



# Evaluating the performance of RegCM4.0 climate model for climate change impact assessment on wheat and rice crop in diverse agro-climatic zones of Uttar Pradesh, India

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## Abstract

The paper aims to explore the biasness in the RegCM climate model outputs for diverse agro-climatic zones of Uttar Pradesh, India, with emphasis on wheat (*Rabi* growing season) and rice (*Kharif* growing season) yields with and without bias correction using quantile mapping approach for the baseline period of 1971–2000. The result shows that RCM highly underestimated the maximum and minimum temperature. There exists a bias towards lower precipitation in annual and Kharif and higher in Rabi along with strikingly low intense warm (maximum temperature >45 °C and 40 °C) and high cold events (maximum temperature < 20 °C and minimum temperature < 5 °C) in the RCM simulation and biased towards low extreme rainfall > 50 mm/day. Bias correction through quantile mapping approach, however, showed excellent agreement for annual and seasonal maximum and minimum temperature and satisfactory for extreme temperatures but drastically failed to correct rainfall. The study also quantified the biasness in the simulated potential, irrigated, and rainfed wheat and rice yield using DSSAT (Decision Support System for Agro-technology Transfer) crop model by employing observed, RCM baseline, and RCM baseline bias-corrected weather data. The grain yields of RCM-simulated wheat and rice were high while the bias-corrected yield has shown good agreement with corresponding observed yield. Future research must account for the development of more reliable RCM models and explicitly bias correction method in specific to complement future analysis.

**Keywords** Climate change · RegCM4 · DSSAT · Wheat · Rice · Bias correction · Quantile mapping · Uttar Pradesh

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## 1 Introduction

During recent decades, scientific community and policy makers are recognizing the changing climate and its impacts on world food security in general and its regional impacts considering projected increase of global mean surface temperature by 0.3 °C (minimum of RCP2.6) to 4.8 °C (maximum of RCP 8.5) for 2081–2100 (Kumar et al. 2013, IPCC 2013). Climate projections developed for South Asia region show that India might witness an increase in mean annual temperature by 2–3 °C in midterm (2045–2065) and by 3–5 °C in long-term (2081–2100) future (IPCC 2013). The increase in temperature is expected to be more in northern India with overall projected increase in mean annual precipitation with a shift in rainfall pattern (Jain and Kumar 2012; Auffhammer et al. 2012; Akhter et al. 2017; Basha et al. 2017). A trend analysis for Uttar Pradesh shows a significant increase in annual mean and minimum temperature by 0–1.5% and 1.5–3% for the period of 107 years (1901–2007) decreases in rainfall by 0–8% in east UP and 16 to 24% in west UP though insignificant for the period of 141 years (1871–2011) (Mondal et al. 2015).

The impact of climate change on different sectors is a topic of extensive research but there is a plausible evidence of climatic impacts on agriculture that is heterogeneous and ambiguous (Arumugam et al. 2015). Climate change may negatively affect wheat and rice yield in some major wheat and rice-producing regions of the world (Challinor et al. 2010; Auffhammer et al. 2012; Jain and Kumar 2012; Licker et al. 2013; Yang et al. 2017). Globally observed, wheat yield showed decline of 0.6 ton/ha/dec to 0.40 ton/ha/dec in 2000s while rice observed a little increase of 0.5 ton/ha/dec to 0.6 ton/ha/decade in 2000s (Lobell and Gourdji 2012). In a study, BIRTHAL et al. (2014) projected that with significant change in temperature and rainfall up to 2100 for Indian region, a reduction by 15% in rice yield and by 22% in wheat yield may be observed. Recent evidences indicate less frequent but more intense monsoon rainfall in India during the latter half of the twentieth century, thus increasing the risk of drought and flood damage to the country's wet season (Kharif) rice crop with expected 40% runoff of the total rainfall (Goswami et al. 2006; Mall et al. 2006; Dash et al. 2009; Auffhammer et al. 2012; Jain and Kumar 2012; IPCC 2013; Singh et al. 2017).

To quantify the impact of climate change on crop productivity, crop growth simulation models with input from several GCM and RCM are being used in large scale (Mall and Gupta 2000; Aggarwal and Mall 2002; Mall and Srivastava 2002; Challinor et al. 2010; Shinde and Modak 2013; Chattaraj et al. 2014; Tao et al. 2014; Yadav et al. 2015; Zacharias 2015; Singh et al. 2017; Dar et al. 2017, Mall et al. 2017). A study by Gourdji et al. (2013) using CMIP5 multi-climate model (RCP8.5 emission scenario) projected substantial vulnerability for wheat in South Asia for 2050s. A study by Pathak et al. (2003) using CERES crop model for the Indo-Gangetic Region reported a decrease in wheat (8.3 to 7.5 Mg ha<sup>-1</sup>) and rice yield (10.9 to 10.3 Mg ha<sup>-1</sup>) with 1.7 MJ m<sup>2</sup> per day reduction in solar radiation. Similarly, an increase in minimum temperature by 1.78 °C showed a decline in rice (10.9 to 10.0 Mg ha<sup>-1</sup>) and wheat yield (8.3 to 8.1 Mg ha<sup>-1</sup>). A future projection for Uttar Pradesh using InfoCrop model and input from PRECIS shows a decline by 4 to 7% in irrigated and rainfed rice yield by 2020 to 2080 (Kumar et al. 2013) and 25 to 30% for wheat yield by 2050 to 2080 (Kumar and Aggarwal 2014). Similarly, Dasgupta et al. 2013 using PRECIS reported reduction in grain production by 5% for UP.

But climate output employed to run the crop simulation model is often associated with the bias. Bias correction is a frequently used method employed to match RCM data to observed data before using it as an input to climate impact model (Qian et al. 2016). Evidences show that

phenomena like summer convective precipitation are not convincingly taken care by RCMs at 10-km resolution and beyond (Kendon et al. 2014; Meredith et al. 2015). This is because, RCM many a times fails to perfectly represent orography, land surface feedbacks (Maraun 2016), and inherit systematic model errors due to inadequate conceptualization, parameterization, and spatial averaging within grid cells (Qian et al. 2016). Due to this, uncertainty in model simulation is high (Jacob et al. 2014). Thus, the impact assessment model demands bias correction/bias adjustment of the input climate data (Maraun 2016).

Uttar Pradesh being the largest producer of wheat and rice in India on account of its largest share of wheat area (34%, 1st in India, 9.7 mha) and production (35% 1st in India, 30.3 MT), and rice area (13%, 3rd in India, 5.95 mha) and production (13%, 3rd in India, 14.0 MT) (DES 2016). There is still substantial scope to increase both area and productivity of wheat-rice crops in Uttar Pradesh to meet the 2050 India's demand if proper crop management is executed to cope the climate risk by using reliable climate predictions. The present study aims to assess the performance of RegCM4 for agro-climatic zones of Uttar Pradesh by quantifying the bias associated with it before and after bias correction using quantile mapping approach in comparison with the observed data (1971–2000) with particular emphasis on wheat (Rabi) and rice (Kharif) growing season. The detailed objectives of the study are as follows: Comparison of simulated baseline, bias-corrected baseline, and observed (i) maximum and minimum temperature, rainfall, rainy days, rainfall intensity; (ii) extreme maximum temperature days  $> 45^{\circ}\text{C}$ ,  $> 40^{\circ}\text{C}$ ,  $< 20^{\circ}\text{C}$  and extreme minimum temperature days  $< 5^{\circ}\text{C}$  and rainfall extreme  $> 50\text{ mm/day}$ ; and (iii) comparison of potential, irrigated, and rainfed wheat and rice yield simulated through CERES-wheat and CERES-rice.

## 2 Materials and methods

### 2.1 Study area and data

The State of Uttar Pradesh (UP) has distinguished itself as an “agricultural State” located between  $23^{\circ} 50' - 30^{\circ} 45' \text{ N}$  latitude and  $77^{\circ} 04' - 84^{\circ} 38' \text{ E}$ . Detailed information about the study site is presented in Fig. 1 (IWMP, 2009). Daily gridded climate data (1971–2000) for temperature ( $1^{\circ}$  latitude  $\times$   $1^{\circ}$  longitude) and rainfall ( $0.25^{\circ}$  latitude  $\times$   $0.25^{\circ}$  longitude) was obtained from the India Meteorological Department, and solar radiation ( $1^{\circ}$  latitude  $\times$   $1^{\circ}$  longitude) was obtained from NASA-POWER (NASA/POWER; [power.larc.nasa.gov](http://power.larc.nasa.gov)). Baseline RCM climate data (1971–2000) were obtained from CCCR-IITM for RegCM4.0 (LMDZ) developed by the National Center for Atmospheric Research (NCAR) in ICTP Italy in 2010 (Giorgi et al. 2012) with a 50-km horizontal resolution. Due to difference in horizontal resolution of variables, temperature data were re-gridded to IMD rainfall scale using bilinear interpolation method and RCM rainfall was re-gridded to IMD rainfall scale using kriging interpolation method. For the Indian subcontinent, RegCM4 performs to its finest. RegCM4 has the ability to replicate present day climate features over the study region (Gao and Giorgi 2017)

### 2.2 Crop simulation

The calibrated and validated CERES-wheat and CERES-rice crop models by Mall et al. (2016) and Singh et al. (2017) for different agro-climatic zones have been used in simulating the crop

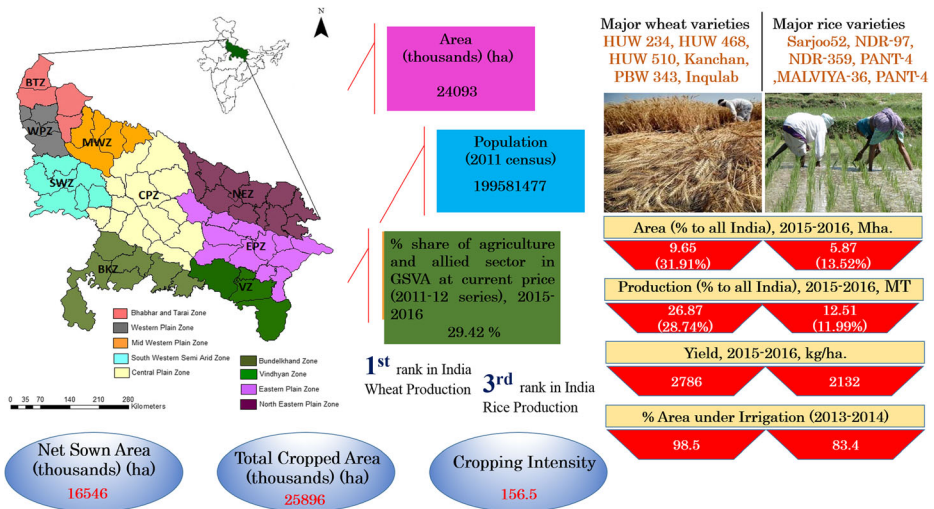


Fig. 1 Detailed description of Uttar Pradesh (source: DES 2016, Mall et al. 2017)

yield in the study. It simulates crop yield, growth, and development based on some crop characteristics (Hoogenboom et al. 1994). The observed, RCM, and RCM bias-corrected climate output was used to simulate the wheat and rice potential, irrigated, and rainfed yield through DSSAT4.5 crop model. The crop yield was simulated for wheat and rice at three levels of management:

- (1) Potential yield is simulated considering no water and nitrogen stress on crop growth.
- (2) Irrigated wheat yield was simulated using application of 120 kg N/ha in three split doses of 60 kg/ha, 30 kg/ha, and 30 kg/ha at 0, 20, and 60 days after sowing and 5 irrigations, whereas for rice, three split doses of nitrogen of 35 kg/ha, 60 kg/ha, and 60 kg/ha at 0, 25, and 45 days after sowing with irrigation when required.
- (3) Rainfed productivity was simulated assuming no irrigation and 30 kg/ha basal nitrogen application for wheat and rice

### 2.3 Estimation of biasness and bias correction

The bias estimation of RCM climate output was done by comparing its mean and standard deviation for annual and seasonal phase with observed climate. The goodness-of-fit statistics was used to calculate the difference between observed and simulated yields using the following equations:

Percent of deviation (D%)

$$D\% = \left[ \frac{S_i - O_i}{O_i} \right] \times 100\% \quad (1)$$

$S_i$  and  $O_i$  define simulated and observed yield (t/ha). D% close to zero refers to very good agreement between simulated and observed yield (Araya et al. 2015).

Index of agreement (I)

$$I = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (|S_i - S_m| + |O_i - O_m|)^2} \quad (2)$$

$S_m$  and  $O_m$  refers to means of simulated and observed yield respectively. I vary from negative infinity to 1. I close to zero shows better agreement between the observed and simulated yield (Willmot 1982).

Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (S_i - O_i)^2}{n}} \quad (3)$$

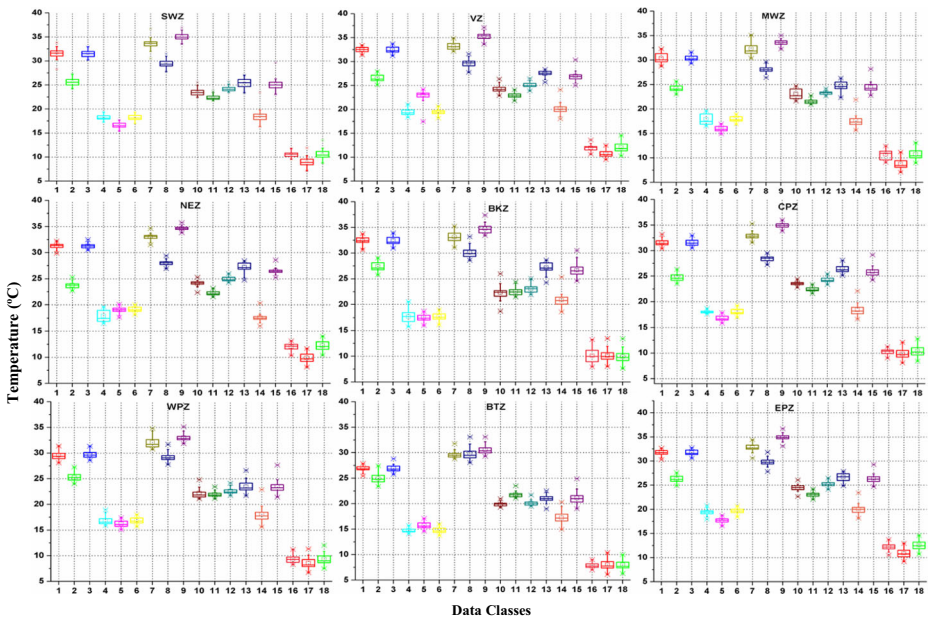
RMSE is a statistical error in the model. RMSE close to zero indicate good performance of the model.

The quantile mapping approach used in the study for removing biasness of the RCM data is done by fitting a cumulative probability distribution (CDF)  $F_{obs}(x_{obs})$  to the observed values and fitting another distribution  $F_{grid-c}(x_{grid-c})$  under the current climate to the RCM data in a grid and by mapping the grid value to the probability distribution of the observations to derive the “bias-corrected” grid data  $x_{grid-c-corrected}$  for the current climate as below (Qian et al. 2016).

$$Z_{model-present-corrected} = F_{obs}^{-1} (F_{model-present} (Z_{model-present})).$$

### 3 Result and discussion:

The RCM highly underestimates the annual, Rabi, and Kharif maximum temperature and very slightly the minimum temperature throughout the agro-climatic regions. The RCM baseline showed a mean underestimation of  $5.5 \pm 1.6$  °C for maximum temperature annually, where out of nine zones, seven zones underestimated the temperature  $\geq 5$  °C (Fig. 2). The underestimation in Rabi maximum temperature was even higher with mean underestimation of  $6.8 \pm 1.6$  °C (highest of  $9.6 \pm 0.1$  °C in NEZ), where out of nine zones, eight zones underestimated the temperature  $\geq 5$  °C. The mean underestimation in Kharif maximum temperature was  $3.4 \pm 1.5$  °C and only single zone underestimated the temperature  $\geq 5$  °C. On the other hand, minimum temperature showed very slight underestimation annually and seasonally. The mean underestimation for annual, Rabi, and Kharif minimum temperature is  $0.2 \pm 1.8$  °C,  $1 \pm 0.9$  °C, and  $0.8 \pm 1.2$  °C respectively. Bias correction has shown excellent agreement with the observed temperature, and except Rabi minimum temperature (mean underestimation of  $1.6 \pm 0.5$  °C), the difference for annual and seasonal maximum and minimum temperature was close to zero. A similar study carried by Zacharias et al. (2015) using PRECIS for the Indo-Gangetic plain reported similar findings where they found underestimation in annual (0.24–2.36 °C), Kharif (0.32–4.92 °C), and Rabi maximum (0.11–3.24 °C) and Rabi minimum (0.27–3.21 °C) temperature and very slight overestimation in annual (0.02 °C to 0.5 °C) and Kharif minimum (0.27 °C to 0.93 °C) temperature. Importantly, their study reported more underestimation during Kharif than Rabi just opposite to our findings. Yet, another study by Maity et al. (2017) using RegCM4 reported underestimation in mean surface temperature for monsoon period (Kharif



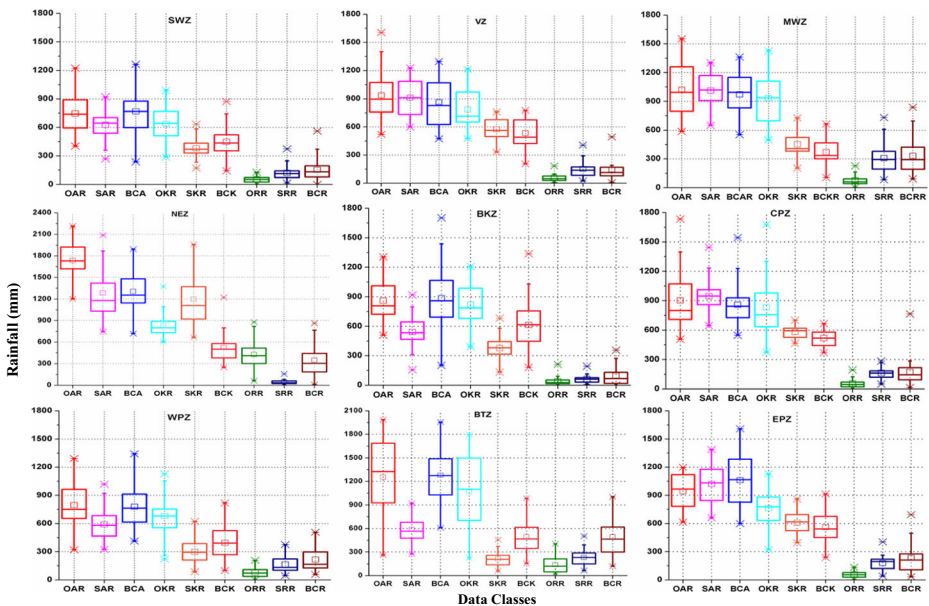
**Fig. 2** Comparison between observed, RCM (RegCM4.0), and RCM bias-corrected (RCMBC) annual and seasonal temperature for the period 1971–2000. The boxes mark the 25% and 75% quartiles while the whiskers give the minimum and maximum values. 1, 2, 3—observed, RCM, RCMBC annual maximum temperature; 4, 5, 6—observed, RCM, RCMBC annual minimum temperature; 7, 8, 9—observed, RCM, RCMBC Kharif maximum temperature; 10, 11, 12—observed, RCM, RCMBC Kharif minimum temperature; 13, 14, 15—observed, RCM, RCMBC Rabi maximum temperature; 16, 17, 18—Rabi minimum temperature respectively

period) that corroborates with our study. A striking point worth mentioning here is that the RCM shows a substantial decline in maximum temperature and slight decline in minimum temperature comparative to the observed climate data. This suggests a decrease in diurnal temperature difference and night warming. Indian wheat has shown susceptibility to increasing night temperature especially post anthesis reducing the overall production (Rao et al. 2015). Similarly, night warming in rice was found to arouse the night respiration rate but decrease the [photosynthesis](#) rate; consequently, a significant reduction in aboveground biomass accumulation was recorded with additional reduction in seed setting and grain filling particularly of inferior kernels (Dong et al. 2014). This trend is supposedly incorporated in the future projection as well. Further detailed data inspection brings out changed climatic averages for RCM in comparison to the observed (Fig. 2).

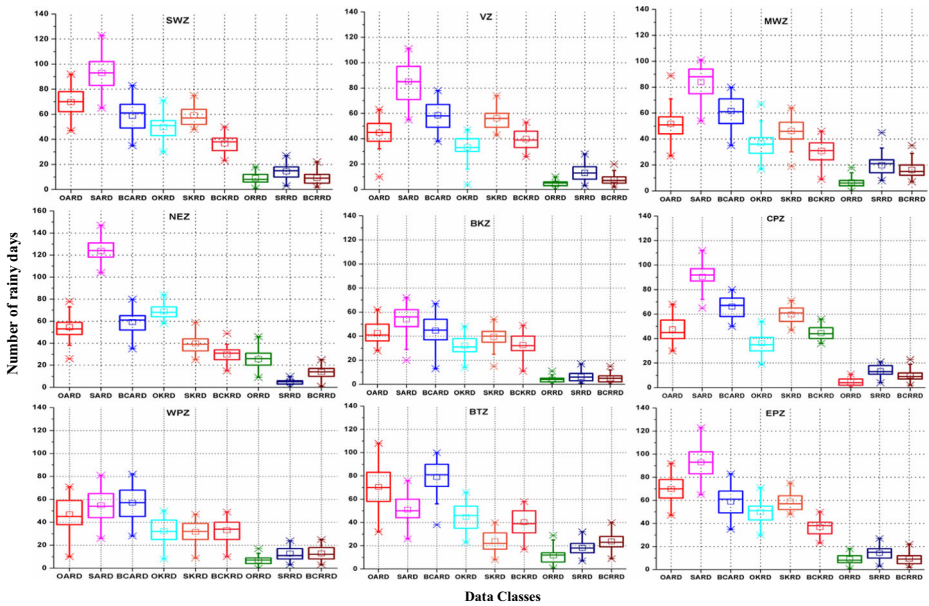
Rainfall showed a large heterogeneity in precipitation distribution (Fig. 3). The RCM have shown a high dry bias in annual (223 mm except NEZ, CPZ, and EPZ) and Kharif (378 mm) rainfall on the other hand it has shown a high wet bias in Rabi rainfall (139 mm) (Fig. 3). Bias correction satisfactorily complemented annual rainfall but no improvement has been found for Rabi and Kharif season (Fig. 3). A study by Dash et al. (2013) and Pattnayak et al. (2013) has found an overestimation of rainfall simulated by RegCM where major portion of northeast India have shown a wet bias opposite to what have been found in our study. But Singh and Oh (2007) using RegCM found reduced precipitation over northeast India that coincides with our findings. In a study by Maity et al. (2017) covering a similar study area reported dry bias associated with RegCM4 for Indian summer monsoon. Contrary to precipitation, the RCM

overestimated the annual ( $31 \pm 20$  days, except BTZ), Kharif ( $16 \pm 9$  days, except BTZ), and Rabi ( $9 \pm 5$  days) rainy days while bias correction fairly corrected the days up to certain magnitude (Fig. 4). Bias correction may not efficiently change the relative day-to-day variations of RCM data and require advance investigation to deal with current bias-correction methodologies to deal with this issue. The collective effect of rainfall amount and rainy days is described in terms of rainfall intensity (RI). High rainfall intensity has negative consequences for crops through nutrient loss and hydrology and brings challenges and opportunities to make resilient management strategies (Dourte et al. 2015). The simulated RI shows high underestimation, whereas the bias corrected shows concordance with the observed for most agroclimatic zones. The model performance for rainfall intensity was evaluated by Taylor Diagrams (Taylor 2001) (Fig. 5). Among nine zones, RI only in SWZ is showing a significant correlation with observed (0.38 at 95%) (Fig. 4). However, the simulated bias-corrected RCM rainfall intensity over MWZ, BKZ, CPZ, WPZ, BTZ, and EPZ performed well and has a significant correlation coefficient (CC) at 95% level of significance lying in the range of 0.36–0.48 (Fig. 5).

Averaged across the nine zones, difference in extreme temperature and rainfall days in RCM output relative to those of the baseline climate is shown in Table 1. A large underestimation was observed for maximum temperature  $> 45$  °C (zero for all zones) and  $> 40$  °C up to 146 days in VZ. Contrary, a large overestimation was observed for maximum temperature  $< 20$  °C up to 4072 days in NEZ and minimum temperature  $< 5$  °C up to 803 days in SWZ in the RCM (Table 1). The bias correction tool however gave a very reliable output with a huge difference from RCM simulation and far less difference from observed. Dash et al. (2013), however, found an overestimation in warm days and warm nights comparative to observed values. In case of rainfall extreme, rainfall  $> 50$  mm/day showed underestimation up to

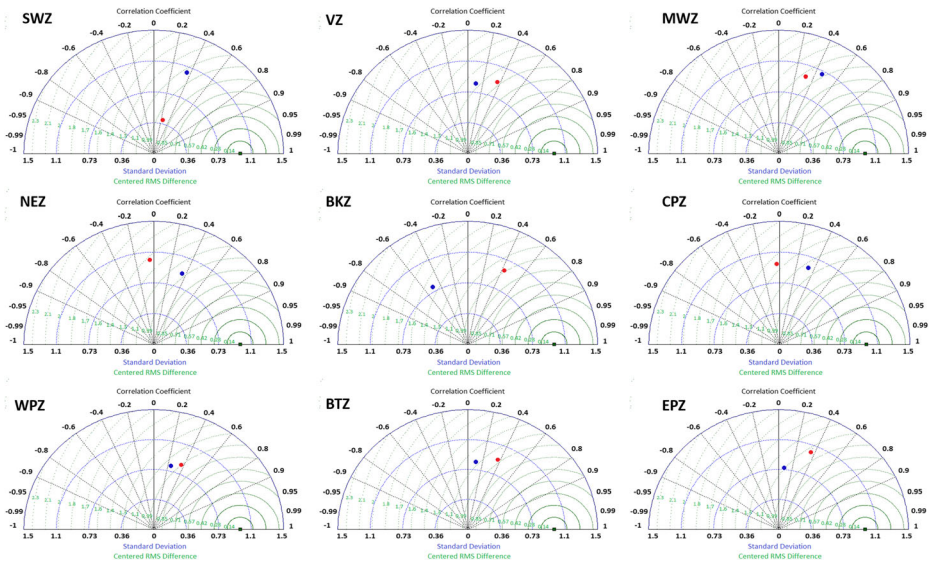


**Fig. 3** Comparison between observed, RCM (RegCM4.0), and RCM bias-corrected (RCMBC) annual and seasonal rainfall. The boxes mark the 25% and 75% quartiles while the whiskers give the minimum and maximum values. S- simulated, O- observed, A- annual, K- Kharif, R- Rabi, R- rainfall



**Fig. 4** Comparison between observed, RCM (RegCM4.0), and RCM bias-corrected (RCMBC) annual and seasonal rainy days. The boxes mark the 25% and 75% quartiles while the whiskers give the minimum and maximum values. S- simulated, O- observed, A- annual, K- Kharif, R- Rabi, RD- rainy days

170 days in BTZ but an overestimation up to 70 days in EPZ (Table 1). The extreme rainfall on a single day creates a situation of flood and destroys the crop. Also, they are not useful to crops, as the water absorption rate for crops is low and they require a sustained water



**Fig. 5** Taylor diagram of rainfall intensity over nine agro-climatic zones of Uttar Pradesh for 1971–2000. The green dot represents observed IMD data, blue dot represents the RegCM4 data, and red dot represents RegCM4 bias corrected (regressed rainfall intensity)



**Table 1** Total number of extreme temperature and rainfall days in different categories for observed, RCM-simulated, and bias-corrected RCM-simulated climate data for the period 1971–2000

S. No.	Maximum temperature									Minimum temperature			Rainfall		
	> 45 °C			> 40 °C			< 20 °C			< 5 °C			> 50 but < 100 mm/day		
	Obs.	Sim.	BC	Obs.	Sim.	BC	Obs.	Sim.	BC	Obs.	Sim.	BC	Obs.	Sim.	BC
SWZ	87	0	75	1272	110	1082	467	2913	521	219	803	313	99	12	66
VZ	137	0	89	1541	146	1111	167	2456	138	102	242	125	92	10	47
MWZ	20	0	2	683	12	586	562	3247	623	151	727	215	107	43	68
NEZ	0	0	0	29	2	343	330	4072	300	31	347	52	162	124	199
BKZ	130	0	54	1623	37	1372	199	3124	238	506	734	591	99	5	86
CPZ	15	0	48	983	39	840	236	3124	258	330	414	407	87	14	43
WPZ	29	0	0	494	116	524	905	3083	985	495	654	407	72	13	32
BTZ	0	0	0	25	91	4	1877	3324	1944	885	991	1132	145	11	104
EPZ	36	0	25	1623	37	770	199	3124	178	506	37	591	120	17	94

availability for good soil moisture and self-absorption. A similar study by Dash et al. (2013) using RegCM and Zacharias et al. (2015) using PRECIS showed overestimation in extreme weather conditions on all—India basis.

To quantify the impacts of RegCM model bias in baseline simulations on crop performance, rice (*Kharif* season) and wheat (*Rabi* season) yields before and after bias correction were simulated using the observed weather, RCM baseline, and RCM bias-corrected baseline weather representing different agro-climatic zones of UP in DSSAT crop model. The RCM-simulated wheat yield shows an overestimation for all zones except BTZ that ranges from 1.5 to 26% for potential, 4.4 to 30.1% in irrigated, and 4 to 34.2% in rainfed. Contrary, after bias correction, most zones showed negative deviation in wheat yield with observed that goes maximum to 20% except in MWZ (Table 2). However, rainfed wheat yield showed large spatial heterogeneity (Table 2). The positive deviation of the model wheat yield in comparison to the observed yield is might be because of the underestimation of Rabi maximum and minimum temperature and high simulated Rabi rainfall. The temperature mainly impacts first spikelet initiation to anthesis and much sensitive for grain yield (Abrol and Ingran 1996). Increasing temperature from 21/16 °C to 30/25 °C leads to low grain length (1.49 to 1.51 mg/grain/day) and grain weight (Abrol and Ingran 1996). Consistent high temperature from mid-February to April may reduce viable florets and grain filling duration. A study by Gourdji et al. (2012) explores that during the grain-filling stage that is considered the hottest part of the season, wheat yields displayed most sensitivity to warming in this phase. Rice, however, showed spatial heterogeneity in irrigated and rainfed. The deviation in rice yield varies from 0.13 to 29% in potential, –9.7 to 16.6% in irrigated, and –18.2 to 30.3% in rainfed. The main reason behind this is an underestimation in the Kharif rainfall by the RCM. Bias correction performed very unsatisfactorily for rainfed by comparative performance of potential and irrigated (Table 2). The unsatisfactory performance of bias-corrected rainfed rice yield is probably due to more number of days with temperature greater than 40 °C and the underestimation in Kharif rainfall over most of the zones. High temperature exposure in rice at anthesis prevents anther dehiscence and pollen shedding that results reduced pollination and low grain numbers (Zheng and Mackill 1982). Thus, future yield loss will be seen in areas

**Table 2** Deviation (D%), index of agreement (I), and root mean squared error (RMSE) for DSSAT4.5-simulated wheat and rice potential, irrigated, and rainfed yield using observed, RCM, and RCM bias-corrected climate data. The abbreviation WBC represents without bias corrected and BC represents with bias corrected

Stations	Wheat																									
	D%				I				RMSE																	
	Potential	BC	WBC	Irrigated	BC	WBC	Rainfed	BC	WBC	Potential	BC	WBC	Rainfed	BC	WBC	Potential	BC	WBC	Rainfed	BC	WBC					
SWZ	1.5	-1.8	4.4	-14.0	-20.1	29.1	8.4	4.0	-5.0	0.46	0.38	-0.35	1.70	-0.89	0.45	-0.37	0.86	0.23	-0.13	0.03	2.0	1.2	1.9	1.3	0.6	0.6
VZ	13.3	-19.5	29.1	-20.1	30.5	22.5	33.3	28.7	11.0	0.15	0.04	0.15	1.70	-0.89	0.45	-0.37	0.86	0.23	-0.13	0.03	2.0	1.2	1.9	1.3	0.6	0.6
MWZ	3.2	24.8	22.5	30.5	-3.1	30.1	34.2	9.7	28.7	0.31	0.56	-4.22	0.58	-4.22	0.15	0.04	0.15	1.70	-0.89	0.45	2.0	1.2	1.9	1.3	0.6	0.6
NEZ	23.4	-7.2	30.1	-3.1	30.1	34.2	9.7	28.7	11.0	-3.40	0.04	-4.22	0.58	-4.22	0.15	0.04	0.15	1.70	-0.89	0.45	2.0	1.2	1.9	1.3	0.6	0.6
BKZ	15.3	-3.3	20.4	-6.0	-7.6	10.1	23.7	9.9	4.7	0.02	0.38	0.50	0.46	-0.03	0.00	0.00	0.46	0.16	-1.22	0.01	1.7	1.8	1.6	1.9	0.7	0.6
CPZ	4.9	-4.7	10.1	-7.6	4.9	8.8	4.9	4.7	2.9	0.53	0.34	0.37	0.37	0.50	0.37	0.37	0.37	0.16	-1.22	0.01	1.1	1.5	1.1	1.2	1.4	1.4
WPZ	5.4	7.7	8.8	4.9	4.9	8.8	4.9	4.7	2.9	0.42	0.34	0.37	0.37	0.50	0.37	0.37	0.37	0.16	-1.22	0.01	2.0	1.6	1.5	1.4	0.5	0.5
BTZ	-19.7	4.6	-12.4	4.9	-15.3	27.0	5.6	-4.8	-16.1	-1.04	0.49	-1.16	-0.23	-0.38	-1.16	-0.23	-0.23	-0.05	-0.40	0.03	1.8	1.2	1.1	1.6	0.7	0.9
EPZ	26.0	-7.3	27.0	-15.3	4.9	8.8	4.9	4.7	2.9	-0.20	0.50	-0.38	0.42	-0.38	-0.38	0.42	0.42	-0.13	0.03	2.0	1.2	2.0	1.2	1.9	1.3	0.6

Rice														
Stations	Potential				Irrigated				Rainfed					
	WBC	BC	WBC	BC	WBC	BC	WBC	BC	WBC	BC	WBC	BC	WBC	BC
SWZ	23.2	-4.2	16.6	-3.5	27.9	15.3	-18.2	18.1	-4.10	0.92	-1.96	0.86	0.23	-0.15
VZ	12.8	-11.4	-1.7	-9.5	18.2	6.4	-18.2	18.1	-1.05	0.78	0.47	0.09	-0.87	0.52
MWZ	-6.8	-9.2	10.6	9.2	25.1	-15.7	25.1	7.5	0.00	-0.44	0.46	0.44	0.30	0.68
NEZ	29.1	-5.8	2.9	4.0	-2.1	-11.0	-11.0	-1.87	-4.05	0.94	-0.10	-0.64	-0.34	0.68
BKZ	20.5	-0.7	7.8	-0.5	2.1	-11.0	-11.0	-1.87	-4.05	0.94	0.26	0.42	0.05	0.35
CPZ	17.3	-7.1	-6.4	1.7	22.9	-11.0	-11.0	-1.87	-4.05	0.94	-0.06	0.60	-0.46	0.64
WPZ	13.7	3.2	-9.7	4.8	28.6	-15.7	-16.8	-0.23	-0.23	0.63	-0.19	0.79	-0.34	0.12
BTZ	7.6	15.9	15.7	15.4	30.3	28.7	28.6	0.00	0.00	0.19	0.34	-0.06	-1.55	-0.56
EPZ	0.13	-2.8	-9.0	-18.5	19.7	30.3	19.7	0.70	0.70	0.20	0.10	-0.29	-3.30	-0.27

where conventional agricultural practices are performed with further increase in seasonal and extreme temperatures.

## 4 Conclusion

The study attempts to bring forth the positive and negative aspects of RegCM in simulating regional characteristics of climate parameters and its impact on yield estimation. Climate models are often biased representations of observed time series necessitating correction process (Teutschbein and Seibert 2012). Keeping that, the study employs bias correction approach to correct the RCM output and identify the difference between the RCM and bias-corrected RCM. The estimated wheat and rice yield was compared with those simulated with direct RCM output. The study finds that the bias-corrected RCM variables better fitted with fitted observed values than the uncorrected RCM climate variables with more constricted variability bounds. In entirety, a single RCM shows constrain in simulating all the aspects of Indian climate. Therefore, exploring the capacity of existing models would be beneficial. The bias correction approach though did excellent in estimating temperature but has limited ability in estimating extremes and rainfall. With the colder weather in the RCM, the baseline was found to positively affect the simulated wheat crop yields. However, as the extreme temperature period does not coincide with the rice period, the RCM output has less impact on rice yield. Estimation of yield after bias correction shows minimum deviation relative to observed. Soil characteristics, weather, topography, and region-specific uncertainties in the RCM output will display false climate change impacts. Better understanding of ambiguous and indeterminate degree and direction of biasness in the RCM will be essential in making countermeasures as a part of policy making when dealing with future impacts of climate change to progress adaptation measures within the framework of regional strategies.

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