significant rise of temperature in India with non-significant variation of rainfall in the future. The calibrated DSSAT model is used to simulate the water limited potential yield (Y_w) and actual yield (Y_a) in each grid of the study area by providing the required soil and weather information for the historical, transition and future periods. It is seen that both Y_w and Y_a may get reduced in future with respect to the historical period and, as a result, the yield gap (Y_g) of the study area remains almost the same throughout the study period. This may occur possibly because of increased temperature which reduces floral reproduction, causes sterility due to stomatal closure and reduces fertilization in the study area (Satake & Yoshida 1978; Nishiyama & Satake 1981; Matsui *et al.* 1997). The reasons for rice yield decline are reported in the literature as increase in maximum temperature (Amgain *et al.* 2006) and minimum temperature (Pathak *et al.* 2003; Amgain *et al.* 2006), decrease in solar radiation (Pathak *et al.* 2003; Amgain *et al.* 2006) and change in rainfall (Boonwichai *et al.* 2018). Yoshida & Parao (1976) and Horie *et al.* (1995) found that as the average temperature increased above the optimum temperature (22–23 °C), rice yield declined linearly with an increase in temperature up to 30 °C, followed by a sharp decline thereafter. The initial linear decrease was due to the shorter crop duration caused by increased temperature and the sharp decline after 30 °C was because of spikelet sterility from high-temperature damage. Excessive rainfall can leach nutrients out of the crop root zone or enhance the denitrification process of nitrogen fertilizer which may lead to less nitrogen availability for the crop growth. Singh *et al.* (2016) reported that excessive rain conditions during the crop maturity period adversely affect crop growth and development at critical life stages and ultimately the yield. Mishra *et al.* (2013) mentioned that the variation in crop yields among the locations is mainly because of variations in the solar radiation availability, which affects the daily photosynthesis. Debnath *et al.* (2018b) performed sensitivity analysis of weather data by changing the daily values of T_{max}, T_{min}, R_s and rainfall to identify weather variables most affecting the actual yield. This study showed that the combined effect of R_s and rainfall decreased the rice yield more significantly than other factors in late transplanting conditions. Spatial patterns of mean Y_w and Y_a indicated that relatively higher yield could be produced in Chhattisgarh due to the availability of favourable environmental conditions along with a better distribution of seasonal rainfall. The spatial yield results in all major rice-growing states contradicted the results of Soora *et al.* (2013) which indicated that climate change is expected to benefit rice yield by ≈10–15% in Andra Pradesh, Tamil Nadu, and Karnataka. The study reveals that a huge yield gap (>1.5 t/ha) may occur in Chhattisgarh, Jharkhand, Karnataka, Kerala, Punjab, Tamil Nadu, Uttaranchal and West Bengal, and modified strategies may be required in these states to sustain rice production. Srivastava (2014) found a 28.26% average yield gap in Uttar Pradesh, which is mainly caused by socio-economic, credit institutional/policy related factors, extension services and lack of improved technology. Fuss *et al.* (2015) reported that changes in yield variability may have even more important effects on food security than climate change projections. Therefore, management systems and stabilizing yields should be developed in the future to ensure food security in an environmentally sustainable way. Local or national statistics often do not provide farm yield with detailed information about production systems. This indicates that there is an urgent need to improve local or national statistics for detailed yield gap assessment. The yield gap assessment is the initial step towards enhancing rice yield and consequently improving food security. It is necessary to examine the extent to which yield gaps can be reduced by technical and institutional innovations in an economically and environmentally sustainable manner, as potential yield and economically optimal yield can differ across areas, especially for rainfed systems. Such analysis is rarely performed after a yield gap assessment but, if it is carried out, it will help investment in agricultural production. Finally, an interesting outcome of the study is that the expected yield gap shows positive hope for rice yield improvement though the changing climate could reduce the rice yield in future.

CONCLUSIONS

The impact of climate change on rice yield gap in the major rice-growing states of India has been analyzed by using the DSSAT model for identifying the regions that offer the best hope for meeting projected crop production demands and the regions where modified strategies may be required to sustain rice production. The trend of seasonal climate variables shows an expected increase in maximum temperature, minimum temperature and rainfall, and a decreasing trend in solar radiation in the future (2030 and 2040s) over the study area. Consequently, average spatial water limited potential rice yield is expected to reduce from 3.62 t/ha in the historical period to 3.11 t/ha and 3.02 t/ha during the 2030 and 2040s, respectively. Similarly, the average actual yield under the rainfed conditions is also expected to reduce from 2.13 to 1.67 and 1.62 t/ha during these future periods. However, the average rainfed yield gap remains almost the same throughout the study period (≈1.40 t/ha). The temporal analysis of yield gap reveals that the water limited potential yield and actual yield, respectively, have decreased in 30.8 and 23.3% of the study area during the historical period and are expected to decrease in considerably large portions of the study area (30–60%) under future climate condition (2030 and 2040s). The results also reveal an increasing yield gap in 20.9 and 22.2%, stagnated yield gap in 29.7 and 26.5% and decreasing yield gap in 49.4 and 51.3% of the study area during two future periods. The statistical analysis reveals that the output of the RegCM4 model has performed well for simulating water limited potential yield and actual yield as compared to the other two regional climate models in the study area. This study assumed a single rice cultivar, a fixed date of transplanting, fixed timing and quantity of fertilizer applications as the overall representatives to all rice-growing states in India, which may vary for farmer to farmer in the study area during the kharif rice cultivation. This poses limitations and a number of observation details may bring out subtle differences within the study area. Nevertheless, the finding of the study contributes to understanding the consequences of climate change on rice yield gap and future food security concerns in India, which is essential for agricultural policy planning and the selection of mitigation strategies to reduce the rice yield gap. The study also has the potential to be translated for other parts of the world, and for crops to develop adaptation strategies to reduce the crops yield gap for improving regional and global food security.

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DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories. The climate data could be downloaded from http://cordex-ea.climate.go.kr/cordex/. The soil information of the study area could be assessed through http://swat.tamu.edu/docs/swat/india dataset/FAO_soils.7z. The observed rice yield data could be downloaded from www.indiastat.com.

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