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Evaluation of Bias Correction Methods for Regional Climate Models: Downscaled Rainfall Analysis Over Diverse Agroclimatic Zones of India

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Key Points:

- Linear scaling (SCL) and empirical quantile mapping (EQM) performed well, particularly for simulating wet days (R95)
- Local intensity scaling (LOCI) method was relatively less effective in correcting the errors
- No distinct variation noted among correction methods to reproduce dry bias (CDD)

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Regional climate models (RCMs) are routinely applied for regional climate assessments. The RCM simulated rainfall typically overpredict the light rain/drizzle events. To correct the typical errors noted in RCM rainfall simulations, in this study, three bias-correction methods: linear scaling (SCL), local intensity scaling (LOCI), and empirical quantile mapping (EQM), have been employed. These methods are used to correct monsoon rainfall simulations from 7 RCMs across 14 agroclimatic zones (ACZs) in India from 1970 to 2005. The corrected rainfall data were compared to the observations obtained from India Meteorological Department. The performance of the three methods was assessed using: probability distribution function, consecutive dry day index (CDD), R95 (rainfall distribution at 95th percentile), and spatial correlation. The results vary spatially across the different ACZs. Overall, SCL method is more effective followed by EQM while LOCI was relatively less effective in correcting the errors. Spatial analysis of the rainfall indicates notable improvements over the Western Himalayan Region, which has a complex topography and land use. Error metricsreveal broad improvements across different ACZs, except for Central Plateau Hill Region, East Coast Plain Hill Region, and Southern Plateau Hill Region. The SCL and EQM perform well, and the results are particularly good for simulating wet days (R95), while no distinct variation was found among correction methods to reduce dry bias (CDD). The results provide ACZ and region-specific utilization of an effective bias correction technique for impact assessment studies in the Indian monsoon region.

1. Introduction

The increase in extreme events, particularly heavy rainfall events, is a major threat to sustained crop yields across the globe (Aggarwal, 2008; Bhatt et al., 2019; Guan et al., 2015; Lobell et al., 2011; Madadger et al., 2017; Mall et al., 2006, 2016; Ortiz-Bobea et al., 2021; Rosenzweig et al., 2002). The crop-diverse agroclimatic zones (ACZs) of India mainly receive most of their rainfall during monsoon months (JJAS). Thus increased extreme rainfall events during these four months increase the vulnerability of ACZs to yield loss and increase the sensitivity toward future climate change (Mall et al., 2021; Mishra et al., 2021; Singh et al., 2016; Yadav et al., 2021). To assess the impact of climate change on agricultural production, different agroclimatic models are available (e.g., Jones et al., 2003; Mera et al., 2006; Singh et al., 2010; Qian et al., 2016; Subash & Mohan, 2012), which need various climatic inputs (e.g., temperature, solar radiation, and rainfall). This climatic information is primarily available from global models (GCMs), but these data lack good spatial resolution to carry out regional impact studies. To overcome this issue, high-resolution dynamical downscaling using regional climate models (RCMs) is preferred (Jury et al., 2019; Singh et al., 2018; Giorgi, 2019). However, the RCMs also exhibit systematic biases that are likely dependent on the GCM boundary and model internal dynamics (Giorgi, 2007; Teutschbein & Seibert, 2012). The errors in RCMs, despite their high spatial resolution, lead to large uncertainty in projection studies and limit their application in regional climate change impacts studies (Cubasch et al., 2001; Kattenberg, 1996; Pastén-Zapata et al., 2020; Stocker et al., 2013; Van der Linden & Mitchell, 2009; Wu et al., 2021).

The RCM biases are often due to a combination of factors such as incorrect model initialization, errors in the model parameterizations, the imperfect representation of model physics, as well as the errors in the boundary conditions from driving GCMs (Beniston et al., 2007; Ehret et al., 2012; Jiao & Caya, 2006; Kjellström et al., 2010; Maraun, 2012; Nikulin et al., 2011; Reiter et al., 2018). The typical biases associated with RCM simulated rainfall include overestimating rainy days, especially of very low-intensity, that is, more drizzle days and

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underestimating the frequency of dry days incorrect seasonal variations of rainfall (Cardoso Pereira et al., 2020; Christensen et al., 2008; Dunkerley, 2019; Ines & and Hansen, 2006; Smitha et al., 2018).

Thus, it becomes imperative to correct the RCM simulated meteorological variables before they could be used for impact studies (Mall et al., 2019; Seneviratne et al., 2012). Over the past decades, various bias correction methods are in use, these range from simple scaling approaches to sophisticated distribution mapping, quantile delta mapping and regional quantile delta mapping (RQDM) (Acharya et al., 2013; Chen et al., 2011, 2013; Fang et al., 2015; Gutjahr & Heinemann, 2013; Kim et al., 2021; Miralha et al., 2021; Piani et al., 2010; Sharma et al., 2007; A. Singh et al., 2017, 2021; Teutschbein & Seibert, 2012; Tiwari, Kar, Mohanty, Dey, Kumari, et al., 2016; Voropay et al., 2021; Xavier et al., 2021). Further, the bias in the daily rainfall values not only impact the monthly mean totals but also affect daily intensities, frequency, and other statistical properties at a different timescale that are used in agriculture as well as hydrological studies (Arnell et al., 2003; Choubin et al., 2019; Fowler et al., 2007). A bias correction method is desired to correct both the magnitude as well as the frequency of rainfall distribution.

There are only a limited number of studies that attempt to assess the skill of bias correction methods in correcting daily rainfall; and, the tasks are often limited to GCMs, which due to their coarser-resolution are inefficient to provide the heterogeneous representation of rainfall characteristics over the Indian subcontinent (Acharya et al., 2013; Prasanna, 2018; A. Singh et al., 2017; Tapiador et al., 2019, 2020). In a study over the Kaidu River basin in China, five correction methods viz. linear scaling (LS), local intensity scaling (LOCI), power transformation (PT), distribution mapping (DM), and quantile mapping (QM) were tested for rainfall predictions. The study by (Fang et al., 2015) indicated that the QM methods is good for correcting the frequency-based indices such as standard deviation, percentile values while, the LOCI is effective for correcting time-series-based indices like Nash-Sutcliffe coefficient, R^2. In a similar study over India related to rainfall bias-correction using RCM data, four methods were utilized, that is, LS, LOCI, empirical quantile mapping (EQM), and power transformation (PTR). The results showed that EQM was more skillful than PTR and LOCI. The study further highlighted the variability in bias correction performance depending upon the rainfall characteristics such as seasonal mean, seasonal extremes or inter-annual variability, and the spatial variability across India (Choudhary & Dimri, 2019). There is a high likelihood of significant rainfall bias over the northeast and Himalayan regions as well as over western ghats (Basha et al., 2017; Tiwari, Kar, Mohanty, Dey, Sinha, et al., 2016). Other studies over India to correct rainfall, particularly during the summer monsoon, have employed global circulation model (GCM) output with different empirical/statistical methods (Acharya et al., 2013; Prasanna, 2018; Singh et al., 2017). The coarser spatial resolution and the biases associated with GCMs often limit their use for climate change impact studies and adaptation strategies at the regional and local scale.

Further, because India has a complex topography with heterogeneous elevation and rainfall patterns, there is a need for more region-specific information about the choice of correction methods and the simulation model. Thus there is a lack of evidence on how the performance of bias correction will vary on the choice of correction techniques, rainfall feature, RCMs selected, and spatial scale. Therefore, an effort to correct the RCM-simulated meteorological variables, particularly in climate-sensitive regions, would be helpful to drive climate change impact studies (Fang et al., 2015; Sonkar et al., 2019). Thus, there is an existing need for region-specific information about the efficient bias correction method that can be employed to generate region-specific impact studies that can help in policy and decision-making in agriculture and other fields.

In this context, the present study compares three different bias correction approaches in representing annual and seasonal rainfall, emphasizing monsoon rainfall (JJAS) from RCMs—RegCM and CCAM ensemble over 14 different ACZs of India. The study period considered is from 1970 to 2005 due to the availability of reference rainfall observational data. The bias correction methods include the popular ones owing to their easy implementation in impact studies. The methods also consider those for which sufficient evidence exists elsewhere for their ability to correct rainfall data and for their skills to adjust the statistics of observed data. This is aimed to make the results comparable to studies across the world (Teutschbein & Seibert, 2012).

The paper is structured in the following manner. Section 2 contains methodology, including information on the study area, selection of RCMs and observed India Meteorological Department (IMD) data, bias correction methods, and the statistical measures to assess model performance. Section 3 has the result and discussion about

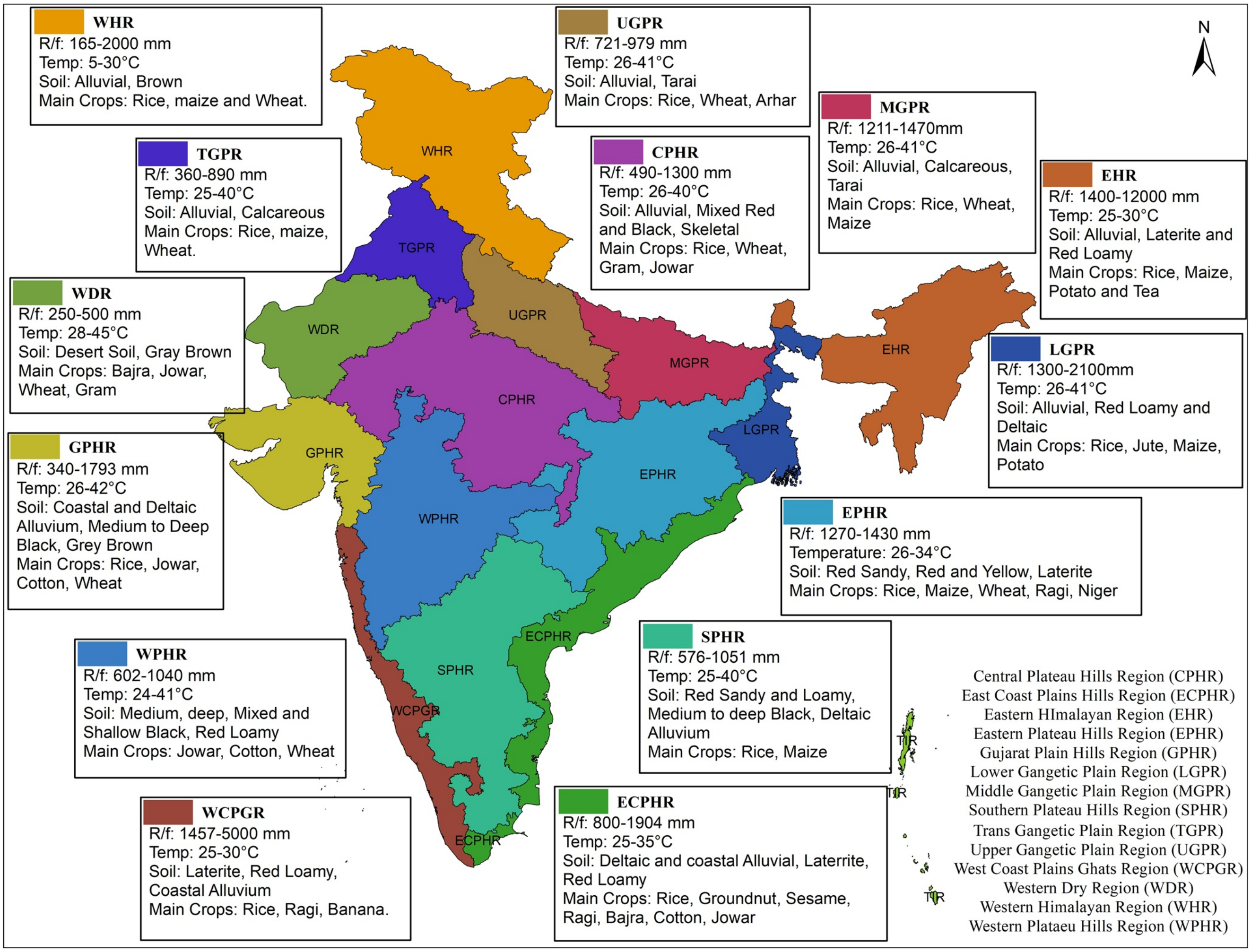

Figure 1. Characteristics of the 14 Agroclimatic zones across India.

the performance of bias correction approaches over different ACZs. Section 4 includes the conclusion and that discussion about the key study findings along with shortcomings and highlights.

2. Material and Methods

2.1. Study Area

The analysis was performed over the 14 (out of 15 total) different ACZs in India. The aim of defining ACZs was to scientifically manage the regional resources to meet food, fiber, fodder and fuel without affecting the status of the natural resources. ACZ is an area under major climate suitable for certain range of crop. The climatic condition of ACZs refers to rainfall, temperature, soil type and water availability which influence the vegetation types. Using Thornthwaite indices, India has been divided into 24 ACZs by Krishnan and Mukhtar Sing, in 1972. The planning commission has further divided the country into 15 broad agro-climatic zones based on climate and soil type, physiography, geological formation, cropping patterns, and crop management strategies such as irrigation and consideration regarding agronomic strategies (Ahmad et al., 2017). Not considered in the study, the 15th zone is not part of conterminous India and is in the islands off the Bay of Bengal and the Arabian Sea. The characteristics of each ACZ are provided in Figure 1.

Table 1
Details of the CMIP5 Models Used for the Analysis

CORDEX South Asia RCM experiment	RCM description	Contributing CORDEX modeling center	Driving CMIP5 AOGCM (https://verc.enes.org/data/enes-model-data/cmip5/resolution)
RegCM (LMDZ4)	The Abdus Salam International Center for Theoretical Physics (ICTP) Regional Climatic Model version 4.1 Giorgi et al. (2012)	CCCR, IITM, India	LMDZ4 (Global variable grid atmospheric model forced with bias-corrected SST); Sabin et al. (2013)
CCAM (six ensemble members)	Commonwealth Scientific and Industrial Research Organisation (CSIRO), Conformal-Cubic Atmospheric Model (CCAM); Mcgregor and Dix (2001)	CSIRO Marine and Atmospheric Research, Melbourne, Australia	ACCESS1.0 Bi et al. (2013); Collier and Uhe (2012) CCSM4 (Community Climate System Model 4) Gent et al. (2011) GFDL-CM3 (Geophysical Fluid Dynamics Laboratory Climate Model version 3) Griffies et al. (2011) CNRM-CM5 Voldoire et al. (2013) MPI-ESM-LR (Max Planck Institute for Meteorology, Germany, Earth System Model) Giorgetta et al. (2013) NorESM1-M (Norwegian Climate Center Model (Bentsen et al., (2013))

Note. Source: http://cccr.tropmet.res.in.

2.2. Data

In the present study seven dynamically downscale climate projections obtained using two regional climate models namely Regional Climate Model version 4 (RegCM4) (Giorgi et al., 2012) developed at The Abdus Salam International Center for Theoretical Physics (ICTP), Italy and Conformal-Cubic Atmospheric Model (CCAM) developed at Commonwealth Scientific and Industrial Research Organisation (CSIRO) Australia. The CCAM ensemble consist of 6 members obtained by forcing different lateral boundary conditions from Atmosphere-Ocean coupled General Circulation Models (AOGCMs) which are ACCESS1-0, CCSM4, CNRM-CM5, GFDL-CM3, MPI-ESM-LR and NorESM1-M. And RegCM4 output is generated from LMDZ4, AOGCM. The lateral boundary condition provides physically consistent spatiotemporal variations of climatic parameters at a smaller spatial grid. It also affects the spatial distribution of surface temperature and seasonal precipitation of the simulation. The output dataset provides high resolution regional climate change information that have the potential to analyze climate change impact at a fine scale which accommodates the effect of local topography on regional climate conditions. These RCMs produce fine scale processes and information by resolving topography, coastline and land surface heterogeneities that are useful for climate change impact assessment. Model descriptions are provided in Table 1. The LMDZ and CCAM ensemble daily data is available at $0.5° \times 0.5°$ spatial resolution for 1970–2005 (historical). Both the LMDZ and CCAM ensembled have been obtained from the Coordinated Regional Climate Downscaling Experiment- South Asia (CORDEX-SA) portal, which is managed by the Center for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM). CORDEX is a World Climate Research Program (WCRP) framework that evaluates the performance of the regional climate model through a set of experiments. We selected CCAM ensemble and LMDZ in our study, building on prior work that showed relatively good performance of these models in simulating India's temperature and precipitation fields (Mall et al., 2018; Singh et al., 2021). Further, these studies have performed bias correction of the above RCM to suggest that these models can be used for the impact studies over India owing to their efficiency in correcting the spatial heterogeneity to match the observed data (Mall et al., 2018; Singh et al., 2021).

The daily observed rainfall data was obtained from the IMD for the same period as the model runs (1970–2005). The IMD data are at $0.25° \times 0.25°$ spatial resolution (Pai et al., 2014). The observations were regridded to $0.5° \times 0.5°$ resolution using the bilinear interpolation method to homogenize the spatial scale between the RCMs and the observed (Voropay et al., 2021). Bilinear interpolation is commonly used for climate grid interpolation and hence adopted. The bilinear interpolation method for re-gridding retains the structure of the original

Table 2
Definition of Symbols Used in Equations

Symbols	Parameter
P	Rainfall (precipitation)
D	Daily
bc	Bias corrected
mod	Model
obs	Observed
μm	Monthly mean
th	Threshold
sf	Scaling factor
ecdf	Empirical cumulative distributioan function
*	Bias correction in the intermediate stage
*r*mod, obs	Pattern correlation coefficient for the model and observed
σ	Standard deviation

and interpolated data (results) with reasonable accuracy. As a result, several studies over the Indian region have adopted this method for creating lower resolution regridded data (Acharya et al., 2013; Singh et al., 2021).

2.3. Bias Correction Methods

The bias correction methods considered are for correcting rainfall estimates over the region of interest (Christensen et al., 2008; Teutschbein & Seibert, 2010; Varis et al., 2004). For the India domain, the ACZs have wide ranges of average rainfall, and it is unlikely that one method of correction applied in a region is transferable to the other. Thus the study employed different bias correction methods. In broad terms, the bias between observation and simulated variable is identified, and a transformation algorithm is used to adjust the model output. The bias is assumed to be stationary for the study period (and while not considered in this study, the method used to correct the historical will also likely be applicable for future projections).

Three bias correction methodologies: SCL, LOCI, and EQM, that have been used in prior studies were considered (Acharya et al., 2013; Chaudhary et al., 2019; Fang et al., 2015; Prasanna, 2018; Singh et al., 2017; Teutschbein & Seibert, 2013). The use of these methods in the rainfall variables is well explored in Fang et al. (2015) and Teutschbein and Seibert (2013) at various complexity levels ranging from simple scaling to intermediate LOCI to sophisticated QM method. No clear discussion was found in the literature to showcase the performance of complex methods over simple methods in the improvement of RCMs, especially over the Indian monsoon region. The current work has targeted this need. There are alternatives to these bias correction methodologies considered, for example, the power transformation (Fang et al., 2015) or the, Delta-change (Teutschbein & Seibert, 2013). However, these methods appear to be well suited for corrections related to future climate projections and are not preferred approaches for the historical data bias correction over the Indian domain.

The three bias correction methods: SCL, LOCI, and EQM, are discussed in the following sub-sections. The variables and indices used in the equations are given in Table 2. The steps involved in rainfall bias correction for each ACZ are shown in Figure S1.

2.3.1. Scaling (SCL)

The SCL: scaling or the linear scaling approach is based on the multiplicative term, which can adjust the biases in the model by agreement between monthly mean rainfall of corrected values and that of observation (Lenderink et al., 2007). This approach is an attempt to exactly match the monthly mean rainfall of observed and corrected. In the first step, the monthly scaling factor is calculated as a ratio of the long-term monthly mean of observed data and control (model data for historical time period) data. In the second step, each of the daily values from the uncorrected model rainfall for a specific month is multiplied by the monthly scaling factor of that specific month. Mathematically, the method can be stated as follows:

$$Pd_{\mathrm{bc}} = Pd_{\mathrm{mod}} \frac{[\mu_{\mathrm{m}}(Pd_{\mathrm{obs}})]}{[\mu_{\mathrm{m}}(Pd_{\mathrm{mod}})]} \tag{1}$$

The limitation of this method is that, since correction is based on mothly mean factor it may destort the distribution of inter-monthly variation which further influence other moments of probability distribution of daily rainfall value.

2.3.2. Local Intensity Scaling (LOCI)

The LOCI: local intensity scaling approach (Choudhary & Dimri, 2019; Schmidli et al., 2006; Teutschbein & Seibert, 2012) is an advancement over linear scaling. This method is to adjust the wet-day frequency and intensity of precipitation time series of a model by identifying a threshold which implies the number of model simulated days greater than the threshold value matches the number of observed days with precipitation greater than 0 mm. So, if the average number of simulated rainy days of specific month greater than observed number then precipitation less than the threshold value redefined to 0 that is, no rainfall. This method is able to significantly remove the high number of drizzle days found in RCMs output. LOCI correction is performed in three steps:

1. The threshold for wet-day for the month m, $P_{\text{th,mod}}$ is ascertained from the daily time series of raw model rainfall to ensure that the exceedance of threshold matches with the observed wet-day (rainfall > 0 mm) and the days with rainfall less than $P_{\text{th,mod}}$ of the model are redefined as 0 mm rainfall.

$$* \, Pd_{\text{bc}} = \begin{cases} 0, & \text{if } \; Pd_{\text{mod}} < P_{\text{th,mod}} \\ Pd_{\text{mod}}, & \text{otherwise} \end{cases} \tag{2}$$

2. Taking only wet-days into account (i.e., observed days with rainfall >0 mm and model days with the rainfall $>P_{\text{th,mod}}$), the scaling factor sf is calculated based on long term monthly mean wet-day intensities.

$$sf = \frac{\mu_{\text{m}}(Pd_{\text{obs}})|(Pd_{\text{obs}} > 0 \;\text{ mm})}{\mu_{\text{m}}(Pd_{\text{mod}})|(Pd_{\text{mod}} > P_{\text{th,mod}}) - P_{\text{th,mod}}} \tag{3}$$

3. The scaling factor is then multiplied with the raw model daily values to get the bias-corrected model data.

$$Pd_{\text{bc}} = * \, Pd_{\text{mod}} \cdot \text{sf} \tag{4}$$

According to the definition after the bias correction, the mean, wet day frequency, and intensity should match with observation. The limitation of LOCI method is that it unable to adjust the differences in frequency distribution of rainfall and, temporal distribution of daily rainfall occurrence is also not corrected through this method.

2.3.3. Empirical Quantile Mapping (EQM)

The QM is a non-parametric approach applicable for different rainfall distributions (Fang et al., 2015). It can effectively correct bias in the mean, standard deviation, and wet-day frequency as well as quantiles (Themeßl et al., 2012). The EQM approach calibrates model cumulative distribution function (CDF) by adding to the quantile of observed rainfall distribution both the mean and individual delta change in corresponding quantiles (Cannon et al., 2015). This quantile to quantile matching blends the moment of probability distribution function (PDF) of the model (Piani et al., 2010) by using the PDF of observation, incorporating both the PDFs and CDFs, and then building a transfer function. This function transforms the raw model rainfall into corrected model rainfall. After this transformation, the CDFs of the model and observation theoretically should be the same.

$$Pd_{\text{bc}} = \text{ecdf}^{-1}_{\text{obs,m}}(\text{ecdf}_{\text{mod,m}}(P_{\text{mod,m,d}})) \tag{5}$$

The above three corrections are used for the mean annual cycle, the spatial distribution of seasonal mean rainfall, 95th percentile, and consecutive dry day index (CDD). The limitation of the method is that It correct mean variance and frequency and intensity of wet days and does not account for temporal distribution of daily rainfall occurrence.

2.3.4. Statistical Analysis

The performance of the bias correction method for rainfall has been evaluated using various statistical measures. The best and worst-performing bias correction method for each of the 14 ACZ has been decided based on the statistical scores. The performance of RCM outputs in simulating rainfall after bias correction has been evaluated using long term annual and seasonal cycle to compare the climatology. To evaluate spatial heterogeneity in rainfall during JJAS a spatial plot of JJAS mean (uncorrected and bias corrected) has been constructed. In order to evaluate the ability to correct the bias representing dry and wet extremes, CDD where number of consecutive dry days period with more than 5 days per time period and 95th percentile rainfall value have been used. Both the extreme rainfall indices show whether the bias correction methods are able to reproduce the dry and wet extremes respectively, which will be useful in extreme rainfall studies. Further, the zone-wise performance of all the RCMs output, before and after bias correction, has been quantified with a set of statistical parameters. Taylor's diagram is used to analyze the improvement in model performance after bias correction (Taylor, 2001). The Taylor diagram gives a summary about correlation (r) between observed, uncorrected, and bias-corrected model

10.1029/2021EA001981

data, together with standard deviation (SD) and centered root mean square difference (RMSE), which measures differences between two fields as represented below.

$$RMSE = \sqrt{\left[\frac{\sum_{i=1}^{n}((Y^{\text{mod}} - Y^{obs})^2}{N}\right]} \tag{6}$$

where Y^{mod} and Y^{obs} represent rainfall data for model and observation respectively.

The other statistical indices used are coefficient of variation (CV), mean absolute error (MAE), percentage bias (P_{BIAS}), Wilmott's degree of index (d) and Skill Score (SS).

The CV, a ratio of standard deviation to the mean, shows the dispersion of data points in a data series around the mean.

$$\text{CV} = \frac{\sigma}{\mu} \tag{7}$$

MAE demonstrates the average error between observed and model uncorrected and corrected rainfall data (Fang et al., 2015).

$$\text{MAE} = \frac{\sum_{i=1}^{N} |Y_i^{\text{obs}} - Y_i^{\text{mod}}|}{N} \tag{8}$$

P_{BIAS} measures the percentage change in the model simulation with observation.

$$P_{\text{BIAS}} = \frac{\sum_{i=1}^{N}(Y_i^{\text{obs}} - Y_i^{\text{mod}})}{\sum_{i=1}^{N}(Y_i^{\text{obs}})} \tag{9}$$

Wilmott's degree of the index (d) and skill score (SS) have been used to evaluate model skills compared with observation.

$$d = 1 - \frac{\sum_{i=1}^{n}(Y^{\text{mod}} - Y^{\text{obs}})^2}{\sum_{i=1}^{n}(|Y_i^{\text{obs}} - Y^{\text{mean}}| + |Y_i^{\text{mod}} - Y^{\text{mean}}|)^2} \tag{10}$$

where Y^{mod} and Y^{obs} are observed and simulated rainfall, and N is the total number of observations and Y^{mean} is the mean of observed rainfall; d is used as a standardized measure of the agreement between observed and simulated rainfall (Willmott, 1981). The value of d ranges from 1 (perfect match) to 0 (no agreement with model and observation).

The skill scores (SS) were calculated following Maurya et al. (2018), to assess the potential skill of RCMs simulation before and after bias correction.

$$\text{SS} = r^2\text{mod, obs} - \left[r_{\text{mod,obs}} - \left(\frac{\sigma_{\text{mod}}}{\sigma_{\text{obs}}}\right)\right]^2 - \left[\left(\frac{\mu_{\text{mod}} - \mu_{\text{obs}}}{\sigma_{\text{obs}}}\right)\right]^2 \tag{11}$$

where $r^2\text{mod, obs}$ of the right-hand side is the pattern correlation coefficient between simulated and observed rainfall.

3. Results and Discussion

3.1. Annual and Seasonal Cycle of Rainfall

The CCAM ensemble and LMDZ simulation performance are compared with the IMD observed annual cycle (Pattnayak et al., 2017) based on long-term monthly mean rainfall over different ACZ, and is shown in Figure 2. The comparison shows a large underestimation in mean monthly rainfall (5 to >200 mm) between the observed and the model data for different months across different ACZs. The underestimation is more prominent in the monsoon season (JJAS). Some exceptions exist among the ACZs that exhibited overestimation in the model data, like WCPGR, EHR, ECPHR, and SPHR. However, the results after the three bias correction methods show the close agreement of the corrected data with the observed IMD data. Moreover, the degree of agreement between

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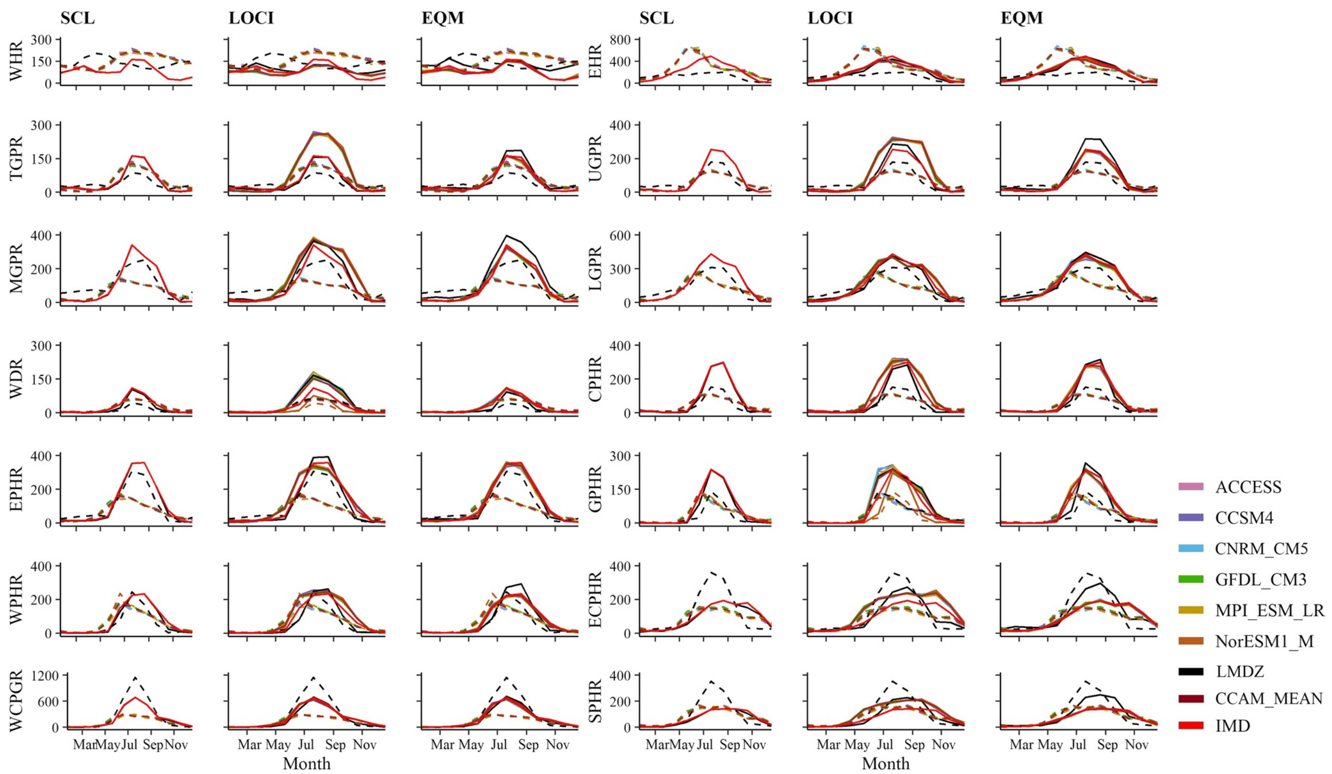

Figure 2. Mean annual cycle of rainfall (mm) of IMD (observed) and CORDEX-RCMs for 1970 to 2005 for different ACZs of India (dotted line shows uncorrected model while solid line is for bias corrected model output).

the observed and bias-corrected rainfall data varies from region to region. Further, the regional topography, elevation, and selection of RCMs for the study also influence the perforation of correction methods (Table S1).

Among the three bias correction approaches, SCL yielded good overall agreement between observed and bias-corrected long term mean. Although the LOCI method was not adequate for correcting the mean for the entire time series, it yielded satisfactory results for the winter season. The EQM method showed satisfactory performance of the ensembled model in agreement with the observation during winter and post-monsoon season, but the LMDZ shows overestimation. The linear-scaling method adjusts monthly mean rainfall values so that the variability in the corrected data is consistent with the raw RCM data (Graham et al., 2007). But the limitation in this approach is that it corrects all events with the same correction factor and is, therefore, unable to correct frequencies.

The detailed interpretation of the performance of the bias correction method for selected RCM outputs varies from region to region.

In WHR, the LMDZ model shows good agreement with the IMD observations in the monsoon season. The Eastern Himalayan Region (EHR) shows an underestimation in the monsoon rainfall much by the LMDZ while both the models show a general overestimation in other seasons. The LMDZ underestimation is also noted for pre-monsoon and post-monsoon. The bias correction shows better performance by SCL than LOCI and EQM.

The prime reason for this larger bias in both WHR and EHR is likely the complex topography in these ACZs. Also, there are relatively few weather stations in the Himalayan regions and therefore, the interpolated IMD data also has high uncertainty over this region.

For the IGPR (Indo Gangetic Plain Region) that includes Trans Gangetic Plain Region (TGPR), Upper Gangetic Plain Region (UGPR), Middle Gangetic Plain Region (MGPR), and Lower Gangetic Plain Region (LGPR), both the model results show considerable underestimation in the monsoon season. The CCAM ensemble achieves relatively better results than LMDZ in simulating rainfall in other seasons. The bias correction methods show substantial improvement in the model output across the ACZs with the exception of UGPR (where only SCL shows fair performance). Further, SCL and EQM outperformed LOCI that performs relatively well for LMDZ but not for the CCAM ensemble.

Western Dry Region (WDR) showed considerable bias (underestimation) for both the CCAM ensembled and LMDZ model for the monsoon season and relatively less bias (overestimation in most cases) for the other season, which was further reduced following the corrections by SCL and EQM (modest by LOCI). A similar result was observed by CPHR and EPHR. However, in the case of EPHR the performance of EQM was poor than SCL and LOCI in correcting monsoon rainfall for LMDZ model.

For the WPHR, GPHR and SPHR zones, only SCL method performed satisfactorily in correcting monsoon rainfall for LMDZ.

Both the models were unable to capture the rainfall in WCPGR and ECPHR correctly. But the bias correction methods were able to minimize the biases for WCPGR and ECPHR in both models. HoweverLOCI method was not as efficient as EQM and SCL in correcting CCAM ensemble and LMDZ.

The findings from the study are supported by the results from Choudhary and Dimri (2019), which show improved performance of rainfall simulations in India after bias correction. They concluded that the EQM method performed best relative to LOCI and SCL. However, they also highlighted variation in the degrees of success for the rainfall characteristic and the spatially varying success of the bias correction method applied. The findings by Teutschbein and Seibert (2012) also showed an improvement in uncorrected RCM climate variables after bias correction approaches. But the ability to correct the data varied depending upon the statistical properties such as standard deviation or percentiles. Among the various bias correction methods used by Fang et al. (2015), to correct precipitation data over the Kaidu River basin in China, the PT and QM performed best in correcting the frequency-based indices (standard deviation, percentile values) while the LOCI was superior for correcting time-series-based indices (e.g., Nash-Sutcliffe coefficient, $R2$).

3.2. Spatial Heterogeneity in Monsoon Rainfall Before and After Bias Correction

The spatial distribution of JJAS mean rainfall over India for uncorrected and bias-corrected model data against observation is shown in Figure 3. The RegCM output is widely used in different studies over the Indian subcontinent, and therefore it is important to highlight the biases that were apparent in the rainfall fields. The uncorrected CCAM ensemble and LMDZ model underestimated the rainfall over the Indo-Gangetic plains (TGPR, UGPR, MGPR, and LGPR), western ghats (WCPGR), and overestimated in interior peninsular regions (WPHR and SPHR) when compared to observation.

A high degree of variability exists in rainfall over different ACZs because of different topography and climates. The model physics is also expected to have differences in the magnitudes of rainfall over different regions. LMDZ could capture the large-scale features of monsoon rain over the Western Ghats mountainous region (WCPGR) but not over the northeastern parts (EHR). The CCAM ensemble could depict the higher rainfall scenario over the northeastern parts. Overall, results indicate that SCL shows good agreement with the observations. The SCL corrected data could adequately capture the lower rainfall values in the northeast and peninsular India. The SCL method provided good agreement with observation compared to EQM, which showed a small bias, and LOCI, which overestimated the rainfall in each ACZs.

The choice of the model to study rainfall characteristics depends upon the performance of a model. Choudhary and Dimri (2019) showed that the GCM, after bias correction, could capture the rainfall over central, northern, and northeastern parts of India and along the foothills of Himalaya. They further mentioned that each bias correction method performed equally well in simulating mean rainfall for JJAS. While LOCI shows very good improvement in reducing the bias over India, in another study, linear scaling and LOCI showed larger biases similar in magnitude to the uncorrected rainfall much because of failure to represent the intensity of dry days and wet days (Teutschbein & Seibert, 2012).

3.3. Spatial Pattern Correlation (R) and Coefficient of Variation (CV)

The spatial pattern of correlation between observed and uncorrected and bias-corrected annual rainfall across various ACZs is shown in Figure 4. Results indicate that for most ACZs, the correlation of uncorrected CCAM

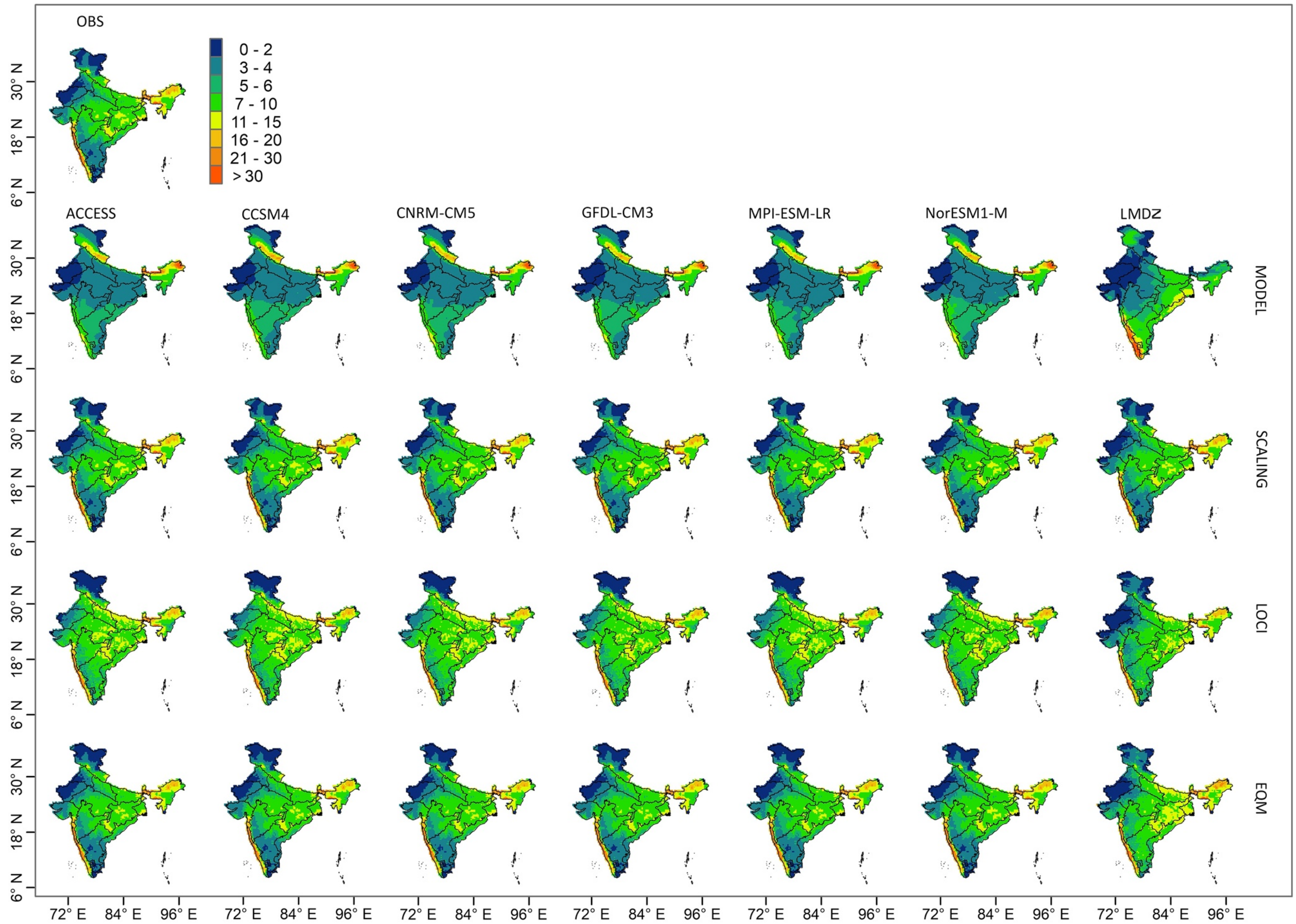

Figure 3. Climatology of JJAS mean precipitation (mm/day) for 1970 to 2005 from: IMD observed data in top row with legend showing rainfall (mm/day), uncorrected (second row); bottom three rows shows output for bias correction method: Scaling, LOCI, and EQM, respectively.

ensemble with observed rainfall ranges between 0.6 and 0.7, while for the WHR and some parts of EHR and SPHR, it ranges from 0.2 to 0.5. For the uncorrected LMDZ, the central part of India comprising CPHR, UGPR, MGPR, EPHR, and northern part of WPHR zones showed spatial correlation above 0.8, while for the WHR, SPHR, and ECPHR, the correlation ranged between 0.2 and 0.5.

The application of various bias correction methods shows improvement in the spatial correlation. SCL's corrected CCAM ensemble data shows most of the ACZs have spatial correlation above 0.8 except for WHR, which was between 0.2 and 0.5. The LOCI and EQM also show high spatial correlation values (>0.8), except over WHR (0.2–0.5), SPHR, some parts of TGPR, WDR, and GPHR the values range between 0.6 and 0.7. For LMDZ, the SCL yielded a spatial pattern above 0.8 for all the zones except SPHR, GPHR, WDR (0.6–0.7), and WHR (0.2–0.5). Whereas, for LOCI and EQM, all the zones showed a correlation above 0.8 except for WDR and some part of SPHR (0.2–0.5) and GPHR (0.6–0.7). Thus, there is a marked increase in spatial correlation between model and observed data due to the closeness of model data with the IMD data after bias correction. There is no marked difference in results obtained from various correction methods. This may be because the distinct skills that different correction methods employ are likely averaged when considering the seasonal mean rainfall. Note that the EQM corrects the values along with the entire distribution. At the same time, LOCI specifically adjusts the frequency and intensity of precipitation on wet days, bringing values corrected values close to observation in different years over the study period. This enhances the ability of LOCI to capture the inter-annual variability.

The findings are again complemented by the results in Choudhary and Dimri (2019). For inter-annual variability (as standard deviation) of JJAS mean precipitation, the application of EQM on RCA4 data could successfully capture the spatial pattern of variability. However, the magnitude varied compared to the observed such as in the

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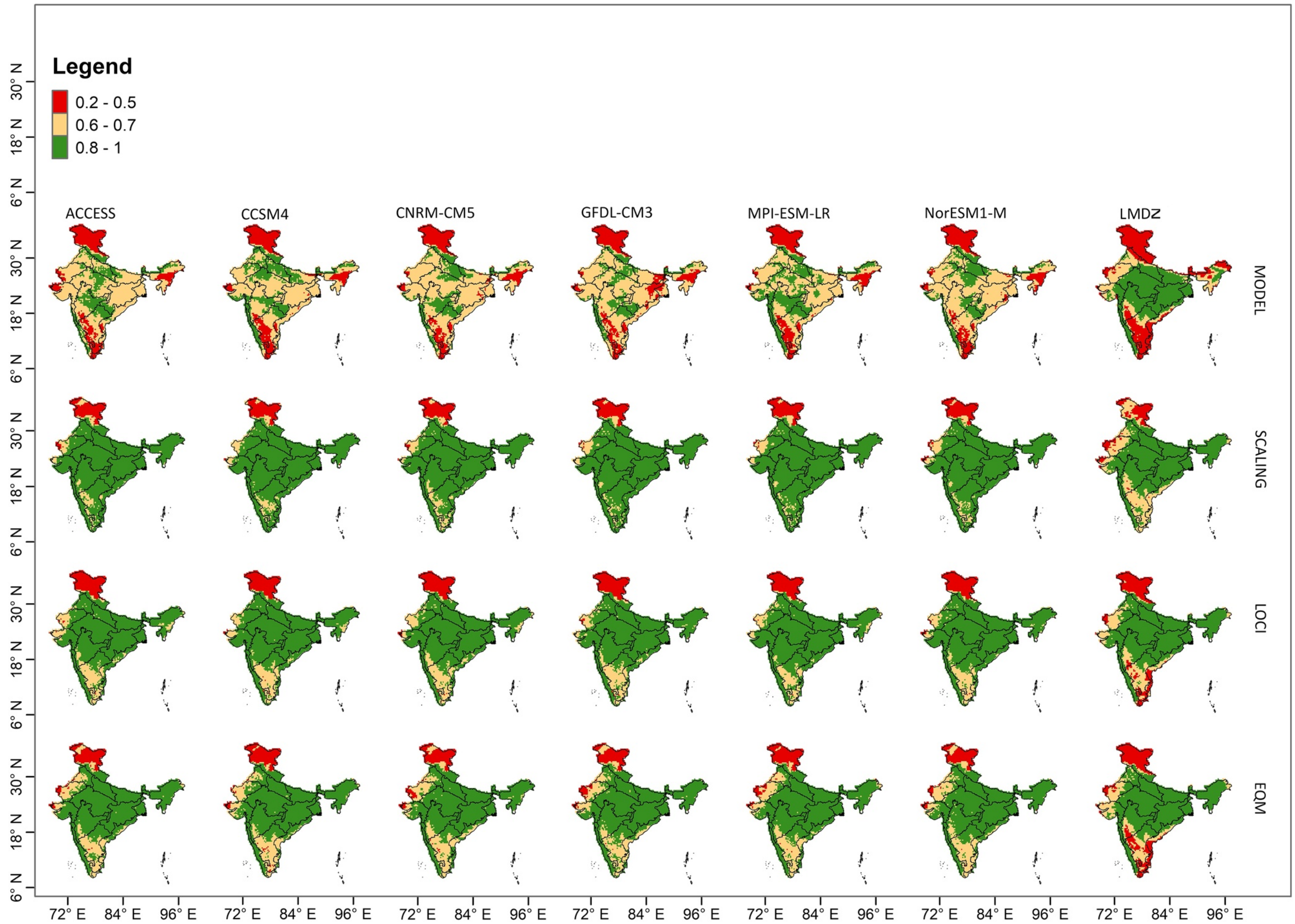

Figure 4. Spatial pattern of correlation for entire data JJAS rainfall data from 1970 to 2005. The first row is the uncorrected, while the second, third and fourth represent the spatial correlation for the bias-corrected output for different correction methods, Scaling, LOCI, and EQM. The legend on the top shows the coorelation range (0–1).

Himalayan stretch, northeast India, parts of central India and along the Western Ghats. The variability did not appear to improve over the southern peninsular region and shows an underestimation for all the methods. They also found that none of the methods like EQM, LOCI, or power transformation were distinctly superior to others, and the SCL failed to capture the variability. CCAM performed similarly; however, in this case, SCL and LOCI did not perform well compared to EQM.

The CV across different ACZs is shown in Figure 5. The uncorrected CCAM ensemble did not match the observation except for few regions in the northern Himalayas, Eastern Himalayas, and some in southernmost India. The uncorrected LMDZ, on the other hand, shows a similar CV as observed though deviations were observed in some zones. The CCAM ensemble and LMDZ data bias-corrected through SCL and EQM show similar CV to observations. In comparison, LOCI did not perform well for the CPHR in the CCAM ensemble and WPHR and some parts of SPHR for LMDZ. In another study (Teutschbein & Seibert, 2012), it was found that not all bias correction methods could correct CV appropriately. For example, the linear scaling and LOCI did not correct the CV, while power transformation was successful up to some extent. In contrast, DM performed best and appropriately captured the CV in the rainfall data.

3.4. Evaluation of Bias Correction Through Skill Score

The skill score (SS) was calculated using three statistical metrics viz. pattern correlation coefficient, standard deviation and mean rainfall for model and observation. Among the three bias correction methods, scaling yielded

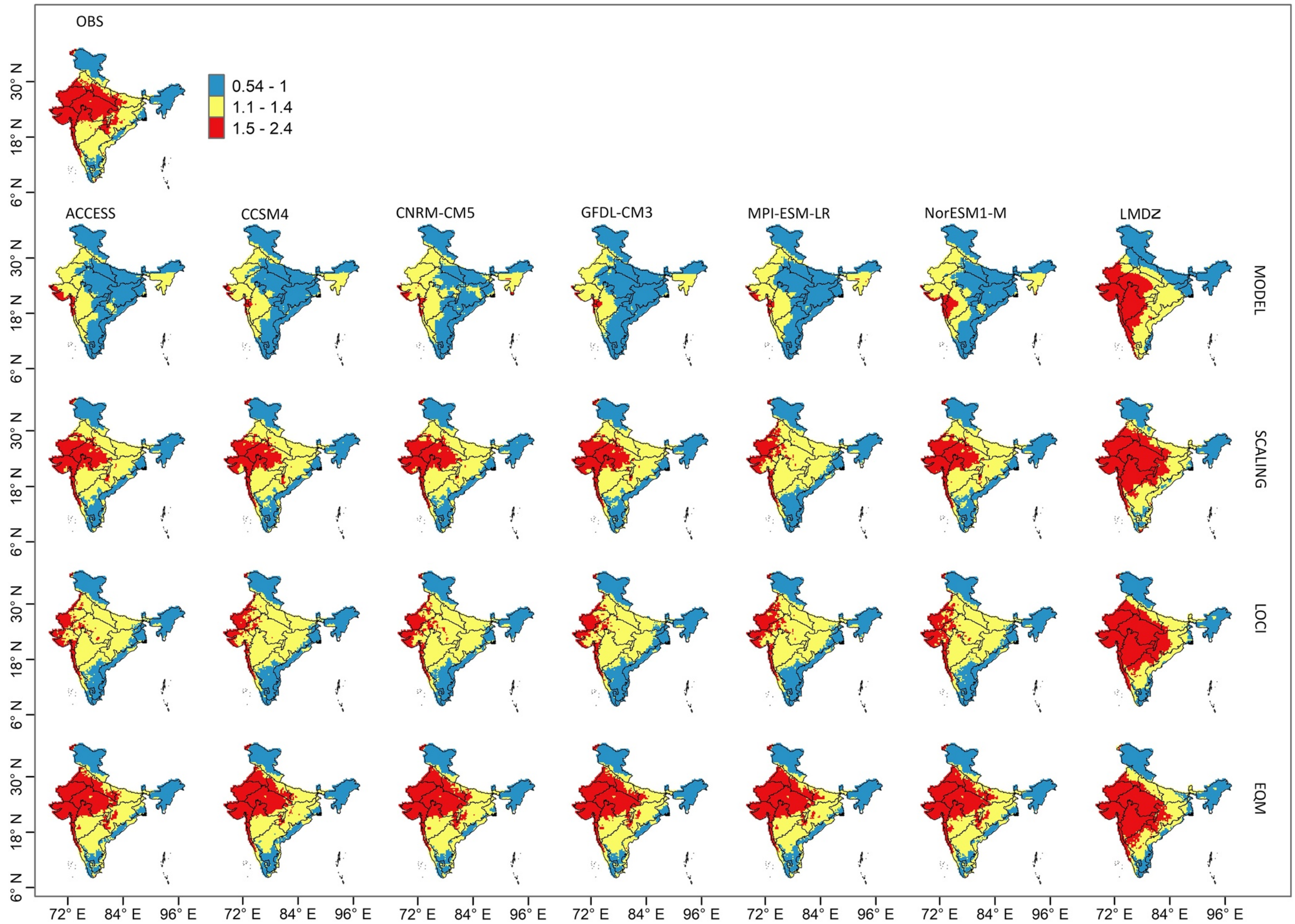

Figure 5. Spatial pattern of coefficient of variation for entire data JJAS rainfall data from 1970 to 2005. The first row is the uncorrected, while the second, third and fourth represent the spatial coefficient of variation for the bias-corrected output for different correction methods, Scaling, LOCI, and EQM.

the best results in terms of performance skill. The zone-wise performance skills are summarized in Figure 6 (Table S2).

The SS was found to be highest for SCL followed by EQM and lowest for the LOCI for almost every ACZ across India. The plausible reason for the performance of SCL and EQM is that SCL could efficiently correct the bias in the mean of daily precipitation (Fang et al., 2015; Lenderink et al., 2007; Teutschbein & Seibert, 2012). In the case of EQM, major biases were adjusted in the probability of dry days and intensity of wet days statistics. Also, the EQM match each day precipitation of the model and is observed by constructing a CDF for both. Thus both could perform better in skill scores (Chen et al., 2013; Gudmundsson et al., 2012; Maraun, 2013). In the case of CCAM ensembles out of 14 ACZs, 7 (CPHR, EPHR, HER, LGPR, MGPR, WCPGR, and WDR) yielded SS below 0.5 for the raw model. After bias correction, the SS approaches 1 for SCL and 0.90 for EQM across ACZs, while for LOCI, it deteriorated and showed the worst result for SPHR (0.23) and TGPR (−0.26). On the other hand, in the case of the uncorrected LMDZ model, out of 14 ACZ, 5 were below 0.5 SS value. After bias correction, SCL show SS values above 0.90, and EQM and LOCI show SS values in the range of 0.8–0.97. The exception was notable for three ACZ; ECPHR, SPHR, and WHR, where the SS was 0.49, 0.38, and 0.46 for LOCI and 0.40, 0.11, and −0.24 for EQM, respectively.

3.5. Comparison and Statistical Evaluation of Bias Correction Methods

The differences in the statistical indicators between corrected and uncorrected rainfall data are compared among three bias-correction methods for each ACZs and presented through Taylor's diagram in Figure 7. The Taylor

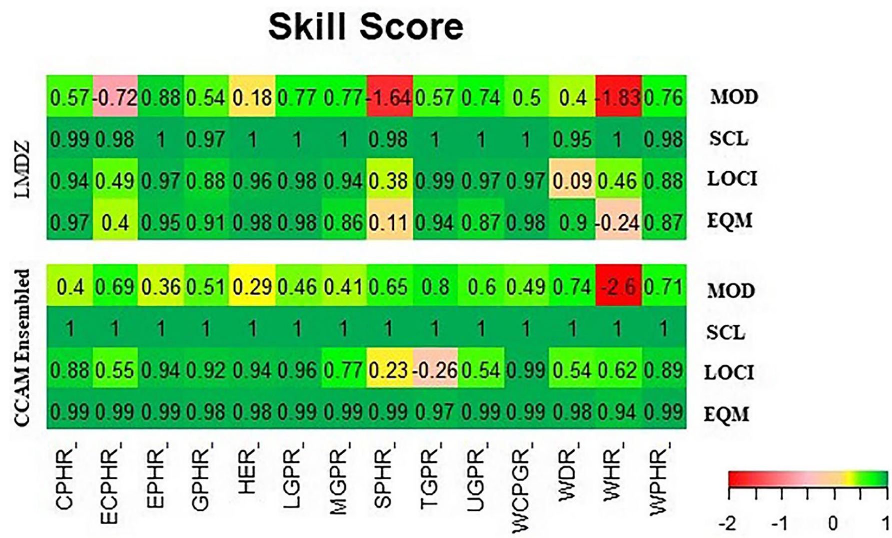

Figure 6. Skill Score for CCAM ensembled output and LMDZ model from uncorrected (MOD) to bias corrected using different methods (SCL, LOCI, and EQM).

diagram captures the spread of spatial correlation of models and bias-corrected data in terms of observations. After bias correction, all the model yielded a higher correlation for each of the ACZ. For most of the ACZs, the uncorrected model data yielded a correlation coefficient of 0.6–0.8 with the observed and showed the highest correlation score of about 0.95 after bias correction. Other statistical indices like RMSE, MAE, Percentage bias, and index of agreement (d) affirm that all the bias correction approach performed effectively for each ACZ (Tables S3–S16). The MAE ranges from 0.47 (CCSM4 for WDR) to 4.07 (LMDZ for EHR). All the three methods found to be able to reduce the magnitude of maximum MAE of 4.07 to 1.1, 1.3 and 1.4 by SCL, LOCI and EQM respectively. The percentage bias for uncorrected model ranges from −57% (LMDZ for WDR) to 81% (ACCESS for WHR) which has been reduced to −21% to 0% respectively by SCL. All the correction methods found to be able to minimize the percentage bias very efficiently. For most of the cases SCL and EQM method outperform to reduce both positive and negative bias over LOCI methods.

The SCL approach is a mean-based method where the monthly mean adjustment factor is applied to the model simulated daily rainfall. This yields a high agreement between monthly mean values (Teutschbein & Seibert, 2012). So, the bias in the mean is eliminated. The other two approaches also minimize the difference in the mean considerably. Since the LOCI method does not correct the mean the CCAM ensemble show a large bias in the mean for almost all ACZ (except for WHR, WCPGR, and EHR). In the case of WHR and WCPGR, the corrected mean equals the observed mean, while in EHR, it shows a negative bias in the mean. In the case of LMDZ, a negative bias is noted for all ACZ except IGPR, SPHR, and WHR, which shows a positive bias. The EQM method successfully achieved correction in the mean for nearly every ACZ across India. In a study over the performance of various bias correction methods based on MAE to simulate rainfall, the method DM performed best, followed by the power transformation, LOCI, and the linear-scaling approach (Teutschbein & Seibert, 2012). Further, the study observed a slight variation among correction methods to correct standard deviation in the daily rainfall values, distinctively for SCL and LOCI that showed larger variability with biases in rainfall of magnitude similar to the uncorrected rainfall values.

3.6. Evaluation of Wet and Dry Extremes

It is important to assess the performance of a model in simulating extreme rainfall. This highlights the need to evaluate the skill of bias correction performance for the extreme rainfall event together with seasonal mean. To assess wet extremes, the 95th percentile in the rainfall values, and for dry extreme, consecutive dry days index (CDD) were calculated.

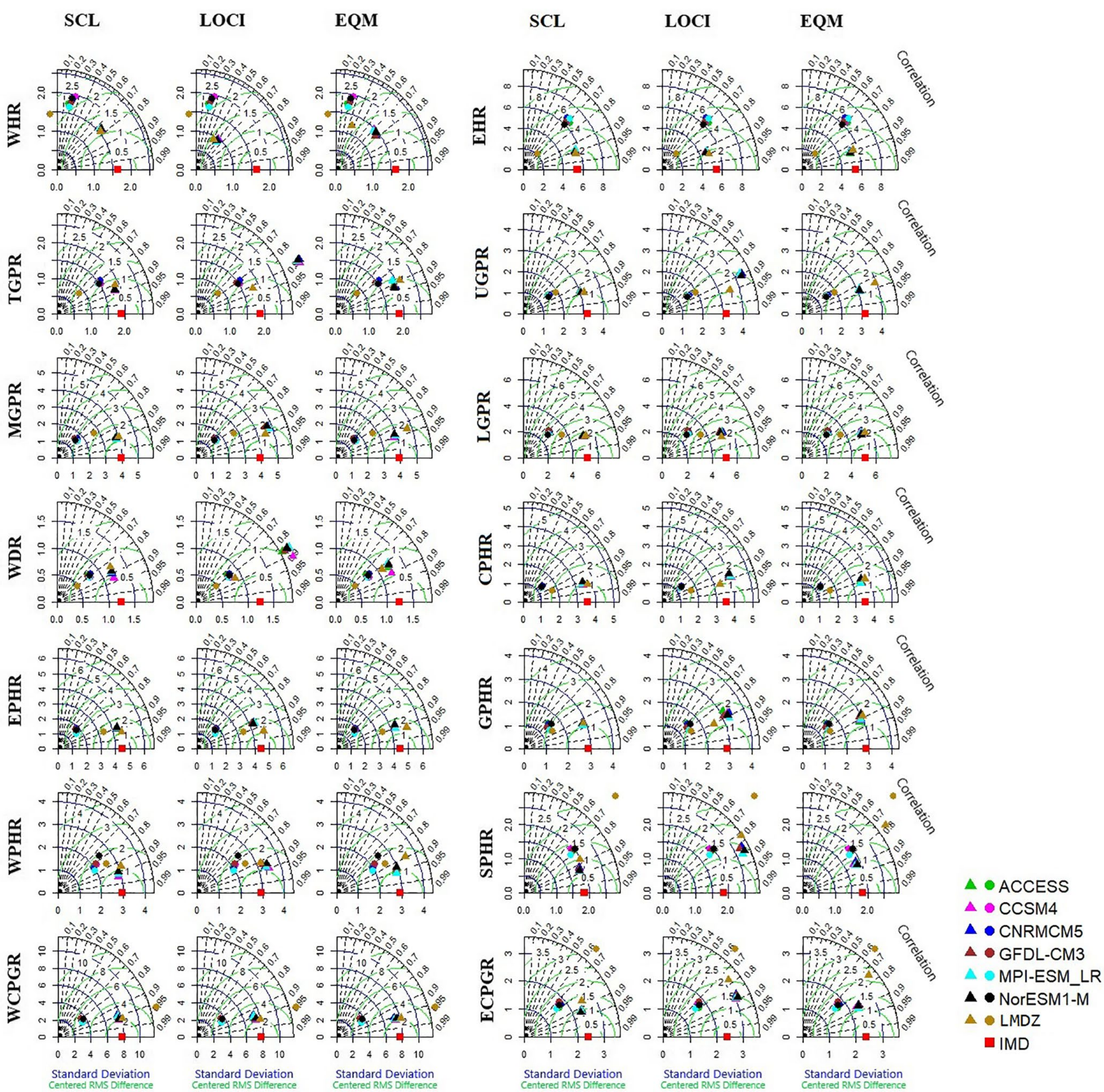

Figure 7. Taylor diagram for the six CCAM ensemble model & LMDZ for different precipitation bias correction methods. The results are shown for the 14 Agroclimatic zones of India, where circle shows uncorrected, triangle shows bias corrected and red square indicates observed.

Figure 8 shows the climatology of the 95th percentile (i.e., the change in the 95th percentile of corrected rainfall data divided by the 95th percentile of observed rainfall data in the baseline period). As compared to the observation, the CCAM ensemble underestimates the 95th percentile rainfall value for almost every ACZ, whereas WHR overestimates 95th percentile value. The LMDZ is found to perform better than the CCAM ensembled. After bias correction, the rainfall at 95th percentile increased to bring the model closer to the observation. The SCL and EQM perform well to bring the percentiles in agreement with observation but the LOCI was unable to correct the wet bias. In earlier studies it is noted that even though SCL could correct the bias in the mean, it is unable to correct for biases in the frequency and intensity of wet-day. The LOCI could adjust the mean as well as frequency and intensity of wet-day (Schmidli et al., 2006). The possible reason for this could be the internal model dynamics and complex topography, heterogeneity in rainfall pattern, intensity, and frequency over the Indian region, that

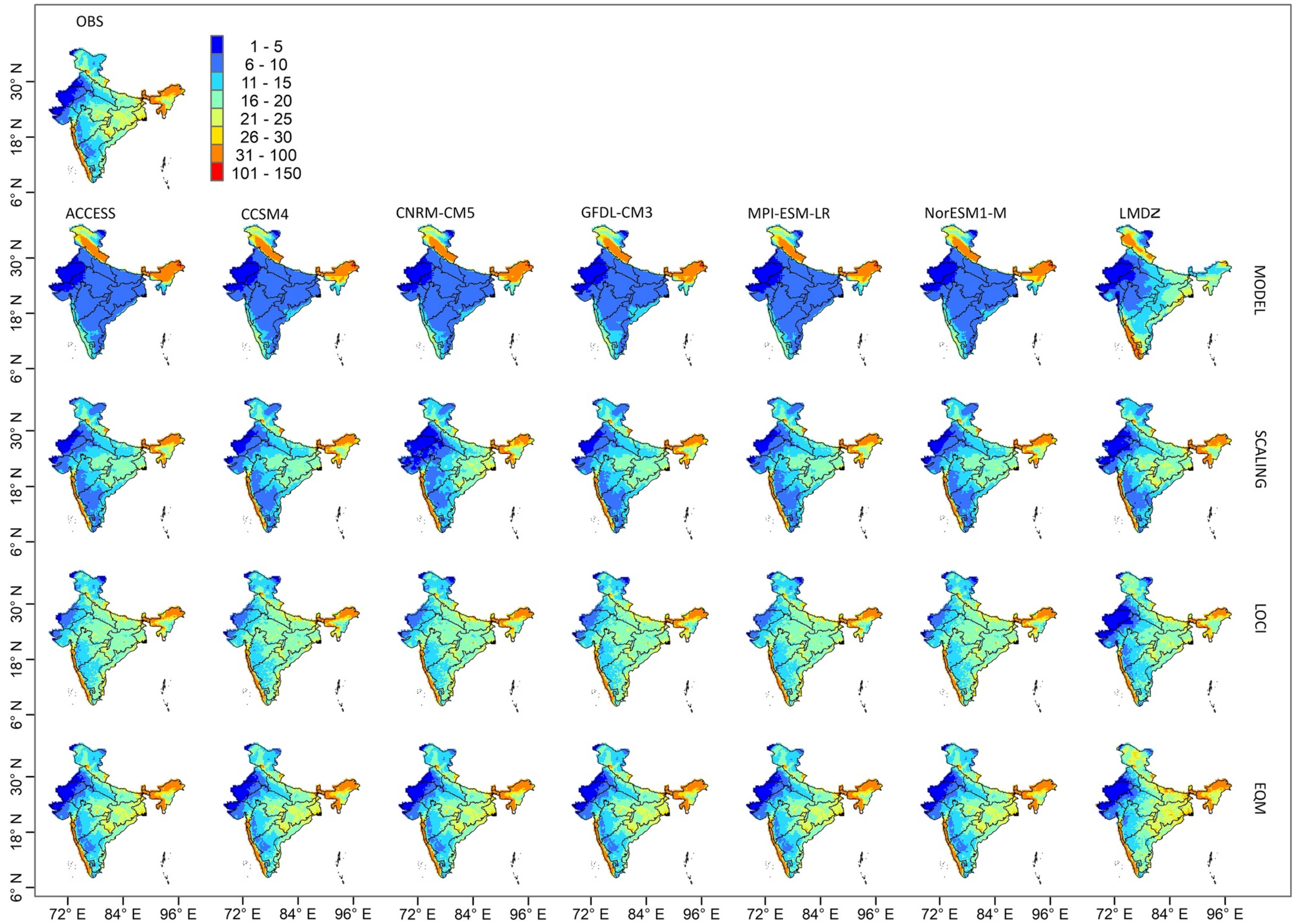

Figure 8. Rainfall distribution at 95th percentile for period (1970–2005) from IMD observed (top row with legend showing rainfall at 95th percentile), uncorrected (second row) and subsequent rows with bias corrected using different methods (Scaling, LOCI & EQM).

the expected performance of the correction methods could not adequately do justice (Dimri, 2021). Supportive evidence of similar finding was reported in Choudhary and Dimri (2019), who found that CCAM overestimated the frequency of very wet days (R95p). They also reported that QM reduced the positive biases over the entire India. Another study over China, report SCL to overestimate the probability of wet days (by up to 41%) while LOCI performs comparatively well (Fang et al., 2015).

The spatial plot for the CDD is shown in Figure 9. The plot shows the a maximum number of consecutive dry days period with more than 5 days per time period having daily rainfall below 1 mm. Compared to the IMD observations, the CDD index shows bias in uncorrected CCAM ensembled where CDD in WDR, GPHR, WHR, and EHR have been underestimated. While for the LMDZ simulation, the index is well captured except in LGPR, which had underestimation. LOCI and SCL methods show improvement in CDD over WDR and GPHR for CCAM ensembled. However, for the LMDZ, the CDD index is overestimated for CPHR and WPHR even after the bias correction. In the case of EQM, the CDD index for WDR and GPHR have been corrected while WHR and EHR still show biases for CCAM ensembled. On the other hand, for LMDZ EQM shows bias for the Himalayan region and LGPR. Similarly, in another study, it is reported that CCAM underestimated the CDD over most parts of India by more than 8 CDD index. Overall, no distinct improvement was observed after bias correction, though, EQM and LOCI still managed to improve the spatial representation of CDD over India (Choudhary & Dimri, 2019). Fang et al. (2015) over China show that LS and LOCI have a very limited ability to reproduce dry days.

Figure 10 shows the PDF plots of the observed, uncorrected and bias correction rainfall for each ACZs of India. The distribution aids the understanding of the performance of each method, especially for studying the extreme rainfall for each of ACZs.The uncorrected models show deviations from the observed curve. However, all three

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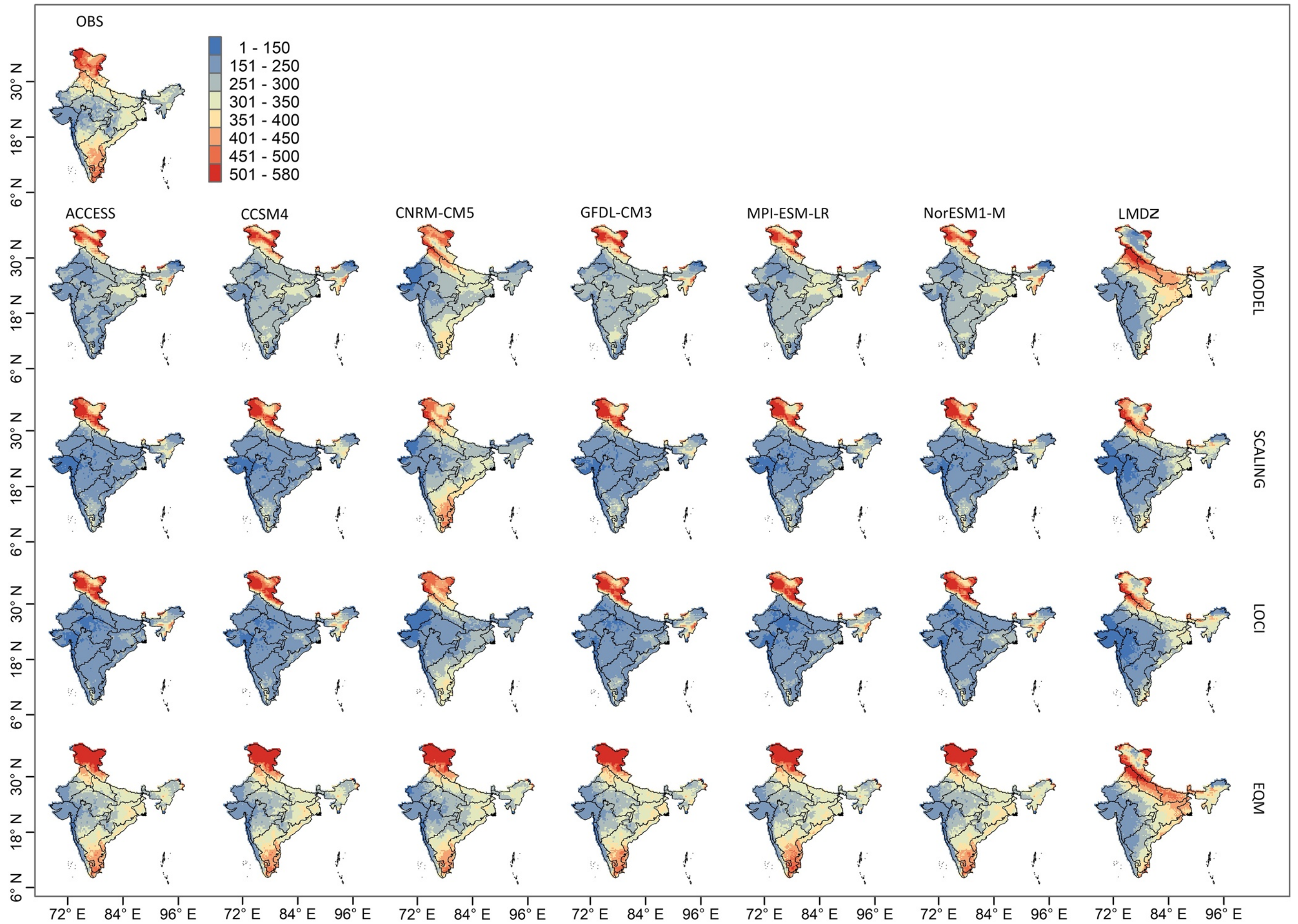

Figure 9. Climatology of cumulative dry day index (CDD) index for 1970–2005 from IMD observed rainfall (top row with legend showing CCD index), uncorrected (second row) and bottom three rows with bias corrected using Scaling, LOCI & EQM method, respectivaly.

bias correction methods performed effectively but differently to adjust the shape of PDF. Mainly the corrected data could capture the peaks in the rainfall data with that of observed and the curve of the observed rainfall in mainly low rainfall range. For WHR, after bias correction through SCL and EQM methods, data seem to be closer to the observed PDF curve except for the LOCI. Among all the models, LMDZ failed to follow the observed PDF curve in the EQM method. However, this was not the case in EHR, as the PDF for all the models followed the observed for each of the methods. In TGPR, a lower rainfall value below the probability of 0.5 followed the density curve. In the LOCI, both lower and higher rainfall values did not follow the observed curve; however, EQM performance was good amongst all three methods. In UGPR and MGPR, the scaling and EQM captured the PDF well while for LOCI, the lower rainfall value below probability 0.3 was underestimated. In the LGPR, all the bias correction methods followed the PDF for CCAM ensembled except LMDZ. The LMDZ overestimated the lower rainfall and underestimated the higher rainfall value for LOCI and EQM except for SCL, which followed the PDF curve. In the WDR region, all the methods failed to capture the PDF for both models. In the CPHR, the CCAM PDF shows underestimation for lower rainfall values, while LMDZ overestimated the values in all three bias correction methods. However, for the higher rainfall values, both the models followed the PDF irrespective of the method used.

The PDF for EPHR was well captured by SCL and LOCI, while EQM overestimated LMDZ for lower rainfall value. In the case of GPHR, SCL and EQM performed well while LOCI underestimated for lower rainfall value below the probability of 0.3. In WPHR, LMDZ overestimated the lower rainfall value for the LOCI method while the other two methods performed well in matching the observed curve. In ECPHR, only SCL, is good for both the model, while for LOCI it is, and in the case of EQM only the CCAM ensemble can match the PDF. All three bias

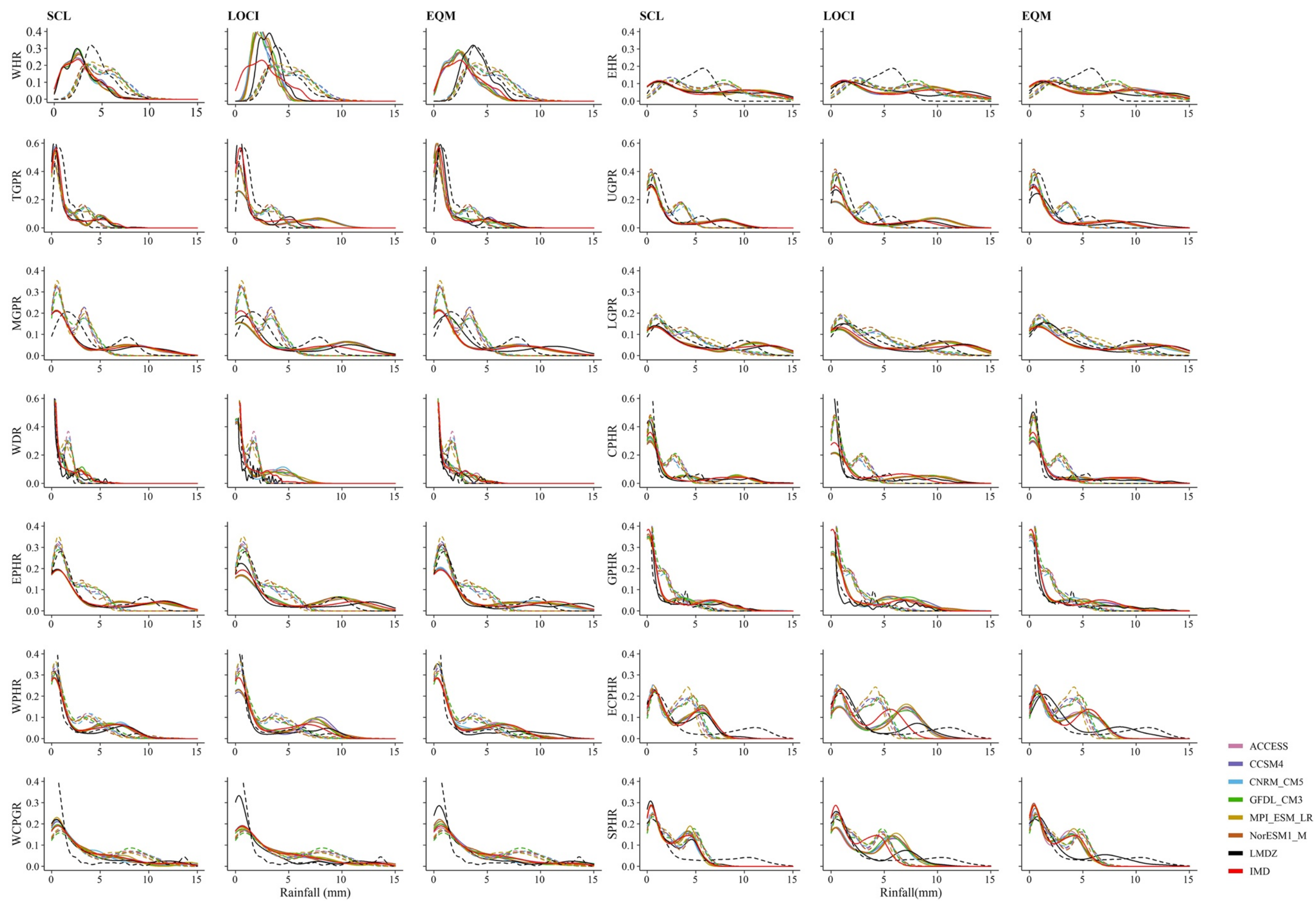

Figure 10. Probability distribution of for rainfall (mm/day) from observation (IMD), the six CCAM models and LMDZ using different bias correction methods for different Agroclimatic zones across India. The period is 1970–2005. The dotted line show uncorrected model and solid line are for bias corrected model.

correction methods proved to be good for all the models except LMDZ, which overestimated the lower rainfall value in the LOCI and EQM method for all ACZs. The PDF was well captured by SCL for the SPHR region for both the model, except by the LOCI method in which both the model were not able to match the observed PDF. However, in the EQM method, the CCAM ensembled was able to match with the observed curve for both the end of rainfall whereas, LMDZ underestimated for the lower as well as higher rainfall end.

The result demonstrates that the performance of bias correction methods relies on their ability to correct daily or monthly mean and variance, frequency and intensity of dry bias and wet bias, extreme events.

4. Conclusion

The performance evaluation of different RCMs to correct rainfall was found to be varying over ACZs in terms of metrics, spatial correlation, pbias, standard deviation, and MAE. This is also evident in the bias-corrected output obtained as RCMs which are largely biased over the Himalayan region (WHR, EHR). The results highlight that the CCAM ensemble outperformed LMDZ. Initial performance of raw CCAM ensemble over WHR, EHR, and EPHR was found to be poor, and it significantly improved after bias correction. The three bias correction methods: SCL, EQM, and LOCI, minimized the bias effectively for the different ACZ except for WHR where the LOCI method shows an average performance. SCL and EQM were found to be the best bias correction methods for all the ACZs whereas LOCI performed better in all the regions except WDR, TGPR, and SPHR for both the model, that is, CCAM ensembles and LMDZ.

It is not known whether these bias correction approaches will be valid in changing climate. This is because methods like EQM base their performance on the stability of biases between model simulations and observations over time (Rajczak et al., 2016). Future studies have to develop new bias correction procedures or improvement in RCM itself.

The important finding of the present study is that performance for the selected RCM's output has improved after bias correction, over the different ACZs across Indian monsoon region. The findings from this study can serve as a benchmark for future microclimatic study. The bias-corrected model outcome appear to be of high quality to be of value to generate the localized agroclimatic yields, and develop climate assessment synthesis.

Data Availability Statement

Authors declare that all data and materials support their published claims and comply with field standards. Authors promote data transparency and agree to provide in case of a request from the journal.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

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