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Assessment of the performance of CMIP5 and CORDEX-SA models over the drought-prone Bundelkhand region, India

Ankur Vishwakarma, Mahendra Kumar Choudhary and Mrityunjay Singh Chauhan

ABSTRACT

The present study evaluates the reliability of the latest generation five best general circulation models (GCMs) under the Coupled Model Intercomparison Project Phase 5 (CMIP5) and their corresponding regional climate models (RCMs) of Coordinated Regional Climate Downscaling Experiment (CORDEX) for the Bundelkhand region in central India. The study is performed on a microscale due to frequent drought events and more climate susceptibility in the study region. Observed daily precipitation data of 35 years (1971–2005) from the Indian Meteorological Department (IMD) have been chosen to check the performance of the models. Bilinear interpolation has been adopted to prepare all the data to obtain them on a common grid platform at a half-degree ($0.5^\circ \times 0.5^\circ$) resolution. The data of the models have been bias-corrected using quantile mapping. Uncertainty of the models has been assessed using Nash–Sutcliffe efficiency (NSE), coefficient of determination (r^2) and a modified method known as skill score (SS). The study concluded that the bias-corrected GCMs played a better role than the CORDEX RCMs for the Bundelkhand region. Earth System Model, ESM-2M of the Geophysical Fluid Dynamics Laboratory (GFDL) has shown better accuracy than all the CORDEX RCMs and their driving GCMs for the study region.

Key words | CMIP5, CORDEX, general circulation model (GCM), quantile mapping (QM), regional climate model (RCM), skill score (SS)

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HIGHLIGHTS

- The study evaluates the performance of the climate models for the central part of India.
- Most of the studies were unable to conclude the clear pictures of climate models in the central part of India.
- Bilinear interpolation has been adopted to regrid the climate data.
- Quantile mapping has been used to bias-correct climate data.
- The performance of the models was evaluated by using specific uncertainty methods.

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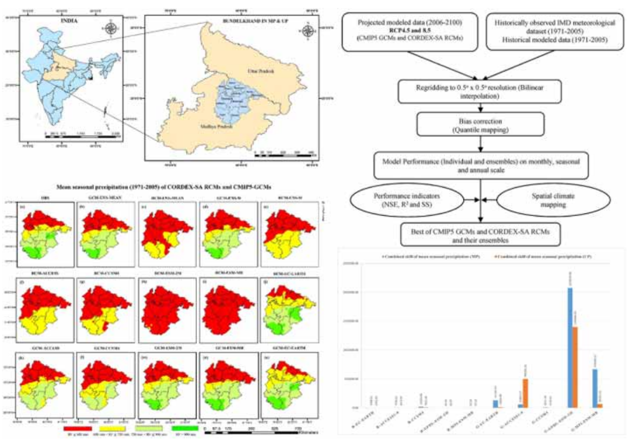
GRAPHICAL ABSTRACT



INTRODUCTION

Coupled Model Intercomparison Project Phase 5 (CMIP5) and the further upgraded CMIP6 general circulation models (GCMs) under the World Climate Research Program (WCRP), Geneva, are now in use worldwide. These models have more accuracy compared to old GCMs to predict future climate variables. Coordinated Regional Climate Downscaling Experiment (CORDEX) is the latest platform providing a structure for the evaluation and comparison of downscaling model performance and establishing a set of measures to generate climate predictions for use in impact studies on a regional scale. WCRP CMIP5 GCM outputs are driving the CORDEX climate change experiments.

Many studies have been carried out regarding the applicability of recent GCMs and regional climate models (RCMs) in the Indian climate and have concluded the best models based on their observed historical data. Mishra *et al.* (2014) have taken GCMs of CMIP5 and compared them with the data of CORDEX RCMs. The study concluded that, statistically, bias-corrected GCMs impart better results than the CORDEX RCMs for most parts of India. Some of CORDEX RCMs provided a better picture of future data. Choudhary *et al.* (2018) also concluded the best five CORDEX RCMs for India and two from the five best models are the same as those found to be the best in Mishra *et al.'s*. (2014) study. Both studies also concluded that the data of any platform could be used after suitable methods of bias correction. Similarly, Singh *et al.* (2017) and Mishra *et al.* (2018) also suggested applying the bias correction approaches before using the CMIP5 GCMs and CORDEX RCMs data for India. Bias correction methods like linear scaling (LS), general quantile mapping (GEQM), gamma quantile mapping (GAQM), and power transmission (PT) could be applied to bias-correct the model data (Homsi *et al.* 2020).

Most of the studies were unable to conclude a clear picture of climate models in the central part of the country. Thus, the best of five CMIP5 GCMs and corresponding CORDEX RCMs have been chosen from the literature survey for India and applied to the Bundelkhand region in central India. The quantile mapping (QM) method has been used to bias-correct the modeled daily data based on the distribution function approach, which efficiently removes historical biases comparative to the observations (Themeßl *et al.* 2012).

STUDY AREA AND DATA

The Bundelkhand region covers 13 districts in the states of Madhya Pradesh (MP) and Uttar Pradesh (UP) in central India and lies between 23°08′ N to 26°30′ N latitude and

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78°11′ E to 81°30′ E longitude. This region is one of the severe drought-prone areas in central India with more significant climate variability. The location map of the Bundelkhand region is shown in Figure 1.

The total area of the Bundelkhand region is 71,619 km^2. The total population of Bundelkhand is 18.3 million (Gupta et al. 2014), and 82% of the total population depends on rain-fed agriculture.

Observed daily precipitation data for 35 years (1971–2005) have been collected from the Indian Meteorological Department (IMD) for 82 rain gauge stations of Bundelkhand. Historical daily precipitation data from 1971 to 2005 have been chosen to evaluate the performance of the models. Data of the five best CMIP5 GCMs were collected from the Earth System Grid Federation (ESGF) (https://esgf-index1.ceda.ac.uk/search/cmip5-ceda and https://cera-www.dkrz.de/WDCC/ui/cerasearch/), and data of the CORDEX South Asia RCMs were obtained from the Center for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM) (http://cccr.tropmet.res.in/home/data_portals.jsp). Table 1 shows a description of CMIP5-GCM and CORDEX-RCM models used in this study.

METHODOLOGY

Data from the five best CORDEX RCMs and their driving CMIP5 GCMs is collected for the Bundelkhand region of central India. Historical daily precipitation data from 1971 to 2005 have been chosen to evaluate the performance of the models using the observed daily precipitation data obtained from the IMD for the region. The flow chart of the methodology is represented in Figure 2.

The following steps are involved in achieving the objectives of this study.

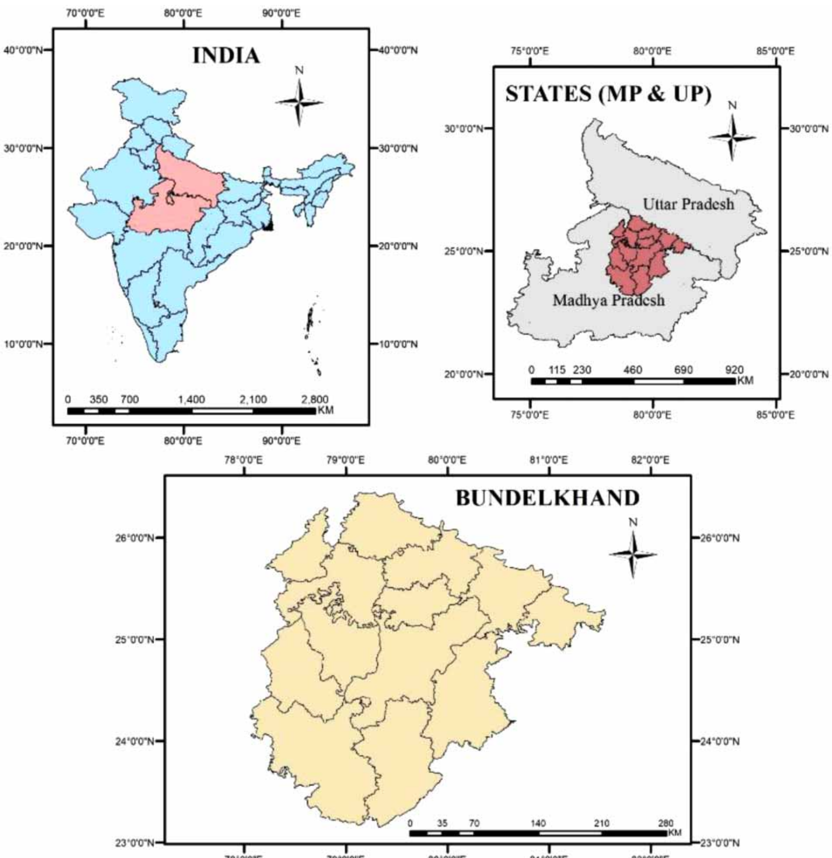

Figure 1 | Location of Bundelkhand in India.

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Table 1 | CMIP5 driving models and CORDEX-SA experiment details

S.No.	CORDEX models	CMIP5 Driving Models	Contributing CMIP5 Modeling Center	RCM description	Contributing CORDEX Modeling Center
1	CCAM-CSIRO-ACCESS1-0	ACCESS1-0	CSIRO, Australia	Commonwealth Scientific and Industrial Research Organisation (CSIRO), Conformal-Cubic Atmospheric Model (CCAM; McGregor & Dix 2001)	CSIRO Marine and Atmospheric Research, Melbourne, Australia
2	CCAM-CSIRO-CCSM4	CCSM4	National Center for Atmospheric Research (NCAR), USA		
3	GFDL-ESM2M-IITM-RegCM4	GFDL-ESM2M	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climatic Model version 4.4.5 (RegCM4; Giorgi *et al.* 2012)	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India
4	MPI-M-MPI-ESM-MR-IITM-RegCM4	MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M), Germany		
5	ICHEC-EC-EARTH-SMHI-RCA4	EC-EARTH	Irish Centre for High-End Computing (ICHEC), European Consortium (EC)	Rossby Centre regional atmospheric model version 4 (RCA4; Samuelsson *et al.* 2011)	Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden

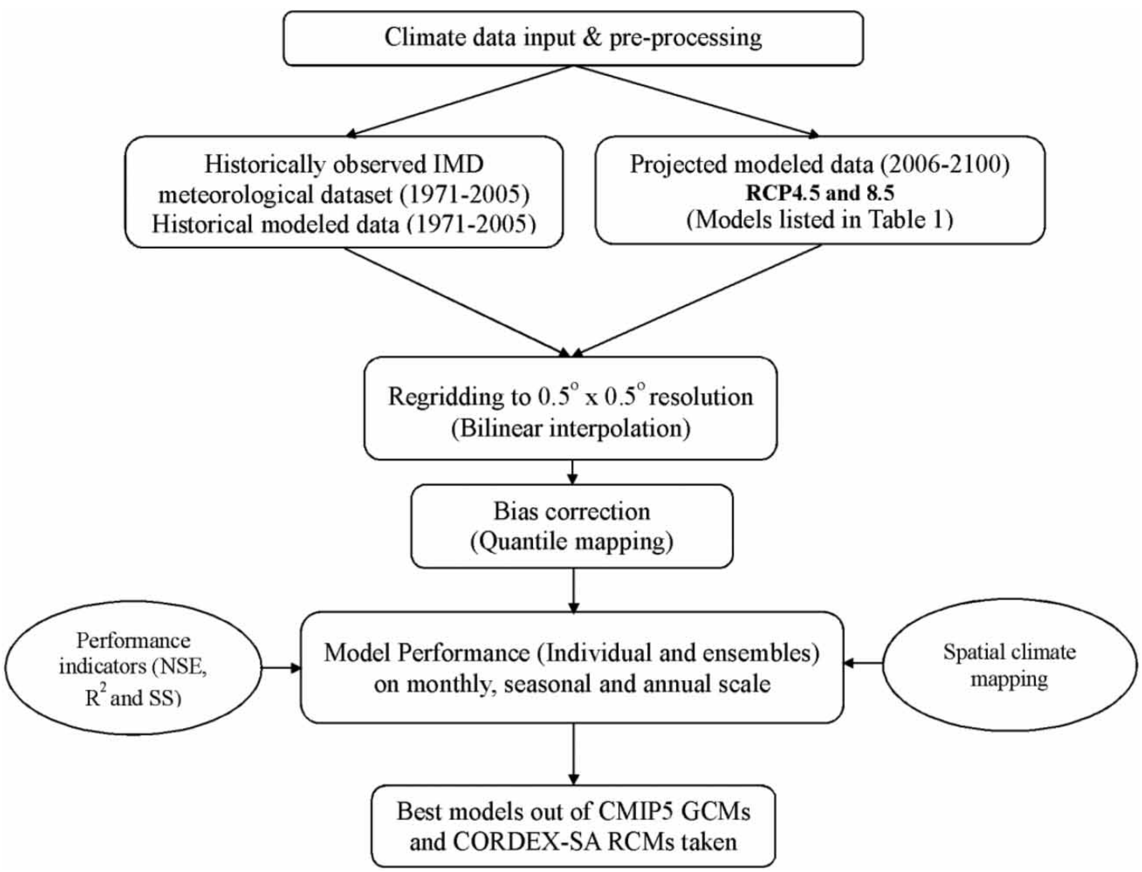

Figure 2 | Flow chart showing the methodology used in the study.

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Preparation of data

The grid sizes of GCMs and RCMs data consist of different resolutions. Hence, before using these data, it is necessary to prepare them and rectify errors by using bias corrections and regridding/remapping processes. The following steps are taken into consideration while preparing the projected data.

Preprocessing

Models' data have been checked for technical and numerical bugs. Metadata integrity was also noted while reviewing the data.

Remapping/regridding

This study deals with half-degree resolution datasets. Thus, it requires spatial interpolation of modeled data on a reference grid. Regridding has been done by Climate Data Operators (CDO) from the Max Planck Institute, which gathers various algorithms for interpolation used by the scientific community. Thus, daily rainfall has been remapped at $0.5° \times 0.5°$ resolution using bilinear interpolation, which is easy to program and apply when the source and destination grids are rectilinear.

Bias adjustment

CORDEX RCM models and their driving GCMs have skills in simulating future climate, but systematic biases have been shown when statistically compared to climatological observations. There are many types of approaches to adjust climate model outputs such as linear scaling, delta methods, quantile mapping method, distribution mapping method, etc. The data are bias-adjusted by the quantile mapping method using observed daily precipitation.

Performance of data

Skill score

Skill score represents an integrated index for measuring model performance and introduces overall model bias, spatial variance, and pattern correlation (Taylor 2001). A combined skill score is the combination of model 'performance' and model 'convergence' skill score. This test is an approach of Dessai *et al.* (2005), a modified version of the skill score utilized by Taylor (2001) and Murphy (1988). Skill score calculated the performance of each model of RCMs and their driving GCMs selected for this study. 'Performance' skill score of the model is determined as:

$$S = \frac{|\overline{x_0}|}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_{i1} - x_{i0})^2\right]^{\frac{1}{2}}} \quad (1)$$

where, N = number of data points (grid cells); x_{i1} = the i^{th} data point of series X_1 for variable x; x_{i0} = the i^{th} data point of series X_0 for variable x; x_0 = the average of X_0 for variable x.

Applying the skill score of Equation (1) to estimate model performance as:

$$S_{performance} = \frac{|\overline{x_{obs}}|}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_{imod} - x_{iobs})^2\right]^{\frac{1}{2}}} \quad (2)$$

where, $S_{performance}$ = model performance skill score; N = number of data points (grid cells); x_{imod} = the i^{th} data point of model simulation for variable x; x_{iobs} = the i^{th} data point of observations for variable x; x_0 = the average of observations for variable x.

Similarly, convergence skill score can be calculated using Equation (3):

$$S_{j,convergence} = \frac{|\overline{x_{ens}}|}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_{ij} - x_{iens})^2\right]^{\frac{1}{2}}} \quad (3)$$

where, $S_{j,convergence}$ = convergence skill score of model j; N = number of data points (grid cells); x_{ij} = the i^{th} data point of model j simulation for variable x; x_{iens} = the i^{th} data point of the ensemble average for variable x; x_{ens} = regional multi-model ensemble average for variable x.

The skill score is applied separately to each RCM and their driving GCM (see Table 1) on the annual, seasonal,

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and non-seasonal precipitation scale. Thus, the combined skill score is calculated as:

$$S = \left(\sqrt{S_{performance}} \times \sqrt{S_{convergence}} \right)^4 \quad (4)$$

Coefficient of determination, r^2

The coefficient of determination is a method to evaluate the reliability of the model between the simulated and observed data. Mathematically, it is expressed as follows:

$$r^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (P_i - \bar{P})^2}} \right)^2 \quad (5)$$

where O and P are observed and predicted values, respectively. The range of this evaluation parameter lies between 0 and 1. Zero indicates no correlation, while 1 shows that the prediction is similar to the observation.

Nash–Sutcliffe criteria

Nash and Sutcliffe proposed efficiency E or η (Nash & Sutcliffe 1970). Mathematically, the formula is expressed as:

$$E = 1 - \frac{\sum_{1}^{n} (O_i - P_i)^2}{\sum_{1}^{n} (O_i - \bar{O})^2} \quad (6)$$

where, O_i = observed data; P_i = modeled or predicted data; $\bar{O}$ = mean of the observed data.

Performance rating of NSE

The Nash–Sutcliffe efficiency ranges from $-\infty$ to 1. One refers to the perfect match of the modeled to the observed data. Efficiency less than 0 means that the prediction or simulations are not reliable and the observed mean is more accurate. The performance rating table (Moriasi et al. 2007) is shown in Table 2.

Table 2 | Performance rating on NSE basis

Performance rating	NSE
Very good	$0.75 \leq \text{NSE} \leq 1.00$
Good	$0.65 \leq \text{NSE} \leq 0.75$
Satisfactory	$0.50 \leq \text{NSE} \leq 0.65$
Unsatisfactory	$\text{NSE} \leq 0.50$

RESULTS AND ANALYSIS

Observed daily precipitation data of 35 years (1971–2005) are used to examine the performance of the best five CORDEX-RCMs and their driving GCMs for the Bundelkhand region. The performance has been checked based on the mean annual precipitation (MAP), mean seasonal precipitation (MSP) for the months of June, July, August, and September (JJAS) and mean non-seasonal precipitation (MNSP). Arithmetic and weighted average of both the RCMs and their driving GCMs have been evaluated to see their ensembles. The ArcGIS tool is utilized to spatially represent the data by the kriging interpolation. The weighted average is calculated based on the results of their skill score test performed to examine the accuracy of the models.

The results of the MAP showed a satisfactory bias for all of the models. Bias-corrected GCM, MPI-ESM-MR indicated the best correlation between observed and modeled annual mean, as shown in Figure 3. Based on NSE and r^2 performance indicators, MAP results were suitable for all of the models for future climate projections.

NSE and r^2 were performed to see the correlation of modeled MAP, MSP, and MNSP results with their observed ones. r^2 could not discriminate between the accuracy of the models, while NSE indicated better results to find the best of all the models. Results of NSE showed that the bias-corrected GCMs performed well as compared to the CORDEX RCMs (Table 3). GCM-EC-EARTH and GCM-GFDL-ESM-2M were found closest to the mean observation.

MSP results indicated a better picture of model performance. Only the model, EC-Earth (CORDEX, as well as its driving GCM), showed the best correlation with the observed precipitation. The spatial distribution of all the models, along with the observed, is given in Figure 4.

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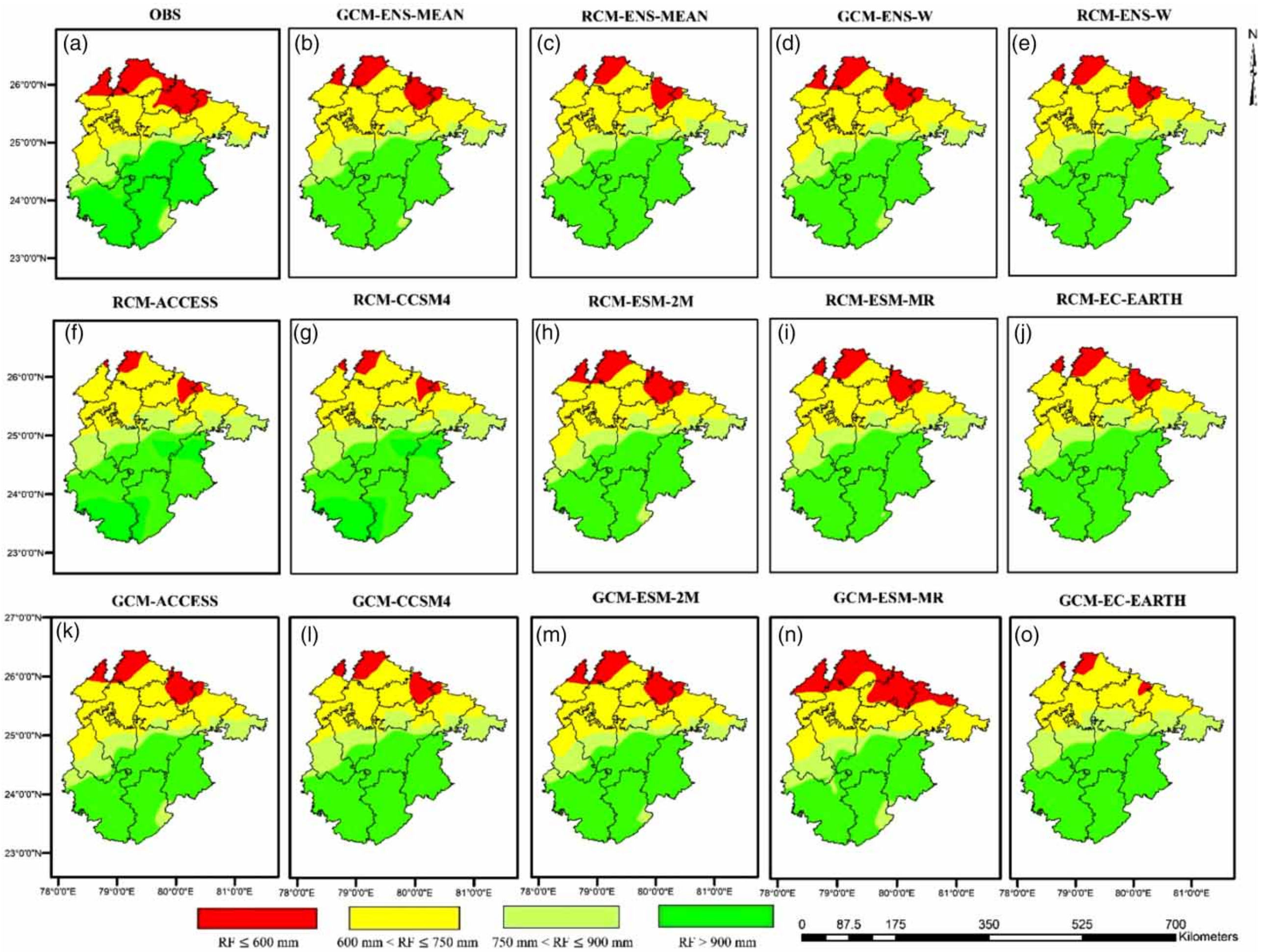

Figure 3 | (a) Observed mean annual precipitation (MAP) for the period of 1971–2005; (b) and (c) arithmetic ensemble mean of MAP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (d) and (e) weighted ensemble mean of MAP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (f) and (j) MAP in the CMIP5-GCMs*; (k) and (o) MAP in the CORDEX-RCMs*. *Models listed in Table 1.

CORDEX-RCMs (except EC-Earth) failed to claim satisfactory performance. Some bias-corrected GCMs found better correlation in the upper Bundelkhand region (ACCESS1-0, GFDL-ESM-2M, and MPI-ESM-MR). At the same time, the ensemble mean of MSP also showed the least bias for bias-corrected GCMs where RCMs did not perform well. The weightage of the weighted ensemble of GCMs and RCMs were distributed based on their skill score test.

No relevant relationship was found for MNSP results with observed data for any of the climate models. Some parts of the lower Bundelkhand showed a relationship for GCM and RCM of EC-Earth, and some for the GCM of MPI-ESM-MR, which can be seen in Figure 5. Ensemble results of MNSP also failed to claim any satisfactory relationship with the observed data.

There was minimal variation found in MAP results. Most of the models were found closer to the mean observed precipitation. It is necessary to find the most suitable of the selected models over the Bundelkhand region in central India. Thus, the skill score method was chosen to see the model performance, as discussed in the Methodology section. SS was applied for all the bias-corrected CORDEX RCMs and their driving GCMs for MAP, MSP, and MNSP scales.

A combined skill score showed a wide variation among all the models. On the MSP scale, bias-corrected GCM,

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Table 3 | Performance evaluation of models based on NSE and r^2

		NSE			r^2		
S.No.	**Model**	**Annual**	**Seasonal**	**Non-seasonal**	**Annual**	**Seasonal**	**Non-seasonal**
1	RCM-EC-EARTH	0.909	– 0.135	– 4.665	0.997	0.984	0.498
2	RCM-ACCESS1-0	0.884	– 0.495	– 300.873	0.997	0.981	0.396
3	RCM-CCSM4	0.869	– 3.859	– 382.758	0.995	0.984	0.445
4	RCM-GFDL-ESM-2M	0.975	– 3.814	– 855.396	0.996	0.880	0.489
5	RCM-MPI-ESM-MR	0.954	0.948	– 894.622	0.996	0.925	0.525
6	GCM-EC-EARTH	0.844	0.940	– 6.871	0.997	0.992	0.591
7	GCM-ACCESS1-0	0.987	0.854	– 26.293	0.996	0.988	0.545
8	GCM-CCSM4	0.916	0.528	– 149.375	0.998	0.990	0.340
9	GCM-GFDL-ESM-2M	0.981	0.969	– 12.956	0.998	0.994	0.468
10	GCM-MPI-ESM-MR	0.985	0.913	– 4.066	0.995	0.983	0.146

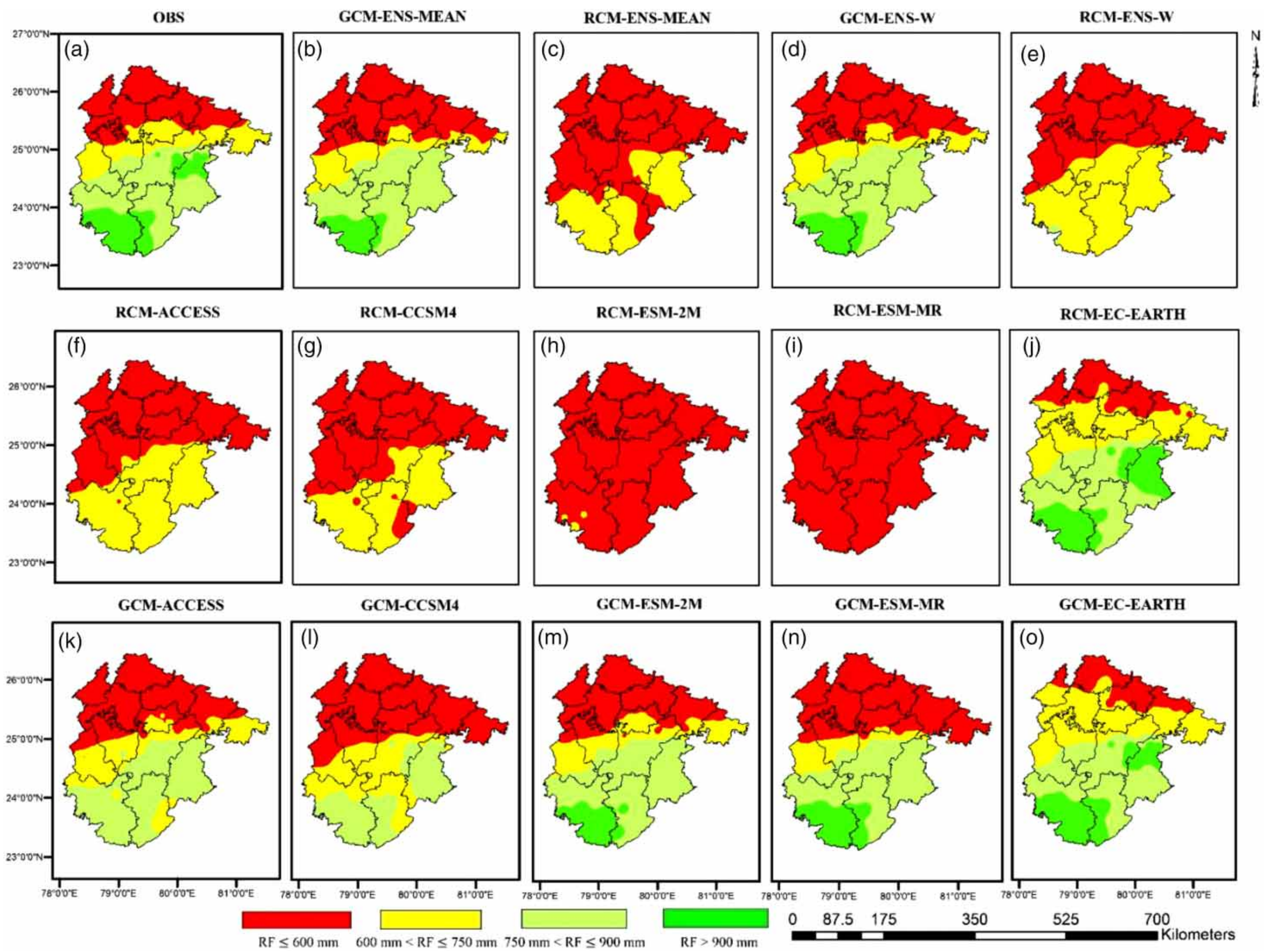

Figure 4 | (a) Observed mean seasonal precipitation (MSP) for the period of 1971–2005, i.e., for JJAS; (b) and (c) arithmetic ensemble mean of MSP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (d) and (e) weighted ensemble mean of MSP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (f) and (j) MSP in the CMIP5-GCMs*; (k-o) MSP in the CORDEX-RCMs*. *Models listed in Table 1.

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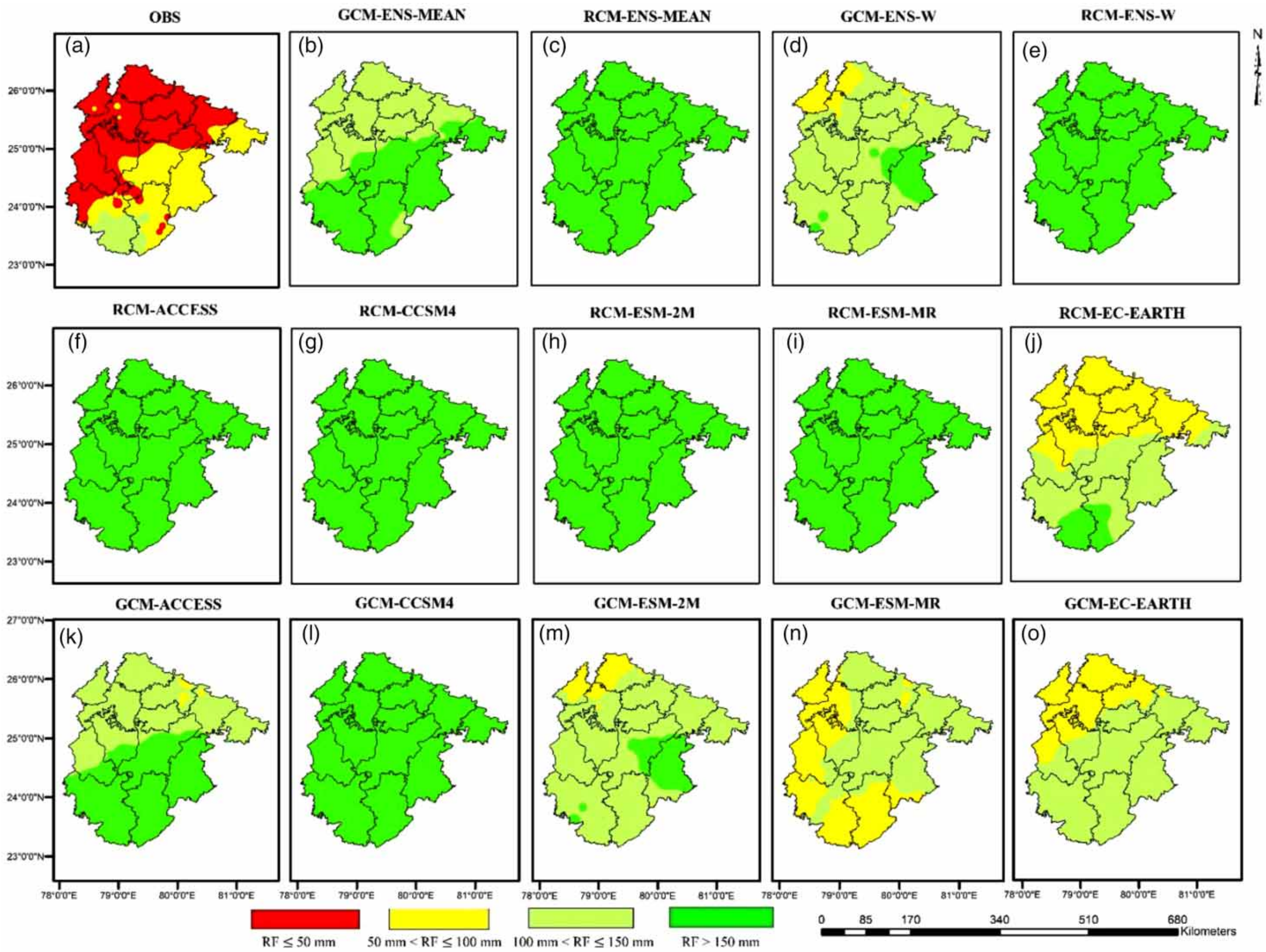

Figure 5 | (a) Observed mean non-seasonal precipitation (MNSP) for the period of 1971–2005; (b) and (c) arithmetic ensemble mean of MNSP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (d) and (e) weighted ensemble mean of MNSP in the CMIP5-GCMs* and CRODEX-RCMs*, respectively; (f) and (j) MNSP in the CMIP5-GCMs*; (k) and (o) MNSP in the CORDEX-RCMs*. *Models listed in Table 1.

GFDL-ESM-2M was found to be the best model showing the highest SS, while the lowest value of skill was seen for the RCM of GFDL-ESM-2M, which is shown in Table 4. Model GFDL-ESM-2M of bias-corrected GCM claimed the best skill score for all the timescales (MAP, MSP, and MNSP). The reduction in skill indicated the significant deviation of the model from the ensemble. Hence, the bias-corrected GCM, GFDL-ESM-2M experiment was found closest to the mean observation line with a highest 'performance' skill of 19.17, a 'convergence' skill of 33.29, and a combined skill of 407441.04.

The upper part of Bundelkhand is more affected by severe drought than its lower part due to the consistent climate variation between them. Thus, a separate skill test was also performed for the upper part (part of UP) and the lower part (part of MP) of Bundelkhand. The bias-corrected GCM, GFDL-ESM-2M experiment was found closest to the mean observation line for both parts of Bundelkhand in central India. The highest values of combined skill for GCM, GFDL-ESM-2M were found for the upper part (2078676.08) as well as for the lower part (1399846.65) of the Bundelkhand, which can be seen in Figure 6.

Table 5 demonstrates the SS on the MNSP scale for all of Bundelkhand. Of all the bias-corrected CORDEX RCMs and their driving GCMs, GFDL-ESM-2M of bias-corrected GCM performed best with the combined score of 26.06.

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Table 4 | Mean skill score for each CMIP5-GCM and CORDEX-RCM (averaged over Bundelkhand region) for MSP (JJAS)

		Skill score (Bundelkhand)			
S.No.	**Model**	**Performance**	**Convergence**	**Combined**	**Rank**
1	R-EC-EARTH	14.86	1.76	680.62	8
2	R-ACCESS1-0	3.18	9.19	856.38	7
3	R-CCSM4	2.77	19.39	2,893.71	5
4	R-GFDL-ESM-2M	1.54	2.81	18.67	10
5	R-MPI-ESM-MR	1.55	2.83	19.20	9
6	G-EC-EARTH	13.80	7.24	9,976.74	4
7	G-ACCESS1-0	8.88	18.11	25,856.13	3
8	G-CCSM4	4.94	7.19	1,260.77	6
9	G-GFDL-ESM-2M	**19.17**	**33.29**	**407,441.04**	1
10	G-MPI-ESM-MR	11.49	19.26	48,960.52	2

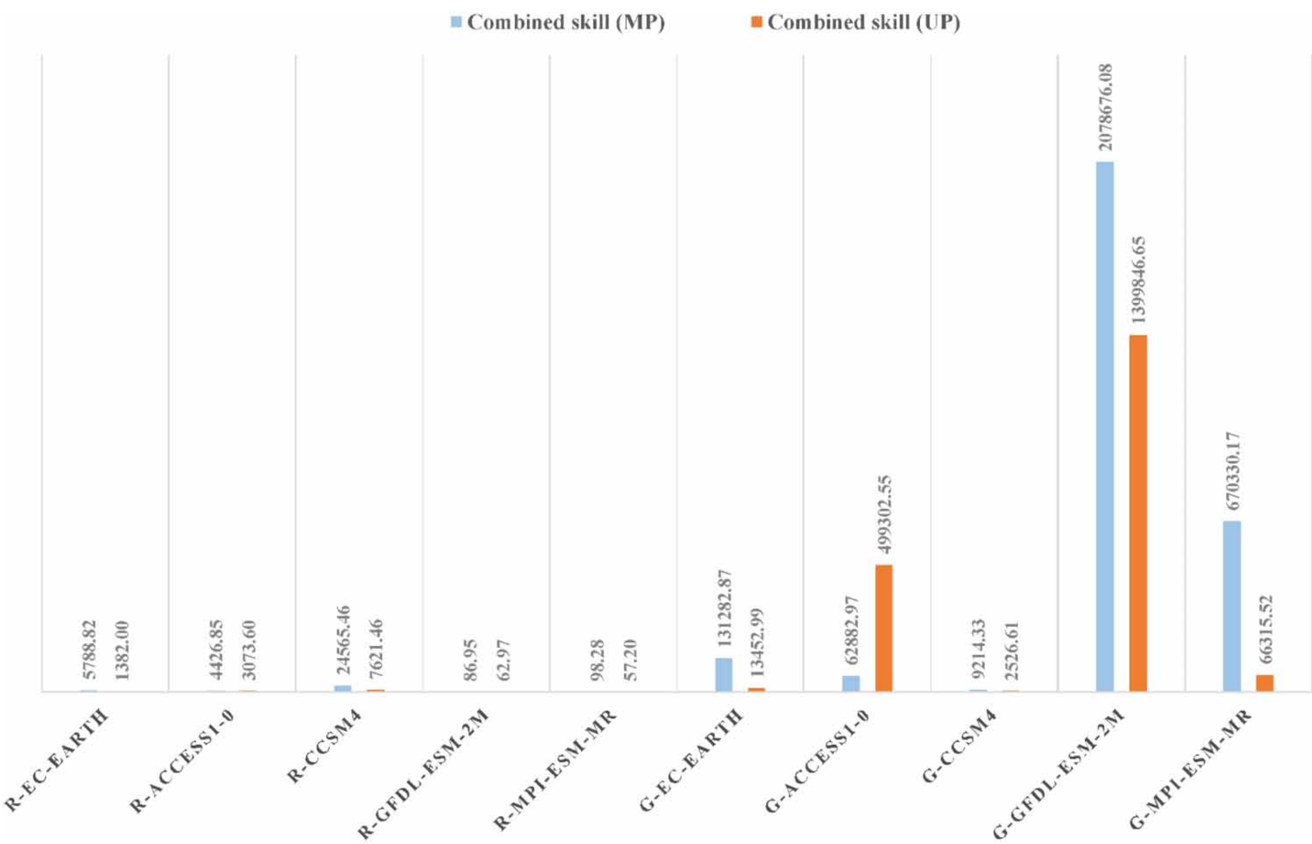

Figure 6 | Mean skill score for each CMIP5-GCMs and CORDEX-RCMs (averaged over upper and lower parts of Bundelkhand region) for MSP (JJAS).

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Table 5 | Mean skill score for each CMIP5-GCM and CORDEX-RCM (averaged over Bundelkhand region) for MNSP

		Skill score (Bundelkhand)			
S.No.	**Model**	**Performance**	**Convergence**	**Combined**	**Rank**
1	R-EC-EARTH	1.70	0.94	2.53	6
2	R-ACCESS1-0	0.23	6.08	1.99	7
3	R-CCSM4	0.21	15.42	10.09	5
4	R-GFDL-ESM-2M	0.14	1.70	0.05	9
5	R-MPI-ESM-MR	0.13	1.59	0.05	9
6	G-EC-EARTH	1.44	2.93	17.76	3
7	G-ACCESS1-0	0.77	5.84	20.35	2
8	G-CCSM4	0.33	1.01	0.11	8
9	G-GFDL-ESM-2M	1.08	4.73	**26.06**	1
10	G-MPI-ESM-MR	1.79	2.15	14.88	4

CONCLUSIONS AND FUTURE SCOPE

The mean seasonal precipitation represented better climate accuracy of the climate models based on rainfall observations on annual, seasonal, and non-seasonal timescales. On the mean non-seasonal scale, results showed poor performance, while on the annual scale, most of the models performed with better accuracy. CORDEX RCMs demonstrated poor performance as compared to their driving bias-corrected GCM results. Models EC-EARTH and GFDL-ESM-2M of bias-corrected GCMs showed the minimum bias and best correlation for MSP as well as for MAP scale, and with some accuracy for the MNSP scale. Based on the combined skill score test, model GFDL-ESM-2M of bias-corrected GCM was claimed as the best experimental model to predict future precipitation over the Bundelkhand region in central India. It is noticed that bias-corrected GCMs depicted a better climate than the CORDEX RCMs. The study revealed that from the five best RCMs and their driving GCMs, bias-corrected GCM-GFDL-ESM-2M could be utilized to predict the future scenario of precipitation in the Bundelkhand region in central India. It is also noticed that the accuracy of climate models for precipitation could be best judged based on their mean monsoon observations.

The focus of the current study was to check the performance of climate models in signifying precipitation for a central region of India. Further, various hydrological indicators like stream flow, drought, and evaporation could be evaluated to discover their behavior in the study region (Wu & Chau 2013; Taormina & Chau 2015; Ali Ghorbani *et al.* 2018). Drought could be evaluated using specific machine learning approaches or satellite-based monitoring (Zhao *et al.* 2018; Shamshirband *et al.* 2020) to forecast future water crisis in the drought-prone region of Bundelkhand, India.

DATA AVAILABILITY STATEMENT

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

REFERENCES

Ali Ghorbani, M., Kazempour, R., Chau, K. W., Shamshirband, S. & Taherei Ghazvinei, P. 2018 Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particle swarm optimization model: a case study in Talesh, Northern Iran. *Engineering Applications of Computational Fluid Mechanics* **12** (1), 724–737.

Choudhary, A., Dimri, A. P. & Maharana, P. 2018 Assessment of CORDEX-SA experiments in representing precipitation climatology of summer monsoon over India. *Theoretical and Applied Climatology* **134** (1–2), 283–307. https://doi.org/10.1007/s00704-017-2274-7.

Dessai, S., Lu, X. & Hulme, M. 2005 Limited sensitivity analysis of regional climate change probabilities for the 21st century. *Journal of Geophysical Research: Atmospheres* **110** (D19). https://doi.org/10.1029/2005JD005919.

Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., Sylla, M. B., Bi, X., Elguindi, N., Diro, G. T., Nair, V., Giuliani, G., Cozzini, S., Guettler, I., O'Brien, T., Tawfik, A., Shalaby, A., Zakey, A. S., Steiner, A., Stordal, F., Sloan, L. & Brankovic, C. 2012 RegCM4: model description and preliminary tests over multiple CORDEX domains. *Climate Research* **52**, 7–29. http://doi.org/10.3354/cr01018.

Gupta, A. K., Nair, S. S., Ghosh, O., Singh, A. & Dey, S. 2014 *Bundelkhand Drought: Retrospective Analysis and Way Ahead*. National Institute of Disaster Management, New Delhi, India, pp. 1–148.

Homsi, R., Shiru, M. S., Shahid, S., Ismail, T., Harun, S. B., Al-Ansari, N., Chau, K. W. & Yaseen, Z. M. 2020 Precipitation projection using a CMIP5 GCM ensemble model: a regional investigation of Syria. *Engineering Applications of Computational Fluid Mechanics* **14** (1), 90–106. https://doi.org/10.1080/19942060.2019.1683076.

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McGregor, J. L. & Dix, M. R. 2001 The CSIRO conformal-cubic atmospheric GCM. IUTAM Symposium on Advances in Mathematical Modelling of Atmosphere and Ocean Dynamics. In: *Fluid Mechanics and Its Application*, Vol. 61. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 197–202. https://doi.org/10.1007/978-94-010-0792-4_25.

Mishra, V., Kumar, D., Ganguly, A. R., Sanjay, J., Mujumdar, M., Krishnan, R. & Shah, R. D. 2014 Reliability of regional and global climate models to simulate precipitation extremes over India. *Journal of Geophysical Research: Atmospheres* **119** (15), 9301–9323. https://doi.org/10.1002/2014JD021636.

Mishra, S. K., Sahany, S. & Salunke, P. 2018 CMIP5 vs. CORDEX over the Indian region: how much do we benefit from dynamical downscaling? *Theoretical and Applied Climatology* **133** (3–4), 1133–1141. https://doi.org/10.1007/s00704-017-2237-z.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50** (3), 885–900. doi: 10.13031/2013.23153.

Murphy, A. H. 1988 Skill scores based on the mean square error and their relationships to the correlation coefficient. *Monthly Weather Review* **116** (12), 2417–2424. https://doi.org/10.1175/1520-0493(1988)116 < 2417:SSBOTM > 2.0.CO;2.

Nash, J. E. & Sutcliffe, J. V. 1970 River flow forecasting through conceptual model. Part 1—A discussion of principles. *Journal of Hydrology* **10**, 282–290. http://dx.doi.org/10.1016/0022-1694(70)90255-6.

Samuelsson, P., Jones, C. G., Willén, U., Ullerstig, A., Gollvik, S., Hansson, U., Jansson, C., Kjellström, E., Nikulin, G. & Wyser, K. 2011 The Rossby centre regional climate model RCA3: model description and performance. *Tellus A* **63** (1), 4–23. https://doi.org/10.1111/j.1600-0870.2010.00478.x.

Shamshirband, S., Hashemi, S., Salimi, H., Samadianfard, S., Asadi, E., Shadkani, S., Kargar, K., Mosavi, A., Nabipour, N. & Chau, K. W. 2020 Predicting standardized streamflow index for hydrological drought using machine learning models. *Engineering Applications of Computational Fluid Mechanics* **14** (1), 339–350.

Singh, S., Ghosh, S., Sahana, A. S., Vittal, H. & Karmakar, S. 2017 Do dynamic regional models add value to the global model projections of Indian monsoon? *Climate Dynamics* **48** (3–4), 1375–1397. https://doi.org/10.1007/s00382-016-3147-y.

Taormina, R. & Chau, K. W. 2015 ANN-based interval forecasting of streamflow discharges using the LUBE method and MOFIPS. *Engineering Applications of Artificial Intelligence* **45**, 429–440.

Taylor, K. E. 2001 Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research* **106** (D7), 7183–7192. https://doi.org/10.1029/2000JD900719.

Themeßl, M. J., Gobiet, A. & Heinrich, G. 2012 Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. *Climatic Change* **112** (2), 449–468. https://doi.org/10.1007/s10584-011-0224-4.

Wu, C. L. & Chau, K. W. 2013 Prediction of rainfall time series using modular soft computing methods. *Engineering Applications of Artificial Intelligence* **26** (3), 997–1007.

Zhao, C., Huang, Y., Li, Z. & Chen, M. 2018 Drought monitoring of southwestern China using insufficient GRACE data for the long-term mean reference frame under global change. *Journal of Climate* **31** (17), 6897–6911.

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