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IMPACT OF CLIMATE CHANGE ON PRECIPITATION AND TEMPERATURE CHANGES IN THE NORTHWEST REGION OF BANGLADESH USING SDSM: A COMPARISON OF CANESM2 AND HADCM3 MODELS

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ABSTRACT

Assessment of climate change-induced precipitation and temperature changes is crucial for the adaptive and sustainable management of water resources in a country. 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 this study, Rajshahi station is taken as the case study area, and two widely applied general circulation models (GCMs), namely the Canadian Earth System Model (CanESM2) and the Hadley Center Coupled Model (HadCM3), are used for the climate change analysis. The results demonstrate that after bias correction, the CanESM2-based downscaling model performs better compared to the HadCM3-based downscaling model. The bias-corrected models for both GCMs are then 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 both GCMs in all scenarios. Considering the worst climate change scenarios for both GCMs (i.e., the RCP8.5 scenario in the CanESM2 and the A2 scenario in the HadCM3), the mean annual precipitation will be decreased by 9.3% and 4.5% in the 2040s and 12.1% and 4.1% in the 2090s. Furthermore, the mean annual maximum temperature will be increased by 0.233°C and 0.245°C in the 2040s and 0.468°C and 0.633°C in the 2090s, whereas the mean annual minimum temperature will be increased by 0.394°C and 0.188°C in the 2040s and 0.394°C and 0.357°C in the 2090s. Thus, the current study concludes that decreased precipitation and increased temperatures will have an effect on the water resources in the study region, leading to a reduction in the overall supply of surface water and groundwater storage. It is expected that the study findings will help water managers and policymakers in developing a framework for sustainable and adaptive water management in the face of climate change.

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 is considered to be one of the most vulnerable countries in the world to climate change. This is due to its unique geographic location, dominance of floodplains and low elevation from the sea, high spatial and temporal climatic variability, extreme weather events, high population density, high incidence of poverty and poor institutional capacity, inadequate financial resources, and poor infrastructure. The IPCC Special Report on the Regional Impacts of Climate Change (2007) indicates that there would be drastic changes in rainfall patterns in the warmer climate and Bangladesh may experience 5-6% increase in rainfall by 2030, which may create frequent large and prolonged floods. In contrary, the country is facing drought in the northwestern region, which greatly affects agricultural activities and food production, water resources, and human health. The moderately drought-affected areas will be turned into severely drought-prone areas within the next 20-30 years (IPCC, 2007). The country has been facing various environmental challenges occurring each year as a result of climate change (Ali & Hossen, 2022; 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

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Bangladesh (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 indispensable to assess changes in future precipitation and temperature due to the impact of climatic change in order to devise ways for planning climate change adaptation strategies.

In order to adopt climate change mitigation and adaptation strategies and to avoid ill-informed decisions about the prospective water resources availability and its sustainable management, planners need knowledge about the impacts of climate changes on meteorological parameters at a local scale. The general circulation models (GCMs) are the main informative tools used for present and future climate change scenarios. Hence, GCMs are widely used in climate change studies all over the world. However, GCMs usually exhibit a very coarse resolution (usually more than 40,000 sq. km), for which their usages are not appropriate for climate change impact studies at a local and/or regional scale (Wilby *et al*., 2002). 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., Mahmood & Babel, 2013; Hassan *et al*., 2014; Mahmood *et al*., 2015; Jaiswal *et al*., 2017; Al-Mukhtar & Qasim, 2019; Jahangir *et al*., 2020; Munawar *et al*., 2022; Rana & Adhikary, 2023). The statistical downscaling task in climate change studies is often performed by using the widely applied Statistical Downscaling Model-Decision Centric (SDSM-DC) software (Wilby & Dawson, 2013). The main advantage of the software is that it is easy to use for statistical downscaling of GCMs for climate variables and freely available for researchers.

In the past, researchers adopted the widely applied SDSM-based downscaling approach for downscaling the GCM models to assess climate change-induced changes in future 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 precipitation and temperatures for the 2040s in near future and for the 2090s in far future over the northwest region in Bangladesh.

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 widely used SDSM-DC software (Wilby & Dawson, 2013). The software is freely available at a dedicated website for SDSM software and related resources (https://www.sdsm.org.uk/). The climate change analysis in the current study is based on two widely used GCMs, namely the second-generation Canadian Earth System Model (CanESM2) and the Hadley Centre Coupled Model version 3 (HadCM3), 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 CanESM2 model considers different Representative Concentration Pathway (RCP) scenarios demonstrating climate change. RCP is a greenhouse gas concentration trajectory adopted by the Intergovernmental Panel on Climate Change (IPCC) of the United Nations. In the current study, the CanESM2 model works under RCP2.6 (low emission), RCP4.5 (medium emission), and RCP8.5 (high emission) scenarios, whereas the HadCM3 model works under A2 and B2 scenarios defining climate changes to generate downscaling results of temperature and precipitation. Finally, the study attempts to compare the performance of both GCMs in statistical downscaling and future projections 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. Rajshahi district is situated between 24°10′ and 24°40′ N latitudes and between 88°20′ and 88°50′ E longitudes, with an average elevation of 23m from the mean sea level. The Padma River, being one of the most important rivers in the country, is the main source of water supply for irrigation and aquatic systems. The location of the study area is shown in Figure 1, which covers an area of about 2,407 sq. km. 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 of about 1250 mm/year in monsoon periods and is extremely hot in the summer season with an average temperature of 34.6°C. Precipitation in the study area is greatly influenced by the significant variation of temperature. The northwestern region of the country is considered a vulnerable area in the context of climate change. In particular, Rajshahi district, which covers a part of the Barind tract region and is dominant in low-scale farming, is highly vulnerable to the potential impact of climate change. Therefore, the current study is an attempt to assess the impact of climate change on future precipitation and temperature changes in Rajshahi district of Bangladesh.

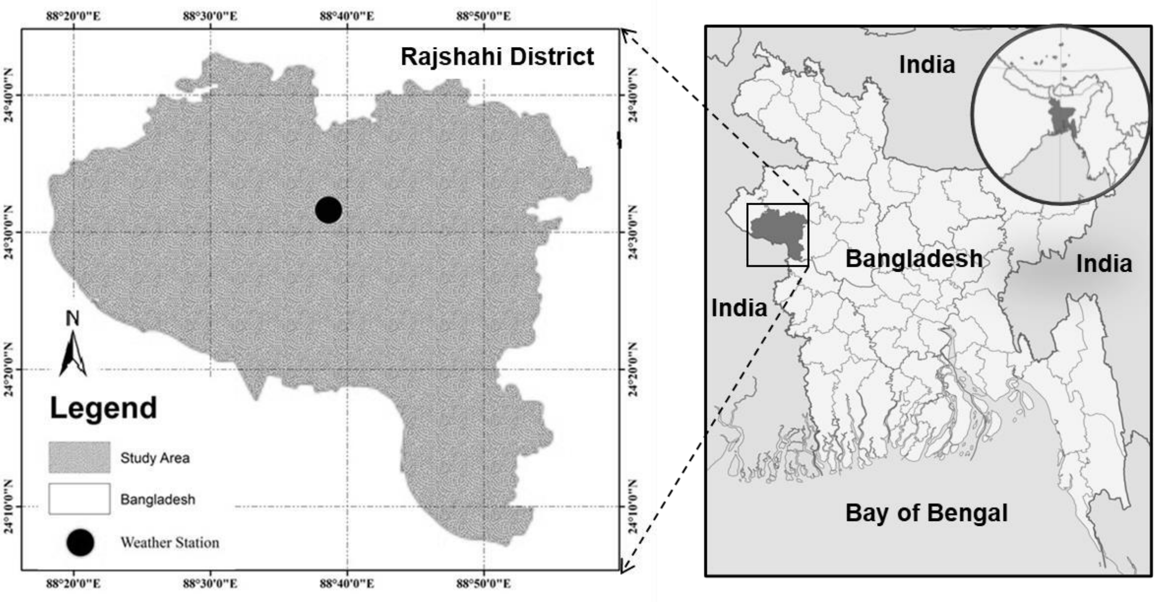

Figure 1: Location of the study area (Rajshahi district) in the northwest region of Bangladesh

In the current study, the observed climate data (precipitation, maximum, and minimum temperatures) from 1975 to 2005 for the Rajshahi station in Bangladesh is used for the analysis. Data are collected from the Bangladesh Meterological Department (BMD). Table 1 presents the details of the collected data, which are used for the model development and analysis in the current study. Two distinct time periods of observed daily data are used for two GCM models considering the data availability of the GCM models. Accordingly, the 1975-2005 period is used for downscaling the CanESM2 model, whereas the 1975-2001 period is used for downscaling the HadCM3 model. CanESM2 and HadCM3 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 used for model validation.

Table 1: Two individual GCM with their scenarios output features

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

The CanESM2 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 consists of twenty-six (26) predictor variables, which are shown in Table 2. The predictor variables data are collected from the Canadian website (https://www.esrl.noaa.gov/psd/data/reanalysis/reanalysis.shtml) to make a bridge between large scale variables (predictors) and local scale variables (predictands).

On the other hand, the HadCM3 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. Based on the observed data, the downscaling model for each of the GCMs is developed, calibrated, and validated, and then bias-corrected. Finally, the bias-corrected models are used for the projection of future precipitation and temperature data up to 2100, from which the analysis of climate change impact on future precipitation and temperature changes over the study area is undertaken for the 2040s in near future and for the 2090s in far future considering different climate change scenarios for both GCMs. The projection of future climates (precipitation and temperatures) for the HadCM3 model is carried out for the 2001-2099 period, whereas for the CanESM2 model, the climate change projections are performed for the 2006-2099 period. Finally, the changes in future precipitation and temperatures for the 2040s in near future and for the 2090s in far future over the study area are assessed.

Table 2: Summary of the NCEP/NCAR reanalyzed predictors

Sl. No.	Description of Predictors	Predictors
1	Mean sea level pressure (Pa)	*mslpgl*
2	1000 hPa Wind speed	*p1_fgl*
3	1000 hPa Zonal wind component	*p1_ugl*
4	1000 hPa Meridional wind component	*p1_vgl*
5	1000 hPa Relative vorticity of true wind	*p1_zgl*
6	1000 hPa Wind direction	*p1thgl*
7	1000 hPa Divergence of true wind	*p1zhgl*
8	500 hPa Geopotential	*p500gl*
9	500 hPa Wind speed	*p5_fgl*
10	500 hPa Zonal wind component	*p5_ugl*
11	500 hPa Meridional wind component	*p5_vgl*
12	500 hPa Relative vorticity of true wind	*p5_zgl*
13	500 hPa Wind direction	*p5thgl*
14	500 hPa Divergence of true wind	*p5zhgl*
15	850 hPa Geopotential	*p850gl*
16	850 hPa Wind speed	*p8_fgl*
17	850 hPa Zonal wind component	*p8_ugl*
18	850 hPa Meridional wind component	*p8_vgl*
19	850 hPa Relative vorticity of true wind	*p8_zgl*
20	850 hPa Wind direction	*p8thgl*
21	850 hPa Divergence of true wind	*p8zhgl*
22	Total precipitation	*prcpgl*
23	500 hPa Specific humidity	*s500gl*
24	850 hPa Specific humidity	*s850gl*
25	1000 hPa Specific humidity	*shumgl*
26	Air temperature at 2m	*tempgl*

2.2 Statistical Downscaling Model Development

In the current study, an 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 widely applied SDSM-DC software (Wilby & Dawson, 2013) is adopted in the current study to downscale precipitation and maximum and minimum temperatures for two GCMs, namely CanESM2 and HadCM3 models. The SDSM-DC software is a user-friendly and open-source software that is widely employed 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.

The current study has employed three sub-models, namely monthly, annual, and seasonal, for statistical downscaling of temperatures 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 (Prf) 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 Model Calibration and Validation

Once the list of most suitable predictors is identified, the downscaling 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 the current 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, Equations (2) and (3) are used for evaluating more accurate predictions of temperature (Tmax and Tmin) and precipitation values, respectively.

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

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

Where the φ_p and φ_T are the bias-corrected values of precipitation and temperature, respectively, $\varphi_{sim,p}$and $\varphi_{sim,T}$ 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 $\overline{\varphi_{sim,T}}$ 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 GCMs). 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 for precipitation and temperatures have been counted describing the local climatic condition. This data duration is adequate according to the IPCC assessment and recommendations (Skea *et al*., 2021).

3. RESULTS AND DISCUSSION

The appropriate predictors are chosen for the percentage reduction factor process using the Equation (1), with less than 60% values considered the most acceptable predictors based on the partial correlation coefficient and p values. The obtained results are given in Table 3. The tick mark (√) in the table indicates the identified most suitable predictors for downscaling each climate variable, either using the HadCM3 model or the CanESM2 model. For the study area, different GCMs are influenced by different atmospheric characteristics for T_{max}, T_{min}, and precipitation variables. As can be seen from Table 3, 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 adequate for statistical downsaling of GCM for climate variables in the SDSM-DC platform, more predictor variables can be used for accurate and stable downscaling results (Gulacha & Mulungu, 2017; Jahangir *et al*., 2020). This strategy is adopted in the current study for statistical downscaling of precipitation, T_{max} and T_{min} over the study area using CanESM2 and HadCM3 models.

Table 3: 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
CanESM2	Prec.				√	√					√			√
	T_{max}	√			√	√							√	√
	T_{min}												√	√
HadCM3	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 4 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 4 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 4: Model applicability check for comparative GCMs during calibration and validation

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

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 Tmin 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 Tmax 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 temperatures (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 temperatures (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.

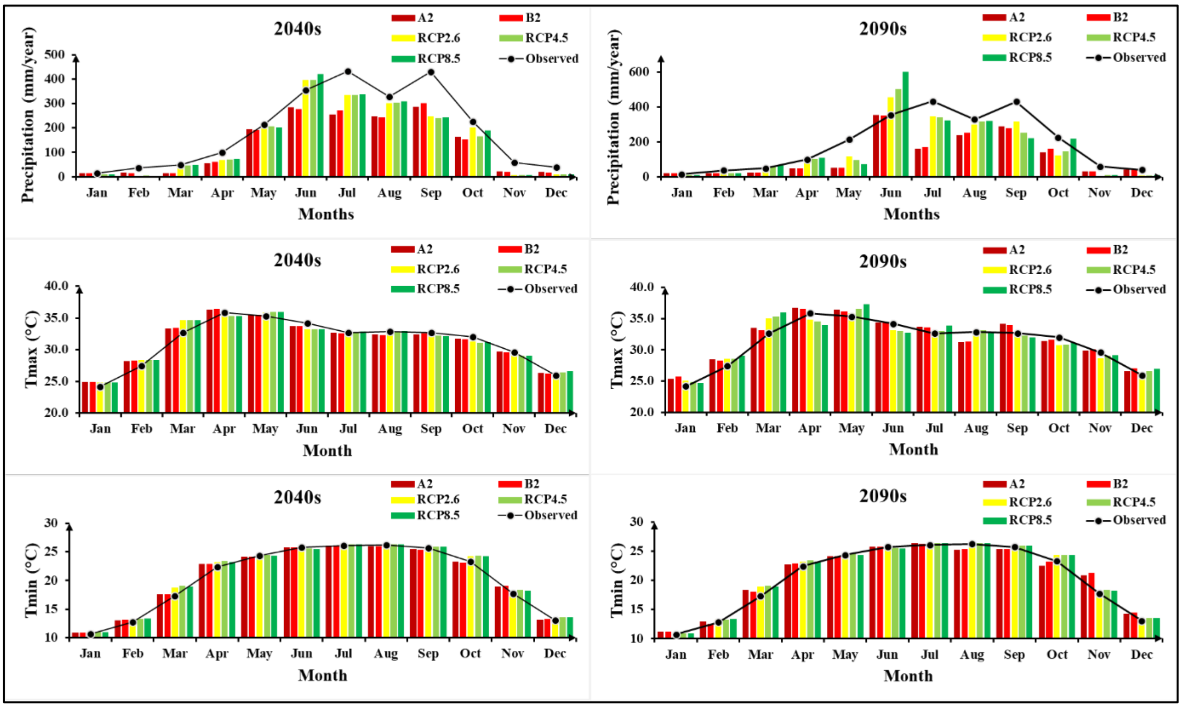

Figure 2: Comparison of the mean monthly precipitation, Tmax, and Tmin for RCP2.6, RCP4.5, RCP8.5 scenarios of the CanESM2 model, and A2, B2 scenarios of the HadCM3 model in the 2040s and 2090s

In any climate change study, it is apparent that the amount of future changes in the climate variables (precipitation, T_{max} and T_{min} in the current study) 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 5. 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.

Table 5: Changes in future mean annual precipitation and temperature for 2040s and 2090s

GCMs	Scenarios	2040s (near future)			2090s (far future)		
		Precipitation (%)	T_{max} (^oC)	T_{min} (^oC)	Precipitation (%)	T_{max} (^oC)	T_{min} (^oC)
CanESM2	RCP2.6	-4.3	0.203	0.375	-9.9	0.195	0.394
	RCP4.5	-7.1	0.204	0.456	-11.3	0.286	0.456
	RCP8.5	-9.3	0.233	0.394	-12.1	0.468	0.394
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

It can also be seen from the downscaling results presented in Table 5 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 9.3% 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, Tmin 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 from the obtained results 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 northwest region of Bangladesh.

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 the current 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 Canadian Earth System Model (CanESM2) and the Hadley Center Coupled Model (HadCM3), are used for the analysis. In order to obtain the comparative result of the climate change impact assessment, the corresponding climate change scenarios of two GCMs—RCP2.6, RCP4.5, and RCP8.5 scenarios for the CanESM2 model and A2 and B2 scenarios of the HadCM3 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 from the obtained results when the worst climate change scenarios for both GCMs (i.e., the RCP8.5 scenario in the CanESM2 model and the A2 scenario in the HadCM3 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 northwest region of Bangladesh.
- 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 in the context of climate change.

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