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Assessment of Annual and Seasonal Climate Change Impact in Rajshahi District of Bangladesh using SDSM

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Abstract

Bangladesh is one of the most vulnerable countries in the world to climate change. In the current study, the statistical downscaling technique is adopted for the statistical downscaling of precipitation and temperature in the Rajshahi district of Bangladesh to assess the changes in long-term mean precipitation and temperature (T_{max} and T_{min}). The anomalies of the annual and seasonal climate change patterns are also explored in this study. In order to investigate the impact of future climate change, the outputs of a high-resolution global climate model, CanESM2, are downscaled at a local scale using the widely used statistical downscaling model (SDSM) under the RCP2.6 (low emission scenario), RCP4.5 (medium emission scenario), and RCP8.5 (high emission scenario) scenarios over the 2023-2050, 2051-2080, and 2081-2100 periods, respectively. The climate data are collected from the Bangladesh Meteorological Department (BMD) for the analysis. The most widely used kriging interpolation is adopted to obtain the spatial distribution of the climate change pattern over the study area, where only the RCP8.5 scenario is considered. The whole task is accomplished by selecting the most suitable list of predictors, calculating the Nash-Sutcliffe efficiency, RMSE, and MAE, and estimating the mean bias error performance between the observed and simulated precipitation and temperature values. After getting satisfactory results, the model is further used for the prediction of precipitation and temperature up to the year 2100. The de-biased technique is used to achieve more accurate prediction results. Overall, the model results demonstrate that the mean annual precipitation and temperature in Rajshahi district are expected to increase over the next century. It is also found that the precipitation will increase from 13% to 33%, whereas Tmax will increase from 0.58°C to 0.95°C and Tmin from 0.79°C to 1.44°C. It is also found from the seasonal analysis that in the winter, a maximum reduction in precipitation is expected from 5% to 17%, whereas a maximum increase in temperature is expected in the monsoon period, with Tmax ranging from approximately 3°C to 5°C and Tmin ranging from 2°C to 3°C for the high emission scenario RCP8.5.

Keywords: *Climate change; SDSM, Statistical downscaling; CanESM2; RCP scenarios.*

1 Introduction

Among various climatic factors, precipitation and temperature are the most important for influencing the global climate. It is crucial now to detect the future climatic change pattern and identify ways to overcome the worst situation (Yan et al., 2022). The results of the Global Circulation Models (GCMs) demonstrate that future air temperature will increase greatly, as will an increase in anthropogenic greenhouse gas concentrations in the earth due to the reflection of heat over the CO_2 barrier at the ozone layer, which will result in extreme weather conditions day by day. At the same time, the precipitation will be changed with respect to latitude, with higher latitudes getting more precipitation than lower latitudes (Zhang and Wang, 2022). It severely affects hydrological aspects such as the timing of rainfall, moisture content of air and soil, evaporation, transpiration, etc., and influences the water body and agricultural sectors. Though some researchers evaluated the increase in air temperature as well as droughts in Bangladesh using long- and short-term projections based on various GCMs from 1980 to 2018 (Kamruzzaman et al., 2022), the GCMs, however, have no significance for a finer resolution in a specific low-resolution area due to their large-scale resolution. Thus, it is compulsory to downscale the technique for making a bridge between the large grid patterns into a small grid, considering the most sensible climatic parameters. Two types of downscaling techniques, namely statistical downscaling and dynamic downscaling, are widely used for the downscaling of GCMs outputs. Statistical downscaling (SD) is based on making a correlation between atmospheric predictors (large scale) and predictands (local scale) of precipitation, temperature, etc. It is a stochastic weather generator as well as a linear regression model with a relatively easy computational procedure relative to a dynamic downscaling model. Another drawback of the dynamic downscaling is that the associated computational procedure is demanding (Ishizaki, 2023).

In the past, researchers employed the widely applied SDSM-based downscaling techniques to downscale the GCM models at local scales and used the downscaled outputs to predict future climate change and illustrate the significant outcomes for predicting rainfall and temperature over the locality (Hassan and Nile, 2021; Ahsan et al., 2022; Rana and Adhikary, 2023). Accordingly, GCM outputs and SDSM-based downscaling techniques have been adopted for evaluating the past climatic pattern (observed) and most possible future (simulated) changes in the current study. The study is demonstrated through a case study area, for which Rajshahi district in the northwestern region of Bangladesh is considered. The main objectives of this study are: i) to identify the most suitable predictor list; ii) to calibrate the two-thirds observed data and one-third for validation for checking the model performance; and finally, iii) to predict the future precipitation and temperature pattern from 2023 to 2100 by adopting bias correction to minimize error. The outcomes of the potential climatic change impact are expected to be supportive of developing and implementing adaptive water resources and disaster management.

2 Methodology

The current study was demonstrated in Rajshahi district, which is located in the northwestern part of Bangladesh. The 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, which is shown in Figure 1. 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 silk industry also depends on temperature and precipitation concentration, which is a famous industry around the world. The net area of the study area is 2,407 km² and the total population is about 2.91 million, according to the current Bangladesh Census (BBS, 2022). The northwestern region of the country is considered a vulnerable area due to the high sensitivity 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 annual and seasonal impact of climate change on future precipitation and maximum and minimum temperatures (Tmax and Tmin) patterns in Rajshahi district of Bangladesh.

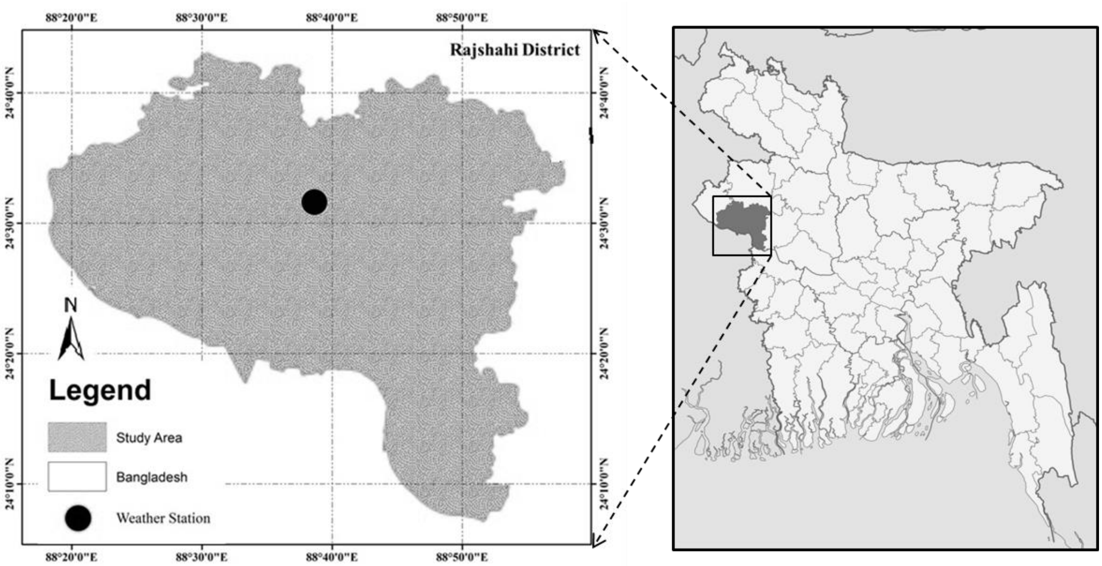

Figure 1. Location of the study area (Rajshahi district) in Bangladesh

Bangladesh has three distinct seasons: summer (March-May), monsoon (June-October), and winter (November-February). The climatic condition of Rajshahi district can be described as a hot and tropical in nature, with less precipitation compared to other parts of the country. Based on the 30 years of observed data analysis (1975-2005), it is found that the mean annual precipitation is 1526 mm, and the average maximum temperature (Tmax) and minimum temperature (Tmin) are found to be 31.2°C and 20.50°C, respectively. According to the seasonal analysis, it is found that approximately 80% of precipitation occurs during the monsoon period, and the maximum temperature is experienced during the summer season.

Long-term observed data from around 30 years (from 1975-2005 data was used for this study) is sufficient and most suitable for long-term future climate change prediction (Liu et al., 2022). The daily observed data for the prediction of climatic factors (precipitation and temperature) in the current study was collected from the Bangladesh Meteorological Department (BMD). The daily observed data (1975-2018) was divided into three individual sub-classes. CMIP5 data can calibrate up to 2005 years of data, so the whole data (1975-2018) was used in checking the model performance by calibration (1975-1995) and validation (1996-2005), and the rest of the data were used for checking the model uncertainty (2006-2018). In addition, necessary 26 climate predictors data were collected from a Canadian website (https://www.esrl.noaa.gov), which includes the National Center of Environment Prediction (NCEP) and CanESM2 for three Representative Concentration Pathways (RCPs), namely RCP2.6, RCP4.5, and RCP8.5, respectively, of CMIP5 (Coupled Model Intercomparison Project Phase 5) GCMs.

The Statistical Downscaling Model (SDSM) is a tool (Wilby et al., 2002) that is widely used by researchers all over the world to predict future scenarios. This tool is internationally recognized, and its performance is satisfactory and justified for long-term climate change studies. The main function of this model is to downscale the GCM data and generate climate data through multiple linear regression (MLR). The selection of the most influencing predictors listed among 26 climate predictors is challenging for climate change prediction because these predictors highly influence future climate scenarios. Hence, the selection of the list of suitable predictors, highly partial correlation, and least *p* values (maximum 0.05) are considered between predictands (precipitation, Tmax, and Tmin) and predictors (NCEP predictors).

The observed (1975-2018) data was subdivided into two stages: calibration (1975-1995), and validation (1996-2005) of the model performance check, and the remaining data (2006-208) were used for the uncertainty analysis. The statistical parameters Nash–Sutcliffe efficiency (NSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were used to calibrate the model. In addition, bias correction performance was checked for these parameters during validation of the model. After that the observed data from 2006-2016 of this study region was also evaluated, and finally, the uncertainty analysis was performed between the downscaled and the observed data. Based on the aforementioned model performance evaluation criteria, the performance of the model for each RCP scenario was checked to identify the most satisfactory model. The widely used GCM model, CanESM2 and daily precipitation, Tmax, and Tmin data were used as the input into the SDSM under three RCP2.6, RCP4.5, and RCP8.5 scenarios and the downscaled outputs of future climates (precipitation, Tmax, and Timn) were generated for 2006-2100 period.

3 Results and Discussion

3.1 Screening of Predictors

Among the 26 predictors, the most suitable predictors are listed in Table 1. As can be seen from the table, the most influential predictor for precipitation is relative humidity at 850 hPa (r850). The predictor is selected as the super predictor, and the rest of the predictors are sequentially 1st, 2nd and 3rd predictors where the percentage reduction (PR) is less than 60% (Mahmood and Babel, 2014). At the same time, the absolute partial correlation (P*r*) values and *p*-values are also satisfied. In addition, the mean temperature and near-surface specific humidity factors are SP for Tmax and Tmin, respectively. Though many researchers suggested only two predictors are enough for statistics, the more predictors listed, the greater the accuracy. The identified predictors are influenced by the geographical location, and altitude of the study area.

Table 1: List of most influencing predictors in downscaling climate variables

Precipitation			**Tmax**			**Tmin**		
Predictors	**Abs *P.r***	***P*-values**	**Predictors**	**Abs *P.r***	***P*-values**	**Predictors**	**Abs *P.r***	***P*-values**
r850			temp			shum		
p800	0.31	0	mslp	0.84	0	r850	0.67	0
p5_f	0.09	0	r850	0.3	0	p500	0.28	0
mslp	0.29	0	shum	0.33	0			
			p500	0.29	0			
			p800	0.73	0			

3.2 Model Calibration and Validation

The performance of the downscaling model for precipitation, Tmax, and Tmin in the calibration and validation stages is presented in Table 2. As can be seen from the table, the calibration and validation (with bias and de-bias) are assessed to check the performance of downscaling models for each climate variable. The statistical indices indicate that the NSE value is 0.644 for precipitation, 0.847 and 0.970 for Tmax and Tmin, respectively, during the calibration period (1975-1995). It is worth mentioning that NSE value 1 explains the best fitting of observed and simulated data for modeling. At the same time, the RMSE is 82.674 for precipitation and 1.390 and 0.960 for Tmax, and Tmin, respectively. Furthermore, MAE values are 55.357, 0.942, and 0.729 for precipitation, Tmax, and Tmin, respectively. Based on the statistical performance measures, it can be concluded that this calibration result is found to be satisfactory for this modelling and further procedure validation can be adopted. During validation period, with bias corrected, and without bias correction is considered because many researchers claim some biases are generated during the generation of long-term future climate scenarios. Comparatively, the validation results are acceptable, and NSE vales are increased. In contrast, RMSE and MAE vales are decreased after bias correction except the case of Tmax. This justifies the validity of using the de-bias technique in the climate change studies in this study.

Table 2: Summary of statistical performance in calibration and validation of downscaling model

Climate variables	Calibration (1975-1995)			Validation (1996-2005)					
	NSE	RMSE	MAE	NSE	RMSE	MAE	NSE	RMSE	MAE
				With-Bias			De-Bias		
Precipitation	0.644	82.674	55.357	0.636	92.688	54.028	0.646	91.420	53.606
Tmax	0.847	1.390	0.942	0.887	1.240	0.934	0.889	1.232	0.952
Tmin	0.970	0.960	0.729	0.975	0.888	0.649	0.988	0.879	0.637

3.3 Future Climate Change Scenarios

Future climate change scenarios are developed under RCP2.6, RCP4.5, and RCP8.5 scenarios from CanESM2 GCM for the period of 2023 to 2100. The precipitation concentration is considered an anomaly percentage, but the temperature (Tmax and Tmin) is considered an anomaly only. Table 3 presents the mean annual precipitation, maximum and minimum temperatures (Tmax and Tmin) in Rajshahi district for 2023-2100. According to Table 3, the mean percent anomaly in precipitation is straightly increased until 2100. At the same time, the temperature (Tmax and Tmin) is also increasing though the increasing rate of Tmin is slightly higher than Tmax. From the beginning of this century, from 2023 to 2050, the precipitation will increase by up to 14% on the basis of the previous data structure from 1975 to 2005. It is also found that about 10% precipitation will be increased in next 30 years later (24.3%) and next 20 years the increasing rate will be same. In the meantime, the temperature (Tmax and Tmin) raising rate shows the continuous incremental graph, where 0.5°C can be increased in the middle of this current century, and the rest of the century, it would be 0.95°C. But the Tmin rate is a slightly straight line with respect to Tmax, where the Tmin illustrates the maximum 1.44°C temperature that can be raised based on observation data. Overall, the RCP8.5 scenarios exhibit the maximum values for all climatic scenarios due to the consequences of high emissions.

Table 3: Mean annual precipitation, Tmax and Tmin in Rajshahi (the study area) for 2023-2100

Climate Variables	2023-2050			2051-2080			2081-2100		
	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5
Precipitation (%)	13.1	13.8	14.7	11.0	17.0	24.3	10.3	18.0	33.2
Tmax	0.38	0.46	0.58	0.36	0.50	0.74	0.31	0.54	0.95
Tmin	0.35	0.58	0.79	0.34	0.68	1.10	0.37	0.77	1.44

Figure 2 shows the annual and seasonal changes in precipitation and temperature (Tmax and Tmin) in the study area. As can be observed from the figure, the mean annual precipitation, Tmax, and Tmin are considered on a seasonal and monthly basis for three future period of 2023-2050, 2051-2080, and 2081-2100 under the three RCPs (RCP2.6, RCP4.5, and RCP8.5 scenarios), respectively. According to the seasonal climate change analysis, it is found that the monsoon period (June-October) will be gradually wetter and hotter. In 2023-2100, around 30%-65% of precipitation will be increased. In addition, in summer, this magnitude will increase from 5% to 20%, but in winter, the rate will decrease from 5% to 17%, respectively. At the same time, the average Tmax in the monsoon season will increase by 3°C to 5°C, and in the summer season, its incremental magnitude will be 1.5°C to 3°C. In contrast, the temperature has decreased in the winter season by up to 3°C over the last century. For Tmin, the only monsoon period showed a significant increment up to around 3°C, but the summer and winter seasons are almost the same based on previous observed values.

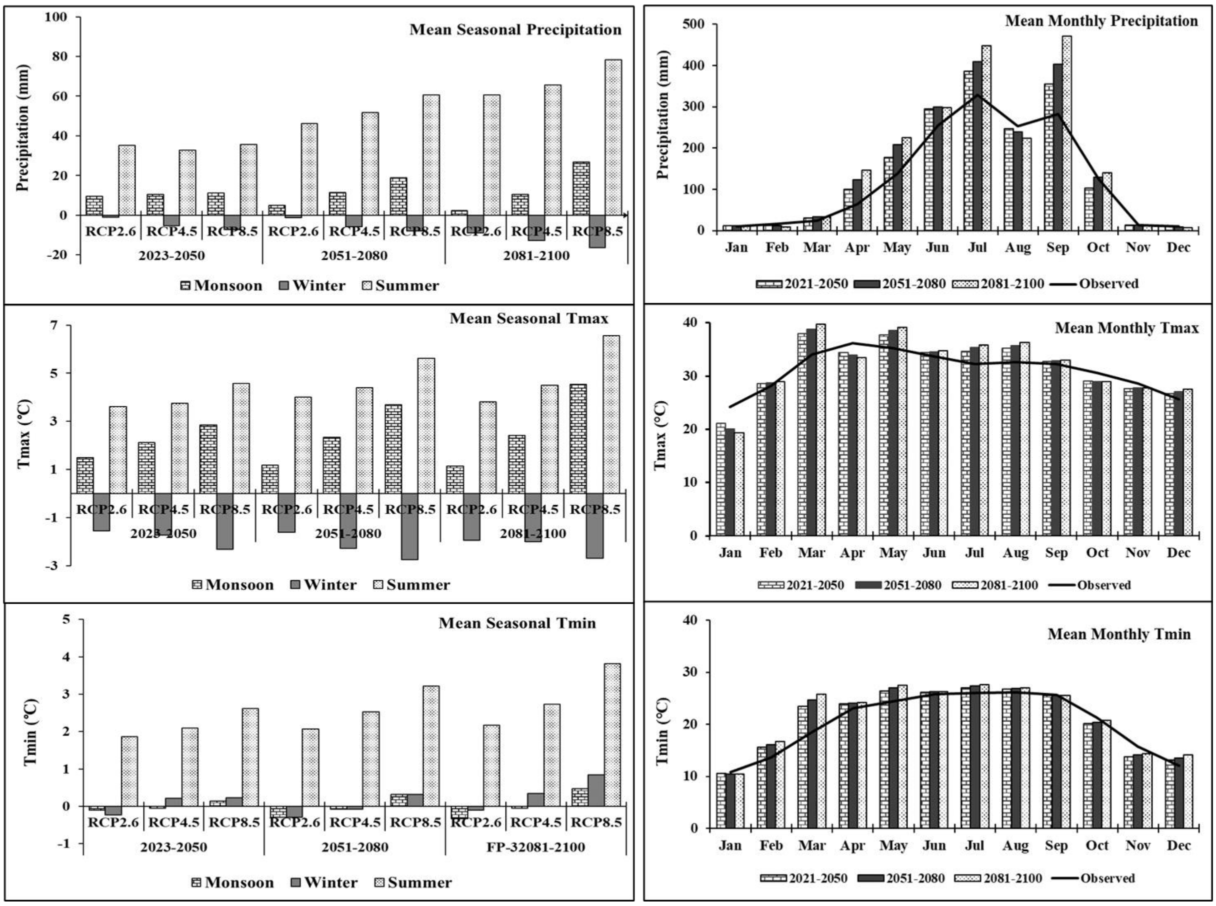

Figure 2. Changes in mean precipitation and temperature in the study area

According to the monthly climate change analysis considering the RCP8.5 scenario as shown in the figure, the temperature and precipitation values are evaluated and compared to the the mean observed values. The most significant month for precipitation is found to be June-September, and about 80% of precipitation occurs during this period. The average monthly rainfall during those months will be 300 to 400 mm. Furthermore, March to August month is found to be highly sensible for both maximum and minimum temperatures (Tmax and Tmin). The mean annual observed Tmax and Tmin values are also validated with the monthly predicted values and found to be satisfactory for all RCP scenarios.

4 Conclusions

In the current study, the Statistical Downscaling Model (SDSM) and CMIP5 data were used to predict the climate change pattern under mean annual, seasonal and monthly precipitation, Tmax, and Tmin under three RCPs (RCP2.6, RCP4.5, and RCP8.5) scenarios for three future time domains: 2023-2050, 2051-2080, and 2081-2100. Mean annual precipitation is considered on a percentage basis, but temperature is considered only an anomaly in the current study. Based on the results of the current study, the following conclusions can be drawn:

- Overall, precipitation, maximum temperature (Tmax), and minimum temperature (Tmin) exhibit a positive trend for all three RCPs (RCP2.6, RCP4.5, and RCP8.5 scenarios) under mean annual, seasonal and monthly based climate change analysis. Maximum positive changes are found in the monsoon season; summer is a moderate change but negative for the winter season.
- The de-bias technique is highly effective to minimize uncertainty between the observed and downscaled values in climate change studies and hence is recommend for similar studies.
- According to the seasonal climate change analysis, it is found that the monsoon period (June-October) will be gradually wetter and hotter. In 2023-2100, around 30%-65% of precipitation will be increased. In addition, in summer, this magnitude will increase from 5% to 20%, but in winter, the rate will decrease

from 5% to 17%, respectively. At the same time, the average Tmax in the monsoon season will increase by 3°C to 5°C, and in the summer season, its incremental magnitude will be 1.5°C to 3°C.

- The most significant month for precipitation is found to be June-September, and about 80% of precipitation occurs during this period. The average monthly rainfall during those months will be 300 to 400 mm. Furthermore, March to August month is found to be highly sensible for both maximum and minimum temperatures (Tmax and Tmin).

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