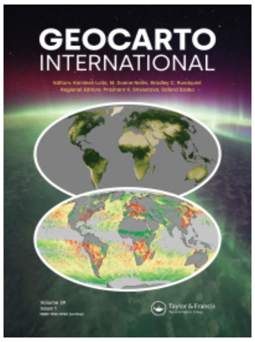

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Future changes of summer monsoon rainfall and temperature over Bangladesh using 27 CMIP6 models

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ABSTRACT

This research aims to investigate the future changes in summer monsoon rainfall and temperature in Bangladesh. The study revealed that INM-CM5-0 is the best model for projecting temperature, while BCC-CSM2-MR is the best model for projecting rainfall over Bangladesh. Using data from a large ensemble of 27 models from CMIP6, the study examined the rainfall and temperature change projections of Bangladesh during the twenty first century relative to the reference period (1981–2014) under SSP2–4.5 and SSP5–8.5. Under SSP2-4.5 and SSP5-8.5, the multi-model ensemble monsoon mean rainfall over Bangladesh will fluctuate between 40 and 260 mm and 100 and 900 mm, respectively. In most parts of the country's north, northeastern, and western regions, the projected changes in spatial patterns of monsoon rainfall indicate an increase in rainfall. The projected temperature indicated that Bangladesh's northwest and west-central areas could face the most significant rise in temperatures, surpassing 3.8 °C under SSP5-8.5.

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KEYWORDS

Summer monsoon; rainfall; temperature; CMIP6; multi-model ensemble; future climate projections; Bangladesh

1. Introduction

Bangladesh's economy is predominantly based on agriculture. The agriculture sector contributes 13.02% of the gross domestic product (GDP) (BBS 2020). Due to Bangladesh's total dependence on agriculture and the frequent occurrence of hydrological hazards such

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as droughts and floods, Bangladesh exhibits a heightened vulnerability to even minor fluctuations in climate (Mohsenipour et al. 2018). Due to its geographically distinctive location, inadequate infrastructure, high-density of population, and relatively low-lying topography, Bangladesh faces significant susceptibility to climate change (Rahman and Islam 2019). Bangladesh, located in the deltaic floodplains of the Ganges, Brahmaputra, and Meghna (GBM) basin, is currently encountering negative consequences resulting from global warming, potential climate change-related disasters, and the accompanying rise in mean sea levels (Kamruzzaman et al. 2023). Therefore, gaining insight into possible climate change is crucial for developing adaptation strategies and enhancing resilience to the consequences of climate change.

Climate projections indicate that rice production in Bangladesh is anticipated to decline by 7.4% annually between 2005 and 2050 due to extreme temperature events (Islam et al. 2019; Ghose et al. 2021). In other ways, under a high-emission scenario highlighted by the Intergovernmental Panel on Climate Change (IPCC 2014), future projections indicate a substantial rise up to 3 °C in the annual mean temperature across South Asia by the end of the twenty first century. As the earth experiences global warming, the frequency and intensity of extreme events are expected to increase with global warming over large parts of the globe as the concentration of water vapor in the atmosphere which supplies the water for precipitation rises in proportion to the saturation concentrations at a rate of about 6–7% per degree rise in temperature according to the thermodynamic Clausius-Clapeyron relationship (Allen and Ingram 2002; Almazroui et al. 2020; Shahi et al. 2021, 2023). Due to the rapid increases of greenhouse gases (GHGs) in the atmosphere, the continuous change in observed air temperature disrupts the global energy balance, which eventually influences other meteorological components like; precipitation, wind circulation, and snow cover (Shahi et al. 2021). Therefore, it is worth noting that precipitation patterns in South Asia, as well as in its corresponding countries, are proportionate to the increase in temperature (Almazroui et al. 2020).

As a climate sensitive country, the summer monsoon accounts for 72% of Bangladesh's annual precipitation (Real et al. 2023). Heavy rainfall during the monsoon season generates devastating floods that damage crops, livestock, and property and claim precious lives. On the other hand, lack of monsoon rainfall causes catastrophic droughts and agricultural failures (Azad et al. 2022). Bangladeshi agriculture depends on timely and equal monsoon rainfall. The monsoon's rainfall and temperature are predicted to be severely impacted by climate change, which could have severe consequences for the country's economy, society, and environment. Hence, scientific community and policymakers require more information on the possibility of future occurrences of these events because the consequences of gradual climate change and extreme weather events could affect nationwide socioeconomic growth in several places (IPCC 2013).

The most essential requirement when predicting future climate change is to obtain accurate projections that are quantitative for the twenty first century rely heavily on Global climate model (GCM) simulations shared through various Coupled Model Intercomparison Project (CMIP) phases (Eyring et al., 2016; Kamruzzaman et al. 2019a; Song et al. 2021). Most of the earlier cited works on Bangladesh's future climate has primarily relied on GCMs from CMIP3 (Hasan et al. 2015) and CMIP5 (Caesar et al. 2015; Pattnayak et al. 2017; Fahad et al. 2018; Hasan et al. 2018; Kamruzzaman et al. 2019b; Bosu et al. 2021; Islam et al. 2022, 2023). Many research scholars have predicted potential variations in precipitation and temperature under various climate change scenarios (Alamgir 2019; Alamgir et al. 2020; Khan et al. 2020; Mondal et al. 2020). However, GCM projections are fundamentally uncertain due to the modeling process, initial conditions, and future scenarios (Katzenberger et al. 2021). Furthermore, no single GCM can fully reflect all atmospheric processes or accurately capture every smaller-scale variation in climate (Almazroui et al. 2020; Ali et al. 2021). Thus, it is commonly recommended to utilize multi-model ensembles (MME) of GCMs for climate modeling, as they help reduce uncertainty and enhance the accuracy of projections (Wang et al. 2021).

The latest advancement in climate modeling, the CMIP6, represents an improved version compared to preceding CMIP generations (Eyring et al. 2019). CMIP6, surpasses previous versions in several aspects, including the number of GCMs and experiments, integration of radiative concentration pathways (RCPs) with shared socioeconomic pathways (SSPs), higher spatial resolution, minimal biases, and accurate illustration of synoptic processes (Mishra et al. 2020; Kamal et al. 2021; Su et al. 2021; Zhao et al., 2021; Hamed et al. 2022; Nashwan and Shahid 2022; Das et al. 2023). The greater ability of CMIP6 climate models to replicate large-scale patterns of climatic variables as compared to earlier CMIPs has been documented in several studies (Gusain et al. 2020; Rivera and Arnould 2020; Kamruzzaman et al. 2021). Shahi et al. (2023) conducted a study where they analyzed 16 models from the CMIP6 to assess how high-impact/extreme precipitation events might change in terms of their spatial and temporal distribution under a high-emission scenario from 1941 to 2070, comparing it to the historical period of 1981–2010.

Climate change is becoming a global concern, prompting extensive research into its elements and parameters. Scientists have utilized GCMs to forecast rainfall and temperature variations in multiple regions. Concerning Bangladesh, several studies (Kamal et al. 2021; Kamruzzaman et al. 2021; Das et al. 2022; Kamruzzaman et al. 2023) have explored the future consequences of climate change using CMIP6 GCMs. Given that the simulation outcomes depend on the choice of models, it is more enlightening to investigate the variations in Bangladesh's air temperature and rainfall using a broad range of models and various scenarios. However, the current understanding of spatial and temporal trends and variability in future rainfall and temperature changes on seasonal and annual scales are still limited. Thus, more research is needed, especially at the regional or national level, to determine if GCMs are suitable for predicting temperature and rainfall and how sensitive local or regional temperature and rainfall changes are to climate change.

There is a lack of studies examining the anticipated alterations in temperature and precipitation for Bangladesh at the annual and seasonal scales. Based on our understanding, no existing studies have analyzed a large number of ensembles of CMIP6 models (27 ensembles), and no studies have determined the best CMIP6 models to explore the changes in summer monsoon temperature and rainfall distribution of Bangladesh for both SSP2-4.5 and SSP5-8.5 scenarios during the twenty-first century. The present study aims to bridge this void. This study will analyze the output from CMIP6 models to investigate the changes in summer monsoons over Bangladesh. This study intends to (1) analyze the historical monsoon pattern over Bangladesh; (2) determine the best CMIP6 models for projecting rainfall and temperature; and (3) project the future changes in summer monsoon rainfall and temperature over Bangladesh during the near future periods (2015–2044), mid future periods (2045–2074), and far future periods (2075–2100). The study's findings will provide crucial information for planners and policymakers in Bangladesh to develop climate adaptation and mitigation strategies.

2. Materials and methods

2.1. Selection of the study area

Bangladesh has a unique geography, standing in the deltas of the Himalayan Rivers and the Bay of Bengal, with a land area of 148.46 thousand km^2. Most of the country's topography is flat, except for some elevated regions in the northeast and southeast. The Intergovernmental Panel on Climate Change has identified Bangladesh as one of the most susceptible to climate change (IPCC 2007). According to Eckstein et al. (2021), Bangladesh, a nation that frequently experiences meteorological disasters, is in seventh place on the list of countries that experienced the most extreme weather events between 2000 and 2019. Four distinct seasons can be noticed in Bangladesh, namely winter (Dec-Feb), pre-monsoon (Mar-May), monsoon (Jun-Sept), and post-monsoon (Oct-Nov) (Kamruzzaman et al. 2019a). The winter season is characterized by low rainfall, while the monsoon season gets most of the annual rainfall. As stated by Kamruzzaman et al. (2019b), the rainfall patterns in the northwest and northeast regions of the country vary from 1500 to 4000 mm. However, the average annual temperature for the country hovers around **25 °C**, with the warmest month being April, according to Rashid (2019). Rashid (1991) classified the country into seven distinct climatic subzones: the northern, north-eastern, north-western, south-western, western, south-eastern, and south-central zones. Climate change is projected to cause a gradual increase in temperature and shifts in rainfall patterns in Bangladesh, which may affect its water supply, agriculture, and public health (Salam et al. 2020). Despite these predictions, little research has been performed on the seasonal variability of global climate change and its impacts on Bangladesh, as there are no precise updated climate projections in CMIP6 datasets. The flowchart of the study is shown in Figure 1.

2.2. Data used in the study

2.2.1. Observational data

The Bangladesh Meteorological Department (BMD) gathered observational data on temperature and rainfall. BMD has a good reputation in Bangladesh for supplying reliable meteorological data and working under the Ministry of Defense of the Government of Bangladesh. The BMD collected and recorded weather data following the World Meteorological Organization's (WMO) standards. BMD has 34 stations located all across the country (Figure 2). The data from BMD has extensive coverage across the country. However, data on temperature and rainfall were gathered from 34 BMD stations between 1981 and 2014 to conduct this research. The meteorological stations were chosen for their geographical placement, ease of access (with less than 2% of the data missing), and consistency, ensuring comprehensive coverage across Bangladesh. To compensate for any missing data at the selected stations, inverse distance weighting (IDW) interpolation was applied, utilizing temperature and rainfall data from nearby stations to fill in the gaps.

2.2.2. Climate model data

The data of the downscaled CMIP6 global climate models (GCMs) were downloaded from NASA. The dataset was downloaded from NASA in NetCDF format and has a 0.25 degrees spatial resolution ($\sim$25 km $\times$ 25 km). Both historical and future (different SSPs) simulation data were downloaded here. The datasets are free to download from the server https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6.

2.3. Model performance evaluation based on historical period

2.3.1. Taylor diagram

At first model, validation was done using the Taylor diagram and various statistical analysis. To evaluate the model's performance even more, the spatial model is assessed using the Taylor diagram and Taylor Skill Score (TSS) method (Taylor 2001). This approach is

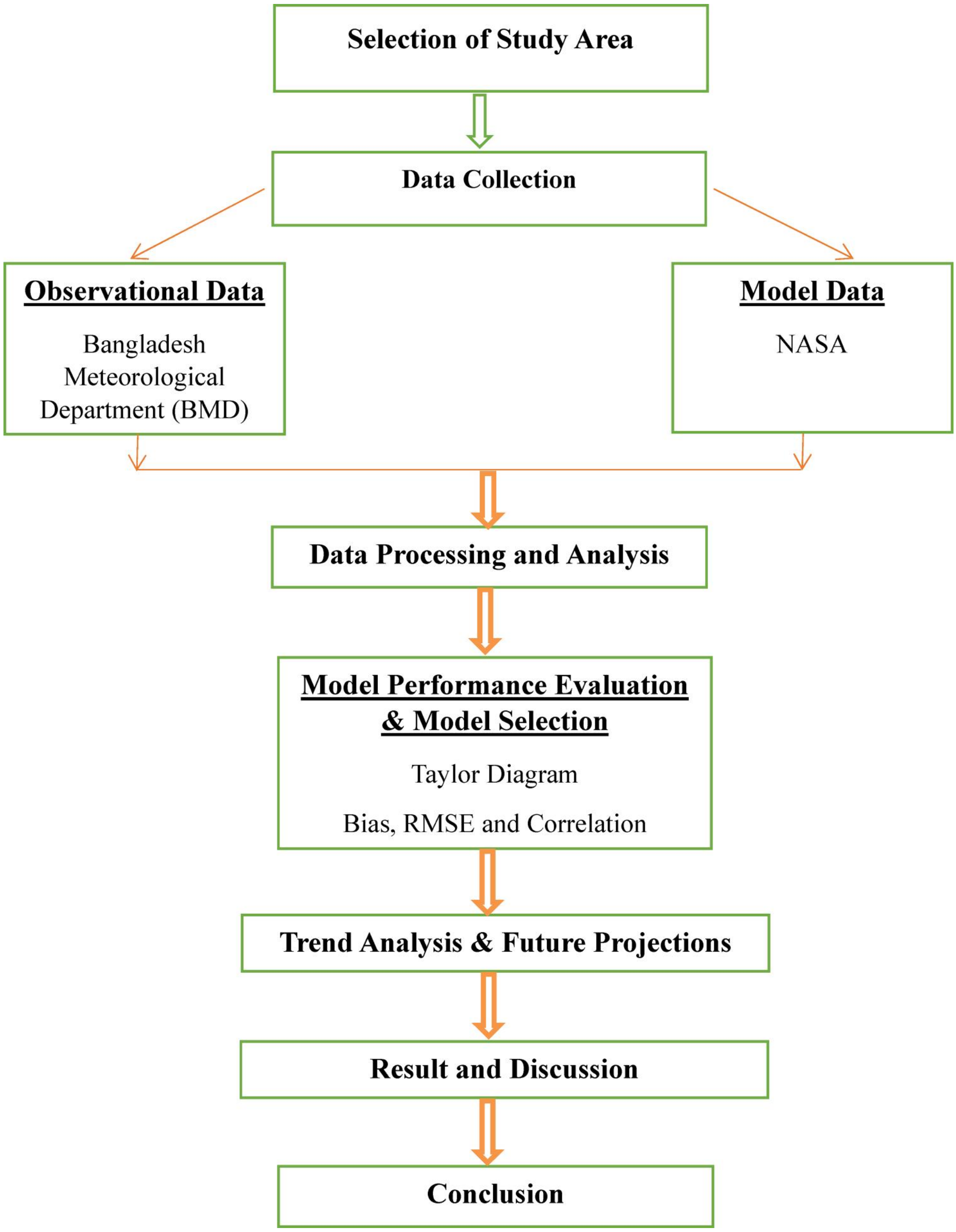

Figure 1. Flowchart of methodology.

commonly used to compare and evaluate similarities between multiple data sets, as demonstrated in previous studies (Taylor 2001; Kusunoki et al. 2006; Wang et al. 2018).

This study utilized the Taylor skill score method to evaluate the ability of CMIP6 models to replicate the spatial distribution of rainfall and temperature across Bangladesh. The TSS was calculated using the following formula:

$$TSS = 4(1 + PC)^2 / \left[\left(\frac{\sigma_{cmip}}{\sigma_{obs}} + \frac{\sigma_{obs}}{\sigma_{cmip}} \right) (1 + PC_0)^2 \right]$$

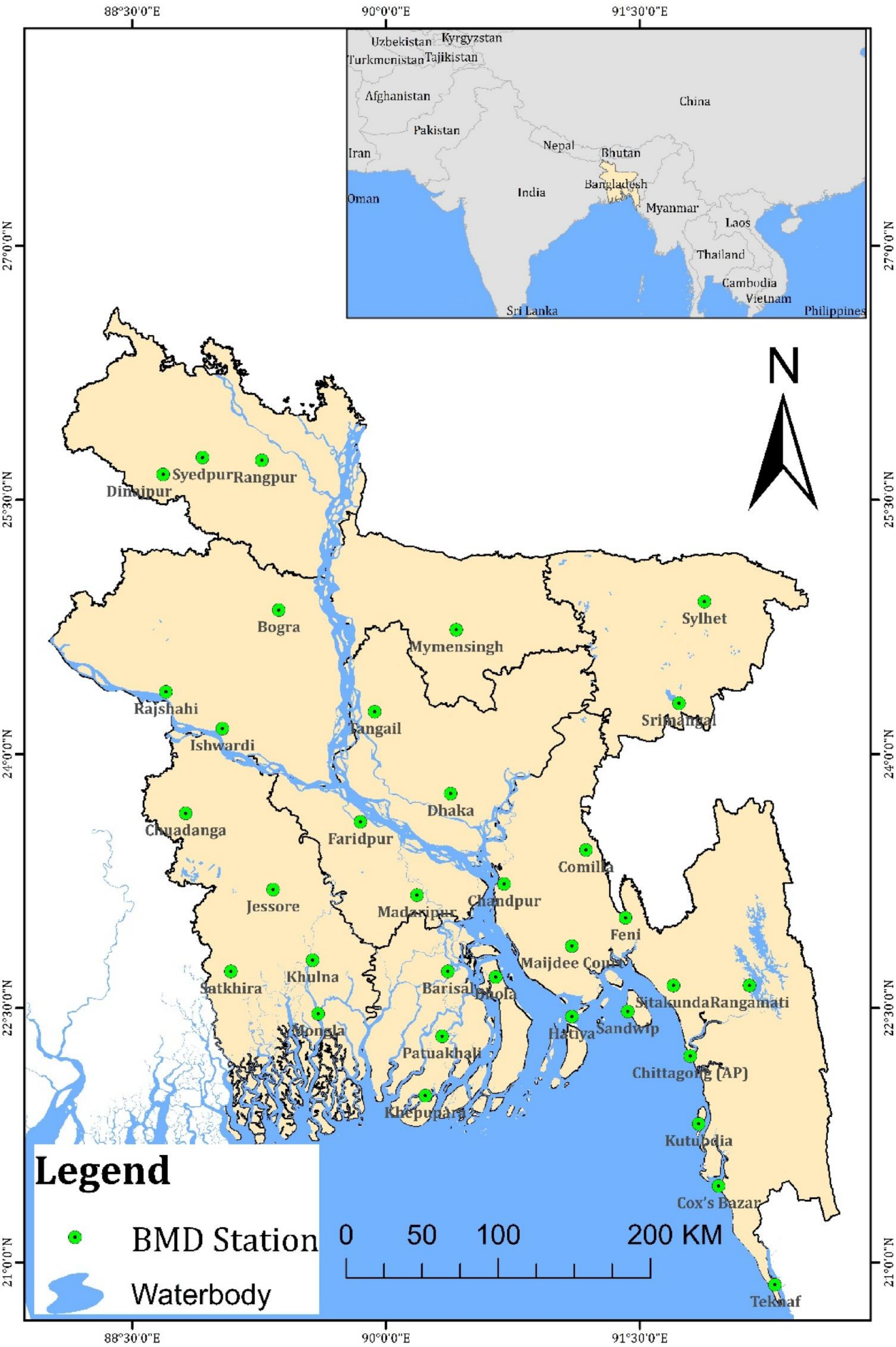

Figure 2. Location of Bangladesh in southeast Asia and the map showing different regions along with BMD stations.

where PC refers to the spatial pattern correlation coefficient within the output of the model and observation. The PC_0 is the highest achievable (here, the threshold is set at 1). Additionally, the variables σ_{cmip} and σ_{obs} represent the standard deviation of simulated and observed patterns, respectively. A score close to 1 denotes that the models and observations agreed perfectly, while 0 indicates poor model performance. The TSS technique has been successfully used in several studies, including those cited in the text (Chen et al. 2011; Zhu et al. 2020; Ayugi et al. 2021; Ngoma et al. 2021).

2.3.2. Bias, RMSE and correlation coefficient calculation

In this analysis, prior to correcting the bias of future GCM outputs, the bias of previous GCM outputs is first computed. Root Mean Square Error (RMSE) is a statistical measure of the discrepancy between predicted and actual values in a dataset (Yue et al. 2021). It is a useful metric for evaluating the accuracy of a predictive model. RMSE of historical GCM outputs were computed to demonstrate the model's absolute fit to the data that is, how closely the observed data match with the model's predicted values (Islam et al. 2023). A better fit is shown by lower RMSE values.

Using 'R' programming, the bias, RMSE, and correlation coefficient were determined (Kamruzzaman et al. 2019a). Bias, RMSE and Correlation Coefficient are calculated using the equations-

$$Bias = \frac{\sum_{i=1}^{n}(O_i - P_i)}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Where, n is the length of the distribution of the data point under analysis, and Pi and Oi, respectively, are the simulation and observed data.

2.3.2.1. Bias correction. The method known as Bias Correction (BC) can adjust the raw daily output of climate models by comparing the mean and variability of observed data during a reference period with the data from the climate models (Gudmundsson 2012). In the context of climate impact modeling, statistical bias correction is often used to account for discrepancies between simulated and observed historical climate data. This correction is achieved through the use of transfer functions that map the distribution of the simulated data to that of the observed data, which can then be used to adjust future projections (Kamruzzaman et al. 2022).

2.3.2.2. Simple quantile mapping (SQM) method for rainfall and temperature. Daily GCM simulations for the period of 1981–2100 were downscaled to ERA5 resolution using the SQM model and then bias-corrected based on ERA5 datasets. This model is generally adopted in climate projection studies to correct biasness from GCMs (Kamruzzaman et al. 2021; Islam et al. 2022). Empirical quantile mapping is used by the SQM method to independently improve GCM simulations (Das et al. 2023; Islam et al. 2023). Compared with delta change and additive models, the quintile mapping model outperforms better to lessen the absolute error between historical and projection for rainfall and temperature (Gudmundsson 2012). Similar to other models, it assumes that biases in the historical phase are alike to those in the forthcoming period. The next three stages were as follows: (1) extracting the GCM data associated with each target ERA5 grid point; (2) evaluating the biases in the GCM; and (3) correcting forecasts for bias. The retroactive period variations between the simulated and observed cumulative distribution functions (also known as CDFs) were computed using the following Equation and used in subsequent simulations for a certain percentile (Kamruzzaman et al. 2019b):

$$X_p'(t) = X_p(t) + F_{obs}^{-1}\left(F_{p.sim}\left(X_p(t)\right)\right) - F_{r.sim}^{-1}\left(F_{p.sim}\left(X_p(t)\right)\right)$$

Where $X_p{}'(t)$ and $X_p(t)$ stand for the bias-corrected and raw future projections for month t, and F(θ) and F−1(θ) are, respectively, a CDF of the monthly data θ and its inverse. Future projection, retroactive simulation, and observed monthly data are denoted, respectively, by the subscripts p.sim, r.sim, and obs (Kamruzzaman et al. 2023). The SQM model has been shown to be more successful than parametric methods at minimizing systematic bias, ERA5 and raw GCM data are employed as inputs in an empirical equation that is not parametric (Gudmundsson 2012; Kamruzzaman et al. 2021).

2.4. Model selection

It is not simple to choose climate models for studies on climate change, but it is also a crucial phase in carrying out such a study. The 27 GCMs were explicitly selected depending on simulations being available for precipitation, maximum temperature (Tmax), and minimum temperature (Tmin) for the historical period (1850–2014) and the future period (2015–2100) under the SSP2-4.5 and SSP5-8.5 scenarios and variant label of r1i1p1f1. The selected models have been extensively used in climate modeling studies, even though there is not a single 'best performing' GCM, and have consistently produced reliable results, as evidenced by previous studies (Almazroui et al. 2020; Kamruzzaman et al. 2021, 2022; Das et al. 2023; Kamruzzaman et al. 2023). We used Taylor's diagram to select the best GCMs. Taylor diagrams, as proposed by Taylor in 2001, serve as a graphical tool to represent the level of agreement between a set of patterns and the observed data. The correlation among the two patterns, the centered root-mean-square difference, and the amplitude of their changes, shown by their standard deviations, are used to determine their similarity. These diagrams are highly beneficial for assessing multiple aspects of complex models and comparing the relative performance of various models, as demonstrated by the IPCC in 2001.

The suitability of GCMs for rainfall and temperature was evaluated by comparing the performance of 27 GCMs using Taylor's diagram. Taylor's method combines the standard deviation and correlation coefficient to select appropriate GCMs. In this study, based on the Taylor diagram, the same ensemble member was chosen among 27 models accessible at NASA. Specifically, all GCM runs for the ensemble member r1i1p1f1 were chosen.

Here,

r = realization which means the initial condition

i = initialization which means the initial starting point

p = parameterization which means model physics

f = forcing

So, r1i1p1f1 means the initial state, initial starting point, model physics, and force are the same for all the models.

The selected27 models are shown below with their country of origin-

ACCESS-CM2 (Australia)	HadGEM3-GC31-MM (UK)
ACCESS-ESM1-5 (Australia)	INM-CM4-8 (Russia)
BCC-CSM2-MR (China)	INM-CM5-0 (Russia)
CanESM5 (Canada)	IPSL-CM6A-LR (France)
CESM2-WACCM (USA)	KIOST-ESM (South Korea)
CMCC-CM2-SR5 (Italy)	MIROC-ES2L (Japan)
CMCC-ESM2 (Italy)	MIROC6 (Japan)
CNRM-CM6-1 (France)	MPI-ESM1-2-LR (Germany)
CNRM-ESM2-1 (France)	MRI-ESM2-0 (Japan)
EC-Earth3 (Europe)	NESM3 (China)
EC-Earth3-Veg-LR (Europe)	NorESM2-LM (Norway)
FGOALS-g3 (China)	NorESM2-MM (Norway)
GFDL-ESM4 (USA)	TaiESM1 (Taiwan)
HadGEM3-GC31-LL (UK)	

2.5. Trend analysis

This study compared the trends of the observed data with the model outputs to assess the efficiency of the ensemble models. The relationship between the models, observations, and indices was evaluated using correlation analysis (Salam et al. 2020). Furthermore, to determine the trends in extreme climate indices (including rainfall and temperature); the nonparametric Mann-Kendall (MK) trend test was used, which is strongly suggested by the World Meteorological Organization (Mann 1945; Kendall 1975). It was used with Sen's slope test (Sen 1968) to explain the trend better. The experiments stated above were all based on a hypothesis. The alternative hypothesis (H1) proposed that the dataset had a monotonic trend, contrary to the null hypothesis (Ho), which presupposed that the data were independent and dispersed randomly. With its Z Kendall coefficient, the MK test gave a notion of the trend's significance, whereas Sen's test gave an estimate of the trend's magnitude with the slope estimator. A 95% confidence level criterion was also used as the basis for the evaluation. An innovative trend analysis (ITA) was used in the time-series dataset to find monotonic trends and sub-trends. To see the annual and seasonal changes, this methodological approach was applied.

2.5.1. Mann–Kendall test (MK)

In hydrology and meteorology, time-series datasets are often analyzed using the Mann-Kendall (Mann 1945; Kendall 1975; Azad et al. 2022) formula for identifying trends. The formula that calculates the test statistic (S) for a series of data (x1, x2, x3, …, xn) for which trends are being examined is as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign\ (X_j - X_k)$$

where 'n' represents the length of the dataset where xj and xk are the observations at times j and k.

$$Sign\ (X_j - X_k) = \begin{cases} +1\ if\ X_j > X_k \\ 0\ if\ X_j = X_k \\ -1\ if\ X_j < X_K \end{cases}$$

A value of S greater than zero indicates an upward or increasing trend in the time-series data, whereas a negative value denotes a downward or decreasing trend. The following equation is able to be used to determine the variance of S, VAR(S):

$$VAR\ (S) = \frac{1}{18}\left\{n(n-1)(2n+5) - \sum_{i=1}^{\rho} \tau_i(\tau_i - 1)(2\tau_i + 5)\right\}$$

The tied group number of observations in group I, which refers to a set of sample data with similar values, is denoted by r, while the extent of the ith tie number is indicated by i. Kendall's t (tau) is used to identify the time-series data statistic (S) and is expressed as follows:

$$\tau = \frac{S}{B}$$

With,

$$B = \sqrt{\frac{1}{2}n(n-1) - \frac{1}{2}\sum_{j=1}^{g} \rho_j(\rho_j - 1)}\sqrt{\frac{1}{2}n(n-1)}.$$

When n is greater than 10, the standardized test measurement Z is determined by the estimation of S and the variance VAR(S) (Gilbert 1987):

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{VAR(S)}}, & if \;\; S > 0 \\ 0, \;\; if \;\; S = 0 & \\ \dfrac{S+1}{\sqrt{VAR(S)}}, & if \;\; S < 0 \end{cases}$$

Z-values that are positive (+) show an upward or increasing trend while negative (-) values indicate a downward or decreasing trend.

2.5.2. Sen's slope estimator

The Sen's slope (Q) represents the median value of N Qi values (as described by Fan et al. 2012).

$$Q_i = \frac{X_k - X_j}{k - j}, i = 1, 2, 3, \ldots, N, k > j$$

In the calculation of the Sen's slope (Q), if a series of Qi values contains an equal number of negative and positive values, along with some zero values in between, then the Sen's slope will be zero. This means that if there are more equal values in a time series, the likelihood of a no-change trend in the series is higher (Rahman and Islam 2019; Salam et al. 2020).

2.5.3. Interpretation of P-value in Mann-Kendall test

In this study, MK test is carried out using R programming in R studio's 95% Confidence level. Therefore, the significance level (α-value) for R is constant = 0.05. In this case, if the *P*-value of the Mann-Kendall test is lower than significance level ($p < 0.05$), then there is statistically significant evidence that the data from the time series show a monotonic trend. If the P-value for the MK test is more than 0.05 (>0.05), it is not statistically significant, away from monotonic trend, and shows strong validates for the null hypothesis.

2.6. Future projections

GrADS was used to demonstrate future projections using grid-to-grid NetCDF data of temperature and rainfall. The CSV data of temperature and rainfall was exploited to demonstrate linear trends. The future rainfall and temperature data are scrutinized for three distinct time periods relative to the baseline period (1981–2014).

Those are -

i. The near-future period: 2015–2044
ii. The mid-future period: 2045–2074
iii. The far-future period: 2075–2100.

The individual analysis of each of the 27 models is performed for both rainfall and temperature in the analysis section, and the multi-model ensemble is used to draw conclusions. The purpose of doing so is to enable a comparison of results across the CMIP6 GCM models.

3. Results

3.1. Model validation

Figure 3a demonstrates that all other models are relatively close to the observation, whereas the CMCC-ESM2 and CNRM-CM6-1 models are very far from it. Thus, these two models are disregarded when making rainfall projections for the future. Before starting the bias-correction process, the accuracy of the model was estimated by calculating the Bias, Root Mean Square Error (RMSE), and Correlation Coefficient of the model's data. It shows the values in Table 1. Therefore, based on Table 1 and the Taylor Diagram's result, the BCC-CSM2-MR model is the most accurate for projecting rainfall over Bangladesh.

The CMCC-CM2-SR5 and TaiESM1 models are marginally off from the observation, whereas all the other models are very close to it, as shown in Figure 3b. So, these two models are disregarded when making temperature projections for the future. Also, for temperature, before starting the bias-correction process, the Bias, Root Mean Square Error (RMSE) and Correlation Coefficient of the model's data is calculated for temperature to figure out the model's validity. Table 2 displays the values.

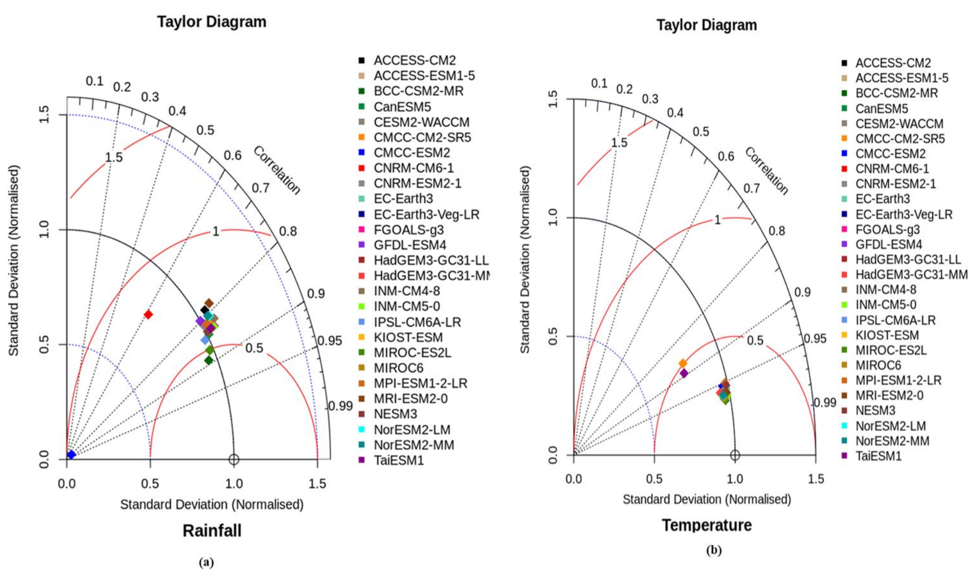

Figure 3. Taylor diagram for rainfall and temperature.

Table 1. Bias, RMSE and correlation coefficient of the monthly data for rainfall.

Model	Bias (mm)	RMSE (mm)	Correlation Coefficient
ACCESS-CM2	10.22	135.40	0.79
ACCESS-ESM1-5	17.07	177.11	0.80
BCC-CSM2-MR	**12.17**	**92.44**	**0.89**
CanESM5	14.98	114.01	0.84
CESM2-WACCM	6.0	128.82	0.81
CMCC-CM2-SR5	5.58	124.10	0.82
CMCC-ESM2	196.78	276.84	0.81
CNRM-CM6-1	11.41	163.08	0.61
CNRM-ESM2-1	13.52	122.73	0.82
EC-Earth3	11.77	124.23	0.81
EC-Earth3-Veg-LR	10.19	119.71	0.82
FGOALS-g3	9.87	119.30	0.83
GFDL-ESM4	15.85	128.24	0.80
HadGEM3-GC31-LL	9.99	120.85	0.82
HadGEM3-GC31-MM	8.02	120.59	0.82
INM-CM4-8	6.82	125.44	0.82
INM-CM5-0	7.50	118.52	0.84
IPSL-CM6A-LR	13.67	110.25	0.85
KIOST-ESM	14.52	116.56	0.84
MIROC-ES2L	13.02	100.38	0.87
MIROC6	11.72	116.14	0.84
MPI-ESM1-2-LR	10.79	122.88	0.82
MRI-ESM2-0	9.60	139.81	0.78
NESM3	9.68	116.21	0.83
NorESM2-LM	3.22	128.75	0.81
NorESM2-MM	3.94	129.38	0.80
TaiESM1	8.73	117.96	0.83

Consequently, INM-CM5-0 is the best model for projecting temperature over Bangladesh, according to Table 2 and the findings of the Taylor Diagram. The data have severe biases, as seen in Tables 1 and 2, and the RMSE values also suggest a lower fit. For these reasons, an effort has been undertaken to bias-correct future data.

The analysis of historical data using Taylor diagrams and various statistical methods reveals that INM-CM5-0 is the best model for projecting temperature across Bangladesh, whereas BCC-CSM2-MR is the best model for projecting rainfall over Bangladesh. Analysis of the historical period reveals a significant rainfall discrepancy between the model and observations. These findings were nearly identically addressed in the earlier studies by Kamruzzaman et al. (2019b), and Bosu et al. (2021).

3.2. Trend analysis

A trend analysis was conducted to compare the observed mean temperature and rainfall data from the years 1981 to 2014 with the multi-model ensemble data from 27 CMIP6 models. The trends of mean rainfall in summer season are presented in Table 3. According to Table 3 for the monsoon season, analysis reveals that the observed and model rainfall trends are not similar in pattern shown in Figure 4a and b. The observed rainfall is showing negative trend although the p value is not significant. As a result, the null hypothesis that there is no trend in the observed rainfall cannot be accepted. On the other hand, ensemble model rainfall shows increasing trend with the significant p value (0.0437). According to Table 4 for the monsoon season, analysis reveals that the mean temperature is increasing by 0.026 °C/year for observed temperature that is significant while it shows also an increasing rate of 0.009 °C/year for CMIP6 ensemble models' temperature in 1981 to 2014, those are represented by Figure 4c and d). Comparatively,

Table 2. Bias, RMSE and correlation coefficient of the monthly data for temperature.

Model	Bias (mm)	RMSE (mm)	Correlation Coefficient
ACCESS-CM2	0.04	0.94	0.97
ACCESS-ESM1-5	0.10	0.95	0.97
BCC-CSM2-MR	0.16	0.91	0.97
CanESM5	0.05	1.01	0.96
CESM2-WACCM	0.29	1.00	0.97
CMCC-CM2-SR5	−3.09	3.59	0.87
CMCC-ESM2	0.04	1.09	0.95
CNRM-CM6-1	0.05	1.00	0.96
CNRM-ESM2-1	0.11	1.03	0.96
EC-Earth3	0.08	1.04	0.96
EC-Earth3-Veg-LR	0.13	0.95	0.97
FGOALS-g3	0.14	1.09	0.95
GFDL-ESM4	0.09	1.00	0.96
HadGEM3-GC31-LL	−0.01	0.99	0.96
HadGEM3-GC31-MM	−0.06	1.01	0.96
INM-CM4-8	0.05	0.99	0.96
INM-CM5-0	**0.03**	**0.94**	**0.97**
IPSL-CM6A-LR	0.03	0.98	0.96
KIOST-ESM	0.01	0.94	0.97
MIROC-ES2L	0.14	0.88	0.97
MIROC6	0.11	0.92	0.97
MPI-ESM1-2-LR	0.11	1.14	0.95
MRI-ESM2-0	0.15	0.99	0.96
NESM3	0.09	1.09	0.95
NorESM2-LM	0.15	0.96	0.97
NorESM2-MM	0.14	0.97	0.96
TaiESM1	−3.0	3.45	0.89

Table 3. Mann-Kendall test and Sen's slope estimation for rainfall of observed (BMD) and CMIP6 ensemble data.

	Observed Data			Model Data		
Time	Z Test	Sen's Slope	P value	Z Test	Sen's Slope	P value
Summer Monsoon	**−0.56**	**−2.82**	**0.5732**	**2.02**	**2.478**	**0.0437**

normalized test statistics (Z) are also shown a positive value that is 5.34 for observed data and 4.83 for models' data. For both (observation and model) temperature shows increasing trend with the significant p value.

The Sen's value and Z value demonstrate a positive (+) trend for both the observed and model data in mean temperature, with a significant trend. In contrast, for rainfall, the Sen's value and Z value demonstrate a negative (-) trend for both types of data. This analysis suggests that the performance of the ensemble models is good. Both the Taylor diagram and trend analysis support the conclusion that the multi-model ensemble comprising 27 CMIP6 models will yield better results for rainfall and temperature projection over Bangladesh.

3.3. Future changes of rainfall on the summer monsoon

Figure 5a–c display the spatial distribution of the SSP2-4.5 scenario-based multi-model ensemble that predicted shifts in monsoon rainfall over Bangladesh for three time periods (near-future, mid-future, and far-future). The most significant increases in precipitation are projected to occur in the northeastern and southeastern regions of Bangladesh, with the amount of increase ranging from 10 to 80 mm in the near-future period (2015–2044), 40–200 mm in the mid-future period (2045–2074), and 40–260 mm in the far-future

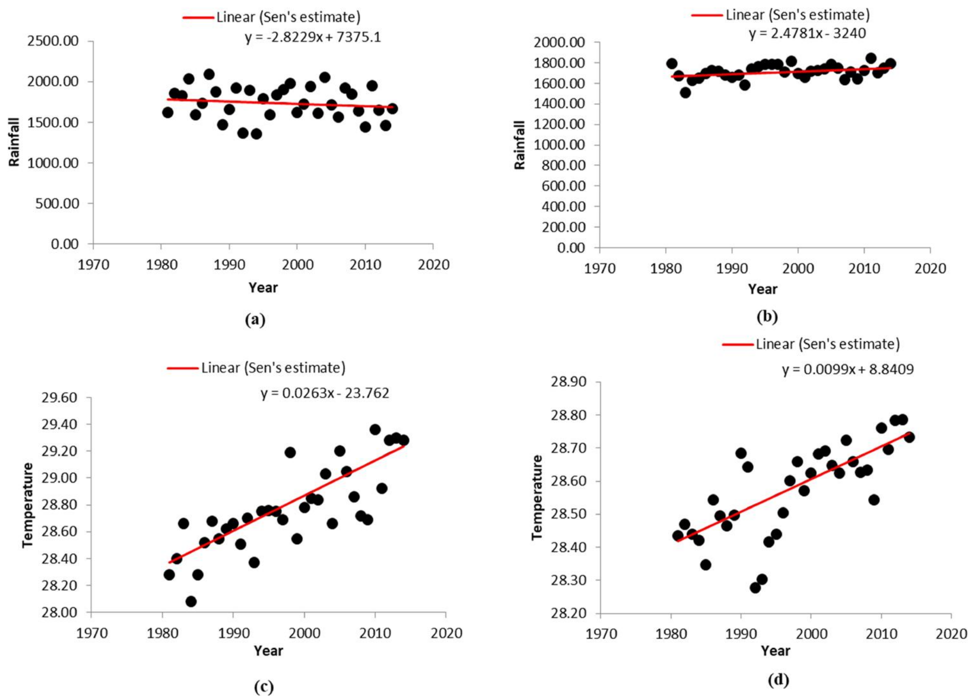

Figure 4. Trend analysis rainfall and temperature. Comparison between (a) observation data and (b) ensemble model's data of mean rainfall in summer monsoon season (1981–2014). comparison between (c) observation data and (d) ensemble model's data of mean temperature in summer monsoon season (1981–2014).

Table 4. Mann-Kendall test and Sen's slope estimation for temperature of observed (BMD) and CMIP6 ensemble data.

	Observed Data			Model Data		
Time	Z Test	Sen's Slope	P value	Z Test	Sen's Slope	P value
Summer Monsoon	**5.34**	**0.026**	**0.00000009198**	**4.83**	**0.0099**	**0.000001346**

period (2075–2100) (Table 5). Other regions show consistent alterations in each future period. On the other side, the spatial distribution of the predicted shifts in summer monsoon rainfall under the SSP5-8.5 scenario showed that the amount of rainfall increases ranges from 0 to 130 mm in the near-future period, 50–350 mm in the mid-future period, and 100–900 mm in the far-future period, which mostly show a rise in the northeastern and southeastern parts of Bangladesh (Table 5).

The line graphs depict the predicted changes in mean monsoon rainfall across Bangladesh for three time periods (near, mid, and far future) under two scenarios (SSP2-4.5 and SSP5-8.5) based on a multi-model ensemble (Figure 6). Both scenarios predict consistent increases in mean rainfall in all three future periods, with the near-future period (2015–2044) showing addition of around 1800 mm, the mid-future period (2045–2074) showing an increase of 1850–1900 mm, and the far-future period (2075–2100) leading a rise of 1880–1900 mm under SSP2-4.5 and an increase of 1800–1870 mm in the near-future, 1860–2050 mm in the mid-future, and 2070–2200 mm in the far-future under SSP5-8.5. All models indicate an upward trend in the mean summer monsoon rainfall. The most significant increase in rainfall is expected in 2075–2100 for all scenarios.

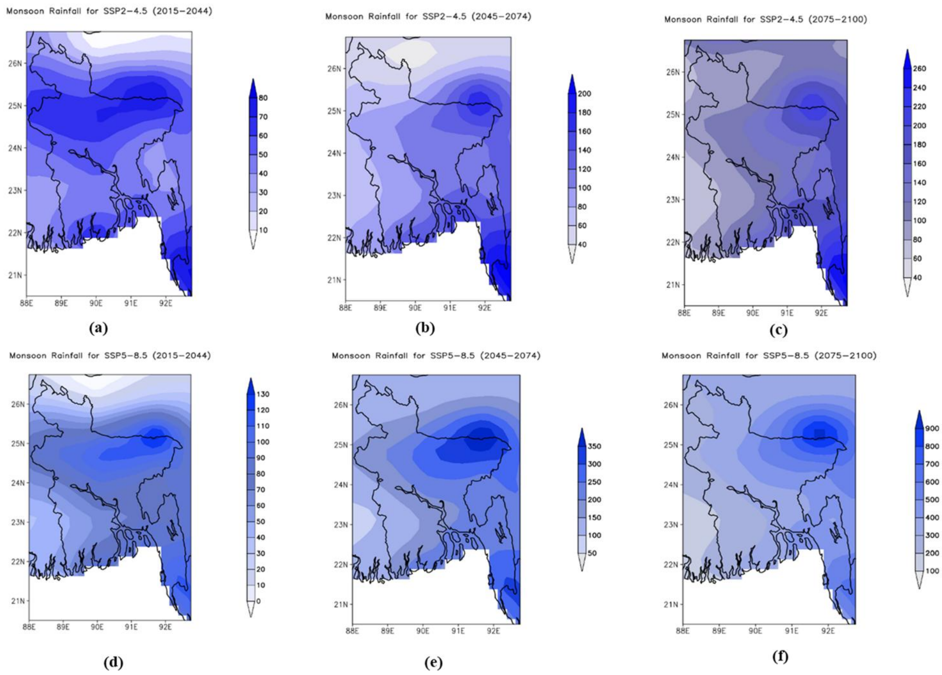

Figure 5. The projected changes in summer monsoon rainfall (mm) under the SSP2-4.5 and SSP5-8.5 scenarios over Bangladesh are shown by the multi-model ensemble in comparison to the reference period (1981–2014).

Table 5. Future projections of changes of summer monsoon rainfall.

Summer monsoon (Rainfall)	Near-future period (2015–2044)	Mid-future period (2045–2074)	Far-future period (2075–2100)
SSP2-4.5	10–80 (mm)	40–200 (mm)	40–260 (mm)
SSP5-8.5	0–130 (mm)	50–350 (mm)	100–900 (mm)

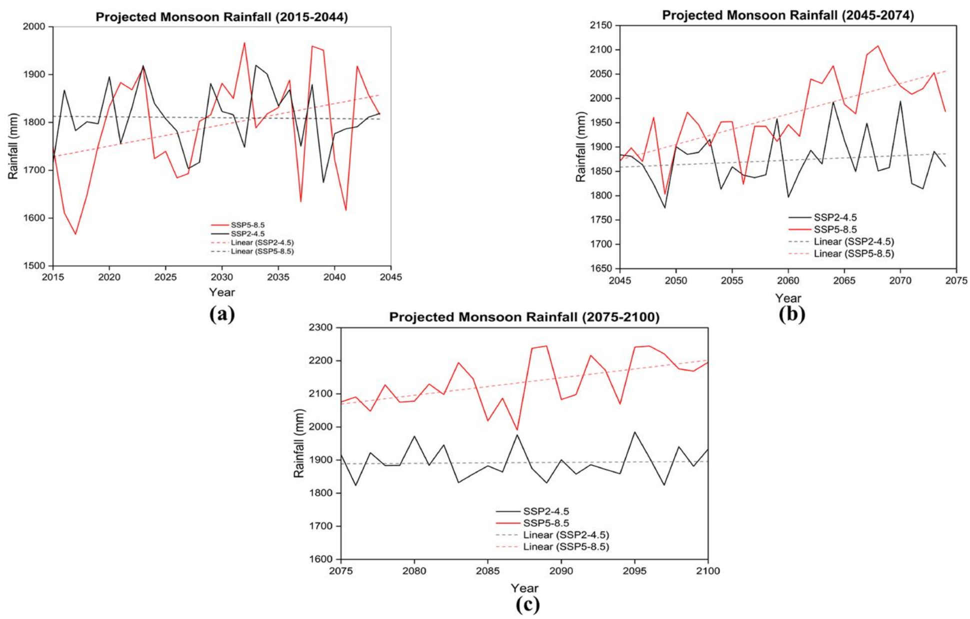

Figure 6. Future projections of summer monsoon rainfall for the SSP2-4.5 and SSP5-8.5.

Table 6. Future projections of changes summer monsoon temperature.

Summer monsoon (Temperature)	Near-future period (2015–2044)	Mid-future period (2045–2074)	Far-future period (2075–2100)
SSP2-4.5	0.48–0.75 (°C)	1.26–1.59 (°C)	1.75–2.15 (°C)
SSP5-8.5	0.51–0.84 (°C)	1.80–2.20 (°C)	3.2–3.8 (°C)

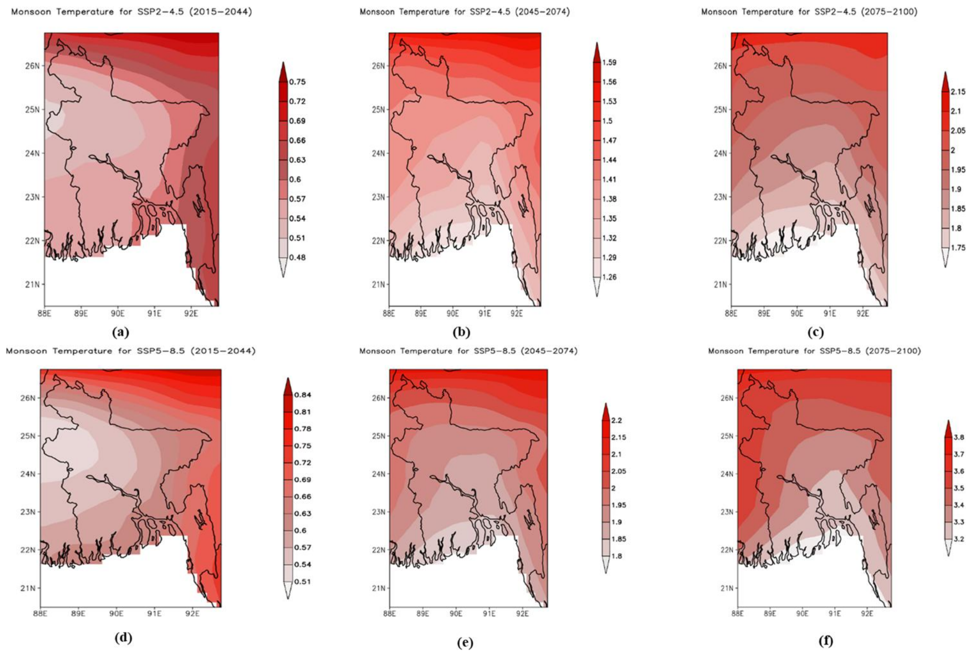

Figure 7. The projected changes in summer monsoon temperature (°C) under the SSP2-4.5 and SSP5-8.5 scenarios over Bangladesh are shown by the multi-model ensemble in comparison to the reference period (1981–2014).

3.4. Future changes in temperature on the summer monsoon

Figure 7 shows the spatial distribution of multi-model ensemble predictions of variations in temperature during the summer monsoon in Bangladesh under the SSP2-4.5 and SSP5-8.5 scenarios. During the summer monsoon, a continuous increase in temperature has been observed in all regions of Bangladesh. Its northwestern, northeastern, and southeastern areas are projected to suffer the most significant temperature increases compared to the reference period. Compared to the reference period, temperatures may increase by up to 0.75 °C for the near-future period (2015–2044) shown in Figure 7a. The increase in temperature is consistent across all regions of the country, but the northwestern, northeastern, and southeastern parts are expected to see the highest increases, ranging from 0.57 to 0.72 °C. For the mid-future period (2045–2074) shown in Figure 7b, the temperature increase may be up to 1.59 °C compared to the reference period. Similar to the near-future period, the rise in temperature is consistent across all regions of the country, but the northwestern and northeastern parts are expected to see the highest increases, ranging from 1.41 to 1.59 °C. For the far-future period (2075–2100) shown in Figure 7c, the temperature increase may be up to 2.15 °C compared to the reference period. The country's northwest will experience the highest projected temperature increases, ranging from 2.05 to 2.15 °C. The remaining regions show consistent changes in temperature compared to the reference period. Overall, the figures suggest that Bangladesh will experience significant temperature increases during the summer monsoon in the future, and the northwestern, northeastern, and southeastern parts of the country are expected to be the most affected. Based on the SSP5-8.5 scenario, the temperature increase is continuous throughout the country and is most pronounced in the northwestern and southeastern parts. In the near future (2015–2044), the increase may be up to 0.84 °C, in the mid-future (2045–2074) up to 2.2 °C, and in the far future (2075–2100) up to 3.8 °C, with the northwestern and west central regions experiencing the most significant increase. Under SSP5-8.5, Bangladesh's northwestern and west-central areas are projected to suffer the greatest temperature increase (over 3.8 °C) compared to the reference climate (1981–2014) (Table 6). Under the SSP2-4.5 and SSP5-8.5 scenarios, the mean monsoon temperature averaged over Bangladesh is expected to rise by 1.9 °C and 3.7 °C, respectively (Table 6). The line graphs illustrate that future projections of temperature may highly increase by about 30.2 °C to 30.6 °C and 31.1 °C to 34.4 °C in the far-future period (2075–2100) over Bangladesh under SSP2-4.5 and SSP5-8.5, respectively (Figure 8).

4. Discussion

4.1. Future changes of rainfall on the summer monsoon

Along with the predicted rise in summer monsoon rainfall and a projected long-term increase in interannual variability, there may also be an increase in the number of stormy seasons and potentially more extreme rainfall events (Turner and Slingo 2009; Sharmila et al. 2015).

These outcomes align with earlier studies that predicted that Bangladesh could see more precipitation during the monsoon season due to climate change. Kamruzzaman et al. (2023) examined the spatial patterns of annual precipitation trends from 2015 to 2100 using the multi-model ensemble (MME). They projected a significant rising trend in rainfall throughout Bangladesh for SSP2-4.5 and SSP5-8.5 scenarios. The spatial distribution of these changes revealed a gradual rise in annual precipitation from the south to the north of the country, particularly in the northeastern regions. These findings align with the results of the current study. While there are tiny variations in the projected magnitudes, the overall findings of this research are substantially consistent with several earlier studies (Chaturvedi et al. 2012; Caesar et al. 2015; Fahad et al. 2018; Kamruzzaman et al. 2021). Pour et al. (2018) analyzed spatial and temporal changes in rainfall in Bangladesh. Their study indicated that climate models projected a rise in monsoon rainfall across every country and region in all Representative Concentration Pathways (RCPs). The highest increase in monsoon rainfall was projected in northwest Bangladesh, ranging from 7.2% to 20.6% under different RCPs. Almazroui et al. (2020) examined precipitation trends across six South Asian countries using 27 CMIP6 ensembles. They found that annual mean precipitation is expected to rise by 4.4% to 17.1% under the three SSP scenarios for Bangladesh. For the high-emission (SSP5-8.5) scenario, the unpredictability of summer monsoon precipitation across Bangladesh is projected to range from 7.5% to 36.9% by the end of the twenty-first century. In another study, Das et al. (2022) emphasized how vulnerable Bangladesh's southeast and some of its south-central regions are too severe flooding brought on by heavy rainfall due to climate change. Iyakaremye et al. (2021) reported that significant variations will be noticed in the mid of the century if the ongoing climate warming continues, which is similar to our study. It is worth mentioning that CMIP6 models and their members may have significant biases (Seneviratne and

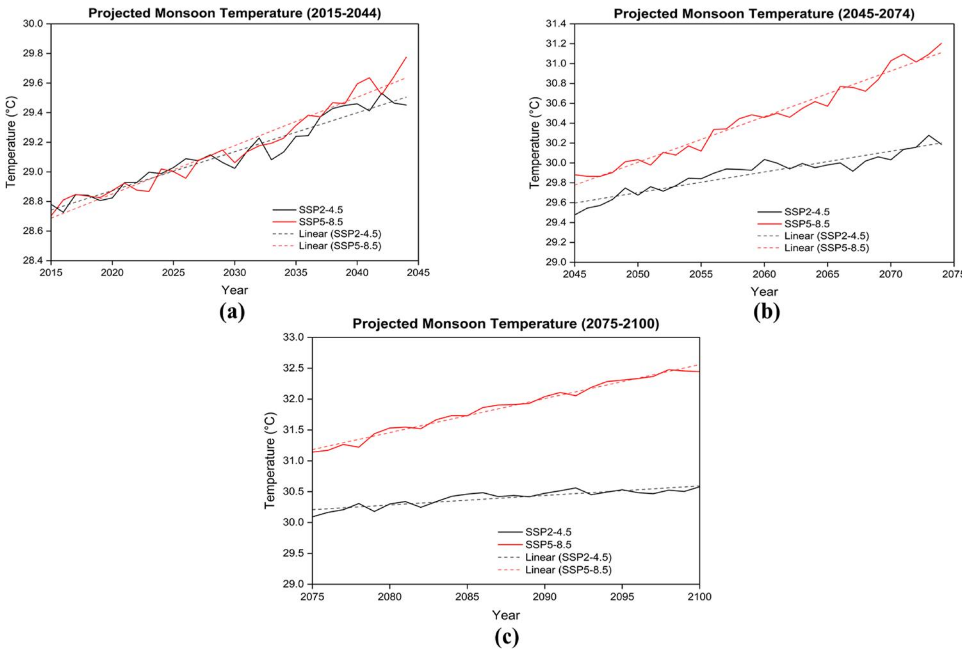

Figure 8. Future projections of summer monsoon temperature for the SSP2-4.5 and SSP5- 8.5.

Hauser 2020), rendering the ensemble of dataset incoherent and perhaps causing the observed variability in regional variations in severe rainfall and temperature events.

The intensified thermodynamic conditions brought about by atmospheric warming are primarily responsible for the rise in mean summer monsoon rainfall (Sharmila et al. 2015). This increase in monsoon rainfall can contribute to sufficient water availability for main crops, particularly several types of rice farmed throughout the monsoon season. However, excessive rainfall during the monsoon period in upland areas often leads to flash floods in the plains (Kamruzzaman et al. 2023). Consequently, there is a higher risk of floods, soil erosion, and crop losses instead of an increase in water supply, especially in river basins with large dams capable of storing excess water until needed (IPCC 2014).

As a result, extreme rainfall events are anticipated to occur frequently on a warming earth. The underlying physical explanation is that global warming triggers atmospheric changes. The atmosphere can hold roughly 7% extra moisture with a 1 °C temperature increase (IPCC 2014). Shahi et al. (2023) conducted a study on India's high-impact precipitation events, employing CMIP6 models. Their findings revealed a substantial link between global warming and the increased frequency and intensity of extreme precipitation occurrences in the future. In particular, during heavy rainfall, the additional moisture brought about by global warming results in a higher long-term rainfall rate. The Bay of Bengal provides the moist air that triggers thunderstorms, which bring rain in different seasons. The increase in sea surface temperature may cause the Bay of Bengal's winds to blow more forcefully and consistently, which may be a factor in the increased rainfall observed in Bangladesh.

4.2. Future changes in temperature on the summer monsoon

Although there is a lack of climate change projections precisely focused on Bangladesh utilizing multi-model ensembles from global climate models, a few earlier studies have used climate models to examine changes in the country's summer monsoon rainfall and temperature. Recently, Kamruzzaman et al. (2023) employed 18 GCMs from CMIP6 models to project future precipitation and air temperature changes throughout Bangladesh. Their findings indicated that under the SSP2-4.5 and SSP5-8.5 scenarios in the far future, the average maximum temperature (Tmax) is expected to increase by 1.60 °C (1.91 °C). In contrast, the average minimum temperature (Tmin) is projected to rise by 2.99 °C (3.69 °C). The study also suggested a significant temperature increase throughout Bangladesh. Islam et al. (2023) analyzed spatiotemporal changes in temperature projections over Bangladesh. According to their analysis of 40 CMIP5 ensemble data, Bangladesh's mean annual maximum temperature is predicted to increase by 0.61 °C and 1.75 °C in the near future and 0.91 °C and 3.85 °C in the far future, under the RCP4.5 and RCP8.5 scenarios, respectively. Similarly, they projected that under RCP4.5 and RCP8.5, the mean annual minimum temperature would increase by 0.65 °C and 1.85 °C in the near future and 0.96 °C and 4.07 °C in the far future, respectively. These findings align with the results of the current study. Like our study, their predicted yearly and seasonal temperature changes were the highest in the central, northern, and western regions. Almazroui et al. (2020) employed 27 multi-model ensembles of CMIP6 datasets to project temperature and rainfall changes across six South Asian countries. Their study projected an annual mean temperature rise of 1.1 °C to 4.0 °C in Bangladesh for the far-future period (2080–1999). Caesar et al. (2015) utilized a regional climate model driven by 17-member ensembles of projections from a global climate model to investigate climate changes in Bangladesh and the upstream Ganges, Brahmaputra, and Meghna systems. According to their study findings, the annual mean temperature will increase by 2.6 °C to 4.8 °C by 2100 compared to the reference period. Alamgir et al. (2019) also assessed spatiotemporal changes in annual and seasonal temperatures in Bangladesh. They employed eight CMIP5 GCMs for statistical downscaling and found that the RCP8.5 scenario will result in a temperature rise of 2.7 °C to 4.7 °C by the end of the century. Their study highlighted that the northern part of Bangladesh experienced the most substantial increases in maximum and minimum temperatures, which is mainly similar to our current study's findings.

The significant temperature increases observed in Bangladesh are likely influenced by multiple factors. Wyser et al. (2020) explored how various forcing datasets, including factors such as greenhouse gas (GHG) concentrations, insolation, stratospheric ozone concentrations, optical properties of stratospheric aerosols, and land use changes, influenced climate model simulations. They emphasized that GHG concentrations are a significant driver of warming. The variations in outcomes among global climate models (GCMs) are likely to be strongly influenced by how these forcing datasets are considered, highlighting the model-dependent nature of the results. Increased GHG emissions resulting from the expansion of industrial and transportation systems, changes in land use and land cover (LULC), and several additional factors have led to the escalation of greenhouse gases (Shahid 2011). Future projections suggest that Bangladesh may experience increased greenhouse gas emissions due to factors like population expansion, uncontrolled consumption of energy, unplanned industrialization and urbanization, expanding transport networks, and changes in land use and land cover. These factors collectively have the potential to drive further temperature rises in the country (Islam et al. 2023).

Temperature increases are anticipated across all timeframes in Bangladesh, according to the multi-model ensemble (MME) projections. Understanding the anthropogenic influences on climate change is paramount for sustainable development. As a result, it is crucial to look at the fluctuations and changes in the factors causing greenhouse gas (GHG) emissions and temperature rises in Bangladesh. This research is necessary to comprehend the potential consequences of future temperature increases in the country. Such knowledge will aid in formulating effective strategies for financial, environmental, and climate change adaptation planning and mitigation, both locally and nationally.

The study's findings indicate that Bangladesh will likely face increased temperature trends. These rising temperatures may negatively affect public health, especially for vulnerable groups like the elderly and children (Allen et al. 2010; Islam et al. 2021). Meanwhile, most of the regions of South Asia including Bangladesh are projected to increase heat stress at the end of the twenty first century at a South Asian region-based study that investigated the projected heat stress and associated socioeconomic issues over the region. The results also disclosed that Bangladesh is in the fourth position to extreme heat events across South Asia, because of the dynamic variations in summer monsoon precipitations in this wet and dry region - which has straight negative results on human health, water scarcity, agriculture, and other socioeconomic perspectives (Ullah et al. 2022a). Moreover, the projected temperature increase may lead to ecosystem changes, potentially impacting biodiversity, ecosystem services, and other ecological processes (Weiskopf et al. 2020). The sharp temperature rise can also have adverse effects on various agricultural aspects. It may disrupt evapotranspiration, soil moisture content, mineralization, and the timing and planning of irrigation. Consequently, future irrigation demands will necessitate higher rates, leading to increased groundwater depletion in several regions of the country (Mainuddin et al. 2022).

Furthermore, floods/droughts are caused by the summer monsoon (June–September) failing, which provides 72% of the annual rainfall, saving millions of lives (Ghose et al. 2021). Summer monsoon precipitation fluctuations cause significant wet and dry episodes, which cause catastrophic weather events and devastating socioeconomic repercussions (Ullah et al. 2022a). The country's summer monsoon precipitation varies annually due to large-scale atmospheric and oceanic variability, including ENSO, PDO, and IOD (Mei Sein et al. 2021; Ullah et al. 2022b). High temperatures will probably harm Bangladesh's main food staple, rice production. Rice yields may decline by 0% to 61% depending on the rise in temperature and specific locations in this country (Hossain et al. 2021). To mitigate these detrimental negative consequences, the study suggests the implementation of strategies such as integrated nutrient management (Naher et al. 2020), the utilization of unmanageable organic materials (Hossain et al. 2017), and efficient water management (Hossain et al. 2021). On the other hand, these measures might eventually make it more difficult for the government to reduce poverty, raising the price of agricultural production. This study can contribute to the global understanding of the impacts of climate change on the summer monsoon and the role of the summer monsoon in the overall climate system. The present research is limited to evaluating the future changes in summer monsoon rainfall and temperature over Bangladesh in the end of the century. This study did not consider the seasonal cycle of rainfall and temperature episodes. Thus, this needs to be investigated in future research. Another limitation is that this study ignores defining extreme values using either a percentile limit (e.g. the 99th percentile of the reference period) or a threshold-based limit and sees how many (in number) extreme values are simulated above that limit in the future period, which deserve further examination.

5. Conclusions

This study aims to assess the performance of 27 CMIP6 models in simulating Bangladesh's historical climate. The results showed that INM-CM5-0 and BCC-CSM2-MR performed better than other models in simulating temperature and rainfall trends. The study found that all models indicate an upward trend in the mean summer monsoon rainfall based on SSP2-4.5 and SSP5-8.5 scenarios. The findings suggest that the increase in precipitation for the far future period is expected to be more expansive than the rises in the near- and mid-futures. The spatial distribution of monsoon rainfall revealed that Bangladesh's northern, western, and northeastern regions would likely receive more rainfall. This may raise both flood and water stresses in these regions. It has highlighted the need to reorganize prevailing adaptation policies, especially those emerging from CMIP6 SSP2-4.5 and SSP9-8.5 scenarios. It is also expected to continuously increase the mean summer monsoon temperature over Bangladesh by the end of the twenty-first century. The most significant increase in temperature is projected to occur in the northwestern and west-central regions of Bangladesh under SSP5-8.5 compared to the reference climate (1981–2014). Any changes in the consistency of summer temperatures and precipitation can substantially influence the biodiversity in these regions. Further modeling can consider the enhanced availability of GCM CMIPs, and use the capability to compare and contrast the different model features. The study indicated that there is significant uncertainty in Bangladesh's summer rainfall and temperature estimates, emphasizing the necessity for further research to reduce these uncertainties in projections for climate change effect evaluations. The projected outcomes would aid in developing climate-smart farming practices and technological innovation. Findings can also be applied to climatological research and assessments of the effects of climate change on Bangladesh. These findings provide valuable insights into the performance of CMIP6 models over Bangladesh and can help build adaptation methods and policymaking related to climate change in the study area.

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