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ORIGINAL PAPER

Regional climate model performance and application of bias corrections in simulating summer monsoon maximum temperature for agro-climatic zones in India

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Abstract

The present study evaluates the performance of Conformal-Cubic Atmospheric Model (CCAM) simulations downscaled from six global climate models (GCMs) (i.e., ACCESS1.0, CNRM-CM5, CCSM4, GFDL-CM3, MPI-ESM-LR, and NorESM-M) and Max Plank's Regional Model (REMO2009(MPI)) obtained from the South-Asia Coordinated Regional Climate Downscaling Experiment (CORDEX) for analyzing the summer monsoon maximum temperature (T_{max}) over the fifteen Agro-Climatic Zones (ACZs) in India. The model simulations are compared with the two sets of observed data obtained from the India Meteorology Department (IMD) and Climate Research Unit (CRU) for the period from 1981 to 2005. The results illustrate that the skill of CCAM regional climate models (RCMs) is higher than the REMO in simulating the T_{max} over all the regions. The spatial patterns of T_{max} in CCAM (CCSM) and CCAM (CNRM) are closer to IMD, while the T_{max} distributions in CCAM (CNRM), CCAM (CCSM), and CCAM (BCCR) agree well with the CRU, and correlation coefficient (CC) is more than 0.6; however, large positive biases in all RCMs are depicted over the Himalayan regions. The inter-comparison among all the RCMs suggest that the CCAM (CNRM) and CCAM (CCSM) are rendering as the foremost models in simulating T_{max} over different ACZs. Performances of these two models also infer the usefulness of the model products for impact studies over the individual ACZs. However, the existing systematic biases in the RCMs impeded the model performance and it is necessary to remove the model bias prior to some real-time application. In this study, two bias correction methods, i.e., linear scaling (LS) and distribution mapping (DM), have been used to correct RCM output bias. It is found that the model performance using DM correction is better than LS method. The performance validations are evaluated based on the probability density function (PDF), CC, and standard deviation (SD) with 95% confidence level. The model evaluation has also been justified using mean absolute error (MAE) index, Nash-Sutcliffe coefficient (NS) index, percent bias (P_{bias}), and the Willmott's index of agreement (d) which confirm the research findings. The results are providing an effective guidance on the usefulness of bias corrected RCMs over a particular ACZs for impact assessment.

1 Introduction

Observation confronts us with information about past climate as well as present climate condition, and according to Field (2014), the information about possible future climate is obtained through the numerical climate models. Nowadays, under vulnerable climate, projecting reliable upcoming changes in future climate is very important to develop the required strategies for reducing losses caused by natural calamities. Climate models are in great importance to study the present and future climatic pattern (Giorgi et al. 2012; Giorgi and Gutowski 2016; Luo et al. 2018; Mall et al. 2018; Bhatla et al. 2018a, 2019a, 2019b). However, various climate models are available worldwide with fine resolution and they are dependent on various assumptions and boundary forcing

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(Almazroui 2012; Bhatla et al. 2018a; Ghosh et al. 2019; Mishra et al. 2020). Depending on particular time period and topography, some models perform well, and some do not. According to Bhatla et al. (2016) and Ghosh et al. (2019), the complexity in model simulation over a particular terrain are generally influenced by many factors such as complex topography, coastal boundary, and lack of unbiased initial and lateral boundary conditions. The effects of regional forcing over the steep topography of the Himalayas and the Western Ghats are not been fully captured by the global models because of their coarse resolutions where regional climate models (RCMs) perform better to capture those local climate properties (Sinha et al. 2013; Dash et al. 2013; Luo et al. 2018; Mishra and Dwivedi 2019; Mishra et al. 2020).

One of the South Asian country India has a very complex topography with heterogeneous elevation and consists four major regions, i.e., the plains, the mountains, the southern peninsula, and the desert, and all are extremely vulnerable at various degree to climate change (Mall et al. 2006). Therefore, it is crucial to evaluate the model performance to estimate the impact of climate change over India and its sub-regions (Kodra et al. 2012; Singh et al. 2018). The coarser spatial resolution ranging from 1.0° to 3.8° and the systematic biases of GCMs limit the examination of the possible impacts of climate change and adaptation strategies on a regional and local scale. The Coupled Model Intercomparison Project 5 (CMIP5) models involve notable uncertainties in capturing/simulating the climate features like regional convection and circulations (Sabin et al. 2013; Huang et al. 2013; Mishra et al. 2014; Jayasankar et al. 2015). On the other hand, the Coordinated Regional climate Downscaling Experiment (CORDEX) has taken by multiple countries to perform regional downscale of global climate models (GCMs) to provide reliable estimate of regional climate for future scenarios (Giorgi et al. 2009, 2012). Mishra et al. (2018) have explored and validated the CORDEX models and their driving GCMs from CMIP5, and compared them against the observed temperature and rainfall over India. They have experienced the satisfactorily model performance in GCMs as well as the CORDEX output but the downscaling does not lower the errors. Various studies have conducted for climate model evaluation using different climatic variables over the Indian region, different sub-regions, and over a particular zone (Déqué et al. 2007; Dash et al. 2013; Mall et al. 2018; Bhatla et al., 2018a,b, 2019a,b). Nowadays apart from ever increasing population, policy and decision-makers need information about how future climate is going to affect the crop production, growth, and finally crop yield to devise the future strategies in different parts of India. Several studies have been carried out on climate change impact on agriculture in India (Yadav et al. 2016; Mall et al. 2018; Bhatla et al. 2020a; Sonkar et al. 2019; Bhatt et al. 2019; Tyagi et al. 2019) and over the world using different GCMs and RCMs output (Piao et al. 2010; Iizumi et al. 2017; Mall et al. 2018; Bhatla et al. 2019a; Sonkar et al. 2020). However, the reliable climatic projection at different agro-climatic zones (ACZs) is not available till date.

Several studies show that the RCMs are better than GCMs (Sinha et al. 2013), but the RCM simulation is biased over the mountainous and other complex topographic region (Murphy 1999; Fowler et al. 2007). All the models possess large biases over the north eastern and Himalayan regions as well as over the Western Ghats (Tiwari et al. 2016a; Basha et al. 2017). These biases make the impact assessment studies very challenging. Evaluating the biasness in model simulation is the outmost important to get the best estimate (Giorgi and Francisco 2000). Several bias correction methods have been developed to correct climate model simulations with the observed meteorological variables, ranging from the simple linear scaling (LS) approach to the sophisticated distribution mapping (DM) (Teutschbein and Seibert 2012). The scaling approach mainly includes the linear or nonlinear formula that adjusts the climatic factors based on the differences between the observed and climate model mean. While DM, the variance scaling method (VS) matches the statistical distribution of regional climate model (RCMs) simulated climatic factors to the distribution of observation. The distribution-based quantile mapping assumes that the climatic factors obey a certain distribution (e.g., Gaussian distributions for temperature) (Fang et al. 2015; Luo et al. 2018). Therefore, an effort to correct the biases in RCM-simulated meteorological variables would be very significant before they are considered for impact studies, especially for those regions where all the meteorological and agricultural variables are very sensitive due to the climate changes (Fang et al. 2015; Sonkar et al. 2019). Generally, VS and DM greatly perform for temperature than a simple LS (Teutschbein and Seibert 2012; Fang et al. 2015; Luo et al. 2018).

Despite of all these recent studies, still there are rare literature to evaluate RCM output for each ACZs. Moreover, studies regarding the best suited model/s along with the best fitted bias correction method/s for a particular ACZs in India is still very limited (Mall et al. 2016). Increasing in the maximum temperature ($T_{\max}$) during monsoon season (Bhatla et al. 2020b) has a great impact on monsoonal crops (Birthal et al. 2014; Zacharias et al. 2015; Sonkar et al. 2019). Previous studies have demonstrated that the increasing rate 0.5 °C of annual temperature and the extreme temperature increasing rate are being expected to 1–4 °C by the mid of twenty-first century over the different parts of India (Kumar et al. 2006; Yang et al. 2012; Hijioka et al. 2014; Bal et al. 2016). So, it is necessary to keep track of changes of temperature in the present conditions. One of the most challenging tasks is to measure the uncertainty of the accuracy in temperature pattern over India as well as over different ACZs. Nowadays, under vulnerable climate, study using RCMs is of great opportunity to understand the climatic pattern for present as well as for future scenario. Moreover, the impact of climate change is not only limited over the large scale; a severe impact in the Indian subcontinent has noticed that is ruling the crop production over the Indian sub-regions (Mall et al. 2006; Field 2014; Hijioka et al. 2014) which is rising the challenges to the food security to feed more than 1.3 billion people of India (Mall et al. 2017; Bhatla et al. 2019a). Apart from increasing population in India, the policy and decision-makers also need the useful information about how future climate will affect the crop production and growth to devise the future strategies in different parts of the agro-economic country India (Mall et al. 2019).

Based on this above motivation, the first objective of this paper is aimed to evaluate the performance using seven different RCMs, viz. CCAM (ACCESS), CCAM (CCSM), CCAM (CNRM), CCAM (GFDL), CCAM (MPI), CCAM (BCCR), and REMO (IITM-CORDEX), in simulating $T_{\max}$ during the Indian summer monsoon (ISM) over India and its fifteen ACZs during 1981–2005. Second objective is to measure the uncertainty in temperature pattern over India as well as different ACZs with and without bias correction.

2 Data and adopted methodology

Daily $T_{\max}$ data at $0.5° \times 0.5°$ resolution from India Meteorological Department (IMD) (Srivastava et al. 2009) and monthly $T_{\max}$ data $0.5° \times 0.5°$ resolution from the Climate Research Unit (CRU) of University of East Angelia are considered as the reference datasets for the period of 25 years (1981–2005). The Coordinated Regional Climate Downscaling Experiment (CORDEX) dataset for the South Asia region has been used. The CORDEX data encompassed the dynamically downscaled data Atmosphere-Ocean coupled General Circulation Model (AOGCM) products run under the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Taylor et al., 2012) for the South Asia region. The detailed description of CORDEX data has been provided in the Table 1. The CORDEX for South Asia data were available from the Earth System Grid Federation (ESGF) and the Climate Data Portal at the Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), through the web portal http://cccr.tropmet.res.in. The RCM simulations of CCAM (ACCESS), CCAM (CCSM), CCAM (CNRM), CCAM (GFDL), CCAM (MPI), CCAM (BCCR), and REMO of IITM-CORDEX are downscaled from the Global Climate Models (GCMs), viz. ACCESS1.0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM-LR, Nor-ESM-M, and MPI-ESM-LR, respectively, over the South Asia CORDEX domain and considered for the present study (Table 1).

This study has explored the model performance over the fifteen ACZs of India. The Planning Commission of India has classified these fifteen ACZs in 1989 depending upon the major crops growing area, climate conditions, soil types, rainfall amount, temperature pattern etc. (Alagh et al. 1989; Pradhan et al. 2014). These ACZs are named as the western Himalayan region (WHR), eastern Himalayan region (EHR), trans-Gangetic plains region (TGPR), upper Gangetic plains region (UGPR), middle Gangetic plains region (MGPR), lower Gangetic plain region (LGPR), western dry region (WDR), central plateau and hills region (CPHR), eastern plateau and hills region (EPHR), western plateau and hills region (WPHR), southern plateau and hills region (SPHR), east coast plains and hills region (ECPHR), west coast plains and hills region (WCPHR), Gujarat plains and hills region (GPHR), and the islands region (IR) (Fig. 1). As the IR is mostly covered by forest and agriculturally is not very important (Pradhan et al. 2014), thus, this region is not considered in this study.

A perfect model's data distribution pattern should resemble with the observation (Piani et al. 2010a). Previous studies showed the distribution diagram as one of the important tools to assess the similarity between model simulation with respect to the observed dataset (Taylor 2001). Mathematically, the formula of Taylor diagram is:

$$E'^2 = {\sigma_f}^2 + {\sigma_r}^2 + 2\sigma_f\sigma_r\rho \qquad (1)$$

where ρ is the correlation coefficient (CC) between model and observation, E' is the centered root mean square (RMS) difference between model and observation, and where σ_f and σ_r are the variances of the model simulation and observation, respectively. Taylor diagram is used to validate simulated seasonal $T_{\max}$ with the IMD and CRU.

2.1 Bias correction

It is necessary to employ the statistical tools for removing the biases to deal the model uncertainty in the simulated results quantitatively. From a long past various multivariate and univariate bias correction methods have been developed (Wood et al. 2004; Leander et al. 2008; Maraun et al. 2010), and several bias correction methods are implemented to minimize the RCM simulated errors to commensurate with observed meteorological variables, such as the simple scaling and DM approach (Teutschbein and Seibert 2012). The scaling approach mainly adjust the climatic factors based on the differences between the observation and RCM means using linear or nonlinear formulae such as the VS method. On the other hand, the DM matches the statistical distribution of RCM simulation to the distribution of the observations. The VS method was developed to correct both the mean and variance of normally distributed variables such as temperature, while DM helps to correct the data distribution by matching the distribution of the model simulation to the observations. Several previous studies (Teutschbein and Seibert 2012; Fang et al. 2015; Luo et al. 2018) reported that the VS and

Table 1 Model details of CORDEX South Asia data (source: http://cccr.tropmet.res.in).

Experiment name.	RCM description	Driving CMIP5 AOGCM	CMIP5 modeling center	Resolution
CCAM (ACCESS)	Commonwealth Scientific and Industrial Research Organization (CSIRO), Conformal-Cubic Atmospheric Model (CCAM). Contributing Institute: CSIRO Marine and Atmospheric Research, Melbourne, Australia	ACCESS1.0	CSIRO, Australia	0.5° × 0.5°
CCAM (CNRM)		CNRM-CM5	Centre National de Recherches Me'te'orologiques (CNRM), France	0.5° × 0.5°
CCAM (CCSM)		CCSM4	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA	0.5° × 0.5°
CCAM (GFDL)		GFDL-CM3	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA	0.5° × 0.5°
CCAM (MPI)		MPI-ESM-LR	MPI-M, Germany	0.5° × 0.5°
CCAM (BCCR)		NorESM-M	Norwegian Climate Centre (NCC), Norway	0.5° × 0.5°
REMO 2009 (MPI)	Description: MPI Regional model 2009 (REMO2009); Contributing Institute: Climate Service Center, Hamburg, Germany	MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M), Germany	0.5° × 0.5°

DM methods have great flexibility to perform on temperature. Thus, the selection of these two important univariate bias correction methods are considered because of their suitability in application of removing the RCM systematic biases over different topographical regions in India.

The temperature is assumed to be normally distributed so Gaussian distribution with mean μ and standard deviation σ (Teutschbein and Seibert., 2012) is described as follows:

$$f_N(x \vee \mu, \sigma) = \frac{1}{\sigma \times \sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\sigma^2}}; x\varepsilon\varepsilon \quad (2)$$

For both bias correction method (VS and DM), the efficacy of the methods is explored with respect to the IMD daily observation as well as with respect to the CRU monthly data for the duration 1981–2005.

2.1.1 Variance scaling

The VS successfully implemented for the bias correction of temperature based on mean and variance (Terink et al. 2010; Teutschbein and Seibert 2012). The equation for VS method is conclusively described on Feng et al. (2015) and the mathematical form is as follows:

$$T_{cor,m,d} = \left[T_{raw,md} - \mu\left(T_{raw,m}\right)\right] \times \frac{\sigma\left(T_{obs,m}\right)}{\sigma\left(T_{raw,m}\right)} + \mu\left(T_{raw,m}\right) \quad (3)$$

$T_{cor,m,d}$ and $T_{raw,m,d}$ are corrected and raw model temperature, respectively, for the dth day of mth month. μ is the expectation operator and μ ($T_{obs,m}$) represents the mean value of observed data at particular month m. σ represents the standard deviation.

2.1.2 Distribution mapping

DM uses the transformation function to remove the bias by adjusting mean, quantiles, and standard deviation so that the distribution of the model and observation should match. Correction using DM method can be done using various methods like probability mapping and empirical cumulative distribution function mapping (ECDF) (Teutschbein and Seibert 2012; McGinnis et al. 2015). Also, the extreme value in the DM bias correction method is preserved (Themeßl et al. 2012). The mathematical expression of DM can be expressed as below:

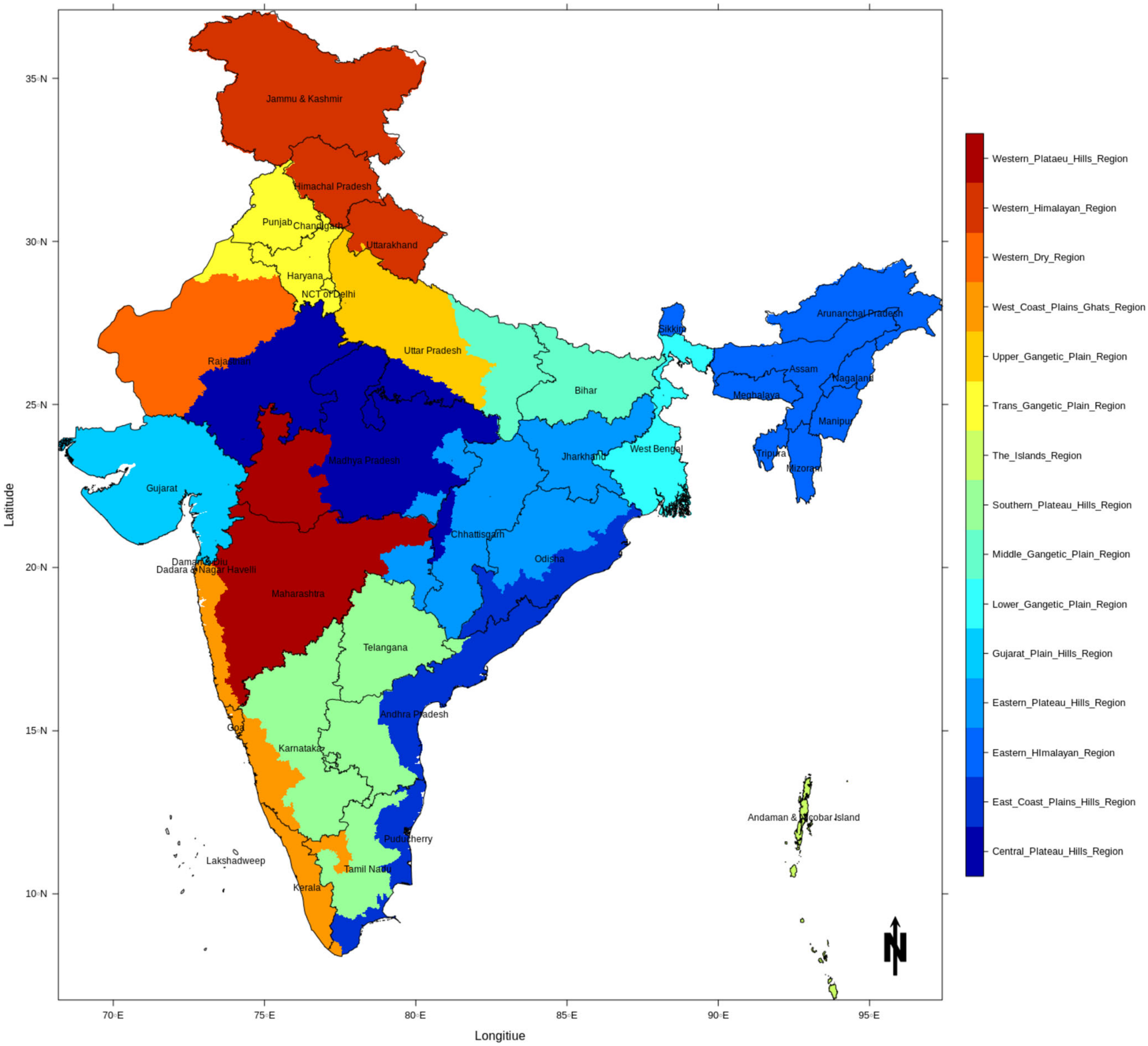

Fig. 1 Agro climatic zones of India

$$T_{cor,m,d} = F_N^{-1}\left(F_N\left(T_{raw,m,d}\vee\mu_{raw,m},\sigma_{raw,m}\right)\vee\mu_{obs,m},\sigma_{obs,m}\right) \quad (4)$$

where F_N^{-1} represents the inverse Gaussian CDF. $\mu_{raw,m}$ is the fitted mean for the uncorrected model, and $\mu_{obs,m}$ is the observed temperature for a given month m. $\sigma_{raw,m}$ and $\sigma_{obs,m}$ are the respective standard deviations for uncorrected model and observe data, respectively.

2.1.3 Performance evaluation of climate models

The performance of climate models has been evaluated based on their abilities to resemble observed temperature. Bias correction methods can be evaluated depending upon the bias corrected model's simulation if they are closer to the observations. Depending on this criterion, the best and worst performing zone for a particular model has been considered. The performance of different models, as well as the bias correction methods, quantifies by a set of statistical parameters to assess the observed and the model simulations. The mean, median, and standard deviation (SD) of the model simulation from the observed data have been applied to study the descriptive nature, variability in the model compared with the observed data (Li et al. 2010; Jakob et al. 2011; Piani et al. 2010a, 2010b). The bivariate correlation between the model simulation and the observed data has been done using CC analysis.

For the related bias and error estimation, two methods, namely percent bias (P_{bias}) and MAE, are applied (Gudmundsson et al. 2012; Fang et al. 2015). The P_{bias} measures the percentage changes in the model simulation with respect to the observed dataset. The positive (negative) P_{bias} values indicate an overestimation (underestimation) in the model simulation (Fang et al. 2015). The MAE demonstrates the average errors between the observed values and model simulated values (Fang et al. 2015).

$$P_{BIAS} = \frac{\Sigma_{i=1}^{N}\left(Y_i^{obs}-Y_i^{sim}\right)}{\Sigma_{i=1}^{N}\left(Y_i^{obs}\right)} *100 \tag{5}$$

$$MAE = \frac{\Sigma_{i=1}^{N}\left|Y_i^{obs}-Y_i^{sim}\right|}{N} \tag{6}$$

where $Y_{i,}^{obs}$ and $Y_{i,}^{sim}$ are the ith observed and simulated variables, and N is the total number of observations.

The Wilmott's degree of index (d) (Willmott and Wicks 1980) and Nash-Sutcliffe coefficient (NS) are another most useful statistical approaches to measure the model skills when compared with the observations. The index of agreement (d) is used as a standardized measure of the degree of model simulation and the observation (Willmott and Wicks 1980), where the value of d ranges between 0 and 1. The value of d equal to 1 shows a seamless match, whereas 0 indicates no agreement in the model simulation with the observation. The NS value indicates the relative magnitude of the residual error in comparison with the observed error (Nash and Sutcliffe 1970). The NS ranges between $-\infty$ and 1, where NS equal to 1 indicates a perfect match.

$$d = 1-\frac{\Sigma_{i=1}^{N}\left(Y_i^{obs}-Y_i^{sim}\right)^2}{\Sigma_{i=1}^{N}\left(\left|Y_i^{obs}-Y^{mean}\right|+\left|Y_i^{sim}-Y^{mean}\right|\right)^2} \tag{7}$$

$$NS = 1-\frac{\Sigma_{i=1}^{N}\left(Y_i^{obs}-Y_i^{sim}\right)^2}{\Sigma_{i=1}^{N}\left(Y_i^{obs}-Y^{mean}\right)^2} \tag{8}$$

where $Y_{i,}^{obs}$ and $Y_{i,}^{sim}$ are the ith observed and simulated variables, Y^{mean} is the mean of observed variables, and N is the total number of observations.

3 Results and discussion

This section explains the study of climatological spatial distribution of average T_{max} in observations (IMD and CRU) and RCMs' simulations for the period from 1981 to 2005. Section 3.1 deals with the evaluation of RCM performance with and without bias correction of T_{max} during June–September (JJAS) over the Indian landmass. Section 3.2 presents the result and the key findings obtained from the RCM evaluation over the fifteen ACZs of India using raw and bias-corrected outputs.

3.1 Evaluation of climate models with and without bias correction over all India

The spatial distribution of model simulated T_{max} is analyzed with respect to the observed climatology of the IMD and CRU over India (Fig. 2). As it is mentioned by Piani et al. (2010a), the spatial distribution of model simulation should look like distribution obtained from the observed data. An increase in T_{max} for monsoon season has a massive impact on monsoonal crops (Birthal et al. 2014; Zacharias et al. 2015). Therefore, it is necessary to study the variability in the mean temperature over the region. The IMD-observed data are showing an average T_{max} between 30 and 45 °C over India where the CRU observation is showing lesser magnitude than the IMD in T_{max} spatial distribution (ranges are between 30 and 40 °C). The extent of T_{max} is more in the western part (40–45 °C) and the central of India (35–40 °C). Over WHR and EHR, all the models illustrate a large deviation in terms of the data distribution. The deviations are more when the simulations are compared with the IMD rather than CRU. The possible reason may be because of the complexities in high elevation (Bhasha et al., 2017) and unavailability of sufficient observation weather station over the regions (Pai et al., 2014). The evaluation among the RCM output shows that the CCAM simulations are closer to the observation (IMD and CRU) dataset than REMO simulation. The overestimation in T_{max} over western part of India and the Indo Gangetic plain (IGP) is also observed in the REMO simulation.

The IMD and CRU possess the temperature ranges of 38–42 °C and 34–38 °C, respectively, where the CCAM models have a range of 42–48 °C, while REMO shows a range of 48–54 °C over TGPR. All the RCMs are underestimating the T_{max} as compared with the observations. The model deviations are more concise in the T_{max} relative to CRU than IMD. A range of 36–42 °C and 33–36 °C in T_{max} is found over MGPR in IMD and CRU data, respectively, where the CCAM model-simulated temperature varies between 36 and 46 °C. So, all the model simulations underestimate the observation over MGPR. Over UGPR and LGPR, all CCAM model-simulated data distributions are well in agreement with IMD but a deviation between 2 and 3 °C is noticed with respect to the CRU. Model simulations are in better agreement with IMD than CRU over MGPR and LGPR. All the model-simulated T_{max} are found closer to the IMD than CRU over central India, where the performance is comprising over WDR, CPHR, GPHR, and EPHR. But the model performance

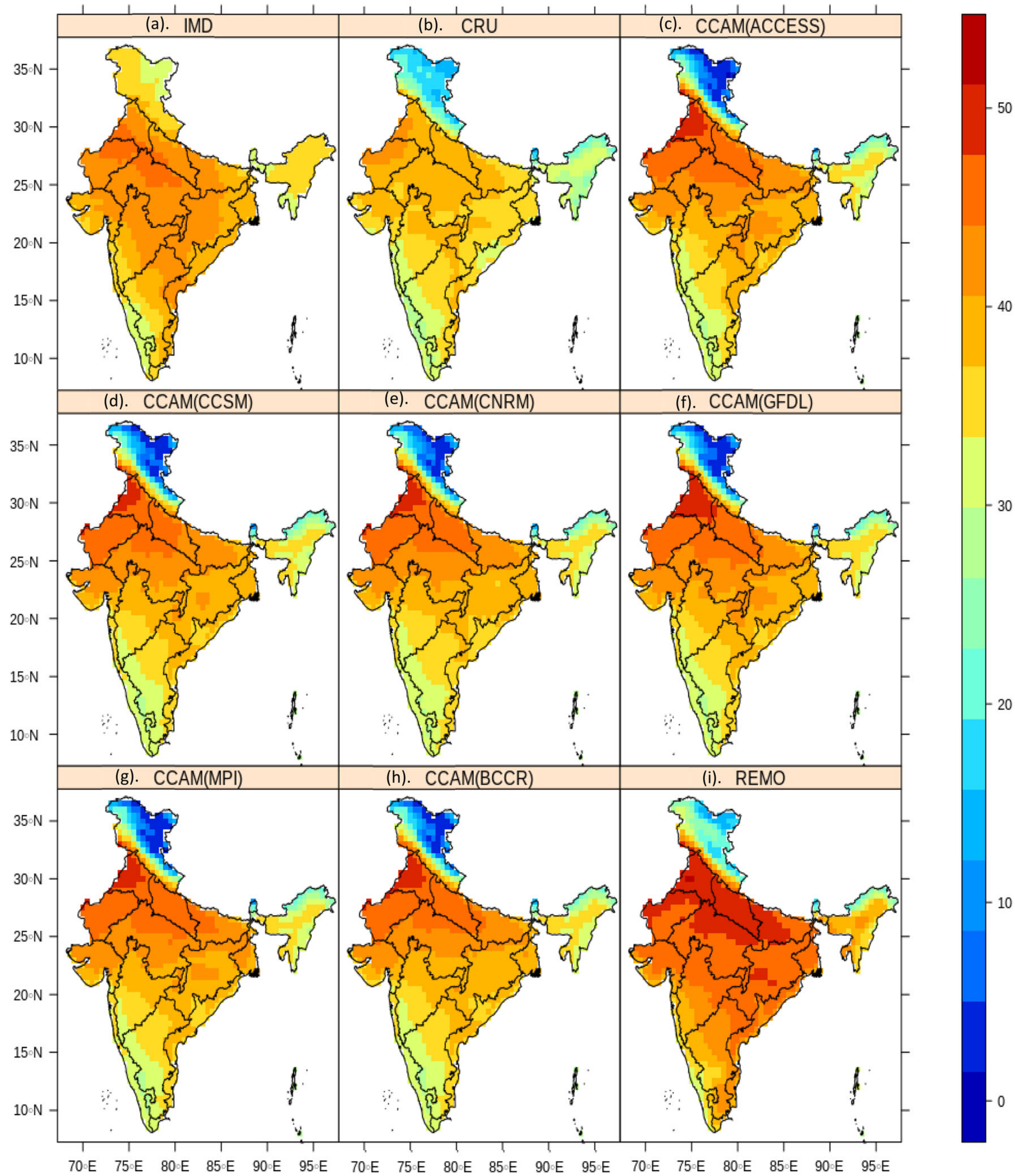

Fig. 2 The observed maximum temperature (°C) in summer monsoon season. (**a, b**) IMD and CRU, respectively, and the RCM simulations of (**c**) CCAM (ACCESS), (**d**) CCAM (CCSM), (**e**) CCAM (CNRM), (**f**) CCAM (GFDL), (**g**) CCAM (MPI), (**h**) CCAM (BCCR), and (**i**) REMO, during 1981–2005 over India and its agro climatic zones

over WPHR, SPHR, and ECPHR regions is similar to the CRU but is different from IMD, where the performance of CCAM (CCSM) and CCAM (CNRM) is better among all the other models over ECPHR. REMO is underestimating the T_{max} compared with IMD and CRU observations over all the regions expect WHR, EHR, and WCPHR. Spatial distribution of RCM simulations over WCPHR is related to the both observations even without bias correction. Overall, it is found that all the model simulated T_{max} is closer to IMD rather than CRU over most of the northern India and central India; however, the simulations are found closer to CRU over the southern India.

In the Taylor diagram (Fig. 3), the blue-dotted lines resemble the standard deviations and the black-dotted lines symbolize the correlations between simulations and observations, while the deep-green-dotted lines correspond to the central root mean square error (RMSE). Figure 3 shows spatial correlation between the models and observed T_{max} (IMD and CRU). It is seen that the correlation values are less than 0.5 for REMO and CCAM (GFDL) whereas higher correlation values (greater than 0.6) are found for CCAM (BCCR) and CCAM (CNRM). The highest correlation (0.71) is achieved for CCAM (BCCR), while the lowest correlation (0.29) is found for REMO when computed with the CRU. So, in terms of spatial CC of different RCMs over all India, CCAM (CNRM), CCAM (BCCR), and CCAM (CCSM) are performing better than the rest of the RCMs used in the present study. The performance of all the RCMs for each ACZs will be discussed in the later sections. Tables 2 and 3 show different time series-based statistics with respect to the IMD and CRU, respectively, as discussed in Section 2. Table 2 shows that CCAM (MPI), CCAM (BCCR), and REMO exhibit higher MAE values (more than 5 °C) with respect to the IMD's T_{max} dataset. On the other side, the lowest MAE and P_{bias} (4.69 °C and 4.83%, respectively) are observed in the CCAM (ACCESS) followed by CCAM (CCSM) and CCAM (GFDL) simulations. After the bias correction, the RCM simulation successfully reduce the value of MAE and P_{bias}. Comparing the results of both bias correction methods on the basis of NS and *d* values, it is illustrated that DM method is superior over the VS method of bias correction (Table 2).

The detailed analysis with respect to CRU for all the RCM simulation is provided in Table 3. All the RCMs except REMO have a higher value of MAE and P_{bias} with respect to CRU observation. The minimum MAE and P_{bias} (4.03 °C and − 6.34%, respectively) values are found in CCAM (ACCESS). The value of NS and *d* gets improved for all the models after bias correction using both VS and DM. The bias-corrected CCAM (ACCESS) model T_{max} using DM method is depicting the lowest MAE and P_{bias} values. Furthermore, the frequency-based statistics (mean, median, and SD) of observed (IMD and CRU), model simulated (raw and bias-corrected) have been evaluated (Fig. 4 and Table 4). It is evident from Fig. 4 that distributions of all uncorrected or raw model simulations are quite different than the observation. For all the RCMs, both bias correction methods, i.e., LS and DM, are performing almost similar regarding distribution of climate data, and this remark corroborates with the previous study by Fang et al. (2015). Furthermore, bias correction methods are performing best when compared with the CRU observations. Concurrently, both the bias correction methods could be able to improve also the RCM model skill when compared with the IMD data; however, the improvement is lesser when compared with the IMD than the CRU data. However, the distribution of bias-corrected data in the interquartile range is still different from the observation. Table 4 refers that both the DM and VS are performing closely with a slightly betterment noticed in DM than VS. The mean value of bias-corrected result is much closer to the IMD mean and SD of T_{max} (39.14 °C and 2.92 °C, respectively) over all India. With respect to the CRU observation, bias-corrected model

Table 2 Statistical skill score of the different regional climate models (raw or simulated, bias-corrected using VS and DM techniques) computed against the India Meteorological Department (IMD) analysis gridded datasets during the baseline period 1981–2005. The model data are interpolated to the IMD grid points before carrying out the statistical analysis

Model .	Method	MAE	*NS*	P_{bias}	*d*
CCAM (ACCESS)	Simulated	4.69	− 6.33	10.08	0.625
	VS	1.49	0.66	− 1.08	0.837
	DM	1.35	0.70	1.006	0.834
CCAM (CCSM)	Simulated	4.83	− 6.91	16.07	0.621
	VS	1.66	0.49	− 2.612	0.829
	DM	1.63	0.52	− 2.02	0.826
CCAM (CNRM)	Simulated	4.99	− 6.74	12.15	0.619
	VS	1.68	0.46	1.083	0.823
	DM	1.64	0.49	− 1.004	0.821
CCAM (GFDL)	Simulated	4.87	− 7.03	11.65	0.629
	VS	1.63	0.48	1.89	0.835
	DM	1.60	0.51	1.19	0.833
CCAM (MPI)	Simulated	5.01	− 7.18	13.01	0.623
	VS	1.71	0.45	1.76	0.831
	DM	1.68	0.48	− 1.14	0.829
CCAM (BCCR)	Simulated	5.01	− 6.83	17.49	0.625
	VS	1.69	0.46	2.81	0.829
	DM	1.66	0.49	1.48	0.827
REMO	Simulated	5.9	− 8.09	19.65	0.689
	VS	1.76	0.31	2.4	0.849
	DM	1.73	0.34	1.98	0.848

Table 3 Same as Table 2 but the statistical skill score is computed against the CRU datasets

Model	Method	MAE	*NS*	P_{bias}	*d*
CCAM (ACCESS)	Simulated	4.03	0.33	− 6.34	0.878
	VS	1.64	0.85	1.01	0.935
	DM	1.38	0.87	0.78	0.935
CCAM (CCSM)	Simulated	4.18	0.423	− 8.36	0.887
	VS	1.81	0.86	1.73	0.937
	DM	1.70	0.88	1.24	0.936
CCAM (CNRM)	Simulated	4.60	0.61	− 6.75	0.890
	VS	1.86	0.85	1.07	0.934
	DM	1.65	0.87	1.02	0.934
CCAM (GFDL)	Simulated	4.62	0.31	− 8.50	0.875
	VS	1.83	0.85	1.50	0.935
	DM	1.54	0.86	1.28	0.935
CCAM (MPI)	Simulated	4.50	0.33	− 8.08	0.878
	VS	1.89	0.84	1.46	0.936
	DM	1.78	0.85	− 1.17	0.935
CCAM (BCCR)	Simulated	4.28	0.34	− 7.53	0.882
	VS	1.92	0.81	1.25	0.933
	DM	1.81	0.85	1.18	0.933
REMO	Simulated	7.83	− 0.73	− 22.79	0.736
	VS	1.90	0.63	9.47	0.937
	DM	1.19	0.67	8.31	0.937

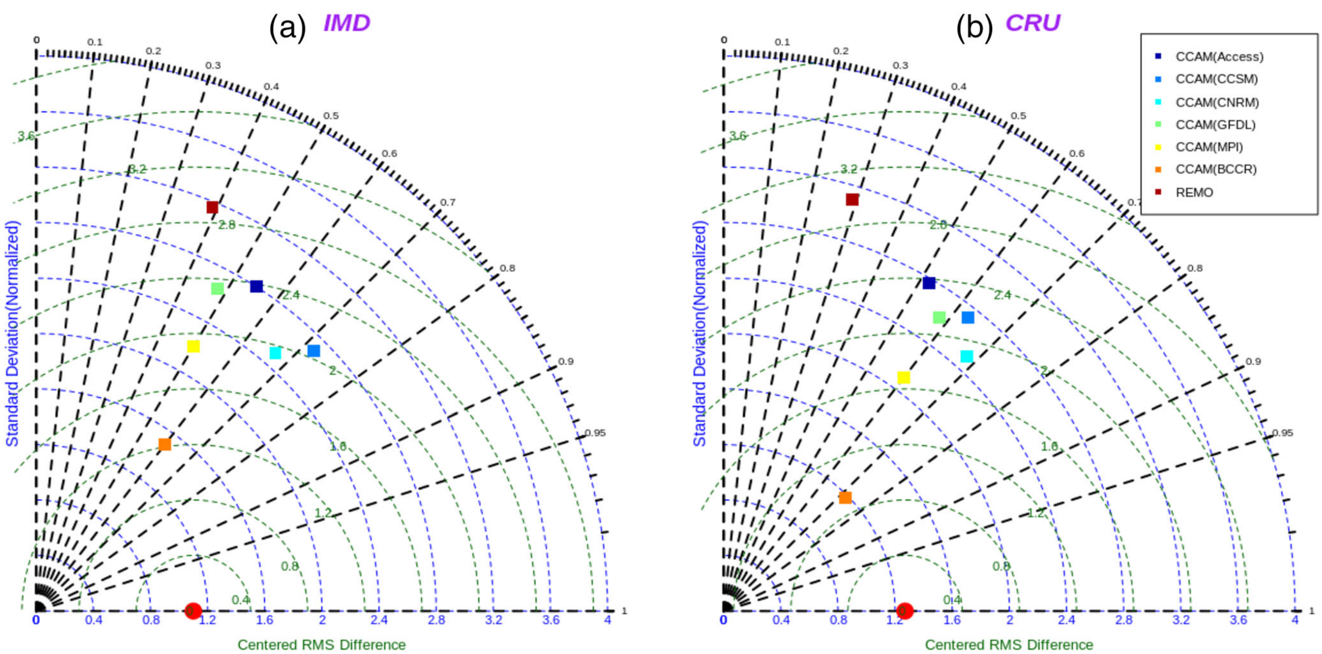

Fig. 3 Taylor diagram representing the spatial correlation, centered RMS difference, and standard deviation of maximum temperature computed between RCM simulations and observations. **a** IMD and **b** CRU for summer monsoon season

Table 4 Frequency-based statistics (unit °C) of observed (IMD, CRU), raw model-simulated, and bias-corrected maximum temperatures over India

		IMD (mean = 39.14, median = 39.34, SD = 2.92)			CRU (mean = 33.68, median = 35.69, SD = 6.46)		
MODEL	Method	Mean	Median	SD	Mean	Median	SD
CCAM (ACCESS)	RAW	36.37	38.16	9.79	36.37	38.16	9.79
	VS	39.14	39.97	2.92	33.68	35.52	6.46
	DM	39.15	39.92	2.70	33.68	35.49	6.35
CCAM (CCSM)	RAW	36.10	38.60	9.50	36.10	38.60	9.50
	VS	39.14	39.91	2.92	33.68	35.52	6.46
	DM	39.14	39.86	2.70	33.68	35.49	6.35
CCAM (CNRM)	RAW	35.95	37.81	9.33	35.95	37.81	9.33
	VS	39.14	39.72	2.92	33.68	34.96	6.46
	DM	39.15	39.69	2.72	33.68	34.94	6.32
CCAM (GFDL)	RAW	36.54	38.83	9.77	36.54	38.83	9.77
	VS	39.16	39.83	2.92	33.68	35.19	6.46
	DM	39.14	39.78	2.71	33.68	35.17	6.35
CCAM (MPI)	RAW	36.40	38.91	9.34	36.40	38.91	9.74
	VS	39.14	39.90	2.92	33.68	35.34	6.46
	DM	39.15	39.85	2.71	33.68	35.32	6.35
CCAM (BCCR)	RAW	36.21	38.32	9.49	36.21	38.32	9.49
	VS	39.14	39.79	2.92	33.68	35.11	6.46
	DM	39.15	39.75	2.72	33.68	35.09	6.33
REMO	RAW	41.35	44.81	8.60	41.35	44.81	8.60
	VS	39.14	40.32	2.92	33.68	36.27	6.46
	DM	39.16	40.25	2.74	33.68	36.26	6.43

simulations are also closer to the mean and SD values except for REMO simulation.

Figure 5 shows the probability density curves of T_{max} for the observed (IMD and CRU), uncorrected, and bias-corrected simulations of RCMs over all India. Model simulations except REMO having probabilities greater than 0.1 are underestimating and probabilities below 0.1 are overestimating the CRU. The REMO-uncorrected simulation is underestimating the observed data set of IMD and CRU. The bias correction method (VS and DM) is performing better for simulations with probability values above 0.1; however, for probabilities below 0.1, all the corrected simulations are overestimating the observed probability. In all CCAM model simulations, both the correction methods are performing almost the same for matching the probability density curve to the observed dataset.

3.2 Evaluation of climate models with and without bias correction for agro-climatic zones

A detailed evaluation of seven RCM simulations of T_{max} has been carried out over 15 ACZs in India during the Indian summer monsoon for the period 1981–2005. The performance of different RCMs with and without bias correction (VS and DM) for each ACZs has also been analyzed in this section.

3.2.1 Performance over Western Himalayan region

It is found that all the RCMs are overestimating the observed T_{max}, i.e., IMD and CRU over WHR (Fig. 6). In Fig. 6, P_{bias} has been found in the ranges of 0.4–1, for most of the CCAM models T_{max} simulation. The large deviation is observed over the Himalayan region because of very complex topographical regions, and RCMs are not able to represent the actual elevation (Sinha et al. 2014) and it may be one possible reason for poor performance of RCMs over that region. The CCAM models simulation exhibits positive P_{bias} between 0.3 and 0.9 except for REMO, where it lies between – 0.2 and − 0.9 (Figs. 6 and 7). After applying VS bias correction method, the P_{bias} values are reduced in the range of 0.05–0.3 compared with IMD, while DM gives better result than VS as P_{bias} values get reduced to 0.05–0.1. The Taylor diagram for WHR correlation shows that the performance of all the models is poor than all the other regions as the correlation of the simulations with observation is found to be lesser than 0.5 (Fig. 7). However, after bias correction, the results get improved as correlations of bias-corrected values are greater than 0.5. The bias-corrected CCAM (BCCR) using DM method shows a correlation of about 0.8 with both IMD and CRU. The REMO also possess correlation as high as 0.8 with IMD T_{max} using VS and with CRU using DM. But comparison between all the RCMs leads to conclusion that CCAM (BCCR) and REMO are preferable than all other models and bias correction method DM is better than VS for WHR.

3.2.2 Performance over Eastern Himalayan region

The model performance of T_{max} simulation over EHR showing P_{bias} values ranges between −0.05 and 0.5 with respect to

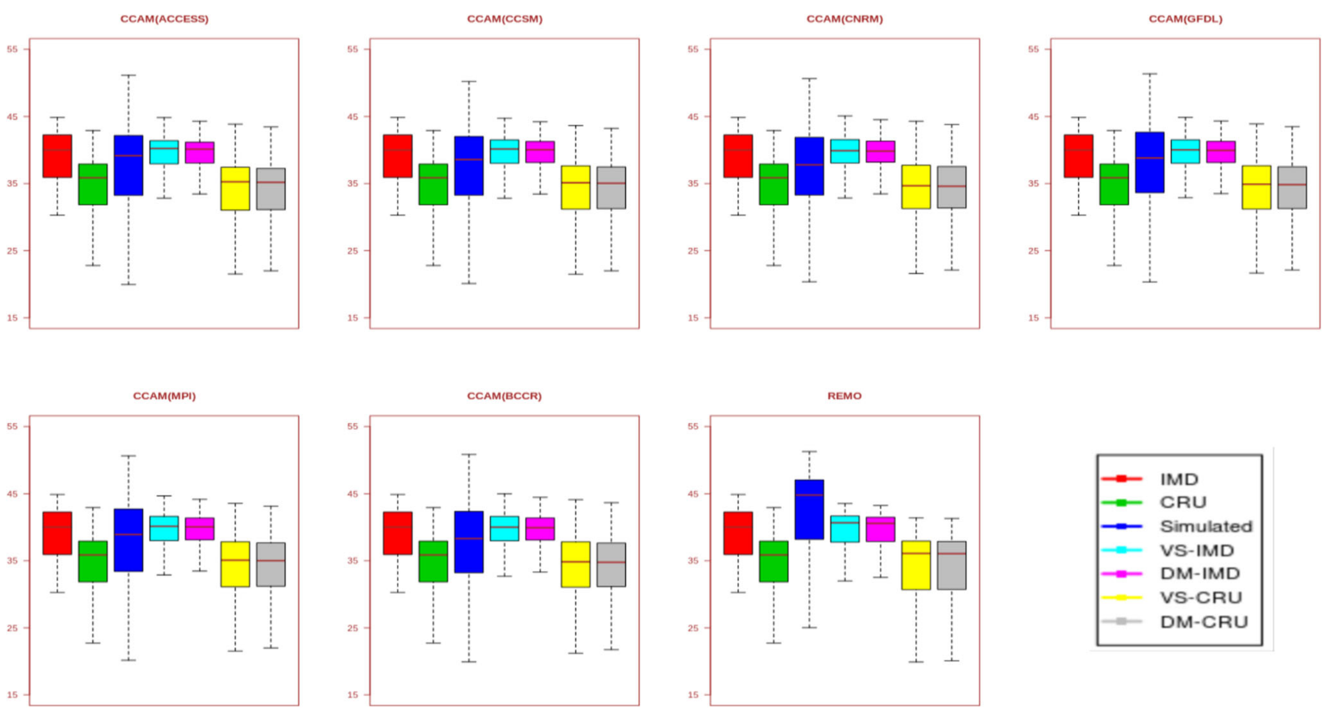

Fig. 4 The boxplot of observed (IMD and CRU), model-simulated (raw), and bias-corrected model simulation of seasonal maximum temperature (unit in °C) using VS and DM method computed against IMD and CRU, respectively, over India during 1981–2005 (as listed in Table 4)

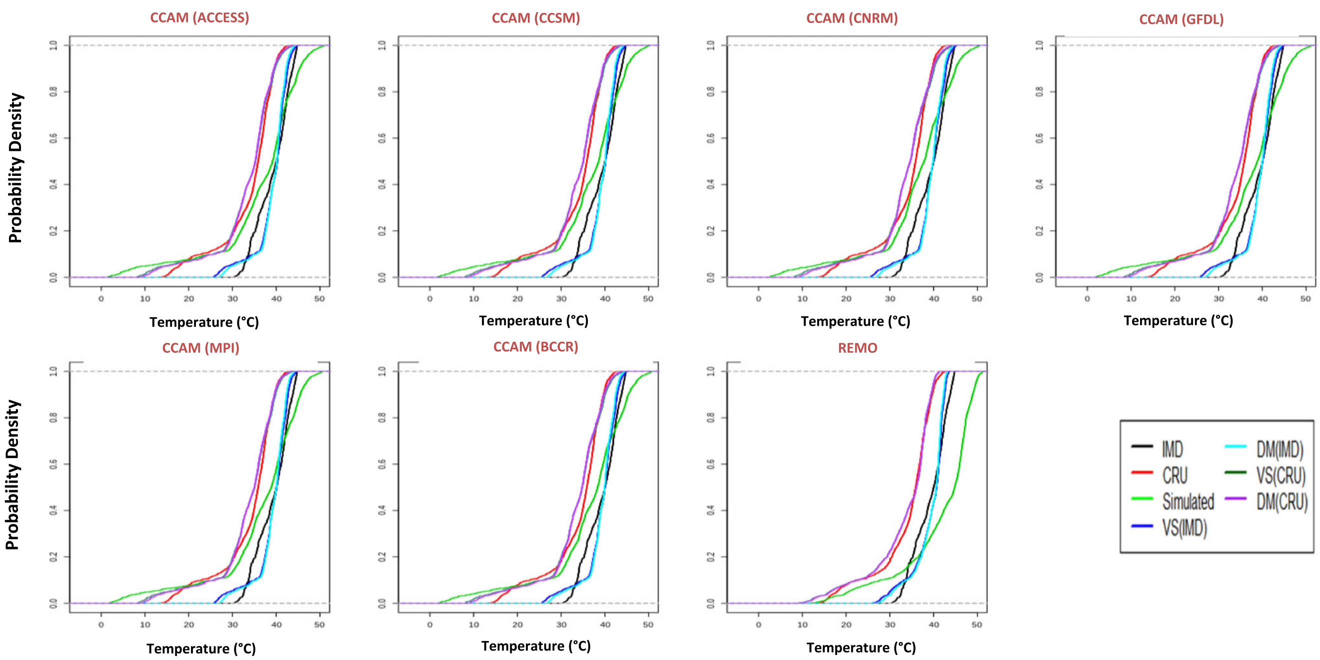

Fig. 5 Probability density curves of maximum temperature (°C) of observed (IMD and CRU), model-simulated (raw), and bias-corrected model simulation using VS and DM method computed against IMD and CRU, respectively, during JJAS

(w.r.t) the observation. The bias correction methods (VS and DM) are applied on all RCM simulations w.r.t IMD observation, which are improving the results over EHR, while for some parts of EHR, results are getting depreciated. With CRU observation, bias correction is improving the result of RCMs as P_{bias} values get reduced. It is seen from the performance evaluation of all the models and bias correction methods in terms of spatial correlation (Fig. 8) that the REMO and CCAM (BCCR) are giving the best results using DM and VS, respectively. The complex topography eventually affects the bias correction output, and it is reported that orographic correction is required to implement on model products for improving the model skill (Tiwari et al. 2016b).

3.2.3 Performance over lower, trans, upper, and middle Gangetic Plains region

The RCM simulation and performance of T_{max} with observation have been analyzed for *lower, trans, upper, and middle Gangetic Plains region.* These regions form the Indo-Gangetic Plains (IGP), which is one of the most important regions of India for agricultural productions. The CCAM models are underestimating the observation (CRU) and showing P_{bias} in the range of −0.1 to −0.3. The analysis illustrates that the model having worst performance is securing the best one after bias correction. For example, in the REMO simulation, P_{bias} were in the range from −0.2 to −0.5; it is noteworthy that after bias correction, the results are improving drastically as the P_{bias} gets reduced to −0.1 to 0.05 over the IGP. The REMO performs the best over IGP after bias correction (Figs. 6 and 7). Both the correction methods are performing almost similar over the IGP. It is noticed that the efficiency of the bias correction is higher when applied on REMO models and compared with CRU over TGPR and UGPR as P_{bias} values get reduced to the range of −0.05 to 0.05. With IMD as a reference, the P_{bias} values of the uncorrected models varied between 0 and − 0.2, and after bias correction, P_{bias} values lie between −0.05 and 0.05. The CCAM (ACCESS), CCAM (CCSM), and CCAM (CNRM) are performing better after bias correction over the TGPR and UGPR, and the Taylor diagrams validate the performances of bias-corrected and without bias-corrected regional model performances. The DM method is performing better over the IGP in all the way although the difference between two methods is negligible.

3.2.4 Performance over Western Dry region

The comparison of several RCM performance to simulate the seasonal T_{max} for ISMR over WDR is indicating that CC computed against both the IMD and CRU observation lies in the range of 0.4–0.5 (Fig. 8). The application of two bias correction methods (VS and DM) is significantly reducing the negative P_{bias} associated with the RCMs. Interestingly, the CC values are greatly enhanced (0.7–0.9) in all the CCAM and REMO simulations after the bias correction. However, it is noticed that the DM bias-corrected CCAM (ACCESS) has the higher skill in representing T_{max} over WDR.

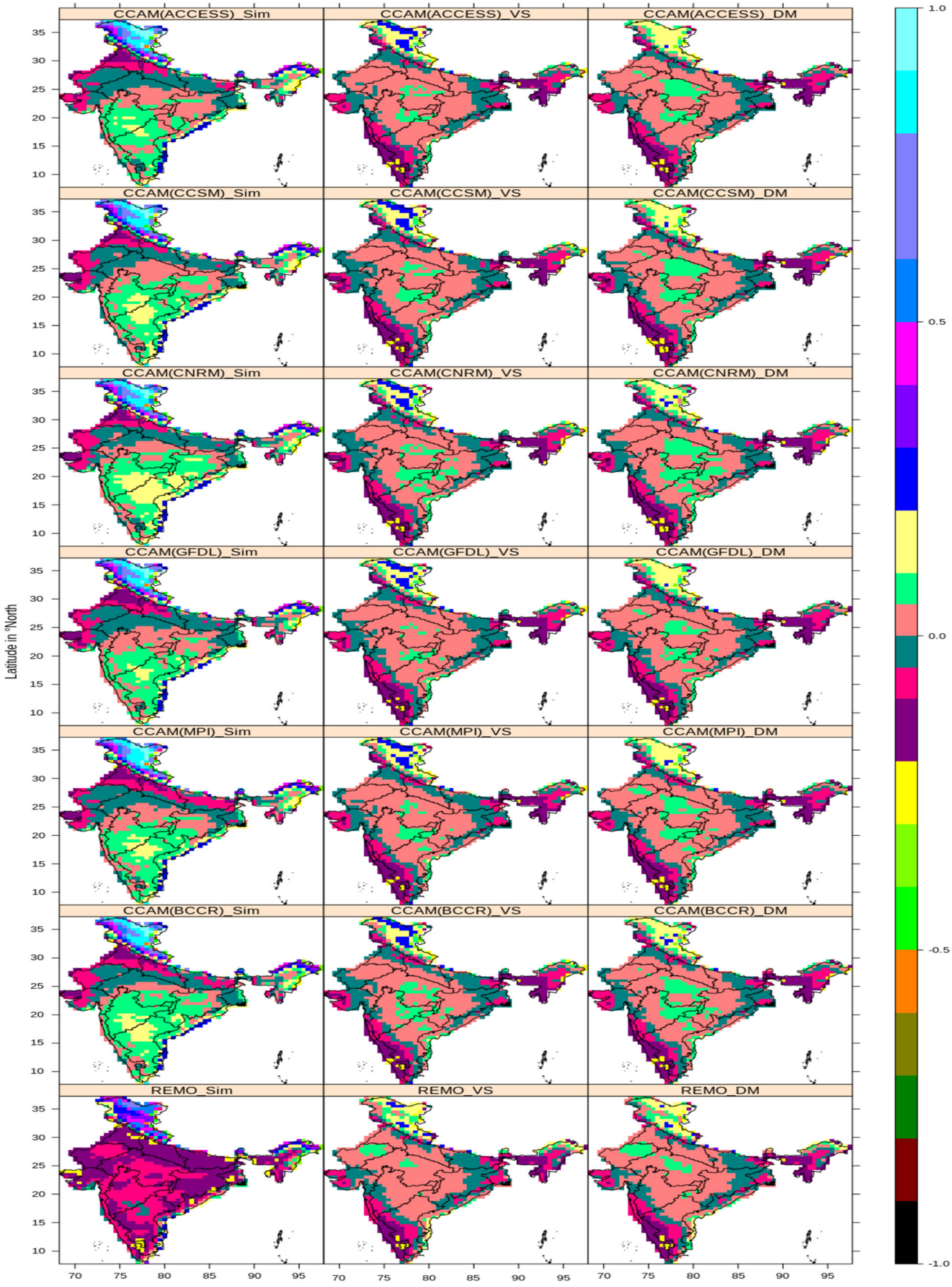

Fig. 6 Spatial distribution of mean percent bias of raw regional climate models' simulation (first column), bias-corrected model simulation using VS method (in second column), and bias-corrected model simulation using VS method (in second column) during 1981–2005 where IMD is considered as reference

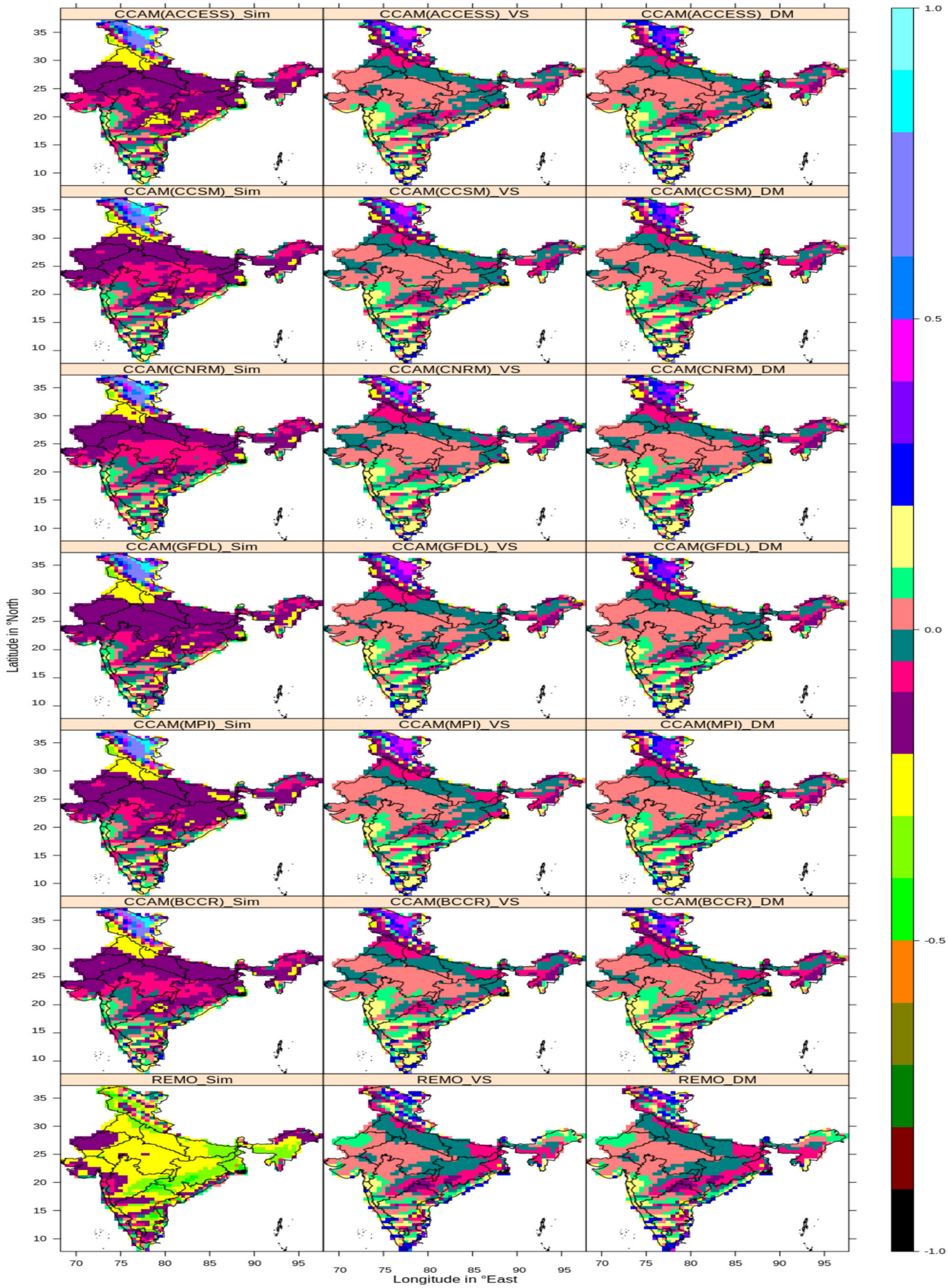

Fig. 7 Spatial distribution of mean percent bias of raw regional climate models' simulation (first column), bias-corrected model simulation using VS method (in second column), and bias-corrected model simulation using DM method (in second column) during 1981–2005 where CRU is considered as reference

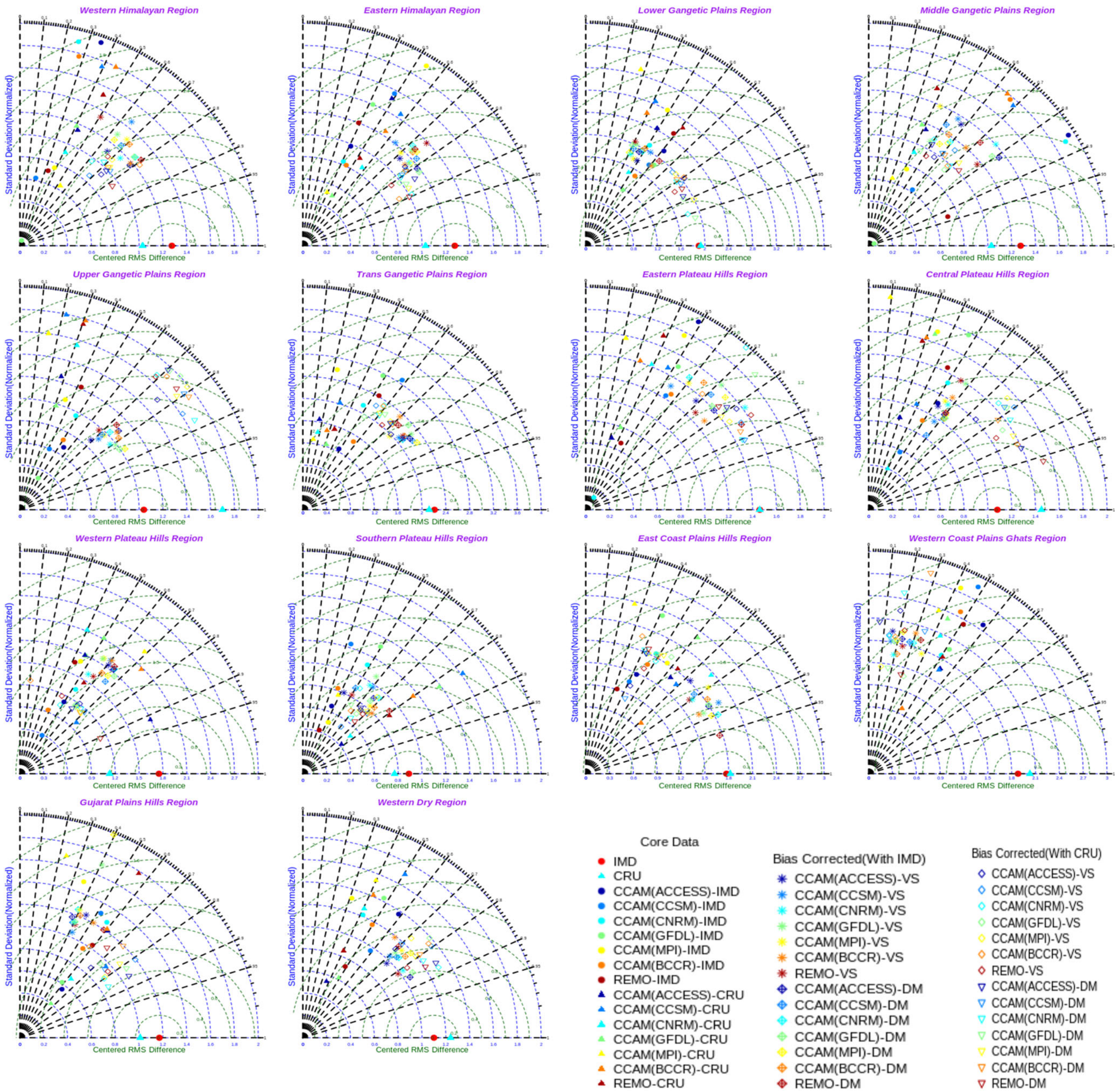

Fig. 8 Taylor diagram showing the spatial correlation, centered RMS difference, and standard deviation of RCMs' simulated raw and bias-corrected (VS and DM) seasonal maximum temperature with respect to the observations (IMD and CRU) for summer monsoon season over different agro-climatic zones of India

3.2.5 Performance over eastern, central, western and southern plateau hills region

The simulated T_{max} of different RCMs are analyzed over the Indian plateau region during ISM of 1981–2005. The Indian plateau region is further subdivided into four important ACZs, i.e., EPHR, EPHR, WPHR, and SPHR. The model simulation of CCAM (ACCESS) over EPHR is in good agreement with IMD's T_{max}, and P_{bias} values vary between −0.05 and 0.1. The RCM models over EPHR are overestimating T_{max} from the observed dataset (IMD) except REMO. It is noteworthy that bias correction method could able to improve the result for all CCAM models where P_{bias} values are getting reduced (from −0.05–0.2 to −0.05–0.05). Over CPHR, all the CCAM model simulation for T_{max} are in good agreement with IMD. The bias correction method VS are performing better than DM with IMD T_{max} although bias correction is desirable for CCAM models for this region. The REMO is overestimating the T_{max} as compared with the observation, and the efficiency of the model is enhancing after the application of the bias correction for CPHR. Over WPHR, CCAM (ACCESS) model is showing the highest correlation (0.92) with CRU data without bias correction. After bias correction (DM), the T_{max} of REMO model become closer to the CRU observation data and showing the CC of 0.9. The rest of the RCM simulations do not hold good over WHPR either with IMD or CRU datasets. The RCM performance over SHPR is different than other plateau regions. Models without bias correction method show the highest correlation (0.8–0.85) with CRU dataset. Model correlation with the IMD's T_{max} data is not good over WPHR which is in the range of 0.3–0.4. Both methods of the bias correction have been applied on the RCM simulation; however, the improvement is not satisfactory. Therefore, the highest P_{bias} and low correlation have been observed in all RCM simulation after bias correction. So, it could be said that the performance of bias correction method also varied spatio-temporally over a region.

3.2.6 Performance over east coast, west coast, and Gujarat Plains Hills region

The RCM T_{max} simulation over Eastern coast is better than western coast Plains Hills region. Most of the RCMs are showing CC in the range of 0.4–0.7 with both the observation over ECPHR (Fig. 8), after the bias correction (DM) with IMD data providing best T_{max} correlation, i.e., 0.96 for the REMO model over ECPHR. The REMO shows that P_{bias} ranges between 0.05 and − 0.4 and − 0.1 and − 0.5, respectively, for IMD and CRU observations (Figs. 6 and 7). All the CCAM models' skill has been notably improved after bias corrections, and bias-corrected T_{max} shows P_{bias} and CC values in the range of 0.05–0.3 and 0.8–0.9 against IMD's T_{max}, respectively. It is perceived that bias-corrected T_{max} could able to reduce the P_{bias} for both the IMD and CRU as reference. The P_{bias} values for bias-corrected T_{max} are in the range of −0.05 to 0.1 against IMD and 0.05–0.3 against CRU. So, bias-corrected RCMs are providing the better result for IMD T_{max} than CRU dataset for this region. The spatial analysis of P_{bias} depicts that both bias correction methods (VS and DM) are deteriorating the result with CRU T_{max}.

All the CCAM models along with the REMOs' T_{max} are evaluated over the WCPHR for the study period. A keen observation from the Taylor diagram and spatial P_{bias} plot with respect to the IMD and CRU data set signifies that none of the bias correction method is helpful in the enhancing of the model performance in representing T_{max} over this particular region. It is indeed a troubling fact that CC values have been reduced in the bias-corrected T_{max} (0.1–0.3) as compared with the raw model T_{max} (0.4–0.55) for all the RCMs with respect to CRU and IMD. The minimum P_{bias} value is observed in the raw CCAM (ACCESS) against the CRU. However, over GPHR, simulated T_{max} is underestimated compared with both the observational datasets. RCM simulations without bias correction were closer to IMD than CRU; however, bias-corrected RCMs gives better result with CRU. Over GPHR, all the bias-corrected RCMs were underestimating the T_{max} compared with IMD observation. Uncorrected or raw CCAM (ACCESS) is performing better when IMD is considered as a reference, while bias-corrected CCAM (CCSM) and CCAM (CNRM) are performing better when CRU is considered as a reference.

The spatial distribution of T_{max} of seven RCM output and application of two univarate bias correction methods, i.e., nonlinear VS and distribution-based DM method, have been proposed to study and evaluate their performance over India and its different ACZs during 1981–2005. The studies prove that the original RCM output is biased in nature with respect to the observation. The validation statistics of raw RCM output highlights the need of bias correction as the performance of RCM T_{max} simulation varies region to region. The applicability on the bias correction methods successfully enhances the performance of all the RCMs in terms of spatial correlation, SD, P_{bias}, and MAE. Over the different ACZs, the performance of RCMs varies due to complex topography that eventually affects the bias correction outputs. The model-simulated results are largely biased over WHR and EHR regions. The CCAM (CNRM) and CCAM (CCSM) are the best performing model to simulate T_{max} during the Indian monsoon season over India and its ACZs. The best fitted model simulation with bias correction has been observed over the Indo-Gangetic Plains, i.e., TGPR, UGPR, MGPR, and UGPR. Over the WCPHR, all the CCAM models are performing quite satisfactory without bias correction but after bias correction, results are overestimated. Hence, it is obvious that the suitability of the bias correction methods is also dependent upon the regional topographical feature and the RCM selection.

4 Conclusion

The average spatial distribution of T_{max} in RCM simulations show a close agreement to the CRU data rather than IMD, especially over the central and southern India. The model simulation shows large bias over the Himalayan region. The CCAM (CNRM) and CCAM (CCSM) are performing well to simulate T_{max} over different ACZs during the Indian monsoon season. The systematic bias correction in RCM simulation using DM method is showing more robust than the VS method. Over Indo-Gangetic Plain, i.e., TGPR, UGPR, MGPR, and UGPR, the bias-corrected T_{max} is showing best fitted with the observation. In contrary, the limitation in bias correction method is observed over WCPHR region, where all the CCAM models are performing quite satisfactory without any bias correction. Overall, the RCM performance varies with the changes of the study area. The possible reasons for spatially varying skill of RCMs are owing to the climate conditions and topographic features of different regions. To estimate climate change effects over India, it is necessary to evaluate the performance of different climate models and applicability of different bias correction methods over different zones before application. It will be interesting to evaluate different physical phenomenon based on the mathematical approach underlying on a climate model. Based on this effort, one can analyze the model performance using suitable basic criterion (physical and mathematical) for a particular topography, climate condition, and different interactions of atmosphere to choose suitable model for a particular zone.

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