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Climate Change Projection over Southwest Coastal Region of Bangladesh Using Statistical Downscaling Model

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Abstract. Bangladesh is considered to be one of the vulnerable countries to climate change. Climate change induced significant changes in precipitation and temperature are becoming evident in Bangladesh and its southwest coastal region, which have already been facing serious water crisis. This demands a sensible and adaptive management of water resources considering future climate change condition. Therefore, the objective of this study is the projection and assessment of the potential climate changes over the southwest coastal region of Bangladesh. In the current study, Statistical Downscaling Model (SDSM) is adopted to downscale a widely used General Circulation Model (GCM), Canadian Earth System Model (CanESM2) for the projection of future precipitation, maximum temperature (Tmax) and minimum temperature (Tmin) under different representative concentration pathways (RCP) scenarios. Identification of suitable predictors, downscaling model development, model calibration and validation, and projection of future climate change are performed in the SDSM platform. The current study is demonstrated through Khulna climatic station in the southwest coastal region of Bangladesh for the projection and assessment of future climate change under RCP2.6, RCP4.5 and RCP8.5 scenarios. Historical precipitation and temperature records for the station are collected from Bangladesh Meteorological Department (BMD) for the 1980-2016 period. Observed climate data for the 1980-2005 period is considered as the base period of which the 1980-1995 period is considered for model calibration and the 1996-2005 period is taken for model validation. In order to minimize the estimation error in SDSM based future climate change projections, bias correction is carried out for the downscaled climate variables. Three time periods including near-future (FP-1: 2021-2050), mid-future (FP-2: 2051-2080), and far-future (FP-3: 2081-2100) are considered in the current study for the assessment of future climate change. The statistical analysis of the observed and downscaled climate variables indicates that there is an overall increase in temperature and precipitation in the southwest coastal region of Bangladesh under three RCP scenarios. Furthermore, it is evident from the comparison of climate change projections under three RCP scenarios that the RCP8.5 scenario exhibits the worst trend of Tmax, Tmin and precipitation in Khulna. The percentage of anomaly of Tmax for near-future, mid-future and far-future periods are found to be 1.3°C, 1.94°C, 2.68°C in Khulna under the RCP8.5 (high emission) scenario. However, the percentage anomaly for Tmin are found to be 1.04°C, 2.01°C, 3.22°C in Khulna under the same scenario for near-future, mid-future and far-future periods, respectively. The percentage anomaly of precipitation in Khulna station under the RCP8.5 scenario is obtained as 6.87mm in near-future, 8.9mm in mid-future, and 13.21mm in far-future periods, respectively. The climate change projection results conclusively demonstrate that the future climate in Khulna is expected to be warmer as well as be wetter relative to the base period, which is expected to have important implications for adaptive management of water resources in the southwest coastal region of Bangladesh.

INTRODUCTION

Climate change has become a burning question nowadays. It is widely accepted all over the world that climate change occurs due to human activities, especially burning of fossil fuels, which are directly responsible for cratering a huge amount of greenhouse gases (Mahmood et al., 2015). Moreover, deforestation and destruction of trees for uncontrolled urbanization and growing industrialization is another cause for increasing carbon dioxide gas (Gebremeskel et al., 2004). According to the Intergovernmental Panel on Climate Change (IPCC) assessment, there is an approximately 1.0°C of global warming above pre-industrial levels caused by anthropogenic activities with an

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approximate range of 0.8°C to 1.2°C. If global warming continues to rise at the present rate, it is expected to reach 1.5°C by 2050 (IPCC, 2018). As a consequence, it is highly likely that global warming and climate change will cause substantial changes of local and regional precipitation patterns as well as hydrological regimes of a basin and/or a country (Huang et al., 2011; Qiu et al., 2016).

Bangladesh is regarded as one of the most vulnerable countries of the world to climate change due to its unique geographical location and geo-morphological conditions. The country has already experienced climate change induced hazards such as floods, droughts, cyclones, storm surge, erratic behavior of precipitation that occur frequently in the coastal part of Bangladesh (Islam et al., 2019). This results in huge loss of lives, property damages and financial loss, ecosystem degradation and destruction of environmental components. Substantial changes in precipitation and temperature caused by climate change are becoming evident more frequently in the country than ever before (Billah et al., 2015). Uncertainty of precipitation and its uneven spatial and temporal distribution results in flooding in one side and causes longer dry spells on the other side evoking drought events (Hossain et al., 2019). These cause direct and indirect impact on the water resources system all over the country, particularly on the coastal region due to its low elevation floodplains from sea.

IPCC (2007) assessment indicates that Bangladesh is likely to have about 5 to 6% increase of precipitation by 2030, which may cause frequent large and prolonged flooding mainly on the low-lying floodplains and the low elevation coastal region of the country. It is also reported that the coastal region of the Bangladesh may go under saline water by 2050 (IPCC, 2001). The coastal region of Bangladesh has already experienced the adverse impacts especially in terms of coastal inundation and erosion, salinity intrusion, loss of bio-diversity and agriculture and large-scale migration (DOE, 2007). On the other hand, north-western region of the country has been facing drought that greatly affects agricultural activities and food production. The moderately drought affected areas are expected to convert into severely drought prone areas by next 30 years (Rahaman et al., 2016; Shahid & Behrawan, 2008).

The southwest coastal region of Bangladesh has been facing serious water crisis, which is expected to be intensified due to the potential impact of climate change. Moreover, the region is often characterized by frequent flash floods during heavy precipitation and cyclonic storm surge. This situation is expected to be aggravated by the adverse impact of climate change (Billah et al., 2015). This demands a sensible and adaptive management of water resources considering future climate change condition. Therefore, the objective of the current study is the projection and assessment of the potential climate changes over the southwest coastal region of Bangladesh.

FIGURE 1. Location of the study area in Bangladesh

MATERIALS AND METHODS

The Study Area

This study is demonstrated through a climatic station named Khulna for the projection and assessment of future climate change, which is located in the southwest coastal region of Bangladesh. The station is located at 22.8°N latitude and 89.58°E longitude with an altitude of 4 m above the mean sea level. Location of the study area is shown in Figure 1. As can be seen from the figure, the study area is located very close proximity to sea and thus extremely vulnerable to climate change. The area has already been affected by climate induced disasters such as floods, cyclones, storm surge, water logging, salinity intrusion, river bank erosion, and shortages of freshwater supply etc. Furthermore, the study area has been facing the climate induced population migration problems (Islam et al., 2019). Hence, the projection and assessment of future climate change for Khulna are undertaken in the current study.

Data Description

Historical climate data such as precipitation and temperature for the Khulna station are collected from Bangladesh Meteorological Department (BMD) for the 1980-2016 period, which have been used for analysis. The NCEP/NCAR reanalyzed predictors together with the observed climate data for the corresponding period are used for modelling in the SDSM platform. In this period, the average annual precipitation in the study area is found to be 1802 mm. Temperature in the study area varies from 21.3°C to 31.1°C with a mean value of 26.2°C. The 26 predictors of NCEP/NCAR reanalyzed predictors with grid resolution 2.5° x 2.5° are downloaded freely from the website (https://www.esrl.noaa.gov/psd/data/reanalysis/reanalysis.shtml), which are given in Table 1. The low emission (RCP2.6), intermediate emission (RCP4.5) and high emission (RCP8.5) predictors of CanESM2 GCM model with 2.8125° x 2.8125° grid resolution are obtained from the Canadian Centre for Climate Modeling and Analysis (https://climate-scenarios.canada.ca/?page=statistical-downscaling) for the period of 1961-2005 and 2006-2100 for the generation of future scenarios.

TABLE 1. Summary of the NCEP predictors used in this study

SN	Description of Predictors	Predictors	SN	Description of Predictors	Predictors
1	Mean sea level pressure (Pa)	*mslpgl*	14	500 hPa Divergence of true wind	*p5zhgl*
2	1000 hPa Wind speed	*p1_fgl*	15	850 hPa Geopotential	*p850gl*
3	1000 hPa Zonal wind component	*p1_ugl*	16	850 hPa Wind speed	*p8_fgl*
4	1000 hPa Meridional wind	*p1_vgl*	17	850 hPa Zonal wind component	*p8_ugl*
5	1000 hPa Relative vorticity of true	*p1_zgl*	18	850 hPa Meridional wind	*p8_vgl*
6	1000 hPa Wind direction	*p1thgl*	19	850 hPa Relative vorticity of true	*p8_zgl*
7	1000 hPa Divergence of true wind	*p1zhgl*	20	850 hPa Wind direction	*p8thgl*
8	500 hPa Geopotential	*p500gl*	21	850 hPa Divergence of true wind	*p8zhgl*
9	500 hPa Wind speed	*p5_fgl*	22	Total precipitation	*prcpgl*
10	500 hPa Zonal wind component	*p5_ugl*	23	500 hPa Specific humidity	*s500gl*
11	500 hPa Meridional wind	*p5_vgl*	24	850 hPa Specific humidity	*s850gl*
12	500 hPa Relative vorticity of true	*p5_zgl*	25	1000 hPa Specific humidity	*shumgl*
13	500 hPa Wind direction	*p5thgl*	26	Air temperature at 2 m	*tempgl*

Statistical Downscaling of Climate Variables

Statistical downscaling consists of a number of steps such as quality control, selection of suitable predictors, model calibration and validation, bias correction, projection of future climate change and comparison. In the current study, statistical downscaling of climate variables that includes development of downscaling models, model calibration and validation, and projection of future climate change are carried out in the SDSM platform. SDSM is developed as a hybrid tool of both multiple linear regression and stochastic weather generator (Wilby et al., 2002), which has been widely applied worldwide for determining future climate scenarios to assess the impact of global

climate change (e.g., Mahmood et al., 2015; Jaiswal et al., 2017; Hasan et al., 2018; Al-Mukhtar & Qasim, 2019). For statistical downscaling, predictors (as given in Table 1) and predictands (precipitation and temperature in the current study) of concurrent periods are analyzed to detect outliers, missing values and compute statistics using the SDSM software in order to use these data for climate change analysis. Two types of downscaling models including unconditional and conditional sub-models are adopted in the current study. The unconditional sub-model is used for downscaling of independent variables (temperature in this study), whereas the condition sub-model is used for downscaling of dependent variables (precipitation in this study). It unconditional sub-model is developed without any transformation whereas the condition sub-model requires fourth root transformation in developing climate change downscaling model.

Selection of predictors

In order to develop the statistical downscaling models, the most challenging and foremost task is the selection of suitable predictors. Variance, correlation matrix, partial correlation (r) and p-values are the four main indicators, which are used to identify the suitable predictors. At first, the partial r and p values are calculated through correlation analysis among all predictors. Predictor's variable should be selected sequentially considering the maximum r-value and minimum p-value. The maximum r-value and smaller p-value ($p < 0.05$) indicate a better association between variables (Al-Mukhtar & Qasim, 2019). At least two predictors must be selected from 26 predictors (Table 1) for downscaling model development. In the current study, a quantitative step-by-step statistical approach is used in the SDSM platform for the selection of suitable predictors, which is detailed in the following.

- The correlation coefficients between 26 predictors and predictands are calculated.
- The predictors with high correlation coefficient (12 predictors in this case) are identified and arranged them in descending order based on their correlation coefficient to identify the super predictor (SP). SP is referred to as the first ranked predictor among all predictors with the highest correlation coefficient.
- Next, the correlation between the SP and remaining predictors (11 in this case) are made and absolute correlation coefficient, absolute partial correlation and *p*-value are obtained through regression analysis.
- The percentage reduction (*PR*) among the remaining predictors (11 in this case) are computed using Eq. (1)

$$PR(\%) = \frac{(P_r - R)}{R} \times 100 \qquad (1)$$

  where, P_r is the partial correlation coefficient, and R represents the correlation coefficient between the predictor and predictand.
- The predictor with a minimum *PR* value in partial correlation is selected as the second most suitable predictor and accordingly the following predictors can be obtained.

Model calibration and validation

From the observed climate data for Khulna station together with the NCEP/NCAR predictors data, the 1980-2005 period is considered as the base period of which the 1980-1995 period (about 70% of total data) is taken for model calibration and the 1996-2005 period (about 30% of total data) is taken for model validation. Different statistical indicators such as root mean square error (RMSE), Nash–Sutcliffe efficiency (NSE) and coefficient of determination (CC) as given in Eqs. (2) – (4) are used to evaluate the performance of downscaling models for each climate variables (precipitation, and temperature in the current study).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}[\theta_{obs}(t) - \theta_{est}(t)]^2}{N}} \qquad (2)$$

$$NSE = 1 - \frac{\sum_{t=1}^{N}[\theta_{obs}(t) - \theta_{est}(t)]^2}{\sum_{t=1}^{N}[\theta_{obs}(t) - \bar{\theta}_{est}]^2} \qquad (3)$$

$$CC = \frac{\sum_{t=1}^{N}[\theta_{obs}(t)-\bar{\theta}_{obs}]\times[\theta_{est}(t)-\bar{\theta}_{est}]}{\sqrt{\sum_{t=1}^{N}[\theta_{obs}(t)-\bar{\theta}_{obs}]^2}\times\sqrt{\sum_{t=1}^{N}[\theta_{est}(t)-\bar{\theta}_{est}]^2}} \quad (4)$$

where, $\theta_{obs}(t)$ and $\theta_{est}(t)$ represent the observed and simulated values of climate variables at time *t*; $\bar{\theta}_{obs}$ and $\bar{\theta}_{est}$ are the mean values of observed and predicted climate variables, respectively and *N* is the number of observations in the time series. RMSE value closer to 0 as well as NSE and CC values closer to 1 demonstrate the best estimation of downscaled climate variables.

Bias correction

Bias correction of downscaled climate variables are necessary to stay away from the over or underestimation of climate variables. Bias correction is adopted using Eqs. (5) – (6) to minimize the estimation error in the downscaled climate variables (precipitation and temperature in this study).

$$P_{bias.correct} = P_{gen} \times \frac{\bar{P}_{obs}}{\bar{P}_{gen}} \quad (5)$$

$$T_{bias.correct} = T_{gen} - \left(\bar{T}_{gen} - \bar{T}_{obs}\right) \quad (6)$$

where, $P_{bias.correct}$ and $T_{bias.correct}$ are the corrected daily time series of precipitation and temperature for future period, respectively for *m* month; P_{gen} and T_{gen} represent the downscaled daily time series of precipitation and temperature, respectively for *m* month; $\bar{P}_{obs}$ and $\bar{P}_{gen}$ are the long-term mean monthly values of observed precipitation and temperature, respectively for the 1980-2005 period; $\bar{P}_{gen}$ and $\bar{T}_{gen}$ are the long-term mean monthly values of downscaled precipitation and temperature, respectively for the 2006-2100 period.

Projection of future climate change

After assessing the accuracy of the downscaling model through calibration and validation processes, the validated model is applied for the project of future climate change over the study area. Three time periods including near-future (FP-1: 2021-2050), mid-future (FP-2: 2051-2080), and far-future (FP-3: 2081-2100) are considered in the current study for the assessment of future climate change. Three emission scenarios are considered for climate change assessment such as low emission (RCP2.6), intermediate emission (RCP4.5), and high emission (RCP8.5) scenarios. The generation of monthly precipitation and temperature is performed for each of the aforementioned time periods and emission scenarios and the relative changes of climate are assessed with respect to the base period (1980-2005). A positive value indicates that there is an increasing trend of climatic change whereas a negative value designates the decreasing trend of climate change in comparison to the base period.

RESULTS AND DISCUSSION

Identification of Suitable Predictors

In order to identify the most suitable predictors for climate change (precipitation and temperature in this case) downscaling, more than 60% of *PR* values (as given by Eq. 1) must be removed. Although two most suitable predictors are generally enough for downscaling model development in SDSM software (Mahmood et al., 2015), two to six predictors are selected in the current study because more predictors usually give more accurate downscaled climate than two (Hasan et al., 2018). The identified most suitable predictors for downscaling of precipitation and temperature for Khulna climate station is given in Table 2. As can be seen from the table, there are five predictors (*s850gl, mslpgl, p850gl, s500gl, p5_fgl*) found suitable for precipitation downscaling. For getting more accurate downscaling results of precipitation using the SDSM software, these variables are mostly responsible because their simultaneous variation affects the saturated phase of water vapor (Jaiswal et al., 2017). Table 2 also shows that six predictors (*p500gl, prcpgl, s500gl, s850gl, shumgl, tempgl*) are found suitable in maximum temperature downscaling (T_{max}) whereas only three predictors (*p500gl, s850gl, shumgl*) have been selected in

minimum temperature downscaling (T_{min}). It is also found that *s850gl* (850 hPa Specific humidity), *s500gl* (500 hPa Specific humidity), *p850gl* (850 hPa Geopotential), and *p500gl* (500 hPa Geopotential) are selected for the downscaling of both precipitation and temperature. However, two predictors including *mslpgl* (mean sea level pressure) and *p5_fgl* (500 hPa Wind speed) are distinctively identified in the precipitation downscaling. This is justified because the predictors exhibit reasonable climatic influence on precipitation.

TABLE 2. List of selected predictors in climate change downscaling for Khulna station

Precipitation	**Temperature**	
	Maximum Temperature (Tmax)	**Minimum Temperature (Tmin)**
850 hPa Specific humidity (*s850gl*)	500 hPa Geopotential (*p500gl*)	500 hPa Geopotential (*p500gl*)
Mean sea level pressure (*mslpgl*)	Total precipitation (*prcpgl*)	850 hPa Specific humidity (*s850gl*)
850 hPa Geopotential (*p850gl*)	500 hPa Specific humidity (*s500gl*)	1000 hPa Specific humidity (*shumgl*)
500 hPa Specific humidity (*s500gl*)	850 hPa Specific humidity (*s850gl*)	
500 hPa Wind speed (*p5_fgl*)	1000 hPa Specific humidity (*shumgl*)	
	Air temperature at 2 m (*tempgl*)	

Calibration, Validation and Bias Correction of Downscaling Models

The downscaling model is calibrated and validated using the identified most suitable predictors. As indicated earlier, two-third (about 70%) of the total data is used for the model calibration and the remaining one-third (about 30%) of the total data is used the model validation. The observed and simulated values of precipitation and temperature in calibration and validation stage are shown in Figures 2-4. As can be seen from the figures, there is a reasonable agreement between the observed and simulated values. The statistical performance including RMSE, NSE and CC between the observed and simulated values in calibration and validation is calculated using Eqs. (2) - (4) and presented in Table 3. As can be seen from the table, the model performance is satisfactory for both precipitation and temperature downscaling. It is also found that that the results of Tmax and Tmin downscaling are found to be better than the results of precipitation downscaling considering all the performance indicators.

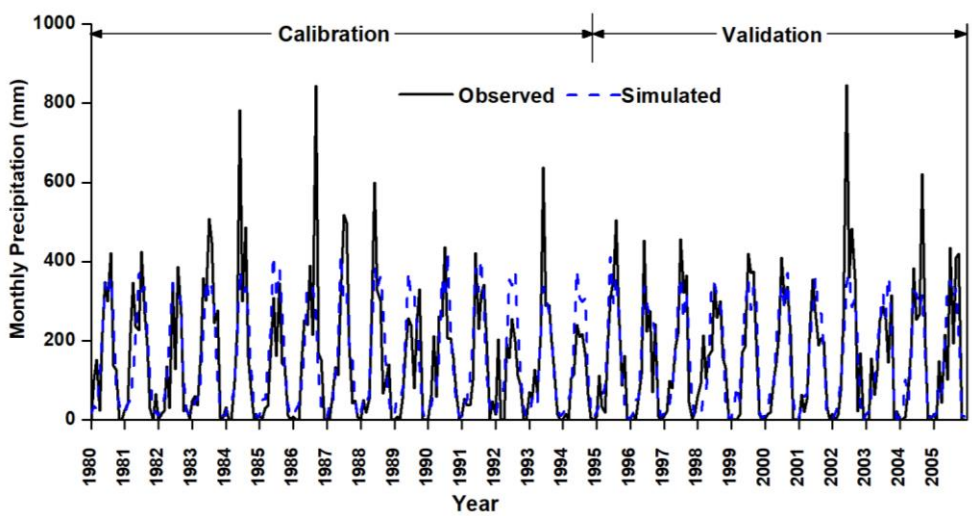

FIGURE 2. Calibration and validation plot for precipitation downscaling in Khulna

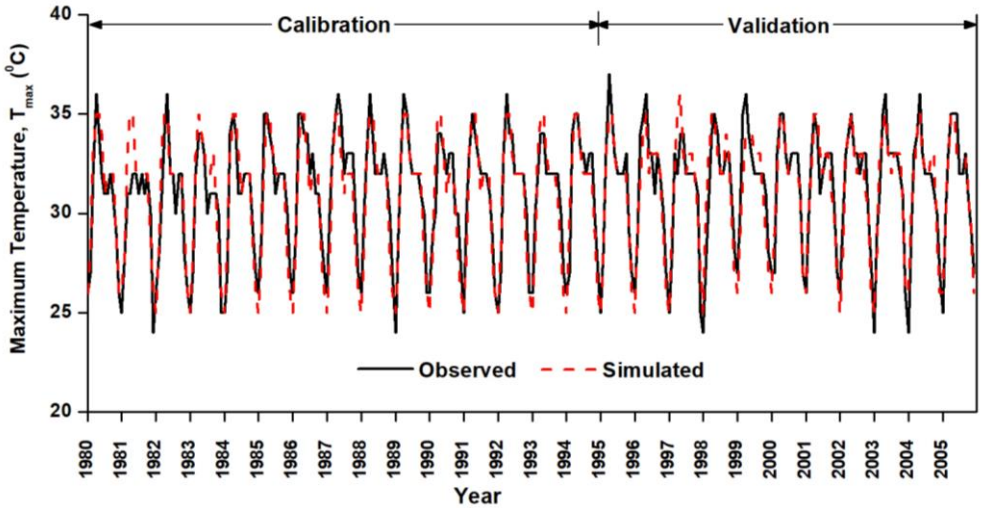

FIGURE 3. Calibration and validation plot for maximum temperature downscaling in Khulna

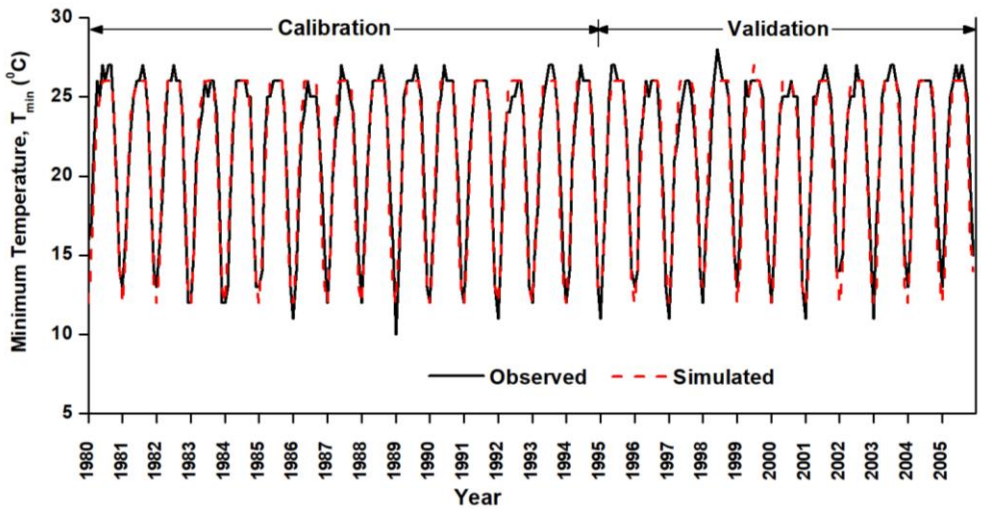

FIGURE 4. Calibration and validation plot for minimum temperature downscaling in Khulna

Furthermore, the results shown in Figures 2-4 and Table 3 indicate that the precipitation downscaling model exhibits comparatively higher error (RMSE value) and lower performance (NSE and CC values) than the temperature downscaling model. The main reason of having higher errors and lower performance in the precipitation downscaling is that precipitation is usually a stochastic event. As a result, simulation of precipitation is always a difficult task. Thus, it can be concluded that the downscaling models for maximum (Tmax) and minimum (Tmin) temperatures perform better compared to the precipitation downscaling model based on the lowest error and the highest efficiency.

TABLE 3. Summary of the performance statistics for model calibration

Climate Variables	Calibration			Validation		
	RMSE	NSE	CC	RMSE	NSE	CC
Maximum Temperature, Tmax (°C)	1.05	0.88	0.89	0.93	0.90	0.94
Minimum Temperature, Tmin (°C)	1.06	0.95	0.96	1.14	0.95	0.97
Precipitation (mm)	105.32	0.60	0.61	108.08	0.54	0.74

It is very common that the downscaled outputs of climate variables consist of bias or errors to some extent in their estimation. Although the results presented in Table 3 suggests that the performance of each downscaling model is satisfactory, errors or biases are generated for this model. Therefore, such bias must be minimized using bias correction formulae given in Eqs. (5) – (6). The results obtained after the bias correction of temperature and precipitation downscaling are presented in Table 4. As can be seen from Table 4, RMSE value is decreased whereas NSE and CC values are rationally increased after applying the bias correction. It is found that after adopting the bias correction, the improvement in error is maximum for Tmin (17.54%), whereas the improvement in model efficiency is maximum for precipitation (15.63% and 8.64%, respectively). These findings clearly demonstrate that after the bias correction, the error is minimized and accordingly, the model performance is increased.

TABLE 4. Statistical performance of temperature (T_{max} and T_{min}) and precipitation downscaling models during validation with and without bias correction

Climate Variables	With Bias			De-bias (Bias Correction)			Improvement in Estimation (%)		
	RMSE	NSE	CC	RMSE	NSE	CC	RMSE	NSE	CC
Tmax (°C)	0.93	0.90	0.94	0.86	0.91	0.95	7.53	1.10	1.05
Tmin (°C)	1.14	0.95	0.97	0.94	0.96	0.98	17.54	1.04	1.02
Precipitation (mm)	108.08	0.54	0.74	95.23	0.64	0.81	11.89	15.63	8.64

Assessment of Climate Change Projection

After checking the performance of the downscaling model at the calibration and validation periods, it is used for downscaling and projection of future climate change up to 2100. The percentage anomaly of climate change is calculated for three future time periods considering three RCP scenarios in Khulna compared to the base period, which are presented in Table 5. It is seen from the Table 5 that the anomaly parentage of Tmax is increased from 1°C to about 1.3°C based on the varying emission scenarios from RCP2.6 to RCP8.5 for the near-future (FP-1: 2021-2050) period. Similar trend of the projected Tmax is also found for the projected Tmin and precipitation during the mid-future (FP-2: 2051-2080) and far-future (FP-3: 2081-2100) periods.

TABLE 5. Anomaly (%) of climate change in the study area

Climate Variables	Near-Future (FP-1: 2021-2050)			Mid-Future (FP-2: 2051-2080)			Far-Future (FP-3: 2081-2100)		
	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5
Tmax (°C)	0.99	1.18	1.30	1.23	1.42	1.94	1.10	1.41	2.68
Tmin (°C)	0.66	1.08	1.04	0.55	1.32	2.01	0.92	1.56	3.22
Precipitation (mm)	5.97	7.88	6.87	8.87	9.55	8.90	14.54	9.33	13.21

Furthermore, it is evident from the comparison of climate change projections under three RCP scenarios that the RCP8.5 (high emission) scenario exhibits the worst trend of Tmax, Tmin and precipitation in the study area. It is found that the percentage of anomaly of Tmax for near-future, mid-future and far-future periods are found to be 1.3°C, 1.94°C, 2.68°C in Khulna under the RCP8.5 scenario. However, the percentage anomaly for Tmin are found to be 1.04°C, 2.01°C, 3.22°C in Khulna under the same scenario for near-future, mid-future and far-future periods, respectively. The percentage anomaly of precipitation in Khulna station under the RCP8.5 scenario is obtained as 6.87 mm in near-future, 8.9 mm in mid-future, and 13.21 mm in far-future periods, respectively.

The projected climate change for Tmax, Tmin and precipitation in Khulna station is shown in Fig. 5. As can be seen from the figure, there is an overall increase in temperature and precipitation in study area up to the end of this century under three RCP scenarios. Figure 5 also reveals that the worst trend of future climate change is demonstrated by RCP8.5 scenario for Tmax, Tmin and precipitation in the study area. Thus, the climate projection results conclusively demonstrate that the future climate of the study area is expected to be warmer as well as be wetter in comparison to the base period (1980-2005), which could have important implications for adaptive management of water resources in the southwest coastal region of Bangladesh.

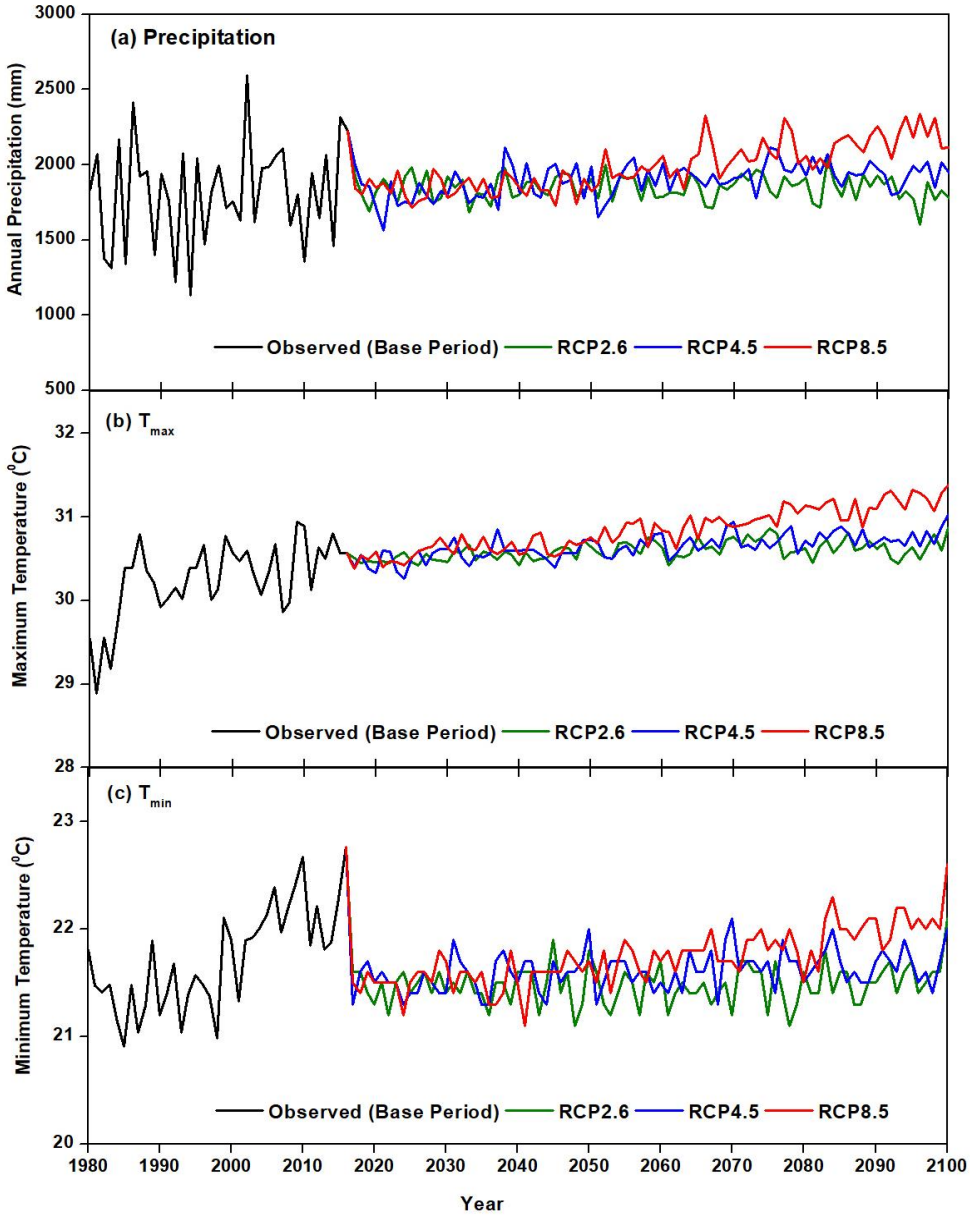

FIGURE 5. Climate change projection in Khulna under different RCP scenarios for (a) precipitation (b) maximum temperature and (c) minimum temperature

CONCLUSIONS

This study has assessed the future climate change compared to the base period 1980-2005 in the southwest coastal region of Bangladesh. The study is demonstrated through Khulna climatic station located in the region for the projection and assessment of future climate change under RCP2.6, RCP4.5 and RCP8.5 scenarios. Average temperature (Tmax and Tmin) and precipitation are mainly generated from annual time series by daily observed data using monthly sub-model. The NCEP/NCAR predictors are employed to calibrate, validate, bias correction, and generation of future climates by using SDSM based on the observed station data using the Canadian GCM, CanESM2. Using the model simulation, projection of future climate change for three future periods including near-future (FP-1: 2021-2050), mid-future (FP-2: 2051-2080), and far-future (FP-3: 2081-2100) are carried out under

three emission scenarios of RCP2.6, RCP4.5 and RCP8.5. The obtained results are compared and the climate change in the study area is assessed. Based on the current study, the following conclusions can be drawn:

- SDSM is highly effective for identifying most suitable predictors for climate change modelling as well as downscaling temperature and precipitation under different carbon dioxide emission scenarios.
- The temperature downscaling (Tmax and Tmin) models performs better than the precipitation downscaling model considering the error and efficiency indicators. This is justified because precipitation is a pure stochastic event and hence, downscaling of precipitation is always a difficult task.
- The bias correction is highly effective to minimize the estimation error and thereby improve the performance of the downscaling models for accurate projection of climate change.
- The statistical analysis of the observed and downscaled climate variables indicates that there is an overall increase in temperature and precipitation in the southwest coastal region of Bangladesh under all three RCP scenarios of RCP2.6, RCP4.5, and RCP8.5.
- It is evident from the comparison of climate change projections of temperature (Tmax and Tmin) and precipitation under three RCP scenarios that the RCP8.5 (high emission) scenario exhibits the worst trend of climate change in the study area.
- This study conclusively reveals that the future climate of the study area is expected to be warmer as well as be wetter relative to the base period, which is expected to have important implications for the adaptive management of water resources in the southwest coastal region of Bangladesh.

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