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Research Article

Importance of Bias Correction and its Techniques: Multi-Model Ensemble vs. Single Climatological Model

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In connection with investigation of the sea level rise dynamics along the coast of Bangladesh, predicted data of precipitation, temperature and evaporation data are needed for hydrological modeling. The study focuses on assessing the impacts of climate change on the Ganges-Brahmaputra-Meghna (GBM) basins in South Asia, by simulating meteorological parameters which do not usually fit exactly with the observed time series in the control period. This paper seeks to find the most adequate bias correction techniques to minimize the errors between observations and climate model simulations in the control period. The analysis revealed a significant bias in the single model climatology, including over estimation of precipitation during the dry season and under estimation during the monsoon season. The CORDEX - South Asia project evaluated six regional climate models by comparing them with observations and a single climatology to detect wet and dry biases caused by incorrect predictions of rainfall and temperature in future climate. Bias correction based on cumulative distribution function was applied to reduce these errors. The bias-corrected ensemble mean of six CORDEX-SA driving GCM experiments was used for hydrological modeling to predict runoff and evapotranspiration for future periods under two Representative Concentration Pathways scenarios (RCP4.5 and RCP8.5). The study revealed that the eastern area, which represents the Ganges basins, had vigorous underestimation during monsoon, particularly the glaciers of Ganges, while the Brahmaputra results were acceptable. The bias correction led to an improvement in under estimation during peak monsoon over the GBM basins, especially in the Brahmaputra and Meghna Basins, and over estimation during the dry season, resulting in reliable predictions in accordance with observed values. The bias-corrected model validations showed a perfection of future predictions up to 0.5 in case of precipitation simulations (not for all sub-catchments), indicating the reliability of the results.

(***Key words:*** *Bias correction, CORDEX, Hydrological modeling, RCP, Regional climate models*)

Coastal zones are ecologically rich, diverse and productive, but highly sensitive to changes in sea level (Oppenheimer *et al.*, 2019; Wong *et al.*, 2014). The low-lying coastal regions and deltas across the world face significant threats due to elevated sea levels. Bangladesh, with its densely populated coastal areas and a flat terrain consisting of broad and narrow ridges and depressions, is particularly vulnerable to the impacts of sea level rise (Brammer *et al.*, 1996). The impacts of sea level rise (SLR) in Bangladesh will be predominantly felt in the coastal area, which in turn will have repercussions on the entire country. An estimated 2,500, 8,000, and 14,000 square kilometers of land, equivalent to 2%, 5%, and 10% of the country's total land area, respectively, will be lost due to SLR of 0.1m, 0.3m, and 1.0m (Ali 2000). These figures highlight the significant extent of potential land loss.

It is important to recognize that SLR is highly non-uniform in space and time and this needs to be understood to provide useful sea-level scenarios and coastal climate services. While in mitigation we consider global changes, impacts and adaptation need to reflect local changes. To make an inventory of potential coastal impacts and adaptation needs thus requires SLR projections that are essentially regional (Slangen *et al.*, 2014) and local (Nicholls *et al.*, 2021a; Woodworth *et al.*, 2019; Wöppelmann and Marcos, 2016).

The vulnerability of the coastal regions of

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Bangladesh to sea level rise and associated natural calamities caused by climate change such as high tide, coastal flooding, coastal erosion, sedimentation in rivers, waterlogging in polders, storm surge, cyclone, and salinity intrusion pose a significant threat to the livelihood and development of this region (Rahman, 2019; Rezaie *et al.*, 2019). It has been observed that under climate change condition, the area of low-saline zone will decrease and area under high saline zone will be increased by 14% in 2050 (Islam *et al.*, 2020). Regional groundwater models are often used to estimate the groundwater balance and analyse storage dynamics of alluvial aquifer systems under historical conditions and future scenarios of development and climate change (Sreekanth *et al.*, 2018; van Dijk *et al.*, 2020; Vrzel *et al.*, 2019). Therefore, it is essential to acquire a thorough understanding of sea level rise dynamics and seasonal variations in the Bangladesh coastal area, including tidal effects, tectonics, subsidence, polder inundation, and overtopping, to help policymakers make detailed planning for different coastal projects, considering sea level rise. The first and most obvious step for this scientific overview is to obtain associated future projections of meteorological parameters, which will aid in prediction and hydrological-hydrodynamic modelling, enabling the development of detailed planning strategies for the sustainable development of the coastal areas of Bangladesh.

Previous studies have attempted to showcase the ability of Atmosphere-Ocean General Circulation Models (AOGCMs) to simulate the meteorological components (Chaudhari *et al.*, 2013) of the Earth's climate system by analyzing the available output of the Coupled Model Inter-comparison (Eyring *et al.*, 2016; Taylor *et al.*, 2012). Most of the studies reported a significant bias in simulating Ganges-Brahmaputra-Meghna (GBM) basin, possibly due to their coarse resolution (Chaudhari *et al.*, 2013).

High - Regional Climate Model (RCMs) have become a common tool in recent decades for dynamically downscaling Global Climate Models (GCMs) or reanalysis data to provide more accurate and detailed regional climate information (Bhatla *et al.*, 2020; Kumar *et al.*, 2006; Mishra *et al.*, 2020; Mukhopadhyay *et al.*, 2010; Ratnam *et al.*, 2017).

Many studies have reported improvements in simulating precipitation characteristics with regional climate models (RCMs) by better representing regional forcings, such as mountain orography, physical processes, and interactions (Chan *et al.*, 2013; Jacob *et al.*, 2014; Mishra *et al.*, 2020). However, a dry bias over India still persists, partly due to the absence of fine-scale regional air-sea interactions (Lucas-Picher *et al.*, 2011). While RCMs can improve the details of GCM simulations through dynamical downscaling over complex terrain, they are limited in their ability to substantially modify large-scale circulation features produced by GCMs. Consequently, regional climate simulations reflect not only model-to-model variations among the driving GCMs but also additional internal biases resulting from the parameterization of physical processes, such as cloud formation, and other factors.

Institute of Water Modelling (IWM, 2023) performed a detailed study for investigating the sea level rise dynamics along the coast of Bangladesh along with the spatial and temporal variation of sea level rise. This paper is for comprehensively assessing the future climatic parameters of the Ganges - Brahmaputra - Meghna (GBM) basin using the Coordinated Regional Climate Downscaling (CORDEX) - South Asia RCMs at a resolution of 0.5° (50 km) for a period of 130 years in accordance with observational data. It examines the impacts of multi-model ensemble versus single climatology and investigates the spatiotemporal variability of precipitation, temperature, and evaporation to reveal notable heterogeneity in the impacts of climate change over the GBM basin. The study also evaluates the accuracy of the model in terms of statistics such as Root Mean Square Error (RMSE) and Nash-Sutcliffe efficiency (NSE). Furthermore, one of the main objectives of the study is to improve dry and wet biases through bias correction and to select the best-matched method for the closest prediction.

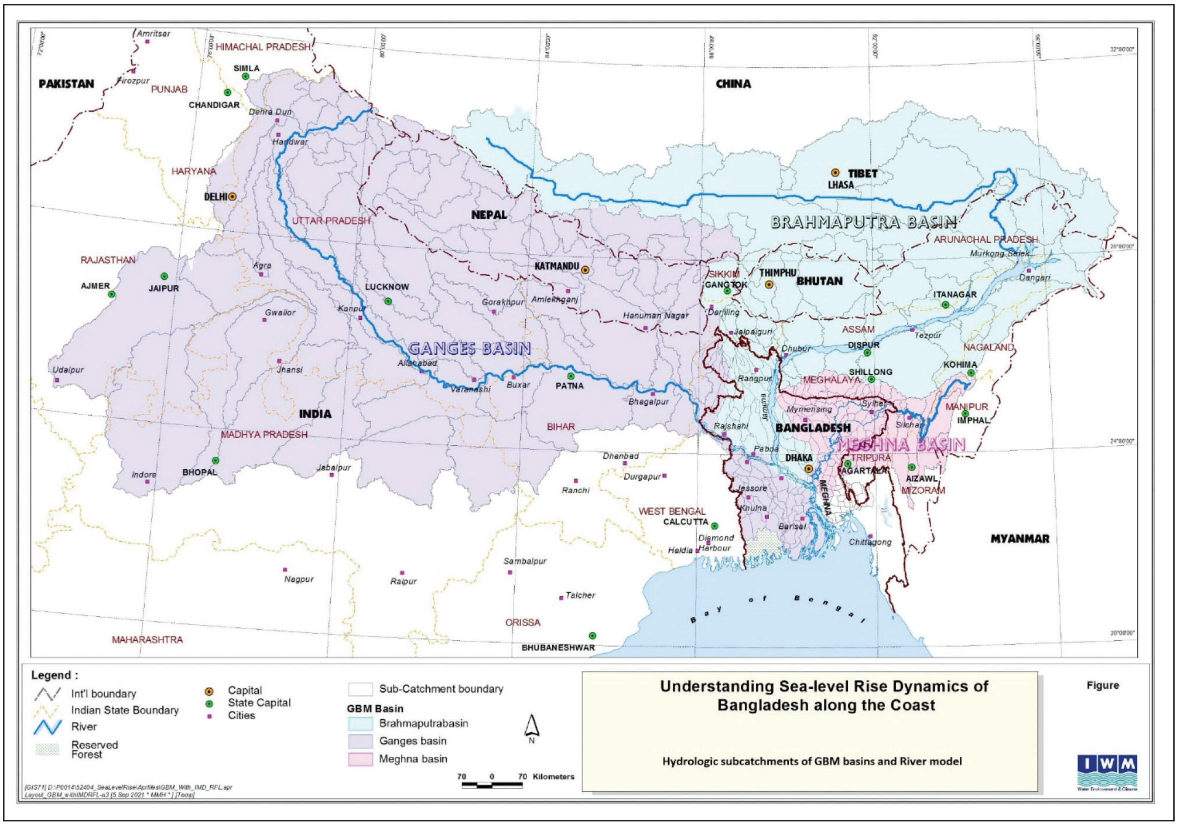

Fig. 1. *Study area*

MATERIALS AND METHODS

Study area

Under the study, understanding sea level rise dynamics along the coast of Bangladesh (IWM, 2023), a detailed study was performed for investigating the relative and absolute sea level rise, and the effect of land-ocean fresh-water fluxes on seasonal to annual mean sea-surface height along the coastline of Bangladesh under different future greenhouse emission scenarios. The focus area of this study was the extensive Ganges, Brahmaputra, and Meghna basins, which cover a vast region encompassing India, Nepal, Bhutan, and Bangladesh. The study area includes 418 sub basins, which are further categorized into 187 sub catchments under the GBM basin model and 231 sub catchments under the Bangladesh river model. The study aims to analyze climate data within this large and complex region, as depicted in Fig. 1.

Approach and methodology

The approach and methodology followed in the study is illustrated with a schematic diagram in Fig. 2. The study utilized the bias-corrected ensemble mean of future climate projections from six different CORDEX-SA driving Global Climate Models (GCMs). These projections have been used to analyze the seasonal, monthly, and yearly variations in climate within the study region. Additionally, statistical analyses have also been carried out to evaluate the efficiency of the models used. These projections were used to analyze the seasonal, monthly, and yearly variations in climate within the study region. Additionally, statistical analysis was carried out to evaluate the efficiency of the models used. The required hydrological and meteorological data were collected from Bangladesh Water Development Board (BWDB) and Bangladesh Meteorological Department (BMD) for basin model and river model development. In addition to this, data from secondary sources, the topographical and hydrological data were collected by IWM's own survey team.

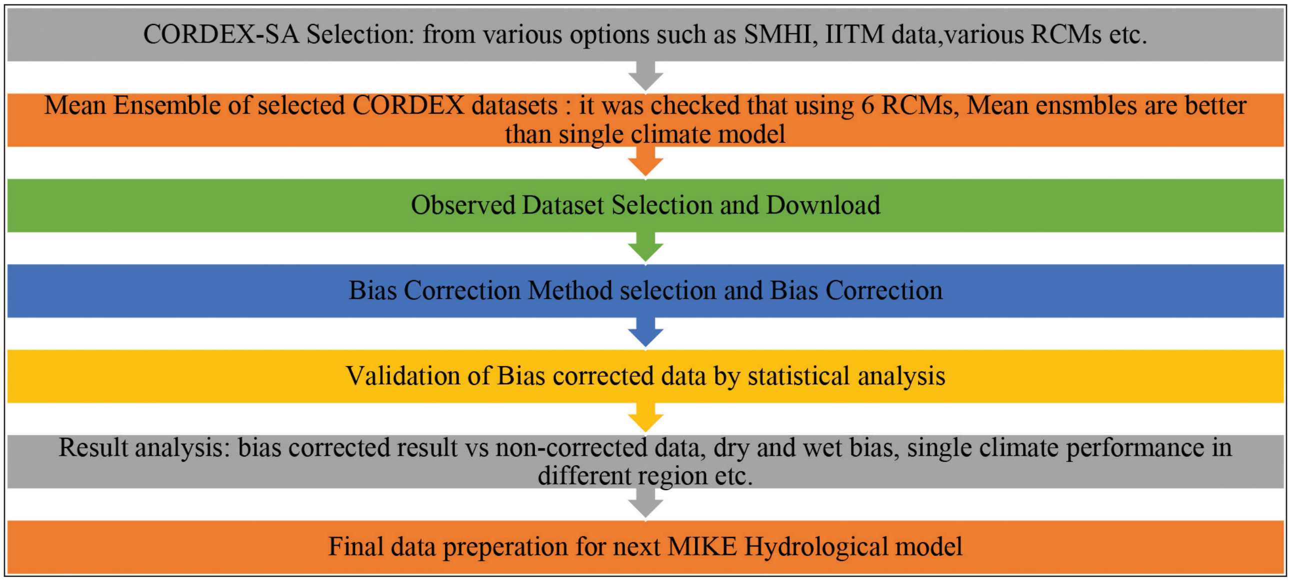

Fig. 2. *Schematic diagram of study approach and methodology*

Model components

This study examines the impact of three key climatic parameters, namely precipitation, temperature, and evaporation for a specific region. The data used in this study comes from six different regional climate simulations, which include CCCma-CanESM2, CNRM-CERFACS-CNRM-CM5, CSIRO-QCCCE-CSIRO-Mk3-6-0,IPSL-IPSL-CM5A-LR, MPI-M-MPI-ESM-MR, and NOAA-GFDL-GFDL-ESM2M. The data used has a spatial resolution of 0.44°, which is roughly 50 km, and covers the region of 19° N & 70° E to 33° N & 100° E.

Although there are two types of data available for this region, namely CORDEX-IITM Pune and CORDEX-SMHI, due to better results for this specific region, CORDEX-IITM Pune data have been used in this study. A comparative analysis of precipitation data of Dhaka station has been performed both for Swedish Meteorological and Hydrological Institute (SMHI) and Indian Institute of Tropical Meteorology (IITM) data also. Fig. 3 shows a comparison of SMHI, IITM vs BMD's precipitation data of Dhaka Station.The analysis shows that IITM Pune data produces more accurate results.

The study period encompasses daily data from 1976 to 2099 for regional climate models (RCMs). The historical simulations cover the period of 1976 to 2005, while the simulations for the years 2005 to 2099 are generated using Global Climate Models (GCMs) under different Representative Concentration Pathways (RCPs). These pathways represent multiple trajectories of greenhouse gas concentrations based on various socioeconomic pathways (Moss *et al.*, 2010), as outlined in the IPCC AR5 report. Two RCPs, namely 4.5 (Thomson *et al.*, 2011) and 8.5 (Riahi *et al.*, 2011), representing medium and high range emission scenarios, respectively have been considered in this study.

To correct for biases in the RCMs, two observed datasets, namely the Indian Meteorological Department (IMD) gridded data and ERA5 [fifth generation European Centre for Medium-Range Weather Forecast (ECMWF) atmospheric reanalysis of the global climate covering the period from January 1950 to present] data have been used for performance validation historically. Both datasets have a resolution of 0.5°×0.5°.

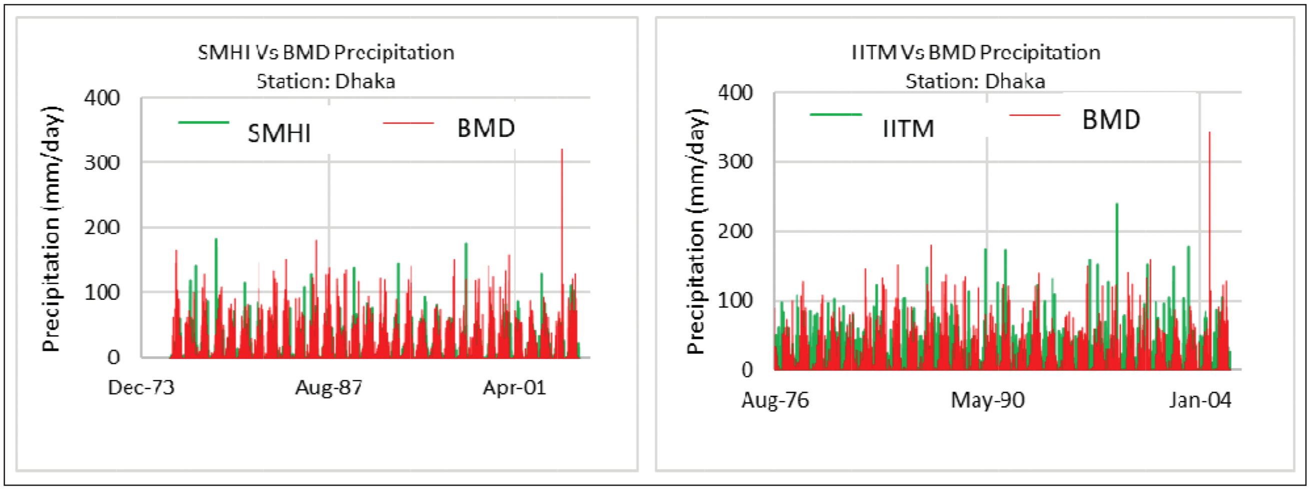

***Fig. 3.** SMHI, IITM vs BMD precipitation at Dhaka station Bangladesh*

Mean ensemble of CORDEX datasets

In connection with this study, six Regional Climate Models (RCMs) of CORDEX-SA IITM have been utilized to create a mean ensemble. Each parameter, including precipitation, temperature, and evaporation, as well as RCP scenarios (RCP 4.5 and RCP 8.5) for the period of 2006 to 2099 have been prepared using the mean ensemble of one data set for each parameter and scenario.

Bias correction of projected climate data

In climate modeling, bias correction is essential as it improves the accuracy of climate model outputs, making them more reliable for various applications, such as hydrological modeling and climate change impact assessments. Statics of temperature and precipitation projects obtained from climate models in the control period do not usually match exactly with those of observation in the same period. So, there remain some errors in the data obtained from climate model which will seriously affect the simulated flow results in future. That's why bias correction of these data is urgent. Bias correction methods try to improve the fitting of climate model simulations to observations in the control period, to enhance the reliability of climate model results in the future period. Enrique *et al.* (2019) analyzed a set of combinations of Bias corrections methods and identified the quantile mapping linear correction technique as the best bias correction method to correct the extreme values of precipitation.

The quantile mapping approach, specifically the cumulative distribution function method, has been widely used to improve the quality of future climatic data in impact assessment models (Reichle, 2004; Singh *et al.*, 2020). This approach is commonly used to correct bias in daily meteorological data series from climate models, ensuring that distributional properties more closely resemble those of historical observations while preserving the entire distribution and extreme values (Cannon *et al.*, 2015). Moreover, it has been suggested that preserving projected trends is important in maintaining the underlying model's climate sensitivity, particularly for variables related to atmospheric moisture such as precipitation. The goal for precipitation is to correct systematic distributional biases in relation to historical observations and, as much as possible, maintain model-projected relative changes (Cannon *et al.*, 2015) while respecting physical scaling relationships with model-projected temperature changes. These findings have important implications for the development of more accurate climate models and effective impact assessment frameworks. The CDF formula is:

$$\text{cdf}_o\,(x') = \text{cdf}_c\,(x) \qquad ...(1)$$

where, cdf_c and cdf_o denote the cdf's of the cordex and observed meteorological parameter, respectively,

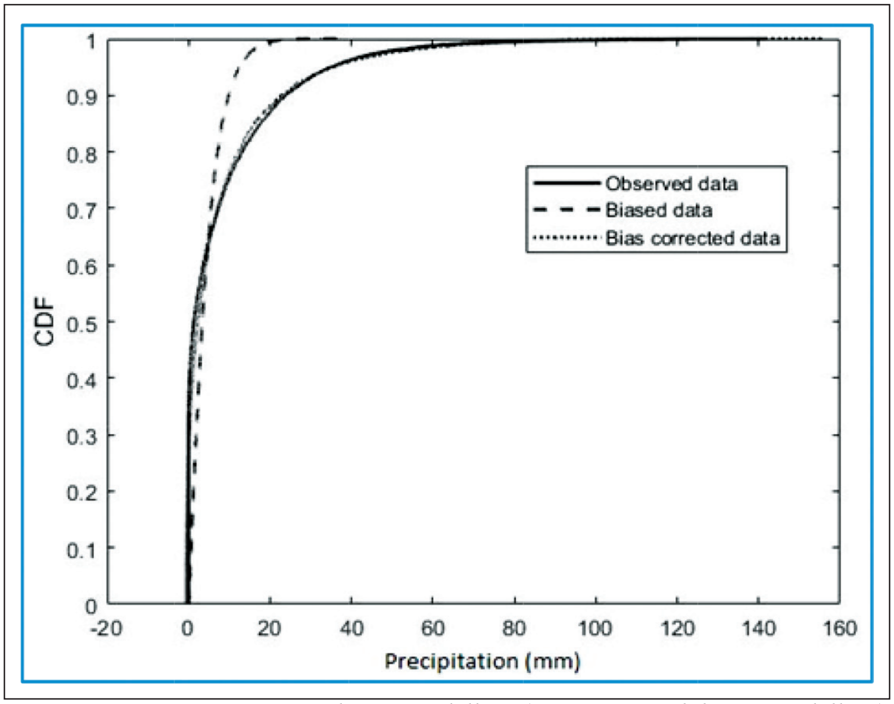

Fig. 4. *CDF vs. precipitation during modelling (Autogenerated during modelling)*

and x is the unscaled cordex climatic parameter. Assimilation systems utilize instantaneous satellite retrievals at the local scale, where Eq. (1) is solved at each location by estimating the corresponding local cumulative distribution functions (cdf). Fig. 4 schematically illustrates how the unscaled satellite retrieval x is transformed into the scaled retrieval x′, using the "ideal" cdf estimated from 1979-2005 CORDEX retrievals. This cdf matching corrects all moments of the distribution function, irrespective of its shape, with statistical errors associated with a limited sample size. However, in practice, only the first few moments, such as mean, standard deviation, and skewness, can be meaningfully estimated (Reichle, 2004). Therefore, we limit our analysis to these moments. Global Climate Models (GCMs) have been found to exhibit an issue commonly referred to as "Drizzle problems", where there are too many low-magnitude rain events in comparison to observational data or stochastic variables such as precipitation and solar radiation (Pierce *et al.*, 2015). Additionally, these models do not accurately represent the inter-annual variability associated with events such as El Niño and La Niña. To address these issues, the quantile mapping technique has been employed to remove systematic bias in GCM simulations and account for GCM biases in all statistical moments. Our analysis, as presented in Fig. 4, demonstrates that bias-corrected data shows improved agreement with observed data. For the bias correction technique, we utilize two datasets; reanalysis data comprising observed data and the CORDEX historical model output for the same period of 1979-2005, and for future bias correction, model data from CORDEX 2006-2099 is used.

Statistical analysis

In order to validate the results of the model, statistical methods were employed to ensure its applicability for further research. Two widely used methods for checking the validity of the model are Root Mean Square Error (RMSE) and Nash-Sutcliffe Efficiency (NSE). The formula of them is:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}}$$

where, i = i^{th} variable, N = number of non-missing data points, x_i = observed value of i^{th} variable, $\hat{x}_i$ = estimated value of i^{th} variable.

$$\text{NSE} = 1 - \frac{\sum_{t=1}^{T}(Q_o{}^t - Q_m{}^t)^2}{\sum_{t=1}^{T}(Q_o{}^t - \bar{Q}_o)^2}$$

where, $Q_o{}^t$ = observed value at time t, $Q_m{}^t$ = estimated value at time t, $\bar{Q}_o$ = mean of observed values, T = total number of steps in time series.

The Nash–Sutcliffe efficiency is calculated as one minus the ratio of the error variance of the modeled time-series divided by the variance of the observed time-series.

RESULTS AND DISCUSSION

Statistical analysis of bias corrected data vs. not-corrected data

The Figs. 5 and 6 depict the monthly evaluation of not-corrected and corrected six ensembled CORDEX-SA IITM data with IMD precipitation for the Yamuna-4 sub-catchment. According to Fig. 5, it has been observed that the not-corrected CORDEX historical model significantly underestimates precipitation during the monsoon season and overestimates it during the dry season in the Yamuna-4 catchment within the GBM basin. To address these biases, a bias correction technique was applied to the model. The corrected model showed a reduction in the underestimation of precipitation during the monsoon season and only a negligible overestimation during the dry season. Statistical analyses, including the Nash-Sutcliffe Efficiency, Percent Bias (PBIAS), and

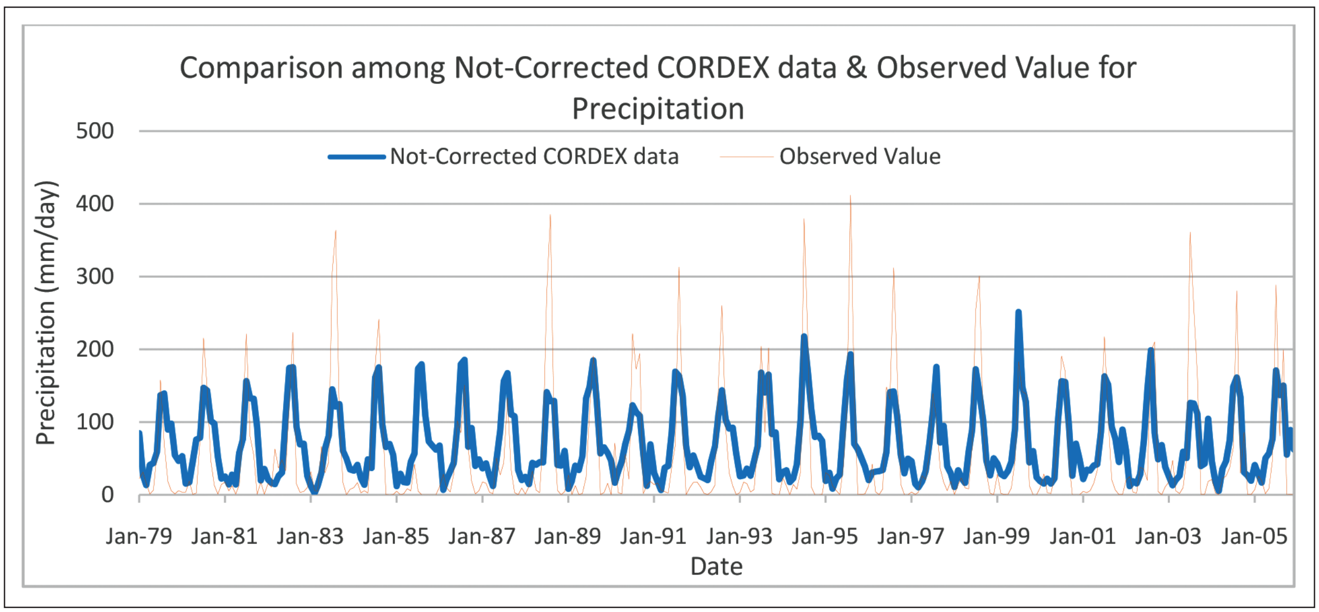

Fig. 5. *Comparison between not-corrected CORDEX and IMD precipitation (Monthly)*

Table 1. *Statistical analysis for precipitation data*

CORDEX model status	Parameter	Value
Before bias correction	NSE	0.4
	RMSE	59.5
After bias correction	NSE	0.5
	RMSE	58

Root Mean Square Error (RMSE), were conducted to evaluate the performance of the corrected model in the Yamuna-4 catchment. The detailed values are given in Table 1.

Several studies have reported that bias-correction improves the root mean squared error and Nash-Sutcliff values. Although climate models may not closely match observed data, a NSE value of 0.5 after

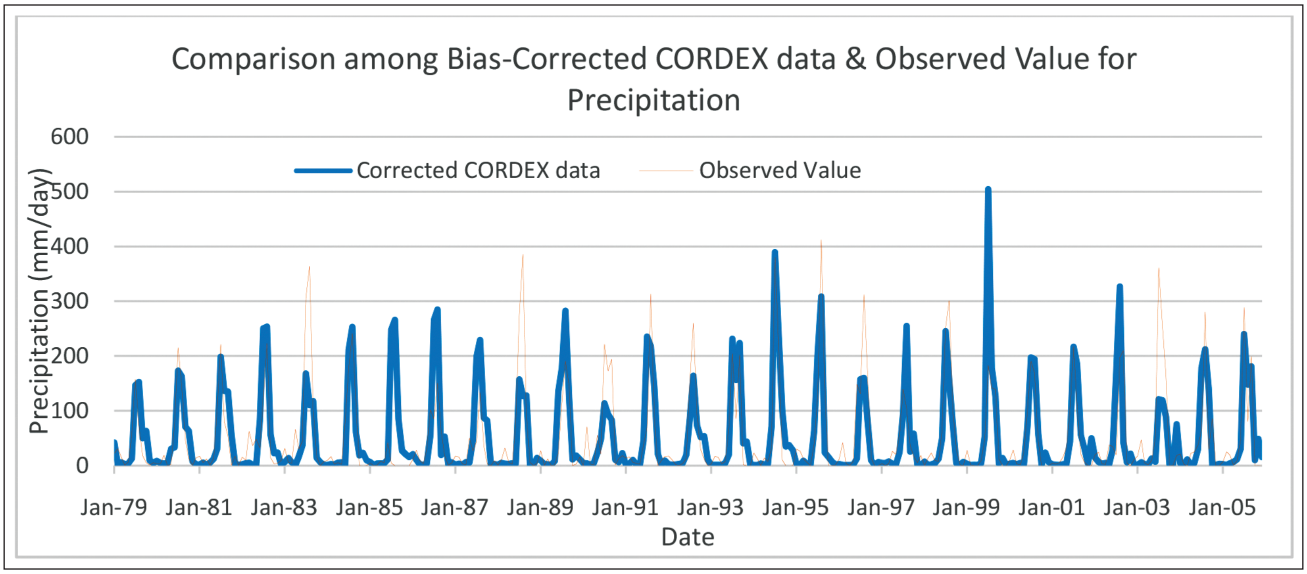

Fig. 6. *Comparison between bias-corrected CORDEX and IMD precipitation (Monthly)*

correction is considered to be too good, as a higher NSE value indicates a better model (Ashofteh *et al.*, 2016). Additionally, a lower RMSE value indicates better model fitness (Ashofteh *et al.*, 2016), thus bias-corrected models are better than non-corrected models. These statistical results were obtained for the Yamuna-4 sub-catchment, but results may vary for different catchments due to model limitations. The analysis shows that the bias-correction method improved the match between observed data and model results for temperature and evaporation.

In most of the sub-catchments, bias correction through quantile mapping of the mean ensemble leads to better estimation of future climate projections when compared to raw projections against observed data. The bias correction method was used to prepare the GBM basin model input boundaries for RCP 4.5 and 8.5 scenarios in future projection years. While there was some overestimation in peak precipitation during the wet season and underestimation during the dry season, the differences were negligible when compared to precipitation.

Fig. 7 shows that non-corrected CORDEX datasets underestimate temperatures during the summer season and fail to accurately predict peak temperatures. However, after bias correction, this irregularity is eliminated as shown in Fig. 8. Corrected CORDEX data significantly reduces biases in temperature projections. The statistical analysis for temperature is given in Table 2. Furthermore, statistical analysis using root means squared error and Nash-Sutcliffe values indicate that bias correction leads to better model fitness, with an NSE value of 0.9 after correction, which is a strong result.

It is important to note that while climate models cannot accurately predict precipitation, they provide

Table 2. *Statistical analysis for temperature*

CORDEX model Status	Parameter	Value
Before Bias Correction	NSE	0.8
	RMSE	2.97
After Bias Correction	NSE	0.9
	RMSE	2.2

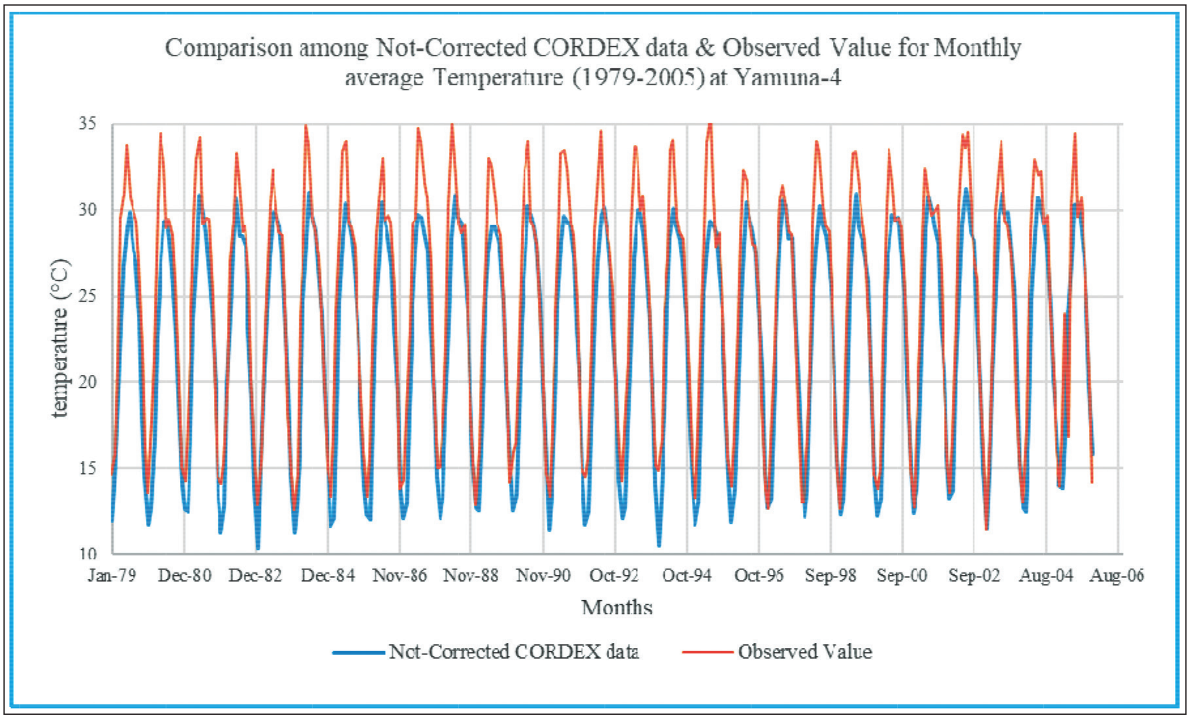

Fig. 7. *Comparison among not-corrected CORDEX data & observed value for monthly average temperature (1979-2005) at Yamuna-4*

the best results for temperature and evaporation. These statistical results are specific to the Yamuna-4 sub-catchment and may vary in other catchments due to model limitations.

Similar to the previous analysis, the bias correction procedure was performed on the evaporation data and the results are illustrated in Fig. 9-10. The outcome of the bias correction demonstrates a remarkable

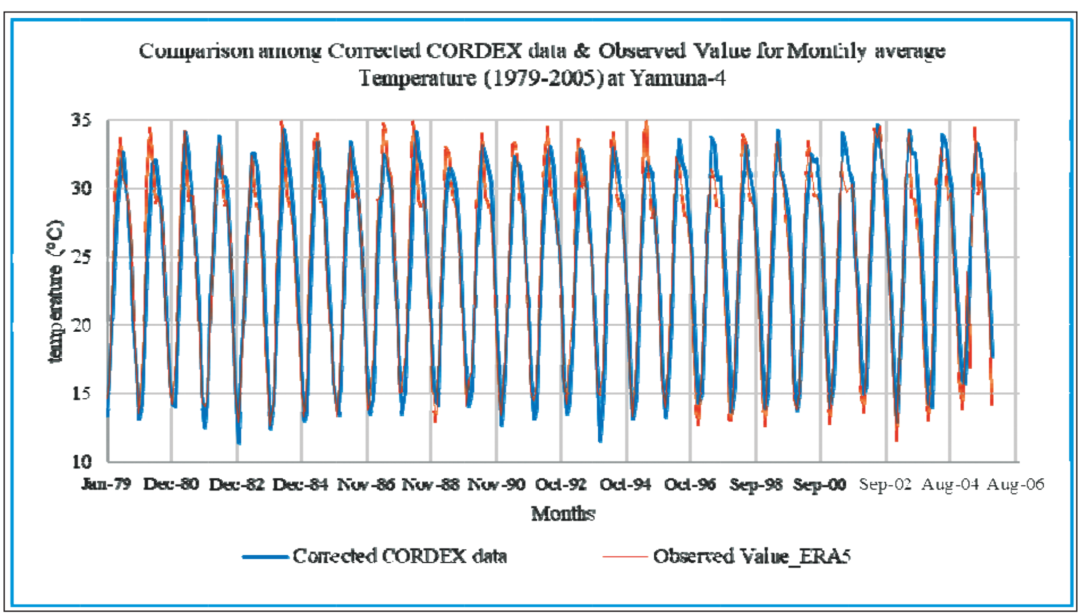

Fig. 8. *Comparison among corrected CORDEX data & observed value for monthly average temperature (1979-2005) at Yamuna-4*

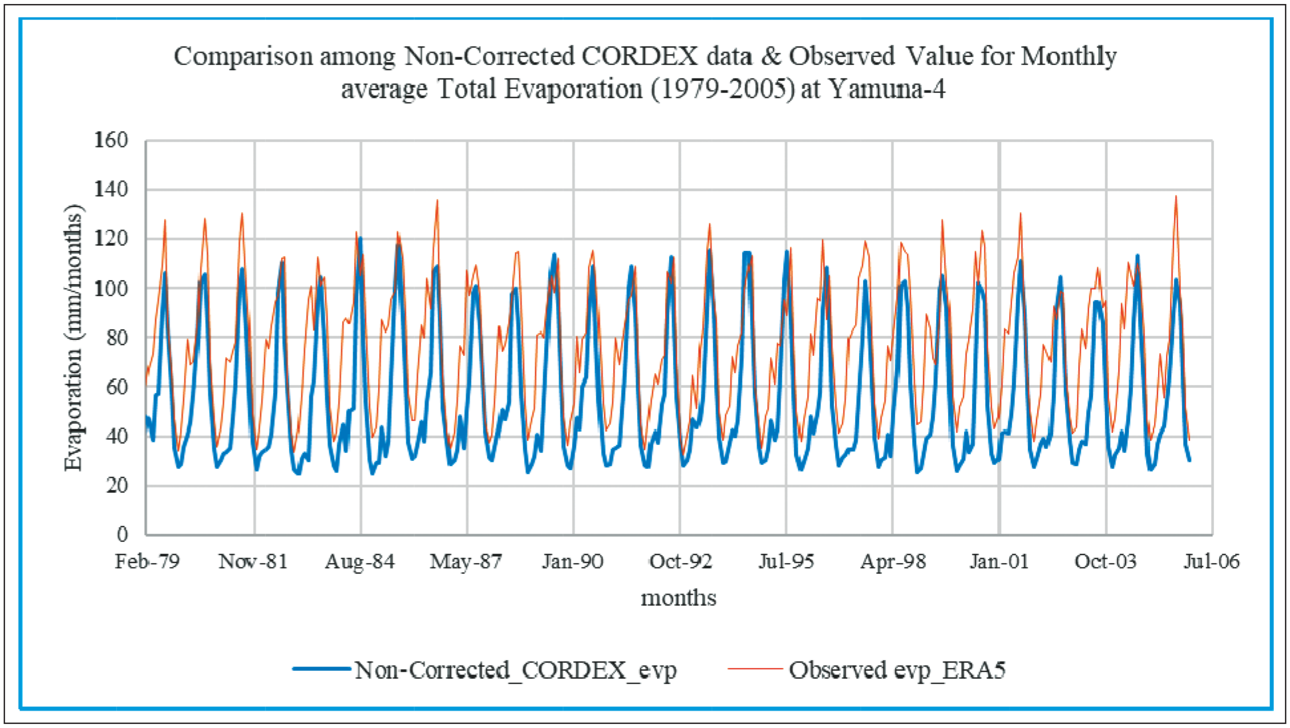

Fig. 9. *Comparison among not-corrected CORDEX data & observed value for monthly total evaporation (1979-2005) at Yamuna-4*

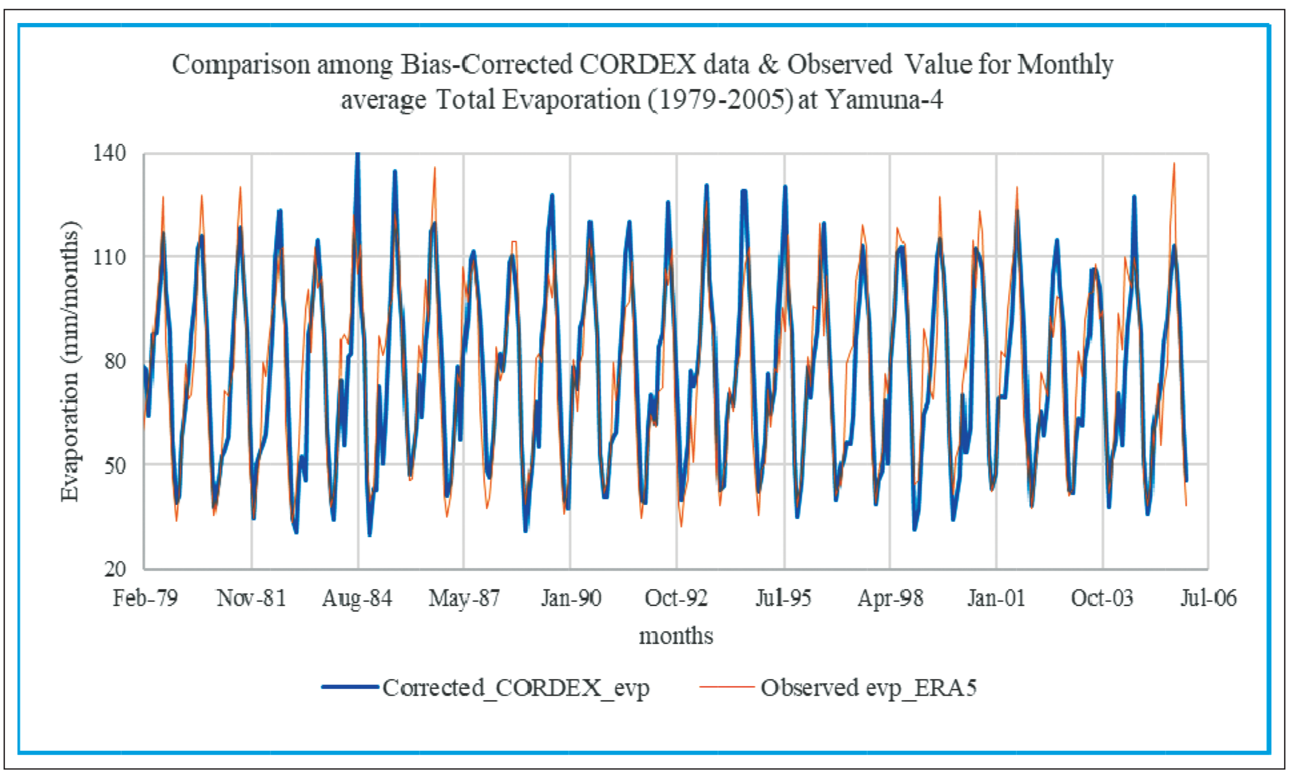

Fig. 10. *Comparison among bias-corrected CORDEX data & observed value for monthly average evaporation (1979-2005) at Yamuna-4*

improvement in the NSE value, with a significant increase from a negative value of –0.006 to an impressive positive value of 0.74, indicating a highly successful outcome. Furthermore, the RMSE values have also exhibited a significant enhancement, implying confirming the efficacy of the bias correction method.

Single climatological model vs. ensembled CORDEX-SA model

Dry bias & wet bias

The analysis of the CORDEX-SA IITM dataset comprised of six Regional Climate Models (RCMs), all of which were investigated in this study. However, it is essential to evaluate which RCM aligns most closely with the observed Indian Meteorological Department (IMD) or ERA data for a specific station or sub-catchment. This can be accomplished through a single climatology check, which enables the identification of the RCMs that best matches for a particular region.

Fig. 11, presents eight datasets of precipitation, including six from the CORDEX IITM single model (CCCma-CanESM2,CNRM-CERFACS-CNRM-CM5, CSIRO-QCCCE-CSIRO-Mk3-6-0, IPSL-IPSL-CM5A-LR, MPI-M-MPI-ESM-MR, NOAA-GFDL-GFDL-ESM2M), one representing the observed precipitation value from IMD gridded satellite of the Yamuna-4 sub-catchment (orange), and another one representing the ensemble CORDEX data (blue). All datasets indicate the monthly average precipitation (mm/month) from 1979 to 2005. Before analysis, bias corrections have been done forall datasets from CORDEX.

The single models displayed a higher level of overestimation during the dry season (winter and pre-monsoon) months of January to April and November to December. GFDL and IPSL datasets had the highest overestimation during January to March and October to December among these models. However, during the peak monsoon season, the precipitation dropped sharply, which was not reflected in the observed IMD value and was not captured by these two models. All six datasets demonstrated underestimation during the

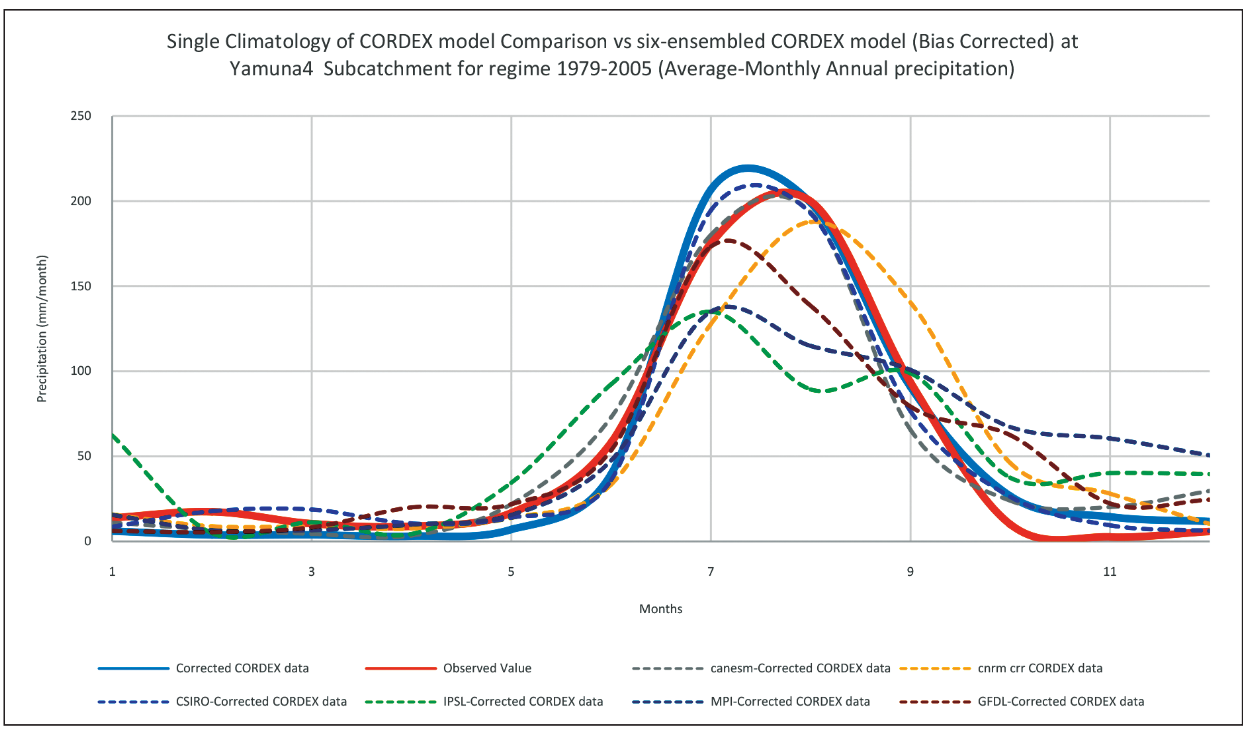

Fig. 11. *Single climatology of CORDEX model comparison (Bias corrected) at Yamuna4 sub-catchment for regime 1979-2005 (Average-monthly annual precipitation)*

peak monsoon, highlighting a limitation of climate models. Among the single models, the Commonwealth Scientific and Industrial Research (CSIRO) dataset was the closest to the observed data during the peak monsoon but showed a time lag.

Performance of six-ensemble model with bias correction

The statistical analysis presented in Table 3 which reveals that the six-ensembled model with bias correction yields a significantly higher NSE value of 0.5, indicating superior performance compared to all other datasets. This finding is further substantiated by the RMSE results, which also demonstrate that the six-ensembled model outperforms the single model As a result, it can be inferred that the six-ensembled model is the most effective approach in this study.

Table 3. *Statistical value of CORDEX models of Yamuna Catchment*

CORDEX model name	Model status	Parameter	Value
Six Ensembled CORDEX	Before bias correction	NSE	0.46
		RMSE	59
	After bias correction	NSE	0.5
		RMSE	58
CCCma-CanESM2,	After bias correction	NSE	-0.2
		RMSE	273
CNRM-CERFACS-CNRM-CM5,	After bias correction	NSE	0.04
		RMSE	79
CSIRO-QCCCE-CSIRO-Mk3-6-0,	After bias correction	NSE	0.3
		RMSE	66
IPSL-IPSL-CM5A-LR,	After bias correction	NSE	-0.38
		RMSE	94
MPI-M-MPI-ESM-MR,	After bias correction	NSE	-0.3
		RMSE	93
NOAA-GFDL-GFDL-ESM2M	After bias correction	NSE	-0.2
		RMSE	90

CONCLUSION

In this study, the performance of six Regional Climate Model (RCMs) has been evaluated for predicting precipitation, temperature, and evaporation data. The analysis revealed a significant bias in the single model climatology, including over estimation of precipitation during the dry season and under estimation during the monsoon season. The application of a bias correction technique based on cumulative distribution function led to improved model fitness, with a significant reduction in under estimation of precipitation during the monsoon season and negligible over estimation during the dry season. The bias correction technique also improved the accuracy of temperature and evaporation data. The results of this study suggest that the six-ensembled model with bias correction outperformed the single models in predicting precipitation, as evidenced by higher Nash-Sutcliffe efficiency and lower root mean squared error values. The findings highlight the importance of applying suitable bias correction methods to improve the accuracy of regional climate models in predicting future climate scenarios. However, it is essential to note that the result of this study varies spatially, and further research is necessary to evaluate the efficacy of the bias correction technique in other catchments. The research outcomes have enriched our comprehension of the constraints inherent in climate models and underscored the significance of adopting bias correction techniques to enhance their efficacy in projecting precipitation, temperature, and evaporation data. The appropriate bias correction methods for refining the accuracy of regional climate models have practical implications for policymakers and environmental agencies to undertake appropriate measures to mitigate the ramifications of climate change.

RECOMMENDATION

The study strongly recommends for bias correction of the predicted data for precipitation, evaporation and temperature available from climate model before using it for hydrologic or hydrodynamic modelling or any other analysis. Without bias correction, the result will not be realistic.

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CONFLICTS OF INTEREST

The authors have no competing interests.

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