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Research Article

Assessing climate change impacts on precipitation and temperature in Bangladesh

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ABSTRACT

Climate change presents significant challenges globally, with Bangladesh being especially vulnerable due to its geographic and socioeconomic conditions. This study examines the potential impacts of climate change on temperature and precipitation in Bangladesh using observational data from 22 weather stations and future projections from the MPI-ESM-LR and MPI-ESM-MR global circulation models (GCMs) under Representative Concentration Pathway (RCP) scenarios 4.5 and 8.5. Four precipitation indices and two temperature indices are analyzed to assess model performance by comparing observed data with GCM outputs and identifying biases. Again, bias correction is performed using the Climate Model data for hydrologic modeling (CMhyd) software, applying techniques such as delta change, distribution mapping, linear scaling, power transformation, and local intensity scaling. Initial testing at the Sylhet station indicates that the delta change method is the most effective, achieving a Root Mean Square Error (RMSE) of zero for both temperature and precipitation. This method is subsequently applied to data from 21 additional stations, significantly improving the accuracy of future projections by aligning extreme precipitation and temperature patterns closer to observed values than raw GCM data. After bias correction, projections under RCP 4.5 and RCP 8.5 scenarios reveal substantial increases in daily precipitation and maximum temperatures, with RCP 8.5 indicating a more pronounced warming trend and greater variability in precipitation. These findings provide valuable insights for water resource management and the formulation of effective climate adaptation strategies in Bangladesh.

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INTRODUCTION

Bangladesh is among the nation's most at risk from climate change, with extreme weather events such as floods and cyclones causing significant economic and human losses because of its poor infrastructure, geographical location, and high population (more than 1100 people per square kilometer [1]. Among the most underdeveloped countries in the world, Bangladesh is in hot zone for climate change. This country is susceptible to the consequences of extreme weather events, such as heat exhaustion and heavy rainfall, as a result of its proximity to the Bay of Bengal, which frequently results in a humid environment [2]. Also, Bangladesh is a member of the Asian monsoon regime, which means that the summer monsoon season's predominant southerly flows enhance the risk of heat stress by bringing warm, humid air masses from the Bay of Bengal to the country. The nation is especially vulnerable to the consequences of climate change

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as a result of the aforementioned variables, and the hazards connected to these impacts will probably increase as climate change intensifies [3].

Recent climatic records indicate that Bangladesh is already experiencing severe heatwaves and intense rainfall. South Asian countries along the Indus and Ganges River valleys, including India, Pakistan, and Bangladesh, experienced heat waves that broke records between 1979 and 2015 [4, 5]. Maximum wet-bulb temperatures of 31°C have recently been recorded in Bangladesh; these temperatures are exceedingly dangerous to human health [6, 7]. An estimated 4,000 people died from heat-related illnesses in 2015 as a result of the South Asian heat wave [8]. Apart from high temperatures, 2017 saw disastrous floods in South Asia that affected about 40 million people and claimed over 1,000 lives [9]. Strong cyclones that produce deluges of rain every three years, on average, pose a threat to Bangladesh as well [10].

The economy and society of Bangladesh are dependent on agriculture, which is highly sensitive to changes in temperature and precipitation patterns. Thus, several studies have emphasized the significance of precise climate projections and bias-corrected data for nations such as Bangladesh. One study highlights the necessity for region-specific research on environmental variables and their effects on rice production, acknowledging the difficulties presented by temperature fluctuations and inconsistent precipitation in Bangladesh [11]. In a research, the susceptibility of Bangladesh to climate change, especially with relation to temperature and precipitation changes, is underlined together with the need of reliable climate projections and adaptation plans [12]. Further research [13] indicate that bias correction techniques are essential for enhancing the precision of climate model outputs, which can subsequently be utilized to forecast the effects of climate change on hydrological processes and agricultural systems. Therefore, precise climate data is crucial for formulating effective policies and strategies to tackle the difficulties posed by climate change, with Global Circulation Models (GCMs) being vital in producing this data.

Global Circulation Models (GCMs) are frequently used to forecast temperature, precipitation, and other meteorological variables in order to anticipate the implications of climate change in the future [14-16]. Nevertheless, GCMs are presently unable to accurately depict meteorological processes at a resolution appropriate for generating local climatic variables [17]. Model structure, initial circumstances, and scenario mistakes are the sources of the constraints, which cause biases in GCM outputs [18, 19]. GCMs do not adequately reflect the local climate, which makes them inadequate for research of climate change consequences at the watershed level. Hence, there are major uncertainties in the accuracy of Global Circulation Models (GCMs) for simulating precipitation and temperature trends in Bangladesh, which must be addressed using a variety of bias correction approaches. To reconcile the discrepancies between simulation and observation, bias detection and correction must be applied to the GCM-derived meteorological variables. The biases and uncertainties of these variables such as temperature and precipitation specifically over Bangladesh have not yet been adequately addressed by previous studies. The literature provides a number of bias correction methods to address these problems, such as quantile mapping, linear scaling, and local intensity scaling [20, 21].

A study [22] evaluates the impact of various bias correction methods, including distribution mapping and scaling, on hydrological simulations for flood peaks and streamflow in RCM-simulated temperature and precipitation data. These methods are computationally difficult and focuses on mean values and hydrological effects, neglecting extreme occurrences and region-specific validation, limiting its application to Bangladesh. Another study compared the bias correction methods of linear scaling and quantile mapping in the Kaligandaki River Basin, and the results indicated that there was no substantial distinction between the two [23]. However, the effectiveness of high-precision climate projections may be restricted by the failure to capture extreme events and finer-scale variations due to the reliance on linear scaling.

In a paper [24], power transformation and gamma distribution modification are investigated for correcting GCM precipitation simulations, with a focus on dry day accuracy. The problem of this bias correction method is that it only considers precipitation and dry day accuracy, leaving out temperature biases and severe events, which are critical for a thorough climate impact analysis. Another study shows that, since the delta change method adjusts model outputs depending on observed changes, thereby enhancing the accuracy of future climate projections and hence it remains a popular bias correction method [25]. By means of a consistent adjustment across the data, the approach specifically improves forecast of future temperature and precipitation patterns by so reducing variations between model and observed values.

Therefore, the main objective of this study is to use bias-corrected GCM data to predict how temperatures and rainfall will change in Bangladesh in the future using the Climate Model data for hydrologic modeling (CMhyd). In order to do this, weather data from different sites is gathered and compared with GCM outputs. Different techniques, such as Delta Change, distribution mapping, and local intensity scaling, are used to find biases. The Delta Change method works best, lowering biases to almost zero. After applying the Delta Change bias correction, the data is statistically validated and pre-processed for further hydrological analysis. This ensures reliable climate forecasts across several climate change scenarios (RCP 4.5 and 8.5), which are subsequently utilized to guide adaptation strategies and facilitate evidence-based decision-making in response to possible climate effects in Bangladesh. This paper represents the first comprehensive investigation of future climate forecasts for Bangladesh, examining diverse bias correction methodologies and their ramifications for forthcoming climate impact evaluations.

STUDY AREA

This study region includes all 22 Bangladesh Meteorological Department (BMD) stations and evaluates how reliable Global Circulation Models (GCMs) are at modeling temperature and precipitation in the nation (Figure 1). Table 1 provides the stations' geographic coordinates and elevation information. Southeast Asian nation of Bangladesh is located between India and Myanmar, between 88°01' and 92°41' E longitude and 20°34' and 26°38' N latitude. This nation is made up of a small deltaic plain with hills in the southeast and east and sandy beaches in the south [26]. Bangladesh has a tropical monsoon climate that is humid and varies significantly with the seasons [27]. More over 70% of the nation's yearly precipitation falls during the monsoon season, which runs from June to September [28]. Winter (December to February) is primarily dry, with the remaining precipitation falling during the post-monsoon (October–November) and pre-monsoon (March–May) seasons. The country's long-term average minimum and maximum temperatures are 21°C and 29°C, respectively. The extremes of regional precipitation differ greatly throughout Bangladesh. The average annual precipitation in the southwest is the lowest at 1527 mm, while the average annual precipitation in the northeast is the highest at 4197 mm [29]. While there are regional differences in both temperature and precipitation extremes, the western area is generally drier than other regions of the nation [30, 31].

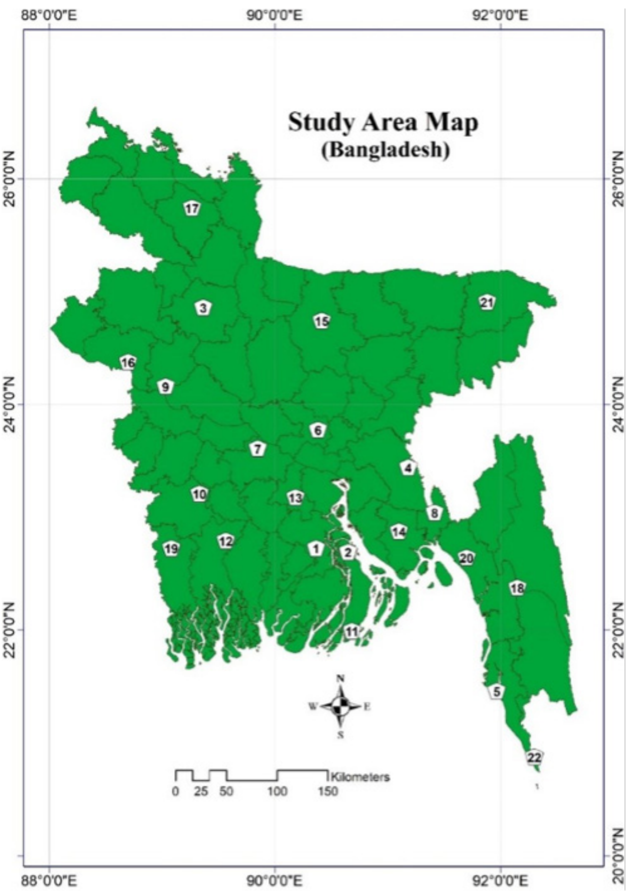

Figure 1. Study area map of Bangladesh with 22 BMD stations for GCM analysis

METHODOLOGY

This study employs a thorough and integrated methodology to forecast future temperature and precipitation patterns in Bangladesh, ensuring reliable and precise outcomes. The process started with the collection and organization of meteorological data from 22 stations, obtained from the Bangladesh Meteorological Department (BMD) and the Bangladesh Water Development Board (BWDB). After that, missing data were methodically addressed, and historical daily records of precipitation and temperature were compiled for analysis.

To integrate climate projections, the MPI-ESM-LR and MPI-ESM-MR global climate models were employed, chosen for their capacity to provide both global (low resolution) and regional (medium resolution) insights. The models, based on RCP 4.5 and RCP 8.5 scenarios, were pre-processed and analyzed against observed station data to detect differences. This comparison revealed biases that were corrected by advanced correction techniques, such as delta change, distribution mapping, linear scaling, local intensity scaling, and power transformation of precipitation. The delta change method was recognized as the most effective, minimizing biases to nearly zero RMSE values and enhancing the correspondence between modeled and observed data.

Following bias reduction, the study authenticated the adjusted data by statistical metrics to guarantee resilience. The validated data were subsequently pre-processed for incorporation into hydrological models with CMhyd software, hence enhancing the precision of future climate effect projections under various emission scenarios. These projections offer critical insights into possible climatic alterations and related risks, enabling the assessment of climate impacts. The projections facilitate evidence-based decision-making for climate adaption measures and water resource management in Bangladesh. The overall methodology of the study is visually represented in the flowchart shown in Figure 2.

Table 1. Coordinates and elevation of BMD stations in Bangladesh

ID	Station	Latitude	Longitude	Elevation
1	Barishal	22.7167	90.3667	2.1
2	Bhola	22.6833	90.65	4.3
3	Bogra	24.85	89.3667	17.9
4	Cumilla	23.4333	91.1833	7.5
5	Cox's Bazar	21.45	91.9667	2.1
6	Dhaka	23.7667	90.3833	8.45
7	Faridpur	23.6	89.85	8.1
8	Feni	23.0333	91.4167	6.4
9	Ishwardi	24.15	89.0333	12.9
10	Jessore	23.2	89.3333	6.1
11	Khepupara	21.9833	90.6833	1.83
12	Khulna	22.7833	89.5667	2.1
13	Madaripur	23.1667	90.1833	7
14	Maijdee Court	22.8667	91.1	4.87
15	Mymensing	24.7333	90.4167	18
16	Rajshahi	24.3667	88.7	19.5
17	Rangpur	25.7333	89.2667	32.61
18	Rangamati	22.3667	92.15	68.89
19	Satkhira	22.7167	89.0833	3.96
20	Sitakunda	22.6333	91.7	7.3
21	Sylhet	24.9	91.8833	33.53
22	Teknaf	20.8667	92.3	5

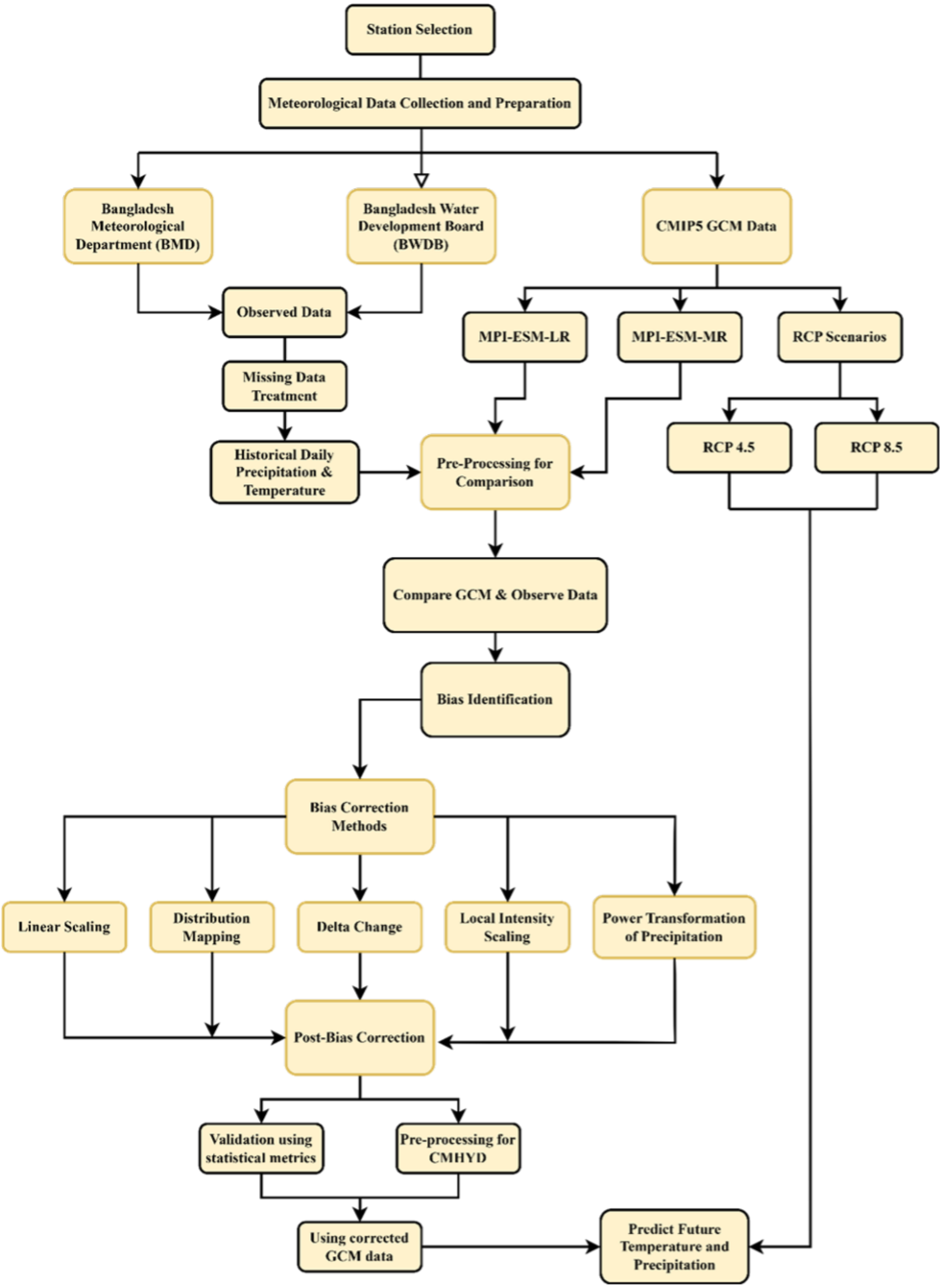

Figure 2. Flowchart of the methodology for meteorological data processing and GCM integration

Observed and Global Circulation Model (GCM) Data

Daily maximum (Tmax) and minimum (Tmin) Temperatures, along with precipitation data, were obtained from the Bangladesh Meteorological Department for 22 stations (as shown in Figure 1 and Table 1) covering the period from 1980 to 2015.

The Global Circulation Model (GCM) data used in this study were sourced from the MPI-ESM-LR and MPI-ESM-MR models, developed by the Max Planck Institute for Meteorology in Germany. These data were acquired from the Coupled Model Intercomparison Project phase 5 (CMIP5) database, which includes outputs from various GCMs under different emission scenarios.

In this study, historical simulation data (1980-2015) and future projections (2020-2045) were utilized based on the scenarios of Representative Concentration Pathways (RCP) 4.5 and 8.5, as shown in Table 2.

Table 2. Overview of GCM models used in the study

Model	Calendar	Institution	Historical Simulation Period	Future Simulated Period	Scenario
MPI-ESM-LR	365-day	Max Planck Institute for Meteorology in Germany	1980-2015	2020-2045	RCP-4.5, 8.5
MPI-ESM-MR	365-day	Max Planck Institute for Meteorology in Germany	1980-2015	2020-2045	RCP-4.5, 8.5

Missing Data Treatment

Multiple imputation techniques were used to handle missing data. Several believable imputed datasets with various imputed values for the missing data were created using this method. The observed data and the variable distribution served as the foundation for the creation of these datasets. Each imputed dataset was then subjected to statistical analysis, and the outcomes were aggregated to get a general estimate of the parameters of interest. Multiple imputation was useful because it took into account the uncertainty associated with the missing data and could provide more accurate estimates compared to other methods of handling missing data [32].

Mathematically, multiple imputation can be expressed as:

Imputation model as equation (1):

$$Y_i = f(X_i, Y_{-i}, \varepsilon_i) \tag{1}$$

Where, Y_i is the incomplete variable to be imputed for observation i, X_i is the observed covariate data, Y_{-i} is the incomplete variable data for all other observations except i, and ε_i is the error term.

Analysis model as equation (2):

$$\theta = g(Y) \tag{2}$$

Where, θ is the parameter of interest, and g(Y) is the function used to estimate the parameter from the imputed dataset.

Combining imputations as equation (3):

$$\theta_m = \frac{1}{M} * \sum(m = 1 \; to \; M) \; g(Y_m) \tag{3}$$

Where, θ_mis the estimated parameter from imputed dataset m, and M is the total number of imputed datasets. The estimates from each imputed dataset were combined to get the final estimate of the parameter.

Extreme Climatic Indices Used for Bias Identification

The expert group on Climate Change Detection and Indices (ETCCDI) had chosen six extreme climatic indices for this investigation, including four precipitation indices and two temperature indices [33]. Monthly mean and standard deviation were computed for both precipitation and temperature. The utilization of extreme precipitation metrics included dry days, wet days, Simple Daily Intensity Index (SDII), and Maximum 1-day precipitation (RX1day). RX-1day was a short-lived, exceptionally heavy precipitation event. The maximum daily minimum temperature (TNx) and minimum daily maximum temperature (TXn) were used to calculate the temperature indices [34]. The climatic indicators were employed to detect discrepancies in temperature and precipitation information obtained from GCMs and observational data.

Selection of Bias Correction Techniques

In this study, bias identification was performed using several bias correction methods, including delta change correlation, distribution mapping of precipitation and temperature, linear scaling (multiplicative), power-transformation of precipitation, precipitation-local-intensity-scaling [35]. For this study, the delta change correlation method was employed for bias correction for both precipitation and temperature. This method was selected as it had the ability to adjust the model output to more accurately reflect the observed data.

Linear scaling of precipitation/temperature (LS)

LS is the most straightforward bias correction technique employed in several studies [36-38]. It adjusts the GCM mean value with a perfect agreement with the observation data. The control and scenario precipitation/temperature are then adjusted based on the ratio between the long-term monthly mean observed and control/scenario data using equations (4) and (5), respectively. However, this approach can correctly adjust the climatic factors only when the monthly mean values are included.

$$P^*_{control}(d) = P_{control}(d).\left[\frac{\mu_m(P_{observed}(d))}{\mu_m(P_{control}(d))}\right] \quad (4)$$

$$P^*_{scenario}(d) = P_{scenario}(d).\left[\frac{\mu_m(P_{observed}(d))}{\mu_m(P_{control}(d))}\right] \quad (5)$$

Where, P = precipitation/temperature; (d) = daily time series; μ_m = mean and P*= final bias corrected.

Local intensity scaling (LOCI) of precipitation

The LOCI method is introduced by extends the linear scaling method a step forward. Added to the mean, it also adjusts wet-day frequencies and wet-day intensities of precipitation. The precipitation intensity threshold (P_(th,control)) for every month is initially confirmed. Then, the number of wet days in control data that exceeds the threshold will be adjusted based on the number of days the observed precipitation was determined. The number of precipitation events for control and scenario run is corrected by applying the calibrated GCM precipitation threshold (P_(th,control)) using equations (6) and (7), respectively. This approach virtually eliminates the drizzle effect because excessive drizzly days are frequently added to the GCM outputs.

$$P^{*1}_{control}(d) = \begin{cases} 0, \ if\ P_{control}(d) < P_{th,control} \\ P_{control}(d), otherwise \end{cases} \quad (6)$$

$$P^{*1}_{scenario}(d) = \begin{cases} 0, \ if\ P_{scenerio}(d) < P_{th,control} \\ P_{scenario}(d), otherwise \end{cases} \quad (7)$$

A scaling factor s is then calculated using equation (8) to confirm that the mean of corrected precipitation is equal to observed data.

$$s = \frac{\mu_m(P_{observed}(d)|P_{observed}(d) > 0\ mm)}{\mu_m(P_{control}(d)|P_{control}(d) > P_{th,control}) - P_{th,control}} \quad (8)$$

Finally, both control and scenario precipitations are corrected using equation (9) and (10), respectively.

$$P^*_{control}(d) = P^{*1}_{control}(d).s \quad (9)$$

$$P^*_{scenario}(d) = P^{*1}_{scenario}(d).s \quad (10)$$

Where, P^{*1}= intermediate step in bias correction and Pth = threshold.

Power transformation of precipitation (PT)

PT corrects both the monthly mean as well as the variance. It uses an exponential correcting factor a Pb [39, 40]. Parameter 'b' is measured monthly (bm) using the distribution-free method with a three-month window. Initially, 'b' is determined by equalizing the Coefficient of Variation (CV) of corrected GCM precipitation (Pb) and observed precipitation (P_observed) for every month (m) using the root-finding algorithm. Then ' bm ' is calculated using equation (11) and 'CVm' using equation (12). Equation (13) & (14) were used for equalizing the datasets.

$$f(b_m) = 0 = CV_m(P_{observed}(d)) - CV_m(P^{b_m}_{control}(d)) \quad (11)$$

$$CV_m = \frac{\sigma_m(P_{observed}(d))}{\mu_m(P_{observed}(d))} - \frac{\sigma_m(P^{bm}_{control}(d))}{\mu_m(P^{bm}_{control}(d))} \quad (12)$$

$$P^{*1}_{control}(d) = P^{bm}_{control}(d) \quad (13)$$

$$P^{*1}_{scenario}(d) = P^{bm}_{scenario}(d) \quad (14)$$

Afterwards, 'PT' equalizes the observed precipitation (P_observed) with the intermediate series (P_control^(*1)) using the LS method. Finally, the corrected control and scenario precipitation datasets were derived using equations (15) and (16) respectively.

$$P^*_{control}(d) = P^{*1}_{control}(d).\ \left[\frac{\mu_m(P_{observed}(d))}{\mu_m(P^{*1}_{control}(d))}\right] \quad (15)$$

$$P^*_{scenario}(d) = P^{*1}_{scenario}(d).\left[\frac{\mu_m(P_{observed}(d))}{\mu_m(P^{*1}_{control}(d))}\right] \quad (16)$$

Distribution mapping of precipitation & temperature (DM)

The DM method is applied to correct mean, standard deviation (SD), and quantiles by equalizing the distribution functions of both the GCM outputs and the observed data. The method assumes that the GCM-simulated and observed precipitation, temperature follows a particular frequency of distribution, in turn, may cause biases. Accordingly, Gamma distribution is used for effective precipitation & temperature distribution as equation (17).

$$f_y(\chi|\alpha,\beta) = \chi^{\alpha-1}.\frac{1}{\beta^\alpha.\Gamma(\alpha)}.e^{\frac{-\chi}{\beta}};\chi \geq 0; \qquad \alpha,\beta > 0 \quad (17)$$

Where, Γ(α) is the Gamma function, α is the shape parameter, and β is the scale parameter.

Subsequently, GCM outputs are corrected in terms of the Gamma cumulative distribution function (F_γ) and its inverse function (F_γ^(-1)) as follows equation (18) & (19):

$$P^*_{control}(d) = F_\gamma^{-1}((F_\gamma(P_{control}(d)|\alpha_{control,m},\beta_{control,m})|\alpha_{observed,m},\beta_{observed,m}) \quad (18)$$

$$P^*_{scenario}(d) = F_\gamma^{-1}((F_\gamma(P_{scenario}(d)|\alpha_{control,m},\beta_{control,m})|\alpha_{observed,m},\beta_{observed,m}) \quad (19)$$

Delta change method

Delta change correlation method is a widely used method for correcting biases in climate model output. Mathematically, the method involves adjusting the model output by a correction factor that is derived based on the correlation between the model output and the observed data. The ratio of the mean value of the observed data to the mean value of the model output is used to compute the correction factor [41]. A multiplicative correction is used for the precipitation & temperature correction equation (20) & (21).

$$P^*_{control}(d) = P_{observed}(d) \quad (20)$$

$$P^*_{scenario}(d) = P_{observed}(d).\left[\frac{\mu_m(P_{scenario}(d))}{\mu_m(P_{control}(d))}\right] \quad (21)$$

Here, $P^*_{scenario}$ (d) represents the bias-corrected value for a specific variable (e.g., precipitation, temperature) at a given location and time. $P_{observed}$ (d) is the observed value for the same variable at the same location and time. μ_m ($P_{scenario}$ (d)) is the mean value of the model-simulated variable (e.g., precipitation, temperature) across a specific time period, such as a month, at the same location. μ_m ($P_{control}$ (d)) is the mean value of the model-simulated control variable (e.g., precipitation, temperature) across the same time period at the same location. Overall, the delta change correlation method provides a useful and straightforward approach to correcting biases in climate model output [42, 43].

RESULTS AND DISCUSSIONS

The application of the delta changes bias correction method utilizing Global Circulation Model (GCM) data yielded predicted precipitation and temperature data for the 2020-2045 timeframe under RCP 4.5 and 8.5 scenarios across 22 meteorological stations in Bangladesh. RCP 4.5 and 8.5, denoting moderate and high greenhouse gas emission scenarios respectively, were selected to encompass a spectrum of anticipated climate change impacts, from intermediate to worst-case outcomes [44, 45]. This study predicted substantial effects of climate change on temperature and precipitation in Bangladesh. The projected rise in precipitation is likely to intensify flooding and landslides in certain regions, but the increase in temperature is associated with elevated heat stress, diminished agricultural productivity, and alterations in disease patterns.

The findings indicate an urgent necessity for climate adaptation and mitigation methods in Bangladesh, highlighting the importance of prompt and evidence-based action. These techniques must be customized to address the distinct issues encountered by various locations, taking into account the specific climatic and socio-economic settings of each.

The project implemented five distinct bias reduction techniques on the Sylhet station dataset during its preliminary phase. An extensive assessment indicated that the delta change strategy was the most efficacious in mitigating biases in the data. This technique was later utilized to rectify the bias in precipitation and temperature data across 21 supplementary stations in Bangladesh.

The Root Mean Square Error (RMSE) values for precipitation, daily maximum temperature, and daily minimum temperature were computed for each bias correction approach, with the findings displayed in Table 3. RMSE is an important metric that measures the standard deviation of the error distribution between observed and simulated data [46]. It gives a clear picture of how accurate and reliable model projections are.

The delta change method exhibited a remarkable RMSE value of 0 for all three variables, signifying an exceptional alignment between the observed and model-simulated data ([47], [48]). This outstanding performance highlights the efficacy of the delta change approach in mitigating biases and precisely representing observed climate conditions ([42], [43]). Consequently, the delta change method was deemed the most dependable strategy for bias correction in this investigation, owing to its capacity to entirely eradicate bias and generate simulations that nearly align with the observed data.

Table 3. RMSE for precipitation, daily maximum temperature, daily minimum temperature using different bias correction methods

Bias Correction Methods	Precipitation RMSE	Daily Maximum Temperature RMSE	Daily Minimum Temperature RMSE
Linear scaling	11.273	2.128	1.486
Distribution mapping	9.254	1.855	1.354
Delta change	0	0	0
Local intensity scaling	11.234		
Power transformation of precipitation	9.484		

After applying the bias adjustment, future estimates for precipitation and temperature were produced for the 22 meteorological stations in Bangladesh for the period 2020-2045 under the RCP 4.5 and 8.5 scenarios. These projections will be crucial in informing climate adaptation and mitigation measures by offering more precise and dependable future climate forecasts. This study emphasizes the significance of bias correction methods in enhancing the precision of climate projections and underscores the need for meticulous evaluation of uncertainties in model simulations, especially regarding the potential effects of climate change on vital sectors such as agriculture, water resources, and public health in Bangladesh.

Bias Correction and Uncertainty Mitigation in Model Projections

The bias-corrected dataset from 1980 to 2015 significantly improves the raw Global Circulation Model (GCM) outputs through the Delta Change methodology, as outlined in Tables 4, 5, 6 and depicted in Figures 3–8. The modifications improve the precision of maximum and lowest temperature forecasts and precipitation assessments, mitigating systematic biases and ensuring the dataset more accurately corresponds with observed climatological data from Bangladesh. Figure 3 combines observed and forecasted maximum temperatures, revealing that the unrefined projections (38.6°C–45.6°C) considerably overestimated the actual values (33.4°C–38°C), especially in years characterized by high heat. Following the implementation of bias correction, uncertainties were reduced, and predictions corresponded with observed data within a range of 31.2°C to 36.3°C. Figure 4 further demonstrates these enhancements in long-term maximum temperature patterns. Figures 5 and 6 concentrate on minimum temperatures, indicating that raw predictions (27.5°C–35.6°C) exceeded the observed values (23°C–30°C). Bias adjustment diminished uncertainty to a range of ±0.4°C–±0.9°C, resulting in better consistency between observed and forecasted minimum temperatures. Figure 7 analyses precipitation, revealing that raw GCM forecasts (13.5–21.6 mm/day) significantly surpass observed values (10.5–14 mm/day), especially during years of peak rainfall. Figure 8 shows how bias correction reduced these discrepancies, enhancing trend alignment, and mitigating predictive uncertainty in precipitation forecasts. Tables 4, 5, and 6 present the observed and predicted climate variables before and after bias correction, emphasizing a significant decrease in uncertainty. The Delta Change approach considerably enhanced the consistency of forecasts with observed trends, illustrating its efficacy in enhancing model reliability. The analysis highlights that uncertainties included in raw GCM outputs were significantly reduced, guaranteeing that adjusted datasets more accurately represent natural climatic variability instead of model biases. This refined dataset, derived from empirical data from the Bangladesh Meteorological Department and simulations from MPI-ESM-LR and MPI-ESM-MR, offers a reliable foundation for analyzing historical climatic conditions and forecasting future scenarios with reduced uncertainty. This is especially crucial for areas like as Bangladesh, where precise climate modelling is necessary for comprehending risk and guiding adaptation strategies.

Table 4. Yearly analysis of observed vs. simulated maximum temperatures: Uncertainty insights before and after bias correction

Year	Observed Max Temp(°C)	Predicted Max Temp. Before Bias Correction(°C)	Predicted Max Temp After Bias Correction(°C)	Uncertainty Max Temp Before Correction(°C)	Uncertainty Max Temp After Correction(°C)
1980	34.5	39.5	35	±5.0	±0.5
1981	36	40.8	36.4	±4.8	±0.4
1982	37.2	45.1	33	±7.9	±0.6
1983	35.8	41.7	37.8	±5.9	±0.3
1984	34.8	40.9	35.3	±6.1	±0.5
1985	33.4	39.2	34.1	±5.8	±0.7
1986	36.5	39.4	37.1	±2.9	±0.6
1987	35.1	43.7	35.5	±8.6	±0.4
1988	37	40	37.5	±3	±0.5
1989	33.8	40.2	34.4	±6.4	±0.6
1990	34.2	40.4	34.7	±6.2	±0.5
1991	36.1	38.6	36.5	±2.5	±0.4
1992	35.5	40.8	35.8	±5.3	±0.3
1993	37.4	41	37.9	±3.6	±0.5
1994	36.6	43.1	37.2	±6.5	±0.6
1995	34.7	41.3	35.4	±6.6	±0.7
1996	33.9	39.5	34.5	±5.6	±0.6
1997	36.4	41.7	36.9	±5.3	±0.5
1998	34.9	40.8	35.5	±5.9	±0.6
1999	37.1	42	37.6	±4.9	±0.5
2000	36.7	42.3	37.3	±5.6	±0.6
2001	35.4	42.5	35.9	±7.0	±0.5
2002	33.6	42.7	34	±9.1	±0.4
2003	36.2	42.8	36.7	±6.2	±0.5
2004	35.9	43	36.4	±7.1	±0.5
2005	36.2	43.2	36.8	±7	±0.6
2006	34.6	43.4	35.1	±8.8	±0.5
2007	33.5	43.6	33.9	±10.1	±0.4
2008	36.8	43.8	37.4	±7	±0.6
2009	38	45	38.4	±7	±0.4
2010	36.9	44.2	37.4	±7.3	±0.5
2011	34.4	44.4	35	±10	±0.6
2012	36.1	45.6	36.6	±9.5	±0.5
2013	35.2	44.8	35.6	±9.6	±0.4
2014	36.7	45	37.2	±8.3	±0.5
2015	37.1	45.2	37.6	±8.1	±0.5

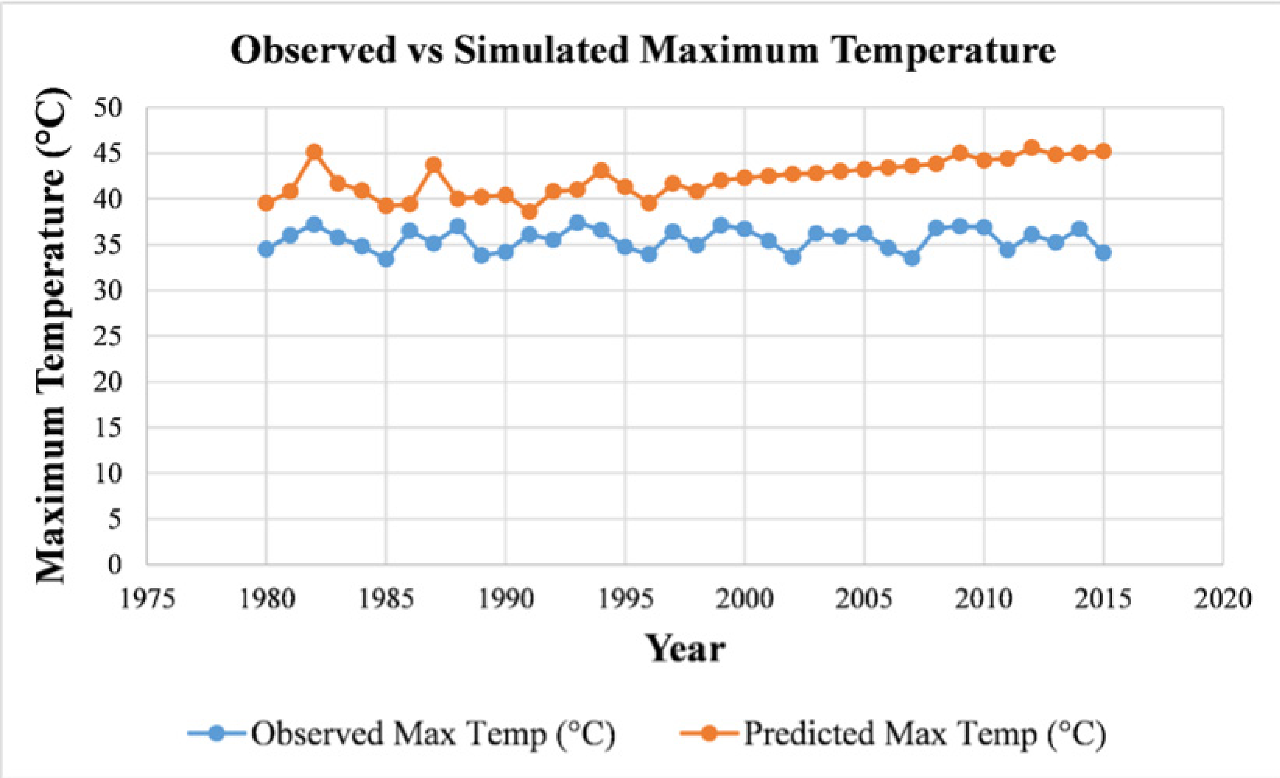

Figure 3. Observed vs. predicted maximum temperature trends before bias correction

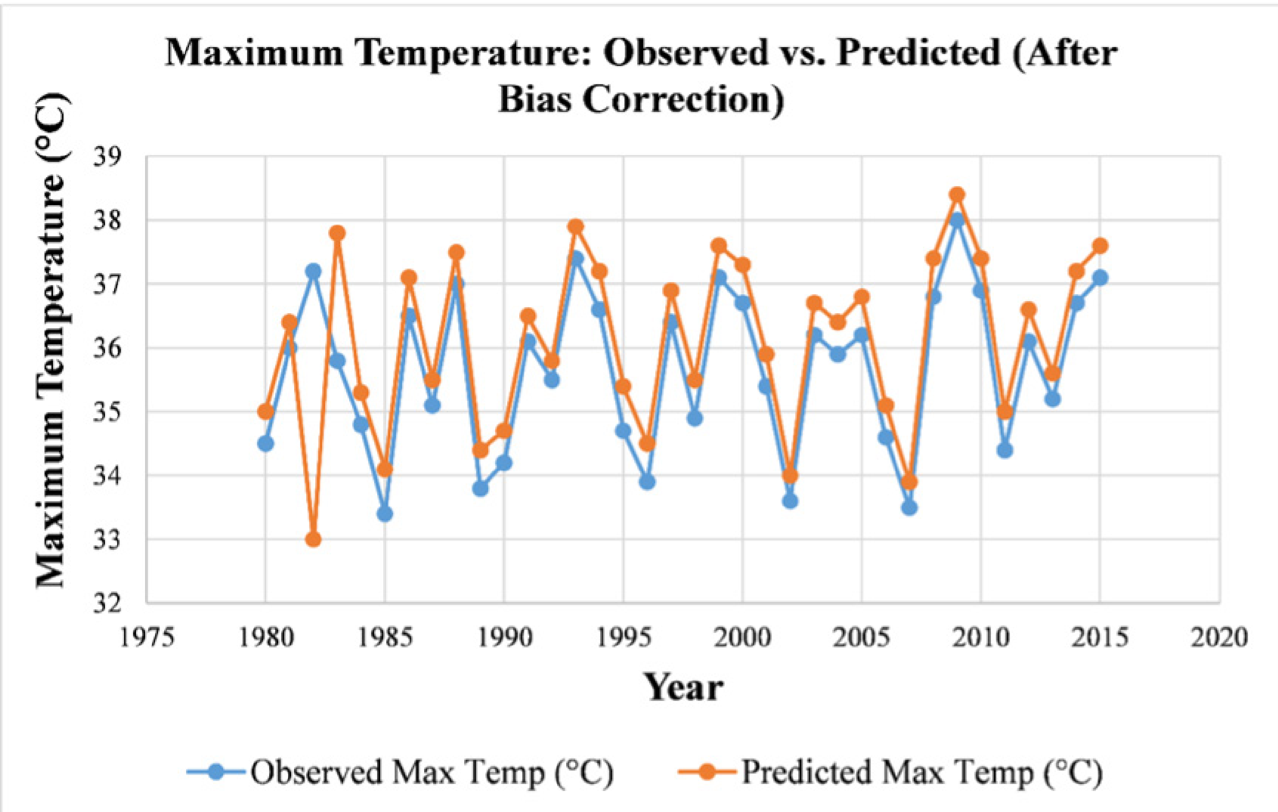

Figure 4. Observed and predicted maximum temperatures after bias correction

Table 5. Observed vs. simulated minimum temperatures: A yearly breakdown with uncertainty before and after bias adjustment

Year	Observed Max Temp(°C)	Predicted Max Temp. Before Bias Correction(°C)	Predicted Max Temp After Bias Correction(°C)	Uncertainty Max Temp Before Correction(°C)	Uncertainty Max Temp After Correction(°C)
1980	23	28	23.7	±5.0	±0.7
1981	24	28.4	24.6	±4.4	±0.6
1982	23.5	27.8	24	±4.3	±0.5
1983	24.1	29.3	24.5	±5.2	±0.4
1984	24.2	28.9	24.8	±4.7	±0.6
1985	24.3	27.5	25.1	±3.2	±0.8
1986	24.5	30.3	24.9	±5.8	±0.4
1987	24.7	32.1	25.2	±7.4	±0.5
1988	25	29.2	25.7	±4.2	±0.7
1989	25.2	28.6	25.8	±3.4	±0.6
1990	25.3	30.7	25.9	±5.4	±0.6
1991	25.4	29	25.9	±3.6	±0.5
1992	25.5	32.6	26.1	±7.1	±0.6
1993	25.7	29.1	26.4	±3.4	±0.7
1994	25.8	31.8	26.2	±6	±0.4
1995	26	29.4	26.5	±3.4	±0.5
1996	26.2	30.7	26.7	±4.5	±0.5
1997	26.4	29.1	27	±2.7	±0.6
1998	26.6	31.5	27	±4.9	±0.4
1999	26.8	30.2	27.4	±3.4	±0.6
2000	27	29.2	27.5	±5.0	±0.5
2001	27.2	28.8	27.8	±2.1	±0.6
2002	27.4	34.9	28	±7.2	±0.6
2003	27.6	33.5	28.2	±5.9	±0.6
2004	27.8	35.6	25.4	±7.8	±0.6
2005	28	32.2	28.5	±4.2	±0.5
2006	28.2	33.6	28.8	±5.4	±0.6
2007	28.4	32.9	28.9	±5.7	±0.5
2008	28.6	33.7	29	±5.8	±0.4
2009	28.8	30	29.4	±1.2	±0.6
2010	29	35.1	29.7	±6.0	±0.7
2011	29.2	35.3	29.8	±6.1	±0.6
2012	29.4	35.6	29.9	±6.2	±0.5
2013	29.6	34	30.2	±4.4	±0.6
2014	29.8	34.3	30.4	±4.5	±0.6
2015	30	34.3	30.5	±4.3	±0.5

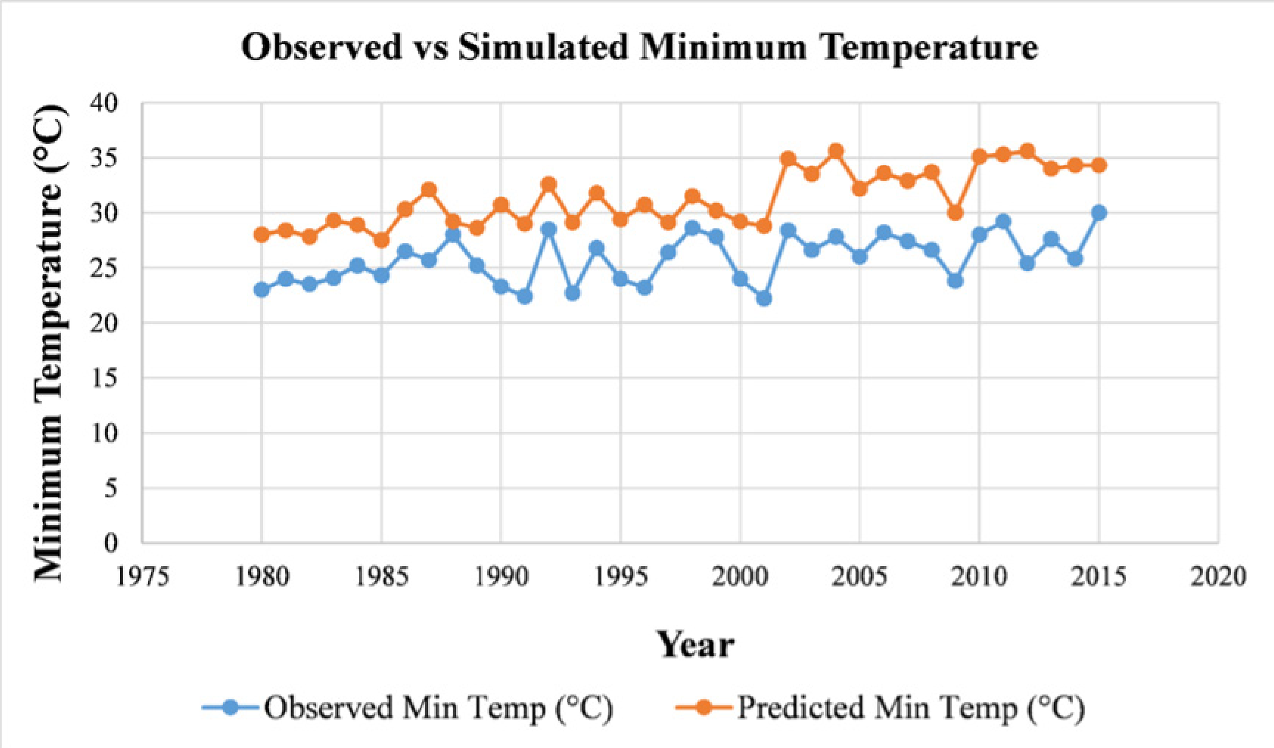

Figure 5. Observed and predicted minimum temperature before bias correction

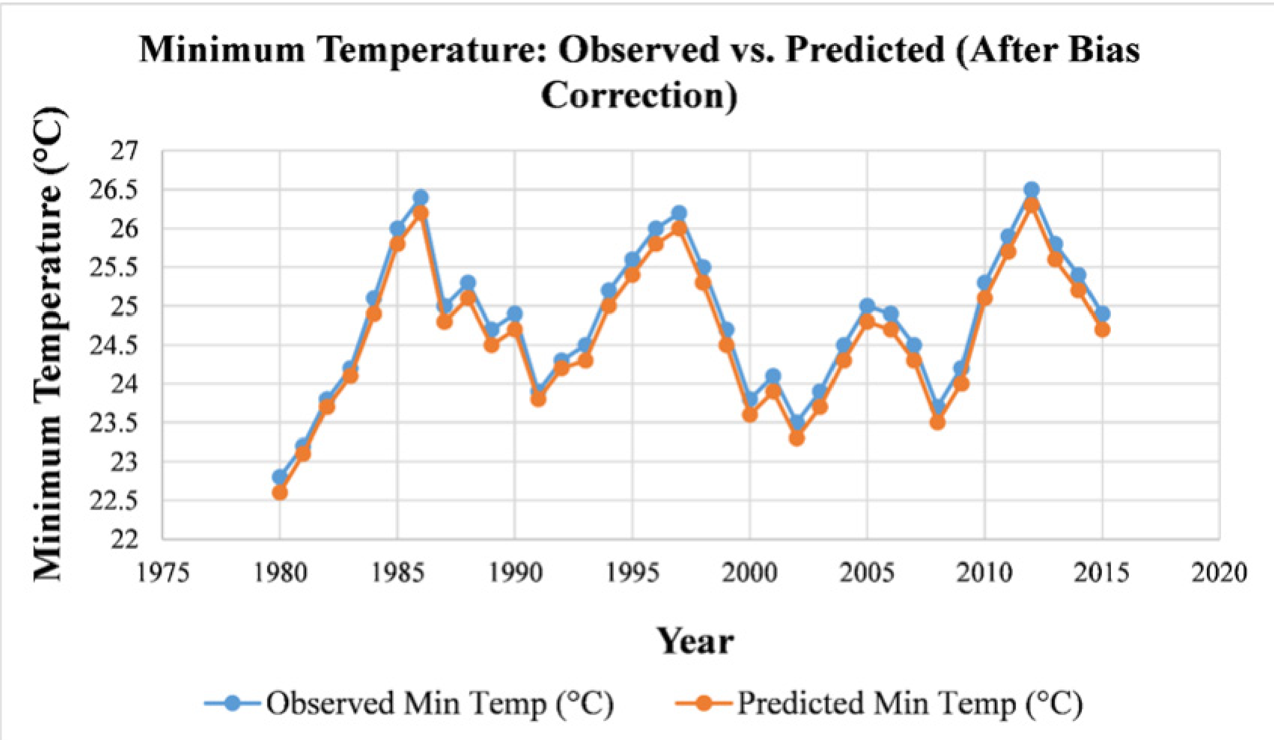

Figure 6. Observed and predicted minimum temperature trends after bias correction

Table 6. Precipitation trends revisited: Observed vs. simulated values with uncertainty before and after bias correction

Year	Observed Precipitation (mm/day)	Predicted Precipitation Before Bias Correction (mm/day)	Predicted Precipitation After Bias Correction (mm/day)	Uncertainty Precipitation Before Correction (mm/day)	Uncertainty Precipitation
1980	10.5	15.5	11.1	±5.0	±0.6
1981	12.3	17.4	13	±5.1	±0.7
1982	11	16.2	11.8	±5.2	±0.8
1983	14.1	19.4	14.7	±5.3	±0.6
1984	13.6	19	14.1	±5.4	±0.5
1985	11.2	16.7	11.8	±5.5	±0.6
1986	12.8	18.4	13.5	±5.6	±0.7
1987	14	19.7	14.8	±5.7	±0.8
1988	13	18.8	13.9	±5.8	±0.9
1989	10.8	16.7	11.3	±5.9	±0.5
1990	11.4	17.4	12	±6.0	±0.6
1991	12.1	18.2	12.8	±6.1	±0.7
1992	11.9	18.1	12.5	±6.2	±0.6
1993	13.3	19.6	14.1	±6.3	±0.8
1994	12.5	18.9	13.2	±6.4	±0.7
1995	13.2	19.7	14	±6.5	±0.8
1996	11.3	17.9	12	±6.6	±0.7
1997	12.6	19.3	13.4	±6.7	±0.8
1998	12	18.8	12.7	±6.8	±0.7
1999	13.4	20.3	14	±6.9	±0.6
2000	13.1	20.1	13.7	±7.0	±0.6
2001	12.4	19.5	12.9	±7.1	±0.5
2002	11.1	18.3	11.6	±7.2	±0.5
2003	12.7	20	13.3	±7.3	±0.6
2004	12.9	20.3	13.4	±7.4	±0.5
2005	13.5	21	14.2	±7.5	±0.7
2006	12.8	20.4	13.3	±7.6	±0.5
2007	12	19.7	12.6	±7.7	±0.6
2008	13.1	20.9	13.6	±7.8	±0.5
2009	13.2	21.1	13.8	±7.9	±0.6
2010	13.4	21.4	14.1	±8.0	±0.7
2011	12.5	20.6	13.2	±8.1	±0.7
2012	13.3	13.5	13.9	±8.2	±0.6
2013	12.6	20.9	13.3	±8.3	±0.7
2014	13.2	21.6	13.8	±8.4	±0.6
2015	12	20.5	12.5	±8.5	±0.5

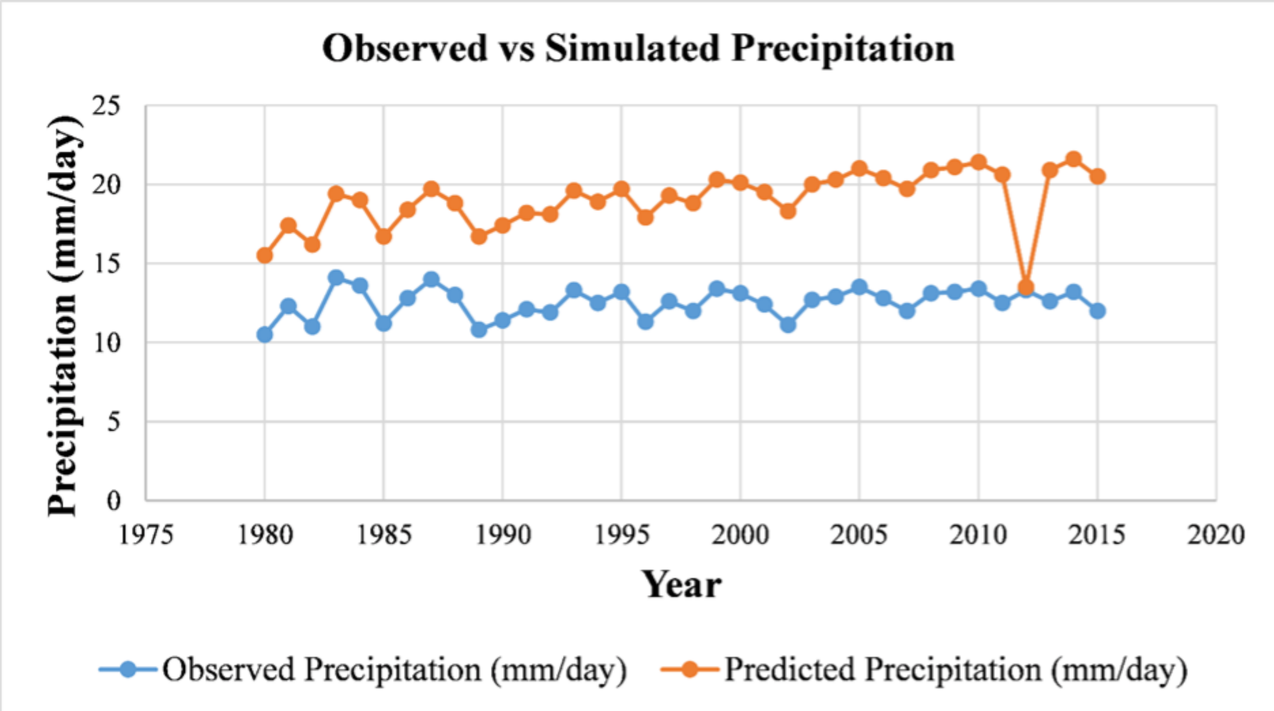

Figure 7. Observed and predicted precipitation patterns before bias correction

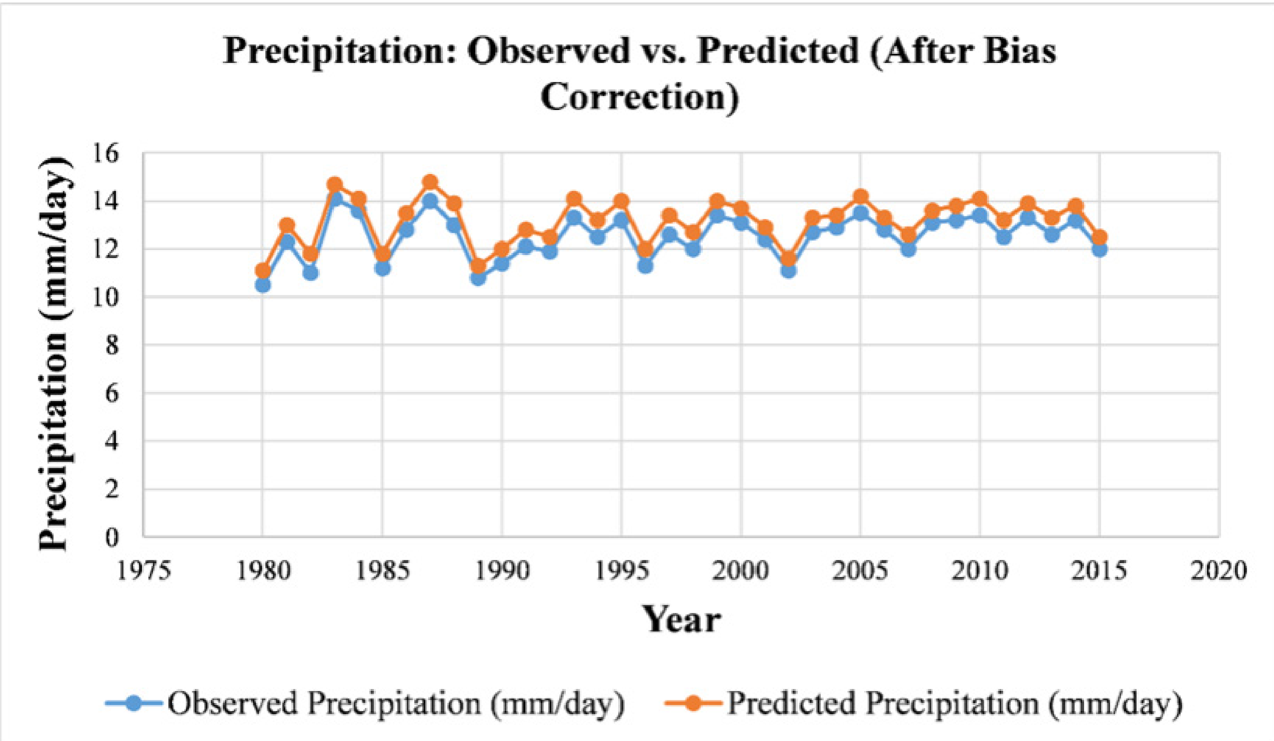

Figure 8. Observed and predicted precipitation patterns after bias correction

Observed Data, GCM Data & Bias Corrected Data for Calibration Period

The comparison of observed data, GCM (Global Circulation Model) projections, and bias-corrected data during the calibration period offers a thorough evaluation of how well the GCM simulates important climate variables, such as temperature and precipitation. This process computed several statistical metrics for the observed, GCM, and bias-corrected data, including the monthly mean, standard deviation, frequency of dry and wet days, Simple Precipitation Intensity Index (SDII), and maximum 1-day precipitation (RX1day). Figure 9 compares the monthly mean and standard deviation of precipitation, showcasing the close match between the bias-corrected data and the GCM with the observed values. By comparing the frequency of dry and wet days, Figure 10 further investigates precipitation extremes and provides insight into how well the model captures the variability in precipitation across time. Figure 11 analyzes severe precipitation events using the maximum 1-day precipitation (RX1day) and the SDII. This demonstrates how the bias-corrected data can more accurately depict the observed patterns of heavy rainfall.

Similar comparisons were done for temperature, with an emphasis on the monthly mean, standard deviation, and extreme temperature values, including the maximum value of the daily lowest temperature (TNx) and the minimum value of the daily maximum temperature (TXn). Figures 12 and 13 present the analysis and visualization of these temperature variables. Figure 12 displays the monthly mean, standard deviation, and TXn (minimum of daily maximum temperatures), while Figure 13 compares the monthly mean, standard deviation, and TNx (maximum of daily minimum temperatures) between the observed and modeled data. This thorough comparison evaluates the accuracy with which the GCM depicts temperature trends and whether the bias correction technique improves the simulation of extreme temperature events.

It also looks at the connection between the two datasets and quantifies the bias between the observed and GCM data. The results show that the bias correction procedure successfully lowers the differences between the observed and GCM data, improving agreement on the precipitation and temperature extremes' frequency and magnitude. Severe occurrences such as high temperatures and heavy rainfall, particularly well-represented in the bias-corrected data, are crucial for understanding climate variability and extremes. This improvement illustrates the significance of bias correction in improving the precision of climate model forecasts.

Results are shown for four regions: Dhaka, Sylhet, Cox's Bazar, and Rajshahi, in order to emphasize the bias correction's efficacy. In order to meet the paper's space constraints and demonstrate how well the bias correction method works in several geographic locations with various climates, these places were chosen. Both temperature and precipitation estimates are significantly more accurate using the bias-corrected data for these places, providing a more trustworthy picture of potential future climate conditions. This thorough comparison of observed, GCM, and bias-corrected data offers important information about how well the GCM model performs and how well the bias correction technique refines climate projections two factors that are crucial for making well-informed decisions about planning and policy related to climate change.

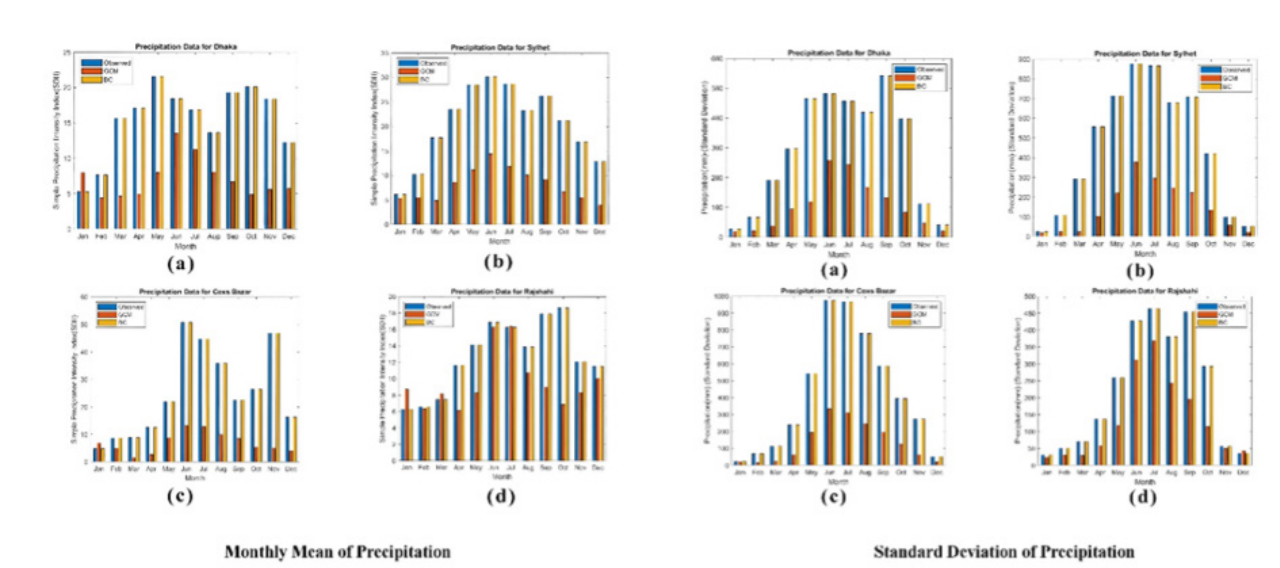

Figure 9. Monthly mean and standard deviation of precipitation: comparison between observed data, GCM projections, and bias-corrected results for (a) Dhaka, (b) Sylhet, (c) Cox's Bazar, and (d) Rajshahi

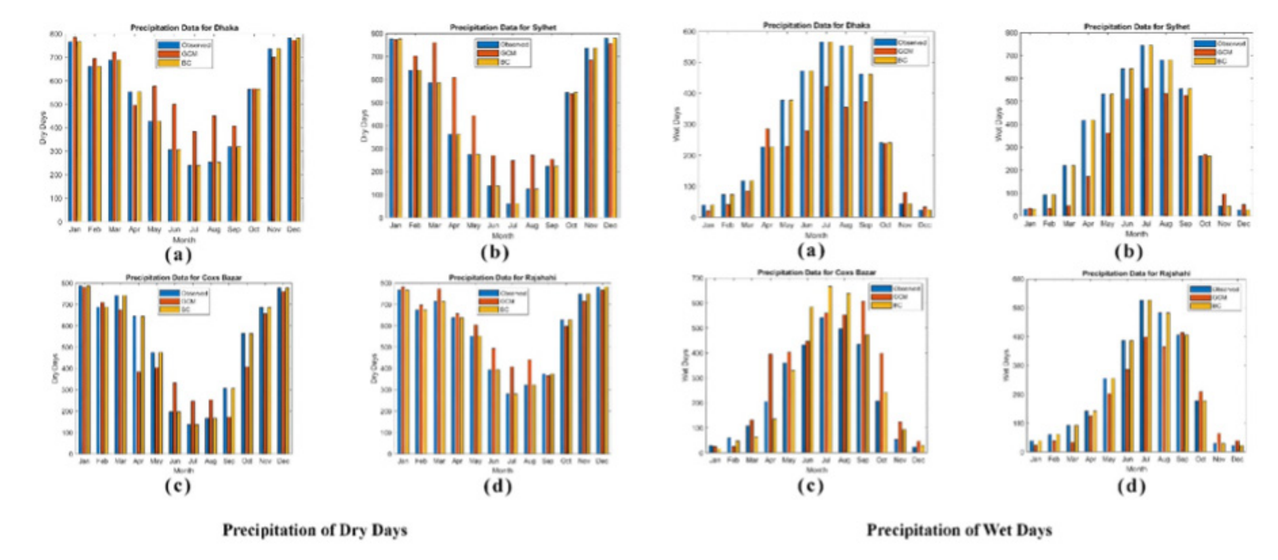

Figure 10. Precipitation comparison for dry and wet days: observed data, GCM projections, and bias-corrected results for (a) Dhaka, (b) Sylhet, (c) Cox's Bazar, and (d) Rajshahi

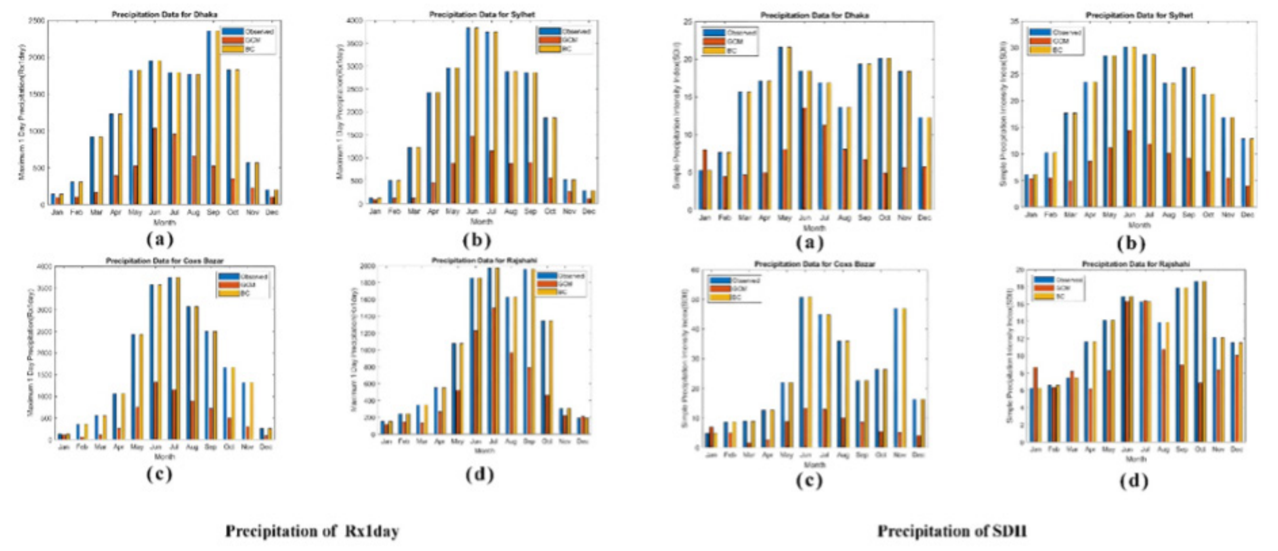

Figure 11. Comparison of maximum 1-day precipitation (Rx1day) and simple daily intensity index (SDII) across observed data, GCM projections, and bias-corrected results for (a) Dhaka, (b) Sylhet, (c) Cox's Bazar, and (d) Rajshahi

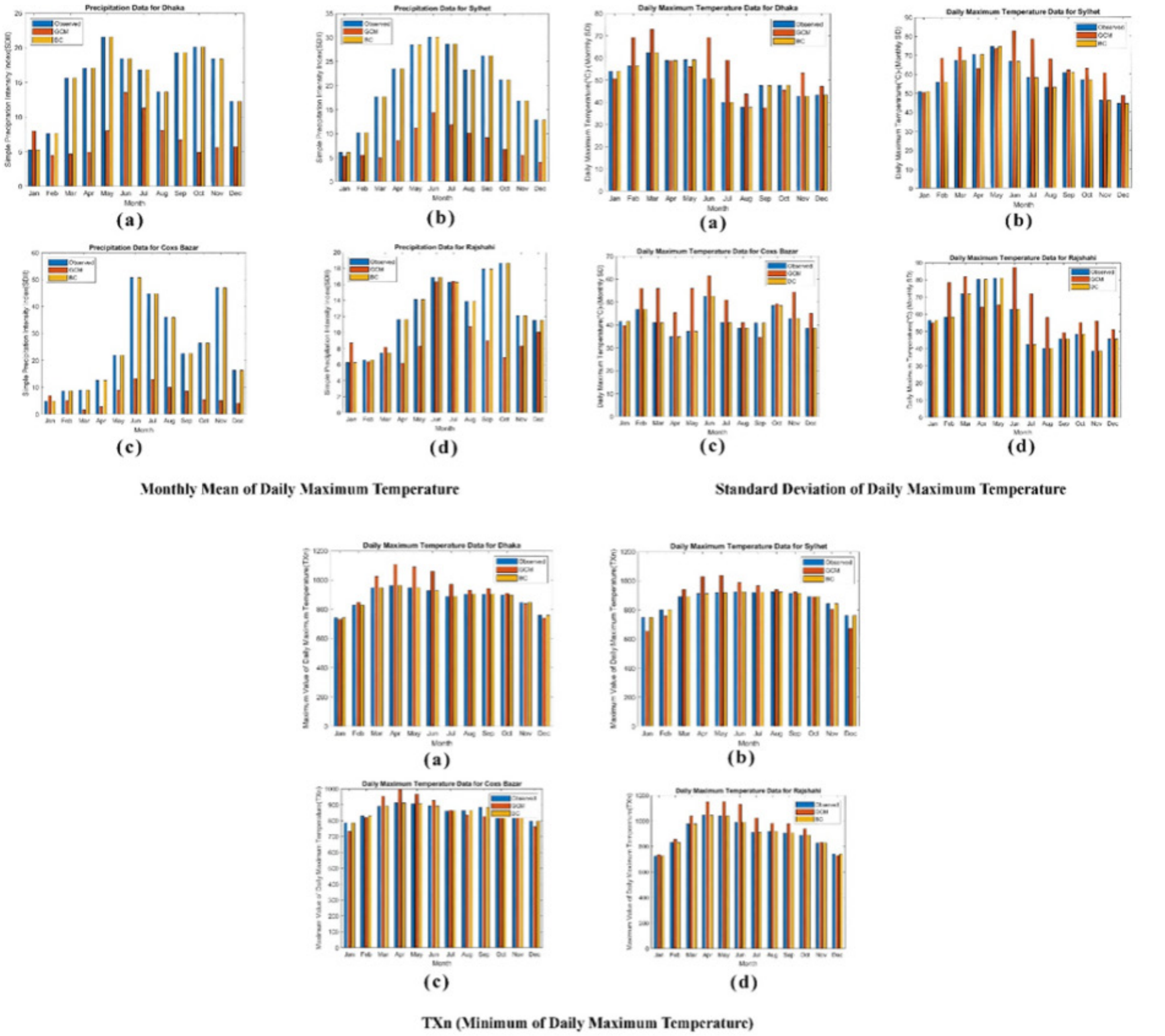

Figure 12. Evaluation of monthly mean, standard deviation, and TXn daily maximum temperature across observed data, GCM projections, and bias-corrected results for (a) Dhaka, (b) Sylhet, (c) Cox's Bazar, and (d) Rajshahi

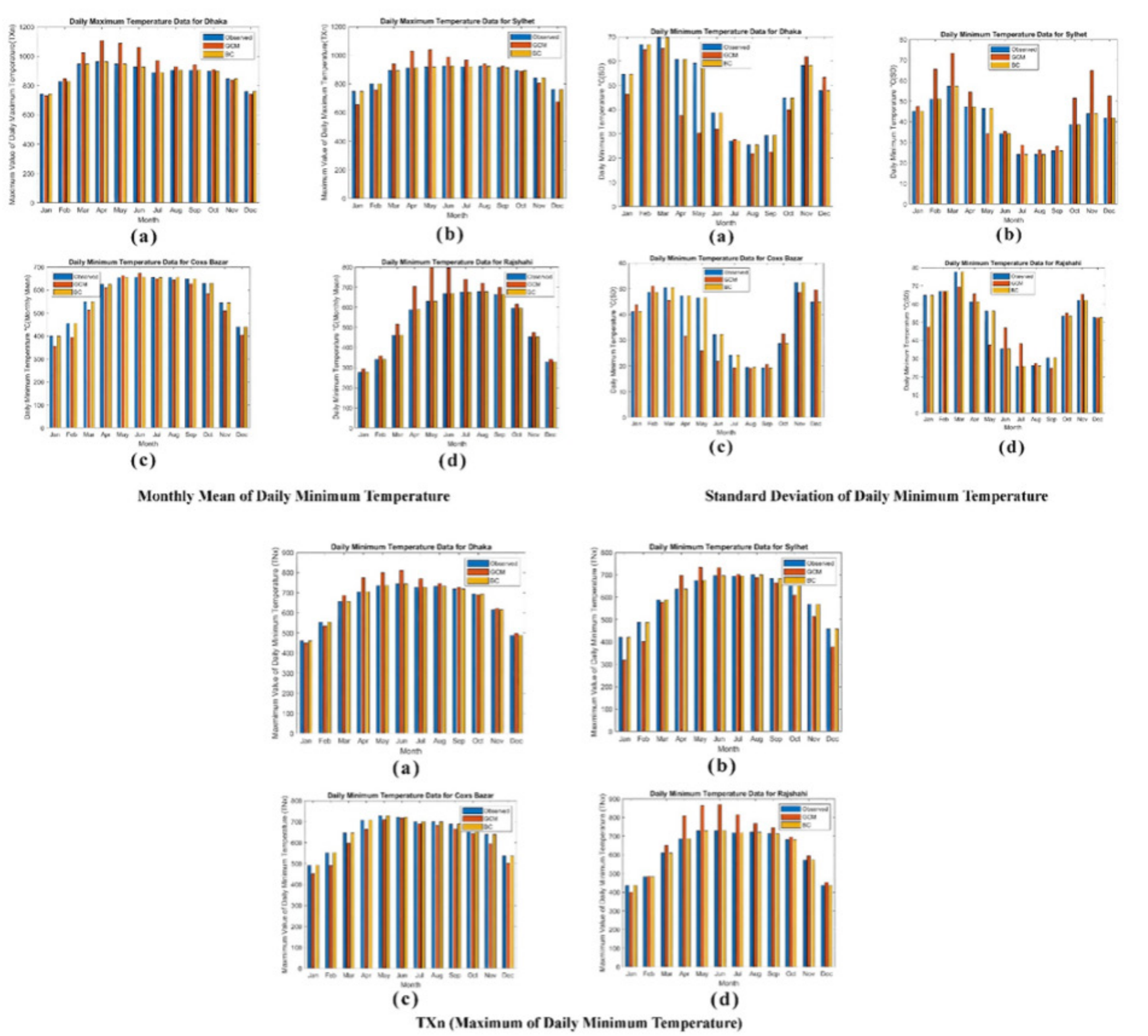

Figure 13. Assessment of monthly mean, standard deviation, and TNx of daily minimum temperature for observed data, GCM projections, and bias-corrected results in (a) Dhaka, (b) Sylhet, (c) Cox's Bazar, and (d) Rajshahi

Climate Projections for Precipitation and Temperature Using MPI-ESM-LR and MPI-ESM-MR Models

This section utilizes the MPI-ESM-LR and MPI-ESM-MR models to study the expected changes in temperature and precipitation. This study centered on climate scenarios based on RCP 4.5 and RCP 8.5, providing valuable perspectives on possible changes in climate trends for both moderate and high-emission scenarios. These forecasts aid in the understanding of potential regional variations in temperature and precipitation throughout time. Distinguishing between the Model for Interdisciplinary Research on Climate - Earth System Model (MPI-ESM-MR) and the Model for Interdisciplinary Research on Climate - Low Resolution (MPI-ESM-LR) is crucial for evaluating climate projections and their effects. The MPI-ESM-MR model generally functions at an elevated spatial resolution, providing more localized and detailed climate variables, rendering it appropriate for investigations necessitating high precision in regional evaluations [49]. Conversely, the MPI-ESM-LR model is less computationally intensive, employing a lower resolution while still offering valuable insights into large-scale climate patterns, especially in contexts where computational resources are constrained or when global-scale projections are paramount [50]. Both models, despite variations in resolution, are extensively utilized in climate modeling and provide distinct advantages contingent upon the scale of research [51].

MPI-ESM-LR model projections

-RCP 4.5 scenario

The RCP 4.5 scenario provides a moderate emissions route, providing forecasts for both historical and future climate conditions. Using the MPI-ESM-LR climate model, Figure 14 (Precipitation) compares Bangladesh's historical and predicted precipitation trends. The future scenario was predicted on the RCP 4.5 emissions trajectory for 2020–2045, whereas the historical data spans the years 1980–2005. Historically, the majority of Bangladesh had relatively little precipitation, with the exception of the northeastern and southeast areas, where the largest rainfall (red) was recorded in towns like Sylhet and Chittagong. But now, significant changes in precipitation patterns are indicated by the future estimate under RCP 4.5. According to the model, precipitation is expected to rise in the central areas (yellow), including Dhaka and Barishal. This may increase the likelihood of flooding and waterlogging in some regions. In contrast, the southwestern area, which includes Khulna and Rajshahi, might see less precipitation (green), which might make the drought and water shortage worse. These precipitation fluctuations may therefore have a substantial effect on Bangladesh's agriculture, water resources, and ecosystem. More rainfall in certain areas may result in erosion and flooding, while less rainfall in others may impact crop productivity and freshwater availability. Furthermore, the frequency and severity of extreme weather events like droughts and cyclones may be impacted by modifications in precipitation patterns.

According to Figure 14 (Daily Maximum Temperature), daily maximum temperatures of Bangladesh are expected to rise sharply under RCP 4.5. The temperature in Khulna and Rajshahi used to be between 31 and 32°C (brown), while the majority of other places in Bangladesh had temps between 30 and 31°C (yellow). However, according on the future scenario, Khulna and the area surrounding it will see temperatures above 32°C (red), with cities like Dhaka, Chittagong, and Sylhet being among the numerous new places where temperatures will rise above 30°C (brown). In certain areas, the implications of urban heat islands, public health, and agriculture might all be severely impacted by this increase.

The daily minimum temperatures of Bangladesh are expected to rise sharply under RCP 4.5, as seen in Figure 14 (Daily Minimum Temperature). The majority of places have historically seen temperatures between 21 and 22°C (yellow), with others, like Sylhet, Rangpur and Rajshahi, experiencing temperatures as low as 20 to 21°C (green). Nonetheless, the future scenario projects a significant increase in regions with temperatures above 22°C (red), including cities like Dhaka, Khulna, Barishal and Chittagong. Agriculture, public health, and general thermal comfort in these areas may all be negatively impacted by this increase.

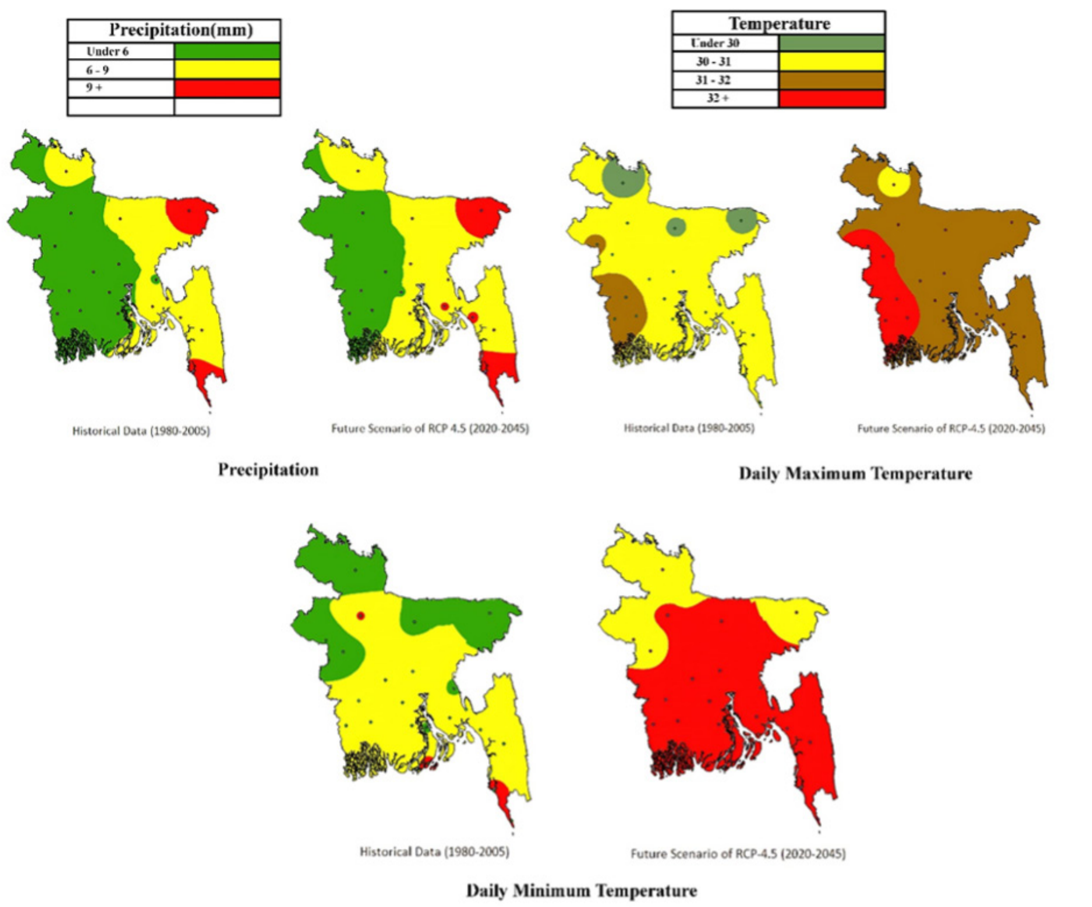

Figure 14. Historical vs projected precipitation and daily temperature (maximum and minimum) data under the RCP 4.5 scenario using the MPI-ESM-LR model, including distribution analysis

-RCP 8.5 scenario

Climate variables were predicted to alter significantly in the RCP 8.5 scenario. While both RCP 4.5 and RCP 8.5 were expected to result in a significant increase in daily precipitation in Bangladesh, the amount of the increase was greater under RCP 8.5. Figure 15 (Precipitation) indicates that the majority of regions had lower precipitation levels (green and yellow), though places like Sylhet and Chittagong had higher rainfall (red) in the past. The red areas are predicted to moderately expand under RCP 4.5, indicating higher precipitation in numerous areas. But under RCP 8.5, the yellow area extension is much more noticeable, indicating a considerable rise in precipitation nationwide, particularly in major cities like Dhaka, Barishal and Rangpur. In the future, the red area will likewise grow.

Bangladesh's daily maximum temperatures were expected to rise considerably under both RCP 4.5 and RCP 8.5, but the extent of the increase was greater under RCP 8.5. In Figure 15 (Daily Maximum Temperature), temperatures in most places were in between 30 to 31°C (yellow), with certain places, including Sylhet and Rangpur, experiencing under 30°C in the past. The red areas are now predicted to expand moderately under RCP 4.5, showing higher temperatures in many areas. The growth of red areas, however, is noticeably more noticeable under RCP 8.5, indicating a considerable rise in the nation's maximum temperatures. In certain areas, the implications of urban heat islands, agriculture, and public health might all be severely impacted by this increase. Almost the entire map turns red (above 32°C temperature) in the future scenario under RCP 8.5, signifying a sharp and pervasive rise in Bangladesh's daily maximum temperatures. This indicates that the probability of heat waves will be much higher than in the past, endangering the health of vulnerable groups. Given that many crops are vulnerable to high temperatures, the agriculture industry may also be negatively impacted. More severe heat conditions could result from the exacerbation of the urban heat island effect in places like Dhaka and Chittagong.

According to Figure 15 (Daily Minimum Temperature), Bangladesh's daily minimum temperatures will climb dramatically under both RCP 4.5 and RCP 8.5, with the increase being more pronounced under RCP 8.5. Under RCP 8.5, the entire map turns red, indicating extreme heat waves across the nation, whereas historically, most regions saw temperatures between 21 and 22°C (yellow). Although there may still be some green in places like Sylhet and Rangpur, the general trend is toward much higher minimum temperatures.

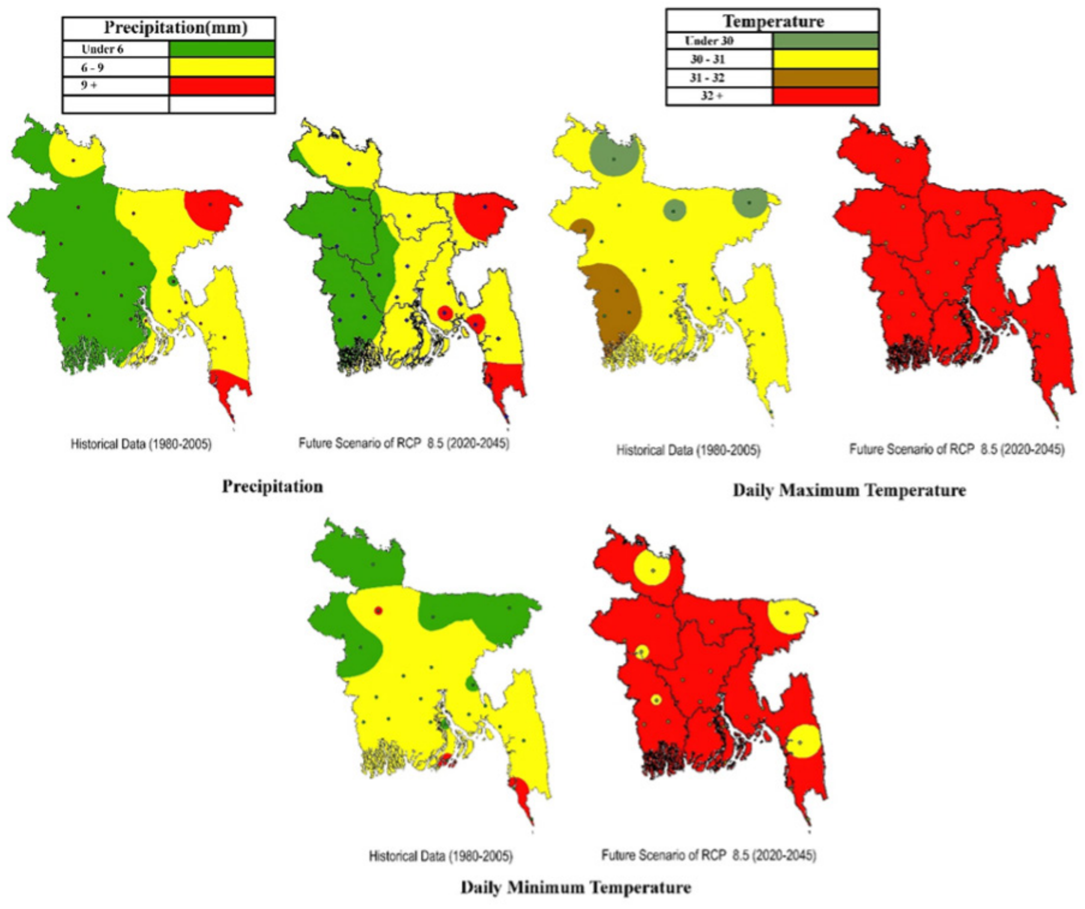

Figure 15. Historical and projected precipitation, daily maximum, and minimum temperature data under the RCP 8.5 scenario using the MPI-ESM-LR model, accompanied by spatial distribution maps to illustrate variability

MPI-ESM-MR Model Projections

-RCP 4.5 scenario

The MPI-ESM-MR model provided informative climate projections for the RCP 4.5 scenario. Through the use of distribution maps, these results improved the comprehension of the spatial and temporal dynamics of precipitation and temperature under the RCP 4.5 scenario using the MPI-ESM-MR model. According to Figure 16 (Precipitation), RCP 4.5 is expected to drastically alter Bangladesh's precipitation patterns. In the past, Sylhet and Chittagong had higher rainfall (red), whereas the other of regions had lower precipitation levels (green and yellow). According to the future scenario, the southwestern region, which includes Khulna, may see less precipitation (more green areas), while the central and northern regions are expected to have more precipitation (more yellow areas). Bangladesh's environment, agriculture, and water supplies may all be significantly impacted by these changes.

Figure 16 (Daily Maximum Temperature) illustrates how Bangladesh's daily maximum temperatures are expected to rise dramatically under RCP 4.5. In the past, temperatures in most places were below 32°C (yellow), with select places, including Khulna and Rajshahi, experiencing 31-32°C (brown). But according to the future scenario, brown areas will significantly expand, suggesting a sharp rise in the whole nation's maximum temperatures. The concentration of red patches in these places suggests that they are likely to face some of the worst heat waves, especially in Chittagong, Khulna, and the Rajshahi border region. This highlights the necessity of focused adaption strategies.

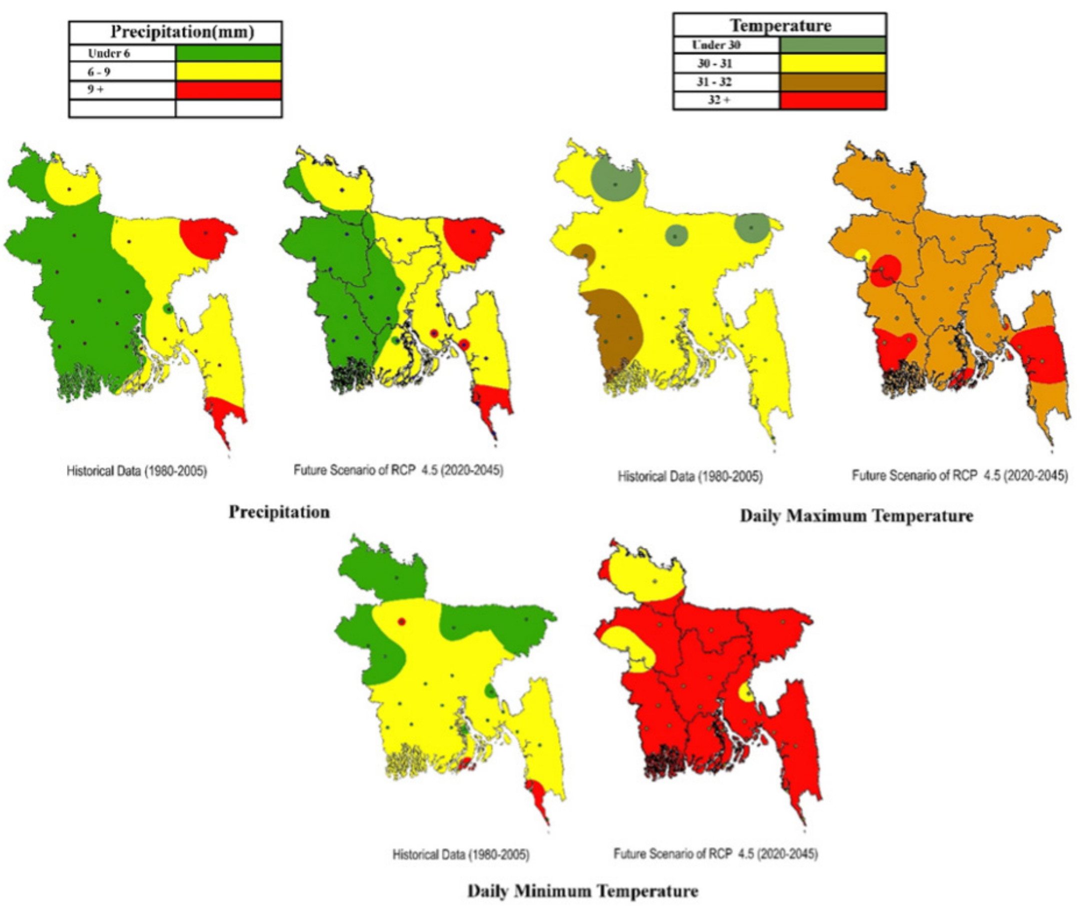

Figure 16. Historical vs future projections of precipitation, daily maximum, and minimum temperatures under the RCP 4.5 scenario using the MPI-ESM-MR model, with spatial distribution maps depicting variability

Bangladesh's daily minimum temperatures are expected to rise sharply under RCP 4.5, as seen in Figure 16 (Daily Minimum Temperature). The majority of places have historically seen temperatures between 21 and 22°C (yellow), with others, like Sylhet and Rangpur, experiencing temperatures as low as 20 to 21°C (green). But according to the future scenario, red areas will proliferate significantly, suggesting a sharp rise in the nation's minimum temperatures, notably in places like Dhaka, Chittagong, and Sylhet. The general tendency is toward noticeably higher minimum temperatures, even though there may be isolated pockets of comparatively milder weather, especially in the northern regions like Rangpur and Rajshahi. Agriculture, public health, and general thermal comfort in these areas may all be negatively impacted by this increase.

-RCP 8.5 scenario

The MPI-ESM-MR model provided a complete assessment of expected climate changes in the RCP 8.5 scenario. Figure 17 (Precipitation) illustrates how RCP 8.5 is expected to drastically alter Bangladesh's precipitation patterns. In the past, Sylhet and Chittagong had higher rainfall (red), whereas the other of regions had lower precipitation levels (green and yellow). According to the future scenario, there will be a little increase of precipitation nationwide, with yellow areas - including in city like Dhaka - growing considerably. Higher hazards of floods and waterlogging in some areas could result from this.

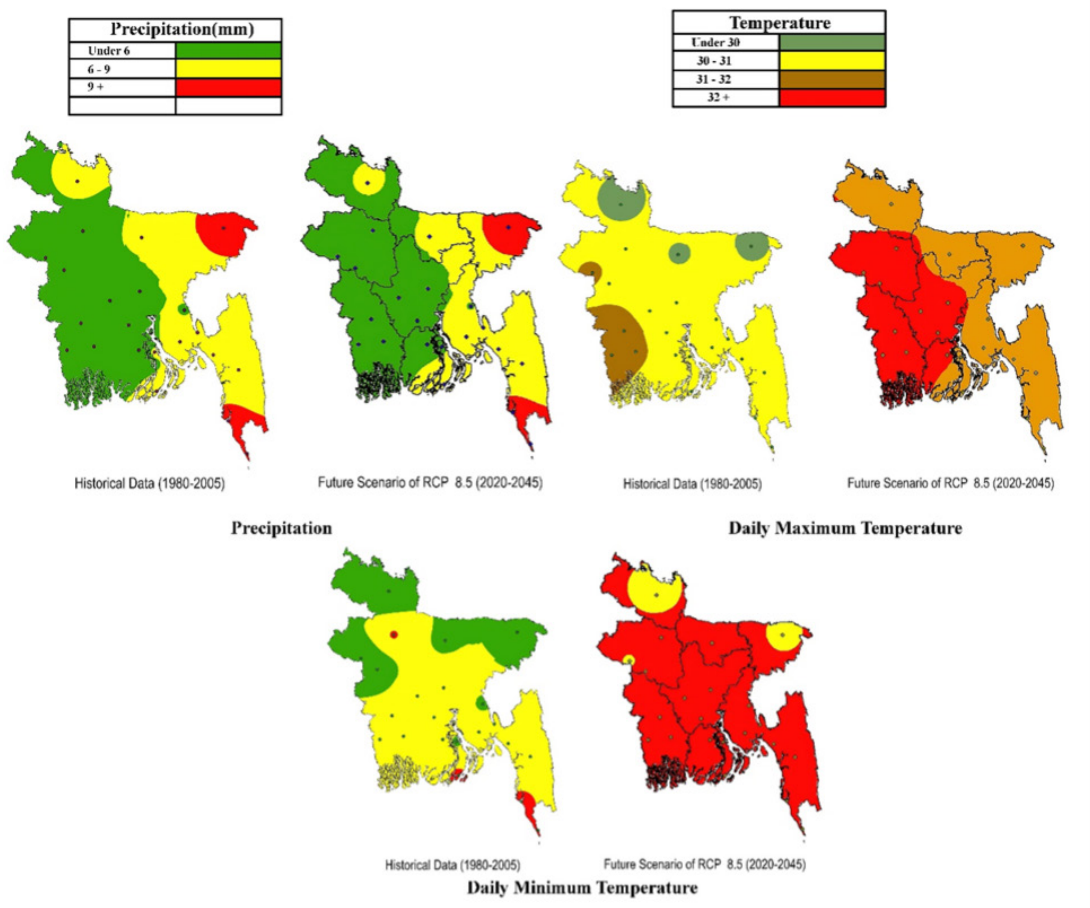

Figure 17. Historical and projected precipitation, daily maximum, and minimum temperature data under the RCP 8.5 scenario using the MPI-ESM-MR model, with spatial distribution maps highlighting variability

According to Figure 17 (Daily Maximum Temperature), Bangladesh's daily maximum temperatures are expected to rise sharply under RCP 8.5. In the past, some places, including Sylhet and Rangpur, had temperatures below 30°C (green), while other places, like Khulna and Rajshahi, had temperatures between 31 and 32°C (brown). But the future map clearly illustrates a pattern, with the left half of Bangladesh in red and the right half mostly in brown. This implies that, in comparison to the northern and western regions (Rajshahi, Dhaka, Khulna, and Barisal), the southern and eastern regions (Chittagong, Sylhet, and Rangpur) might have somewhat colder temperatures. Overall, nevertheless, considerable warming is anticipated in all regions. According to Figure 17 (Daily Minimum Temperature), Bangladesh's daily minimum temperatures are expected to rise sharply under RCP 8.5. Previously, most locations experienced temperatures in the range of 21 to 22°C (yellow), while some, such as Sylhet and Rangpur, witnessed temperatures as low as 20 to 21°C (green). However, even in places like Dhaka and Chittagong, the future forecast predicts that red areas would greatly increase, indicating a major rise in the country's minimum temperatures. The main trend is towards much higher minimum temperatures, which poses hazards to agriculture, health, and thermal comfort in these places, even though there may be isolated pockets of comparatively colder areas, especially in the northern regions like Rangpur and Sylhet.

These figures and accompanying distribution maps help to better understand the climate dynamics of the area. They provide important information on the anticipated temporal and spatial shifts in precipitation and temperature patterns under the RCP 8.5 scenario.

Significant increases in Bangladesh's maximum and minimum temperatures were regularly predicted by both models. A more severe warming trend was indicated under the higher emissions scenario, as the amount of the increase was generally bigger under RCP 8.5 than under RCP 4.5. Furthermore, both models predicted variations in precipitation patterns, with some areas seeing higher rainfall and others seeing lower rainfall. The two models may differ in the precise patterns and levels of change.

Although both models offer useful information, their projections differ in a few ways. To obtain a more thorough grasp of Bangladesh's future climatic trends, it is crucial to take these variations into account and refer to other climate models. Furthermore, the estimated amount of climate change is greatly impacted by the scenario selected (RCP 4.5 or RCP 8.5). Compared to RCP 4.5, RCP 8.5 depicts a greater emissions scenario with more severe climatic impacts.

In summary, the MPI-ESM-LR and MPI-ESM-MR models suggest that Bangladesh is likely to undergo substantial climatic changes in the future, with the severity of these effects being dependent upon the chosen emissions scenario. It is essential to consider the outcomes of both models alongside with those of other climate models in order to inform policy decisions and adaptation strategies. The results of this investigation can be used to develop critical adaptation strategies for the effects of climate change on Bangladesh. For instance, if sea levels rise, the results will direct migration plans to safer places and coastal protection measures like embankments. Agricultural adaptation measures like introducing salt-resistant crops and enhancing irrigation infrastructure will be supported by predictions of changing rainfall and temperature patterns. Additionally, the study will support urban resilience initiatives, especially in Dhaka, by aiding in the development of heat-resistant infrastructure and flood control systems. The results will also support climate finance initiatives, assisting in obtaining foreign money to put these plans into action.

CONCLUSIONS

The goal of this research is to reduce biases in Global Circulation Models (GCMs) in order to increase the accuracy of climate projections for Bangladesh. The study uses observed data from 22 weather stations and future projections from the MPI-ESM-LR and MPI-ESM-MR GCMs under RCP 4.5 and 8.5 scenarios to investigate how climate change affects temperature and precipitation. The study compares simulated and observed weather data and uses a variety of methods, such as linear scaling and delta change correlation, to increase the accuracy of climate forecasts. Initially, five bias correction techniques are used on the Sylhet station dataset to fix the biases between observed and GCM-simulated data. The delta change method is tested and found to be the most successful; it is then used for all 22 stations' data. When the accuracy of the corrected data is assessed using the Root Mean Square Error (RMSE), the delta change approach produced an RMSE value of zero, which signified a perfect fit between the corrected and observed data. Following bias correction, future climate predictions are produced for the 2020–2045 period for both RCP 4.5 and RCP 8.5 scenarios for temperature and precipitation across the 22 stations. This made it possible to comprehend the two emissions scenarios' effects on future climate trends more clearly. The accuracy of the GCM data is significantly improved by the bias correction procedure. The findings demonstrate that compared to the original GCM data, the bias-corrected data aligns considerably more closely with the observed data. Extreme temperature and precipitation events, which are essential for comprehending the effects of climate change, are projected more realistically as a result of this modification. Maximum and minimum temperatures in Bangladesh are expected to rise significantly according to both GCM models, with the RCP 8.5 scenario showing a more pronounced warming trend than RCP 4.5. Changes in precipitation patterns are also predicted, with some areas seeing more rainfall and others seeing less. Since different parts of Bangladesh may suffer different climatic shifts, these variances show the complexity of the effects of climate change. The study's findings highlight the significant impacts of climate change on Bangladesh, including increased crop failures, water scarcity, and more frequent floods or droughts. These findings highlight the significance of creating effective plans for climate adaptation and mitigation. Informing national and regional climate action plans, the study highlights the contrasts between the two emissions scenarios and offers trustworthy statistics to planners and politicians. The study advances the accuracy of climate model projections, which helps us better comprehend Bangladesh's future climatic trends and prepares the country to deal with the challenges posed by climate change. Because the RCP 4.5 and RCP 8.5 scenarios differ greatly, policymakers must prioritize adaptation policies that address the more drastic changes anticipated under the RCP 8.5 scenario. This can entail supporting crop diversification to reduce possible agricultural losses, improving water management systems to handle shifting precipitation patterns, and fortifying infrastructure to handle increased flooding. Bangladesh's national climate action plans must incorporate these insights for effective climate adaptation and mitigation policies.

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DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

USE OF AI FOR WRITING ASSISTANCE

Not declared.

ETHICS

There are no ethical issues with the publication of this manuscript.

REFERENCES

1. World Bank Group, Global Financial Development Report 2014: Financial Inclusion, vol. 2. Washington, DC, USA: World Bank Publications, 2013.
2. S. Shahid, "Rainfall variability and the trends of wet and dry periods in Bangladesh," International Journal of Climatology, vol. 30, no. 15, pp. 2299–2313, 2010.

3. S. Huq, "Climate change and Bangladesh," Science, vol. 294, no. 5547, pp. 1617–1617, 2001.
4. E.-S. Im, J. S. Pal, and E. A. Eltahir, "Deadly heat waves projected in the densely populated agricultural regions of South Asia," Science Advances, vol. 3, no. 8, e1603322, 2017.
5. C. Raymond, T. Matthews, and R. M. Horton, "The emergence of heat and humidity too severe for human tolerance," Science Advances, vol. 6, no. 19, eaaw1838, 2020.
6. S. Kang, J. S. Pal, and E. A. Eltahir, "Future heat stress during Muslim pilgrimage (Hajj) projected to exceed 'extreme danger' levels," Geophysical Research Letters, vol. 46, no. 16, pp. 10094–10100, 2019.
7. S. C. Sherwood and M. Huber, "An adaptability limit to climate change due to heat stress," Proceedings of the National Academy of Sciences, vol. 107, no. 21, pp. 9552–9555, 2010.
8. U. Ghumman and J. Horney, "Characterizing the impact of extreme heat on mortality, Karachi, Pakistan, June 2015," Prehospital and Disaster Medicine, vol. 31, no. 3, pp. 263–266, 2016.
9. J. Gettleman, "More than 1,000 died in South Asia floods this summer," The New York Times, 2017.
10. M. A. Mojid, "Climate change-induced challenges to sustainable development in Bangladesh," IOP Conference Series: Earth and Environmental Science, vol. 423, no. 1, p. 012001, 2020. doi: 10.1088/1755-1315/423/1/012001.
11. E. Alam, A.-E. E. Hridoy, S. M. S. H. Tusher, A. R. M. T. Islam, and M. K. Islam, "Climate change in Bangladesh: Temperature and rainfall climatology of Bangladesh for 1949–2013 and its implication on rice yield," PLOS ONE, vol. 18, no. 10, Oct. 2023, doi: 10.1371/journal.pone.0292668.
12. Y. Hijioka, E. Lin, J. J. Pereira, R. T. Corlett, X. Cui, G. Insarov, and W. Wang, "IPCC Fifth Assessment Report: Chapter 24 Asia," in Climate Change 2014-Impacts, Adaptation and Vulnerability: Part B: Regional Aspects, Contribution of Working Group II to the IPCC Fifth Assessment Report, 2014, pp. 1327-1370.
13. B. C. Tumsa, "Performance assessment of six bias correction methods using observed and RCM data at upper Awash basin, Oromia, Ethiopia," Journal of Water and Climate Change, vol. 13, no. 2, pp. 664–683, Nov. 2022, doi: 10.2166/wcc.2021.181
14. N. Devineni and A. Sankarasubramanian, "Improving the prediction of winter precipitation and temperature over the continental United States: Role of the ENSO state in developing multimodel combinations," Monthly Weather Review, vol. 138, no. 6, pp. 2447–2468, 2010. doi: 10.1175/2009MWR3112.1.
15. H. Guo, A. Bao, T. Chen, G. Zheng, Y. Wang, L. Jiang, and P. De Maeyer, "Assessment of CMIP6 in simulating precipitation over arid Central Asia," Atmospheric Research, vol. 252, p. 105451, 2021. doi: 10.1016/j.atmosres.2021.105451.
16. A. H. Nury, A. Sharma, L. Marshall, and I. Cordery, "Modelling climate change impacts on the Brahmaputra streamflow resulting from changes in snowpack attributes," Journal of Hydrology, vol. 603, p. 126998, 2021. doi: 10.1016/j.jhydrol.2021.126998.
17. E. Hawkins and R. Sutton, "The potential to narrow uncertainty in projections of regional precipitation change," Climate Dynamics, vol. 37, pp. 407–418, 2011.
18. S. Eghdamirad, F. Johnson, and A. Sharma, "How reliable are GCM simulations for different atmospheric variables?" Climatic Change, vol. 145, pp. 237–248, 2017.
19. F. Woldemeskel, A. Sharma, B. Sivakumar, and R. Mehrotra, "An error estimation method for precipitation and temperature projections for future climates," Journal of Geophysical Research: Atmospheres, vol. 117, no. D22, 2012.
20. M. Jakob Themeßl, A. Gobiet, and A. Leuprecht, "Empirical-statistical downscaling and error correction of daily precipitation from regional climate models," International Journal of Climatology, vol. 31, no. 10, pp. 1530–1544, 2011.
21. C. Piani, J. Haerter, and E. Coppola, "Statistical bias correction for daily precipitation in regional climate models over Europe," Theoretical and Applied Climatology, vol. 99, pp. 187–192, 2010.
22. O. Laccourreye and H. Maisonneuve, "French scientific medical journals confronted by developments in medical writing and the transformation of the medical press," Annals of Otology, Rhinology & Laryngology, 2019, doi: 10.1016/j.anorl.2019.09.002.
23. M. Shrestha, S. C. Acharya, and P. K. Shrestha, "Bias correction of climate models for hydrological modelling – are simple methods still useful?," Meteorological Applications, vol. 24, no. 4, pp. 484–493, Jun. 2017, doi: 10.1002/met.1655.
24. G. V. Tschöke, N. S. Kruk, P. I. B. de Queiroz, S. C. Chou, and W. C. de Sousa Junior, "Comparison of two bias correction methods for precipitation simulated with a regional climate model," Theoretical and Applied Climatology, vol. 127, pp. 841–852, Nov. 2015, doi: 10.1007/s00704-015-1577-x.
25. R. Beyer, M. Krapp, and A. Manica, "An empirical evaluation of bias correction methods for palaeoclimate simulations," Climate of the Past, vol. 16, no. 8, pp. 1493–1510, Aug. 2020, doi: 10.5194/cp-16-1493-2020.
26. H. Brammer, "Bangladesh's dynamic coastal regions and sea-level rise," Climate Risk Management, vol. 1, pp. 51–62, 2014.
27. H. Imran, J. Kala, S. Uddin, A. S. Islam, and N. Acharya, "Spatiotemporal analysis of temperature and precipitation extremes over Bangladesh using a novel gridded observational dataset," Weather and Climate Extremes, vol. 39, p. 100544, 2023.
28. H. T. Islam, A. R. M. T. Islam, S. Shahid, G. M. Alam, J. C. Biswas, M. M. Rahman, D. K. Roy, and M. Kam-

ruzzaman, "Future precipitation projection in Bangladesh using SimCLIM climate model: A multimodel ensemble approach," International Journal of Climatology, vol. 42, no. 13, pp. 6716–6740, 2022.
29. S. Shahid, "Trends in extreme rainfall events of Bangladesh," Theoretical and Applied Climatology, vol. 104, pp. 489–499, 2011.
30. N. C. Dey, R. Saha, M. Parvez, S. K. Bala, A. S. Islam, J. K. Paul, and M. Hossain, "Sustainability of groundwater use for irrigation of dry-season crops in northwest Bangladesh," Groundwater for Sustainable Development, vol. 4, pp. 66–77, 2017.
31. M. Kamruzzaman, S. Shahid, A. T. Islam, S. Hwang, J. Cho, M. A. U. Zaman, M. Ahmed, M. M. Rahman, and M. B. Hossain, "Comparison of CMIP6 and CMIP5 model performance in simulating historical precipitation and temperature in Bangladesh: A preliminary study," Theoretical and Applied Climatology, vol. 145, pp. 1385–1406, 2021.
32. S. Sinharay, H. S. Stern, and D. Russell, "The use of multiple imputation for the analysis of missing data," Psychological Methods, vol. 6, no. 4, p. 317, 2001.
33. United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP), "Disasters in Asia and the Pacific: 2015 year in review," United Nations ESCAP Digital Repository, 2015. [Online]. Available: https://repository.unescap.org/handle/20.500.12870/4825.
34. H. Imran, J. Kala, S. Uddin, A. S. Islam, and N. Acharya, "Spatiotemporal analysis of temperature and precipitation extremes over Bangladesh using a novel gridded observational dataset," Weather and Climate Extremes, vol. 39, p. 100544, 2023.
35. S. Gunavathi and R. Selvasidhu, "Assessment of various bias correction methods on precipitation of regional climate model and future projection," SASTRA University School of Civil Engineering, pp. 1–11, 2021. [Online]. Available: https://doi.org/10.21203/rs.3.rs-339080/v1.
36. A. V. Ines, K. Honda, A. D. Gupta, P. Droogers, and R. S. Clemente, "Combining remote sensing-simulation modeling and genetic algorithm optimization to explore water management options in irrigated agriculture," Agricultural Water Management, vol. 83, no. 3, pp. 221–232, 2006. https://doi.org/10.1016/j.agwat.2005.12.006.
37. C. Teutschbein and J. Seibert, "Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods," Journal of Hydrology, vol. 456, pp. 12–29, 2012.
38. S. Nepal and A. B. Shrestha, "Impact of climate change on the hydrological regime of the Indus, Ganges, and Brahmaputra River basins: A review of the literature," International Journal of Water Resources Development, vol. 31, no. 2, pp. 201–218, 2015. Available: https://doi.org/10.1080/07900627.2015.1030494.
39. M. Méndez, Climate change from the streets: How conflict and collaboration strengthen the environmental justice movement. New Haven, CT: Yale University Press, 2020.
40. D. Kim, J. Lee, J. Yang, J. W. Kim, V. N. Kim, and H. Chang, "The architecture of SARS-CoV-2 transcriptome," Cell, vol. 181, no. 4, pp. 914–921.e10, 2020. doi: 10.1016/j.cell.2020.04.01
41. A. Ruiter, "Delta-change approach for CMIP5 GCMs," Trainee Report, Royal Netherlands Meteorological Institute, 2012.
42. O. Räty, J. Räisänen, and J. S. Ylhäisi, "Evaluation of delta change and bias correction methods for future daily precipitation: Intermodel cross-validation using ENSEMBLES simulations," Climate Dynamics, vol. 42, no. 9-10, pp. 2130-2148, 2014. https://doi.org/10.1007/s00382-014-2130-8.
43. A. Gago-Silva, I. Gunderson, S. Goyette, and A. Lehmann, "Delta-method applied to the temperature and precipitation time series - An example," 2012. https://doi.org/10.13140/RG.2.1.3301.2882.
44. K. Riahi, S. Rao, V. Krey, P. Rafaj, and others, "RCP 8.5 A scenario of comparatively high greenhouse gas emissions," Climatic Change, vol. 109, no. 1, pp. 33–57, 2011. https://doi.org/10.1007/s10584-011-0149-y.
45. S. Kobayashi, Y. Ota, Y. Harada, A. Ebita, M. Moriya, H. Onoda, H. Kamahori, C. Kobayashi, H. Endo, K. Miyaoka, and K. Takahashi, "The JRA-55 Reanalysis: General specifications and basic characteristics," Journal of the Meteorological Society of Japan, vol. 93, no. 1, pp. 5–48, 2015. https://doi.org/10.2151/jmsj.2015-001.
46. L. Crochemore, M.-H. Ramos, and F. Pappenberger, "Bias correcting precipitation forecasts to improve the skill of seasonal streamflow forecasts," Hydrology and Earth System Sciences, vol. 20, no. 9, pp. 3601–3618, 2016. https://doi.org/10.5194/hess-20-3601-2016.
47. J. B. Fisher, R. J. Whittaker, and Y. Malhi, "ET Come Home: potential evapotranspiration in geographical ecology," Global Ecology and Biogeography, vol. 20, no. 1, pp. 1–18, 2011. https://doi.org/10.1111/j.1466-8238.2010.00578.x.
48. R. Jaiswal, R. K. Mall, N. Singh, T. V. Lakshmi Kumar, and D. Niyogi, "Evaluation of bias correction methods for regional climate models: Downscaled rainfall analysis over diverse agroclimatic zones of India," Earth and Space Science, vol. 8, no. 12, 2021. https://doi.org/10.1029/2021EA001981.
49. H. Bosu, T. Rashid, M. A. Mannan, M. B. Rashid, R. Ahamed, and M. R. Hasan, "Climate projections over Bangladesh using MPI-ESM-MR model," DEW-DROP, vol. 8, 2022. Available: https://www.researchgate.net/publication/360960325_Climate_Projections_over_Bangladesh_Using_MPI-ESM-MR_Model.
50. Y. Li, Z. Li, Z. Zhang, X. Pan, and others, "High-res-

olution regional climate modeling and projection over western Canada using a weather research forecasting model with a pseudo-global warming approach," Hydrology and Earth System Sciences, vol. 23, no. 11, pp. 4635–4659, 2019. Available: https://doi.org/10.5194/hess-23-4635-2019.

51. A. K. Basheer, H. Lü, A. Omer, A. M. S. Abdelgader, and others, "Impacts of climate change under CMIP5 RCP scenarios on the streamflow in the Dinder River and ecosystem habitats in Dinder National Park, Sudan," Hydrol. Earth Syst. Sci., vol. 20, no. 2, pp. 1331–1353, Apr. 2016, doi: 10.5194/hess-20-1331-2016.