CLIMATE CHANGE IMPACT ON FUTURE PRECIPITATION AND TEMPERATURE CHANGES IN NORTHWEST REGION OF BANGLADESH - COMPARISON OF HADCM3 AND CANESM2 MODELS

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ABSTRACT

Bangladesh is considered to be one of the most vulnerable countries in the world to climate change. A significant impact has already occurred in the country during the last few decades due to the potential impact of climate change, which is expected to be exacerbated in the future. Hence, the assessment of future changes in precipitation and temperature due to the impact of climate change is crucial for water resources and climate change studies to minimize the overall impacts in the region. Therefore, the objective of this study is to explore the impact of climate change on future precipitation and temperature changes in the northwest region of Bangladesh using the statistical downscaling model (SDSM). In the current study, Rajshahi station is taken as the case study area. Two widely applied general circulation models (GCMs), namely the Hadley Center Coupled Model (HadCM3) and the Canadian Earth System Model (CanESM2), are used for the analysis. In this study, a SDSM-based climate change assessment framework is used by making a bridge between large and local resolutions for the statistical downscaling of precipitation and temperatures in the study area. Its applicability is then assessed by using the calibration and validation of the downscaled model with and without applying the bias correction technique. The downscaling results demonstrated that after bias correction, the CanESM2-based downscaling model performed better compared to the HadCM3-based downscaling model. Finally, the bias-corrected models for both GCMs are employed for the projection of future precipitation and temperatures for the 2040s and 2090s, considering climate change scenarios. The precipitation trend is found to be negative for all GCM output scenarios when the worst climate change scenarios (i.e., the A2 scenario in the HadCM3 model and the RCP8.5 scenario in the CanESM2 model) are taken into account. For the 2040s and 2090s, considering A2 and RCP8.5 scenarios, respectively, the mean annual precipitation trend would be decreased by 4.5%, 9.3%, and 4.1%, 12.1%, and the mean annual maximum temperature would be increased by 0.245°C, 0.233°C, and 0.633°C, 0.468°C, whereas Tmin would be increased by 0.188°C, 0.394°C, and 0.357°C, 0.394°C. Based on the obtained results, it can be concluded that the water resources in the study area will be impacted by a decrease in precipitation, resulting in a reduction in groundwater storage. Additionally, an increase in temperature will result in the quick evaporation of surface water resources, which will reduce surface water supplies. It is expected that the outcome of the study will be supportive to policymakers and water managers in developing adaptive water management approaches for the sustainable development of Bangladesh.

Keywords: *Climate change, GCM, SDSM, CanESM2, HadCM3, Statistical downscaling*

1. INTRODUCTION

Climate change and its possible consequences are responsible for causing increasing temperatures, high spatial and temporal variation of precipitation, rising sea levels, loss of wetlands, depletion of groundwater, increased salinity problems, and so on (van der Wiel & Bintanja, 2021; Abbass et al., 2022; Schwartz et al., 2023). Since the late 20th century, it has been widely accepted that human-induced greenhouse gas emissions constitute the primary driver of global warming, indicating a continued warming trend in the future (Liu et al., 2022). The Intergovernmental Panel on Climate Change (IPCC) indicated in their Fifth Assessment Report (AR5) that global temperature rise and changes in global precipitation patterns are currently significant and are threatening future generations (Robinson, 2020).

Bangladesh has been identified as one of the most susceptible countries in the world to climate change. The country has been facing various environmental challenges occurring each year as a result of climate change (Rahman & Islam, 2019). For example, climate change-induced variability in precipitation and temperature and the frequent occurrence of flash floods and droughts are common in the country (Faisal et al., 2021). The northwest region of Bangladesh is, in particular, highly affected by the negative impact of climate change (Rana et al., 2023). Several researchers pointed out that there will be a rise in temperature and a drop in precipitation in the region due to the detrimental effects of climate change (Esha & Rahman, 2021; Rahman et al., 2021; Rana et al., 2023). Therefore, it is vital to detect changes in future precipitation and temperature due to the impact of climatic change in order to devise ways for planning adaptation measures.

Global climate models (GCMs) are widely used in climate change studies all over the world. However, the GCMs models have large resolution, for which their usages are not appropriate for climate change impact studies at a local and/or regional scale. Hence, the GCM outputs are downscaled at a local scale using either statistical downscaling or dynamic downscaling techniques. Due to the high computation burden associated with the dynamic downscaling technique, the statistical downscaling technique finds wide application all over the world due to its simplicity and ease of use for downscaling GCMs (e.g., Hassan et al., 2014; Jaiswal et al., 2017; Jahangir et al., 2020; Munawar et al., 2022; Rana & Adhikary, 2023). The climate change downscaling task is often performed by using the freely available statistical downscaling Model-Decision Centric (SDSM-DC) software (Wilby & Dawson, 2013).

In the past, researchers adopted the widely applied SDSM-based downscaling approach for downscaling the GCM models to assess climate change-induced future changes in precipitation and temperature at local scales (e.g., Chu et al., 2010; Mahmood & Babel, 2013; Jaiswal et al., 2017; Gulacha & Mulungu, 2017; Jahangir et al., 2020; Rana and Adhikary, 2023). Hence, the objective of the current study is to apply the SDSM-based downscaling approach for exploring the past climatic pattern (observed) and most possible future (simulated) changes in climate of the northwest region in Bangladesh over the 2040s and 2090s.

2. METHODOLOGY

In the current study, future changes in temperature and precipitation in Rajshahi station, located in the northwest region of Bangladesh, have been assessed using the SDSM-DC software. The analysis is based on two widely used GCMs, namely Hadley Centre Coupled Model version 3 (HadCM3) and the second-generation Canadian Earth System Model (CanESM2), which are recognized globally for future prediction of climate change (Jaiswal et al., 2017; Gulacha & Mulungu, 2017; Bayatvarkeshi et al., 2020; Virgin et al., 2021). The HadCM3 model works under A2 and B2 scenarios, whereas the CanESM2 model works under RCP2.6 (low emission), RCP4.5 (medium emission), and RCP8.5 (high emission) scenarios to generate downscaling results of temperature and precipitation. Finally, the study attempts to compare the performance of both GCMs in statistical downscaling and future projection of precipitation and temperatures over the study area in order to select the best GCM satisfactory for the statistical downscaling for the study area. The methodology of the current study is detailed in the following sub-sections.

2.1 Study Area and Data Description

The current study is demonstrated through the Rajshahi station in Bangladesh, which is located in the northwest region of the country. It lies between 24°22'26"N latitude and 88°36'4"E longitude. The location of the study area is shown in Figure 1, which covers an area of about 2,407 km^2. The climatic condition in the study area is mostly different from other regions of Bangladesh, and it experiences a warm desert climate zone with maximum rainfall in monsoon periods (about 1250 mm/year) and is extremely hot in the summer season with an average temperature of 34.6°C. In Bangladesh, specifically in the study region, there are several aquifers and surface bodies. Precipitation in the study area is greatly influenced by temperature variability.

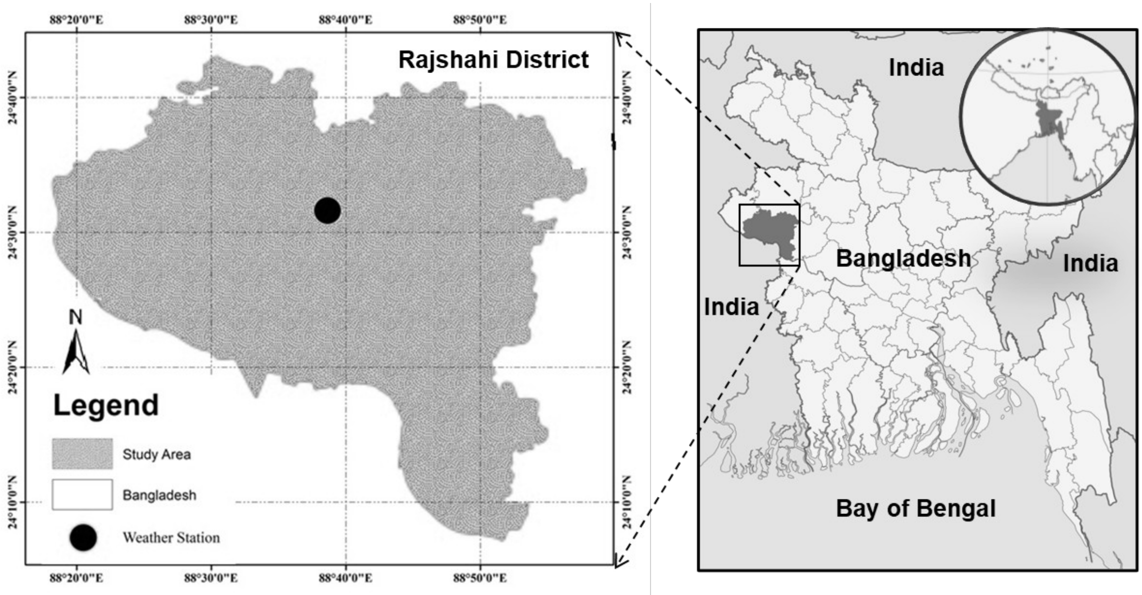

Figure 1: Location of the study area (Rajshahi district) in the northwest region of Bangladesh

In the current study, the observed climate data (precipitation, maximum, and minimum temperatures) from 1975 to 2001 for the Rajshahi station in Bangladesh is used for the analysis. Data are collected from the Bangladesh Meterological Department (BMD). Two distinct time periods of observed daily data are used for two GCM models: the 1975-2001 period is used for the HadCM3 model, and the 1975-2005 period is used for the CanESM2 model. HadCM3 and CanESM2 model data, along with the corresponding emission scenarios, are collected from the corresponding freely available online data sources. Two-thirds of the observed daily data is used for model calibration, and the remaining one-third is for model validation purposes. Table 1 presents the details of the collected data.

Table 1: Two individual GCM with their scenarios output features

GCMs	Emission Scenarios	Data Period	Calibration	Validation
HadCM3	A2, B2	1975-2001	1975-1995	1996-2001
CanESM2	RCP2.6, RCP4.5, RCP8.5	1975-2005	1975-1995	1996-2005

The HadCM3 GCM model consists of two possible scenarios, namely A2 and B2. A2 depicts rapid population expansion worldwide along with a sluggish economic growth rate, although significant technological advancements are being made. The B2 scenario represents a lower rate of world population compared to A2, and it also considers social and environmental sustainability. On the other hand, the CanESM2 GCM model has three RCP scenarios, namely RCP2.6 (low carbon emission), RCP4.5 (moderate carbon emission), and RCP8.5 (high carbon emission) scenarios. In addition, NCEP/NCAR reanalyzed predictor data, which consists of 26 predictor variables, are collected from the Canadian website to make a bridge between large scale variables (predictors) and local scale variables (predictants). Climate projections are undertaken for the 2001-2099 period for the HadCM3 GCM, whereas for the CanESM2 GCM, climate projections are made for the 2006-2100 period.

2.2 Statistical Downscaling Model

In the current study, the statistical downscaling model-decision centric (SDSM-DC) is adopted to downscale two GCM models, namely HadCM3 and CanESM2. SDSM-DC is user-friendly and open-source software that is widely applied all over the world for the statistical downscaling of GCM models. Its decision-making performance makes it more acceptable than other tools. For precipitation, the fourth root of the model transformation and the optimum least squares algorithm with a 0.3 event threshold under a conditional process. On the other hand, for temperature, the none of model transformation and dual simplex algorithm with 0 event sould be used under an uncondtional process. The working function is done by generating weather series based on GCM outputs. The major several steps such as quality control (used for checking missing data, maximum, minimum average, etc.), screening of predictors (used correlation coefficient with large-scale and local climatic variables), calibration, validition, weather generator, summary, frequency, and time series analysis (Jaiswal et al., 2017; Wilby & Dawson, 2013) that is user-friendly and easy to handle.

This study employs three sub-models, namely monthly, annual, and seasonal, for statistical downscaling of temperature and precipitation. In comparison to other sub-models, the performance of the monthly sub-model is pretty excellent (Saymohammadi et al., 2017; Tahir et al., 2018). Annual sub-model performance is appreciated among other models with conditional and unconditonal aspects. The conditional is used for dependent variables such as precipitation and evaporation, and the unconditional is used for independent variables such as temperature (Samadi et al., 2011).

2.3 Screening of Predictors

After checking the predictands file, the most important and difficult task is to identify the appropriate list of predictors. Variance, correlation matrix, partial correlation (r), and p-values are the four main indicators that are used to identify the suitable predictor list. Firstly, the correlation coefficient between predictands (observed values *dat file) and NCEP 26 predictors must be evaluated according to ascending order. Only the top 12 largest values of the correlation coefficient would be selected. Secondly, select the super predictors (highest coefficient values) and also calculate the partial correlation (r) and p-values simultaneously. The maximum r-value and smaller p-value ($p < 0.05$) indicate a better association between variables. Thirdly, calculate the percentage reduction factor (P_{rf}) between SP and the rest of the 11 predictors using Equation (1).

$$P_{rf}(\%)=\frac{P_r-R}{R}*100 \quad (1)$$

where, the $P_{rf}(\%)$ is percentage reduction factor, P_r is the absolute partial correlation, and R is the absolute correlation coefficient between predictors. Higher than 60% values of P_{rf} must be eliminated. However, more than 60% of P_{rf} values must be eliminated to select the most suitable predictor list.

2.4 Calibration and Validation

Once the list of most suitable predictors is identified, the model is calibrated and validated against the observed data. As indicated earlier, two-thirds of the observed data is used for calibration, and the rest is used for validation. In order to measure the statistical performance, the coefficient of determination (R^2) and root mean square error (RMSE) are performed between observed and simulated values for the calibration and validation periods to reach the best statistical agreement. When the RMSE value is equal to zero and R^2 is equal to one for a model, this demonstrates that the model exhibits the perfect relationship between predictands (temperature and precipitation in this study) and predictors

(NCEP/NCAR). It is worth mentioning that the statistical downscaling model often creates some biases during its projection or simulation process. In order to minimize the error, Eqs. (2)-(3) are used for evaluating more accurate predictions of temperature (T_{max} and T_{min}) and precipitation values, respectively.

$$\varphi_p = \frac{\varphi_{¿,p} * \overline{\varphi_{obs,p}}}{\overline{\varphi_{¿,p}}} \quad (2)$$

$$\varphi_T = \varphi_{¿,T} - \left(\overline{\varphi_{obs,T}} - \overline{\varphi_{¿,T}} \right) \quad (3)$$

Where the $\varphi_p$and φ_T are the bias-corrected values of precipitation and temperature, respectively, $\varphi_{¿,p}$ and $\varphi_{¿,T}$ are simulated values of precipitation and temperature, respectively $\overline{\varphi_{obs,p}}$,$\overline{\varphi_{obs,T}}$ are represent the long-term mean observed values of precipitation and temperature, respectively, and $\overline{\varphi_{¿,T}}$ is the long-term mean simulated values of temperature.

2.5 Anomaly in Future Precipitation and Temperature

The future prediction of climatic changes for two future periods of the 2040s and 2090s is calculated with respect to the observed period for two GCM outputs (HadCM3 and CanESM2 models). For the HadCM3 model, the future projection is outlined from 1975 to 2099 under A2 and B2 scenarios, and for the CanESM2 model, from 2006 to 2100 considering RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively. Around 30 years of data have been counted due to the local climate, and it is enough according to the IPCC assessment (Skea et al., 2021).

3. RESULTS ANS DISCUSSION

The appropriate predictors are chosen for the percentage reduction factor process utilizing Equation (1), with less than 60% values considered the most acceptable predictors based on the partial correlation coefficient and *p* values, which are given in Table 2. The tick mark (√) in Table 2 indicates the identified most suitable predictors for downscaling each climate variable, either using the HadCM3 model or the CanESM2 model. For the stuy area, different GCMs are influenced by different atmospheric characteristics for T_{max}, T_{min}, and precipitation. Mean sea level pressure (*mslp*), mean temperature at 2m height (*temp*), and surface-specific humidity (*shum*) are the most influential variables for all climatic variables under the two GCMs. Although a maximum of two predictors is enough for downsaling, more predictor variables can be used for more stable results (Gulacha & Mulungu, 2017; Jahangir et al., 2020).

Table 2: List of identified most suitable predictors for temperature and precipitation downscaling

GCMs	Climate variable	NCEP/NCAR reanalysis predictor variables												
		mslp	p_u	rhum	p5_f	p500	p5th	p8_v	prcp	r850	p850	s850	temp	shum
HadCM3	Prec.	√					√			√				√
	T_{max}	√	√	√										√
	T_{min}	√	√	√										√
CanESM2	Prec.				√	√					√			√
	T_{max}	√			√	√							√	√
	T_{min}												√	√

The daily observed data is separated into two groups, with 70% used for calibration and the remaining 30% utilized for validation of the SDSM outputs. For both the calibration and validation periods, two particular statistical indexes are used to compare statical performance: R^2 and RMSE. Table 3 presents the validation results before and after applying the bias correction formula. As can be seen from the table, after bias-correction of the downscaling results, the applicability of SDSM performance is significantly boosted. The calibration and validation performance of SDSM have been tested for model applicability using two sets of observed data. Table 3 shows that during the course of the Rajshahi station, the two statistical indicators: R^2 ranged from 0.625 to 0.864 for temperature and from 0.652 to 0.691 for precipitation, and RMSE varies from 1.878 to 2.615 for temperature and from 12.503 to 12.542 for precipitation, respectively, during the calibration period. The performance of SDSM during calibration concludes that all the results are within the allowed range, and the overall performance of the HadCM3 model is better than the CanESM2 model for downscaling of precipitation and temperature over the study area.

Table 3: Model applicability check for comparative GCMs during calibration and validation period

GCMs	Model Calibration					
	Precipitation		T_{max}		T_{min}	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
HadCM3	0.691	12.503	0.609	1.923	0.864	2.189
CanESM2	0.652	12.542	0.625	1.878	0.609	2.615
GCMs	Model Validation (with bias)					
	Precipitation		T_{max}		T_{min}	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
HadCM3	0.782	13.235	0.681	1.811	0.881	2.085
CanESM2	0.681	13.205	0.672	1.838	0.861	2.414
GCMs	Model Validation (with bias-correction)					
	Precipitation		T_{max}		T_{min}	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
HadCM3	0.794	12.350	0.651	1.010	0.889	2.043
CanESM2	0.693	12.051	0.679	1.328	0.692	2.391

The validity of the downscaling models is validated using the remaining data set after calibration. The highest R^2 value was found to be 0.881 for T_{min} downscaling using the HadCM3 model before bias adjustment. However, following bias correction, the value marginally rose to 0.889 for T_{min} downscaling using the HadCM3 model. Simultaneously, the highest R^2 was obtained as 0.681 for T_{max} downscaling using the HadCM3 model before the bias correction. However, the highest R^2 was found to be 0.679 for T_{max} downscaling using the CanESM2 model after the bias correction. In addition, for T_{max} downscaling, the lowest RMSE was found to be 1.811 before the bias correction using the HadCM3 model, which was reduced to 1.010 after the bias correction.

For precipitation downscaling without bias correction, the highest R^2 was found to be 0.782 using the HadCM3 model, which was increased to 0.794 after the bias correction was applied. Furthermore, the lowest RMSE was obtained as 13.205 before the bias correction using the CanESM2 model, whereas after the bias correction, it was reduced to 12.051 using the CanESM2 model. Thus, it can be seen from the statistical performance results presented in the table that the simulated and observed values are consistent in most cases. It was also found that the HadCM3 model performed better than the CanESM2 model in most cases. The downscaling results also indicated that there was a strong agreement between the observed and simulated temperature (T_{max} and T_{min}) and precipitation values over the study area. This demonstrates that the downscaling models can be used for the projection of future climates based on different emission scenarios under each GCM.

Figure 2 presents a comparison of mean monthly precipitation and maximum and minimum temperatures (T_{max} and T_{min}) for the corresponding emission scenarios of the HadCM3 and CanESM2 models for the 2040s and 2090s. As can be seen from the figure, there is a declining trend in the mean monthly average precipitation in the study area. On the other hand, the temperature (T_{max} and T_{min}) displays an upward tendency with respect to the observed values for the future periods of the 2040s and 2090s, respectively. It is also found that for precipitation, almost all scenarios are likewise below the observed levels from January to December, although RCP8.5 scenarios exceed the mean monthly precipitation values for June, September, and October. In contrast, for temperature (T_{max} and T_{min}), all scenarios exceed the observed values. Thus, the results demonstrate that there will be less precipitation in the future, along with an increasing temperature over the study area.

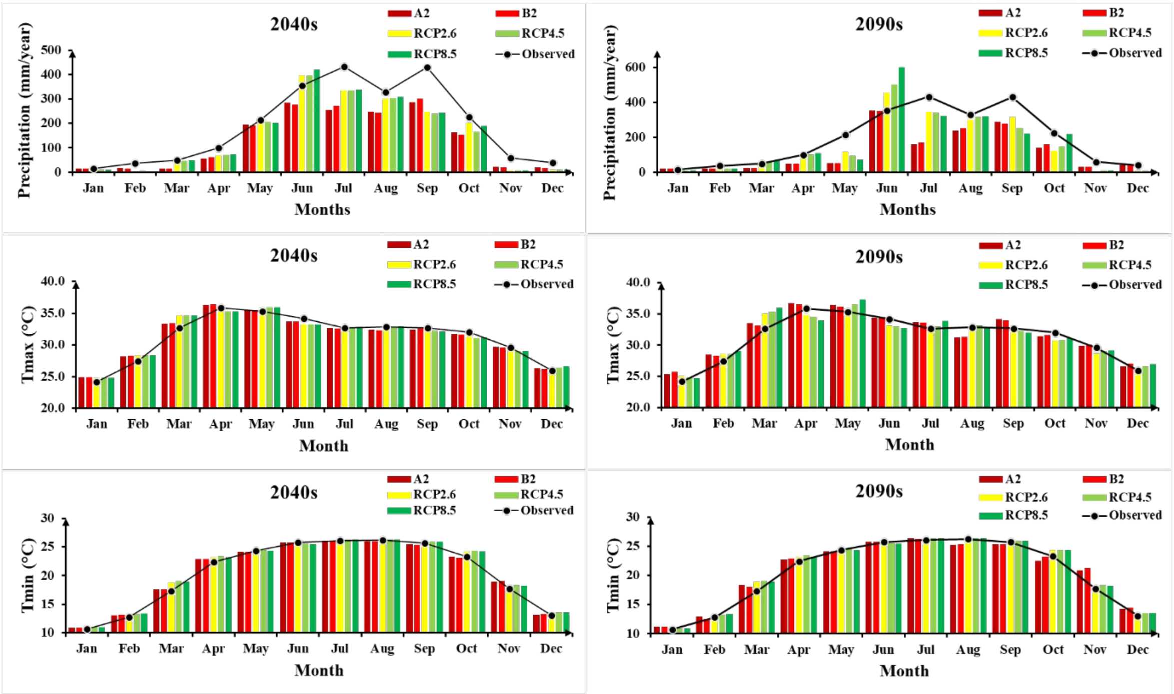

Figure 2: Comparison of mean monthly precipitation, T_{max}, and T_{min} for A2, B2 scenarios of the HadCM3 model, and RCP2.6, RCP4.5, RCP8.5 scenarios of the CanESM2 model for the 2040s and 2090s

In any climate change study, it is apparent that the amount of future changes in the climate variables needs to be quantified. Accordingly, the changes in future precipitation and temperature over the study area based on the two GCMs considering different corresponding climate change scenarios are calculated, which are presented in Table 4. As can be seen from the table, the percentage anomaly in mean annual precipitation gives negative values for all scenarios in both GCMs. This demonstrates that the precipitation pattern decreased with respect to the observed values for the study area. It can also be seen from the downscaling results presented in Table 4 that when the worst climate change scenarios (the A2 scenario in the HadCM3 model and the RCP8.5 scenario in the CanESM2 model) are taken into account, the future precipitation trend is found to be negative. It is evident from the results that for the HadCM3 and CanESM2 models, the precipitation decreased by 4.5% and 9.26% in the 2040s and 4.1% and 12.1% in the 2090s, respectively. At the same time, the model output also shows that for the HadCM3 and CanESM2 models, the mean annual maximum temperature increased by 0.245°C and 0.233°C in the 2040s, whereas 0.633°C and 0.468°C in the 2090s. Further, T_{min} increased by 0.188°C and 0.394°C in the 2040s and 0.357°C and 0.394°C in the 2090s, respectively, for both GCMs. Thus, it can be concluded that the study area is gradually becoming drier and warmer. This has severe implications for the sustainable management of water resources and agricultural activities in the region, which will impact the sustainable development of the region as well as the country.

Table 4: Changes in future mean annual precipitation and temperature for 2040s and 2090s

GCMs	Scenarios	2040s			2090s		
		Precipitation (%)	**T_{max} (°C)**	**T_{min} (°C)**	**Precipitation (%)**	**T_{max} (°C)**	**T_{min} (°C)**
HadCM3	A2	-4.5	0.245	0.188	-4.1	0.633	0.357

	B2	-8.1	0.231	0.188	-5.7	0.639	0.439
CanESM2	RCP2.6	-4.3	0.203	0.375	-9.9	0.195	0.394
	RCP4.5	-7.11	0.204	0.456	-11.3	0.286	0.456
	RCP8.5	-9.26	0.233	0.394	-12.1	0.468	0.394

4. CONCLUSIONS

The current study focuses on the assessment of the impact of climate change on future precipitation and temperature changes in the northwest region of Bangladesh using the statistical downscaling model (SDSM). An SDSM-based climate change assessment framework is adopted in this study for the statistical downscaling of precipitation and temperatures in the 2040s and 2090s, which is demonstrated through the Rajshahi station in the region. Two widely applied general circulation models (GCMs), namely the Hadley Center Coupled Model (HadCM3) and the Canadian Earth System Model (CanESM2), are used for the analysis. In order to obtain the comparative result, the corresponding scenarios of two GCMs—A2 and B2 scenarios of the HadCM3 model and RCP2.6, RCP4.5, and RCP8.5 scenarios for the CanESM2 model—are considered. Based on the findings of the current study, the following conclusions can be drawn:

- The performance of both GCMs (HadCM3 and CanESM2 models) during calibration and validation demonstrates that they are satisfactory for the statistical downscaling and future projection of precipitation and temperatures over the study area. However, the performance of SDSM during calibration concludes that the overall performance of the HadCM3 model is better than the CanESM2 model for the study area.
- The downscaling results of both GCMs are substantially enhanced in all scenarios when the bias correction is applied.
- Based on the climate change projection results, it is found that the future mean monthly and annual precipitation exhibits a declining trend, whereas the daily maximum and minimum temperatures are characterized by a rising trend over this study area.
- The maximum anomalies in future climates are evident when the worst climate change scenarios (the A2 scenario in the HadCM3 model and the RCP8.5 scenario in the CanESM2 model) are considered. The results indicate that there will be less precipitation (negative changes) in the future, along with an increasing temperature (positive changes) over the study area.
- The study finally concludes that the northwest region of Bangladesh is gradually becoming drier and warmer, which has important implications for the sustainable management of water resources and agricultural activities in the region, impacting the sustainable development of the region as well as the country.

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