DOWNSCALING OF A SELECTED GCM RESULTS FOR GBM BASIN USING SDSM

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ABSTRACT
The aim of this research is to perform downscaling using statistical downscaling tools, namely the SDSM (Statistical DownScaling Model), to downscale canESM2 GCM output to examine future change of temperature and rainfall for three time periodsis 2030s, 2050s and 2080s.The R^2, NSE and PBIAS statistical parameters shows good agreement with observed and model simulated data. In case of temperature projection, it is found that the range of monthly temperature change of twenty twostations is -1.1°C to 8.3 °C but 17 stations have their temperature change range between 0.5°C to 3°C. Almost all stations, all season temperature will ascend. Yearly mean temperature will be raised 0.3 to 1.8°C for 2030s, 0.4 to 3.2°C for 2050s and 0.6 to 4.2°C 2080s with respect to base period. The range of sum of monthly rainfall change is -180mm to 240 mm but for 16 stations it is about -50 to +50 mm. The seasonal rainfall % change varies between -48% to +80%. Yearly mean rainfall varies in different stations from -5% to 10% for 2030s, -10% to 30% for 2050s, and -12% to 42% for 2080s. Changes in temperature and rainfall will affect water availability in major rivers. Statistical downscaling scenarios can be applied to the climate change impact assessment to inform strategic decision making and policy.

Keywords: Climate changes; statistical downscaling; temperature and rainfall; canESM2; SDSM

INTRODUCTION
Changes in climate system in recent decades are very much clear because of the observational evidence which confirm the increase in global average air and ocean temperatures (Fischer et al., 2005). These in turn influences the way of living and economy. Specially, the changes in different components (rainfall, temperature, soil moisture, evaporation etc) of hydrological cycle have direct impact on agriculture, productivity of industry, flood, fisheries and many others. Several studies have previously been conducted to assess the impact of climate change on water availability, agriculture, sea level rise etc at different regions (Fischer et al., 2005; Middelkoop et al., 2001). It is evident that Ganges-Brahmaputra-Meghna basin falls under one of the most vulnerable regions with respect to climate changes (Pervez et al., 2015; Masood et al., 2014).So a better understanding of the effects of climate changes on several sectors (e.g., water availability, flood peak etc.) has become necessary to develop resilience to future disasters. Researchers all over the world have already developed some methods to predict different climate change scenarios. General Circulation Model (GCM) is one of the most eminent climate change research advancements and most advanced tool to simulate the climate change response due to change in atmospheric composition. However, GCMs available all over the world have coarse resolution which is not suitable for climate change impact study at a local scale. So these GCM outputs are further downscaled using statistical or dynamic downscaling methods. Dynamic downscaling method is robust, but it requires high computational facilities. Statistical downscaling method uses different statistical methods to obtain higher resolution climate data. Different statistical downscaling methods include Delta change method, Regression methods, Weather generator, Weather typing, etc. In this research statistical downscaling method will be used to downscale different GCMs to study the spatial and temporal change in climatic parameters rainfall and maximum temperature of selected stations in the GBM basins. These downscaled climatic parameters will be helpful for further modeling applications, e.g., hydrologic modeling, flood modeling, morphological modeling etc., to simulate future scenarios.

METHODOLOGY

Study area

The study area consists of three river basins: the Ganges, the Brahmaputra and the Meghna (GBM) basins which are located in south Asia. The drainage area are 96, 2480 km^2 for the Ganges basin, 570,195 km^2 for the Brahmaputra basin and 64871 km^2 for the Meghna basin (Masood et al., 2015). Total areas of 1.6 million km^2 are distributed among India (64 percent), China (18 percent), Nepal (9 percent), Bangladesh (7 percent) and Bhutan (3 percent) (Nepal and Shrestha, 2015). Twenty two weather stationsof GBM basins are chosen to implement the statistical downscaling approach to generate sets of temperature and rainfall projections to assist regional to local scale climate change impact studies. The map of the study area and selected stations for downscaling is shown in Fig1.

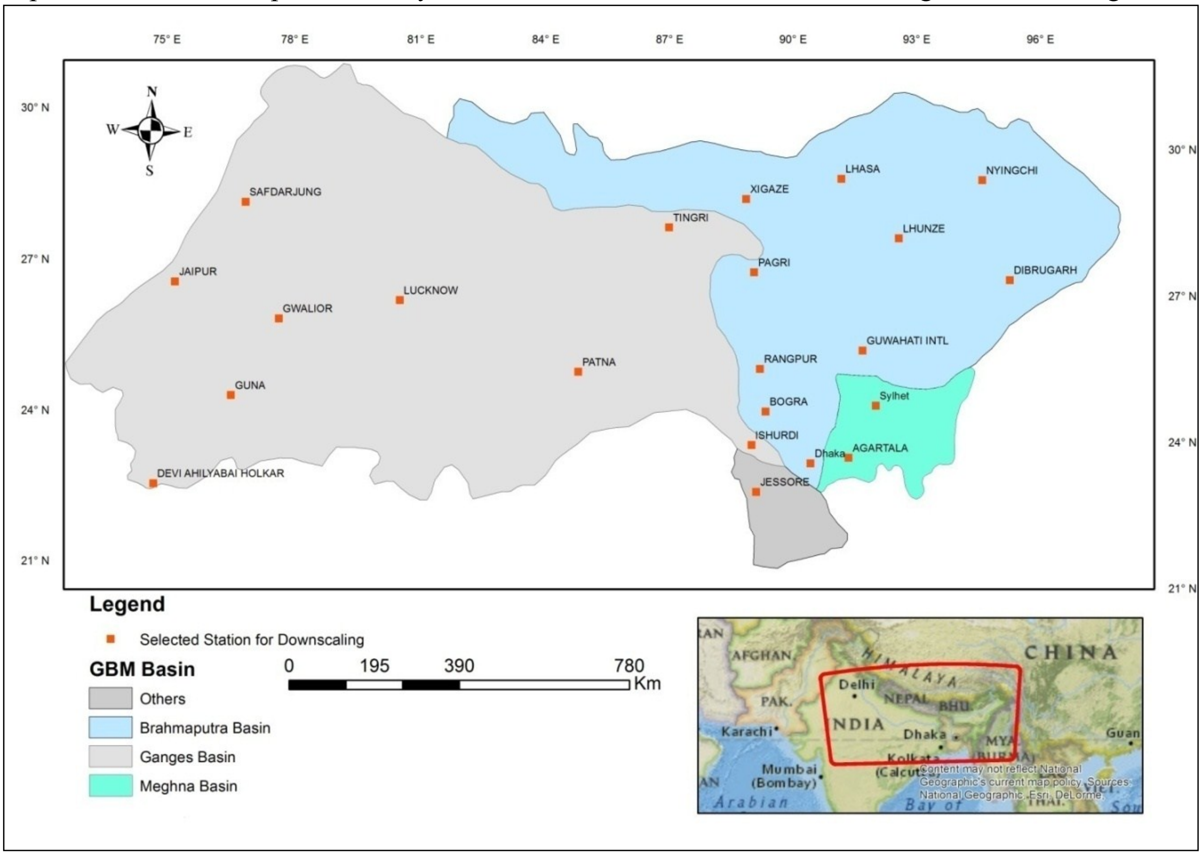

Fig 1: The map of study area and selected stations for downscaling

Data collection

Two distinct sets of data, observed data and synthetic data which include climate model data and reanalysis data are collected for this study. Observed data were collected from Bangladesh Water Development Board (BWDB) and National Climate Data Center (NCDC). Synthetic data were collected from the US National Centers for Environmental Prediction (NCEP)and Canadian Centre for Climate Modelling and Analysis (CCCMA).

Statistical Downscaling (SDSM)

CanESM2 (Canadian Earth System Model) GCM model resultswereselected for downscaling rainfall and temperature future scenarios of GBM basins. The Statistical Downscaling Model (SDSM), developed by Wilby et al. (2002), is used in this study.It is aopen source software. The SDSM is developed on usinga combination of Multiple Linear Regression (MLR) and the Stochastic Weather Generator (SWG) model. The MLR method generates statistical/empirical relationships between NCEP predictors and predictands during the screening process of predictors, and the calibration process of SDSM results in some regression parameters. These parameters, along with NCEP and GCM predictors, are used to generate a maximum of 100 daily time series to fit closely with the observed data during validation, and twenty time series are considered as the standard, a precedent set by other studies as well (Wilby et al., 2002, Gagnon et al., 2005 and Chu et. al., 2010).First step of statistical downscaling is data processing that is done to make the data useable for SDSM input.To develop SDSM, two kinds of daily time series are needed: NCEP predictor daily time series and observed daily time series (Huang et al., 2011). Second and the most important process of statistical downscaling is screening of predictor variables for the predictand to calibrate and validate the model. Predictor variables are selected on basis of a combination of the correlation matrix, partial correlation, and P-value. In this study most used predictor for temperature and rainfall projection are s500, temp and p8_v, p8_z respectively.

RESULTS AND DISCUSSIONS

Calibration and validation of SDSM model for maximum temperature

Table 1 shows all the statistical parameters of all stations for calibration and validation of maximum temperature. The values of R^2range between 0.95 to 0.99 for calibration and 0.91 to 0.99 for validation of all 22 stations. The NSE range is between 0.90 to 0.99 for calibration and 0.76 to 0.99 for validation of all 22 stations. The percentage (%) BIAS range is between -0.07 to 4.25 for calibration and 0.05 to 7.83 for validation of all 22 stations.Based on table 1 it can be concluded that for all 22 stations, the agreement between the modeled and observed maximum temperature is good.

Table 1: Summary statistics for the calibration and validation of maximum temperature for different stations

Stations Name	Calibration			Validation		
	NSE	R^2	PBIAS	NSE	R^2	PBIAS
Bogra	0.96	0.96	0.22	0.92	0.93	-0.94
Jessore	0.94	0.95	-0.25	0.91	0.94	0.44
Rangpur	0.92	0.95	-0.07	0.88	0.96	-0.58
Dhaka	0.97	0.97	-0.10	0.95	0.96	0.85
Sylhet	0.91	0.96	-0.96	0.76	0.91	0.57
Tingri	0.97	0.99	4.25	0.95	0.99	7.83
Pagri	0.97	0.98	3.34	0.95	0.98	6.78
Lhunze	0.98	0.99	-2.38	0.98	0.98	0.91
Xigaze	0.96	0.97	1.71	0.96	0.96	1.53
Guna	0.90	0.95	3.41	0.90	0.92	1.55
Devi	0.97	0.99	1.74	0.93	0.97	2.57
Dibrugarh	0.96	0.97	-0.62	0.95	0.98	0.05
Gwalior	0.98	0.98	0.49	0.98	0.98	0.17
Ishurdi	0.98	0.99	0.14	0.77	0.93	-2.41
Jaipur	0.99	0.99	-0.61	0.99	0.99	-0.55
Lhasa	0.99	0.99	0.68	0.99	0.99	0.75
Lucknow	0.99	0.99	0.35	0.98	0.98	-0.43
Nyingchi	0.99	0.99	-1.92	0.99	0.99	0.52
Patna	0.98	0.98	0.50	0.98	0.98	0.17
Arartala	0.97	0.97	0.16	0.89	0.94	1.94
Gowhati	0.98	0.98	-0.18	0.92	0.93	1.06
Safdarjun	0.98	0.99	1.50	0.97	0.98	2.45

Calibration and validation of SDSM model for rainfall

Table 2 shows all the statistical parameters for calibration and validation of rainfall. The R^2range is between 0.95 to 0.99 for calibration and 0.75 to 0.99 for validation of all 22 stations. The NSE range is between 0.88 to 0.99 for calibration and 0.69 to 0.99 for validation of all 22 stations. The percentage (%) BIAS range is between -0.33 to -16.99 for calibration and -0.65 to -13.25 for validation of all 22 stations. Based on table 2 it can be concluded that for all 22 stations, the agreement between the modeled and observed rainfall is good.

Table 2:Summary statistics for the calibration and validation of rainfall for different stations

Stations Name	Calibration			Validation		
	NSE	R^2	PBIAS	NSE	R^2	PBIAS
Bogra	0.97	0.99	8.85	0.95	0.96	5.11

Jessore	0.89	0.95	-6.86	0.88	0.92	-4.55
Rangpur	0.98	0.97	-2.89	0.97	0.98	6.07
Dhaka	0.98	0.98	1.99	0.97	0.97	-0.76
Sylhet	0.98	0.99	7.12	0.99	0.99	-2.61
Tingri	0.99	0.99	0.99	0.99	0.99	-0.65
Pagri	0.93	0.93	-0.33	0.92	0.95	-5.26
Lhunze	0.98	0.98	4.30	0.98	0.99	7.86
Xigaze	0.98	0.98	-4.31	0.87	0.88	7.95
Guna	0.95	0.96	-5.64	0.94	0.98	12.95
Devi	0.98	0.98	-0.62	0.98	0.98	4.26
Dibrugarh	0.88	0.96	-16.99	0.69	0.75	-13.25
Gwalior	0.94	0.95	-3.88	0.92	0.92	-5.02
Ishurdi	0.95	0.95	-4.25	0.87	0.90	1.11
Jaipur	0.95	0.97	-11.75	0.96	0.98	-9.97
Lhasa	0.94	0.95	10.22	0.95	0.96	11.79
Lucknow	0.96	0.96	-5.25	0.84	0.89	16.36
Nyingchi	0.96	0.96	1.13	0.98	0.98	1.46
Patna	0.97	0.98	1.99	0.94	0.96	9.85
Agartala	0.99	0.99	1.6	0.96	0.96	-2.79
Gowhati	0.97	0.97	4.13	0.95	0.96	2.76
Safdarjun	0.97	0.98	0.53	0.97	0.98	4.26

TEMPERATURE PROJECTIONS

The monthly maximum temperature, percentage changes of seasonal maximum temperature and changes in annual mean maximum temperaturewere projected for the future time periods of 2030s (2021 to 2040), 2050s (2041 to 2060) and 2080s (2071 to 2090) with respect to baseline (1986 to 2005) for RCP4.5 and RCP8.5 scenarios of 22 stations.

Changes in monthly maximum temperature

The range of maximum temperature change is -1.1^{o}C to 8.3 ^{o}C but for 17 stations maximum temperature changes are in the range between 0.5^{o}C to 3^{o}C. Table 3 shows the monthly maximum temperature ranges of 2030s; 2050s and 2080s for scenarios RCP4.5 and RCP8.5.

Table 3: Ranges of monthly maximum temperature changes in ^{o}C of 30s; 50s and 80s for RCP 4.5 and RCP 8.5

Time period	RCP4.5	RCP8.5
2030s	-0.75 to 5.1	-0.7 to 5.2
2050s	-0.8 to 6.0	-0.93 to 6.8
2080s	-1.1 to 7.5	-0.4 to 8.3

Changes in seasonal maximum temperature

Four seasons, e.g., winter, spring, summer and autumn consist of December to February, March to May, June to August, and September to November respectively. The range of maximum temperature changes in winter, spring, summer, autumn are -0.54^{o}C to 6.39^{o}C, 0.39^{o}C to 5.04^{o}C, 0.02^{o}C to 7.79^{o}C and -0.65^{o}C to 4.83^{o}C respectively.Table 4 shows the seasonal maximum temperature ranges of 2030s; 2050s and 2080s for different scenarios RCP4.5 and RCP8.5.

Table 4:Ranges of seasonal maximum temperature changes in ^{o}C of 30s; 50s and 80s for RCP 4.5 and 8.5

Years	2030s		2050s		2080s	
Season	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Winter	-0.54 to 2.73	-0.52 to 3.13	-0.39 to 3.95	-0.46 to 4.27	-0.33 to 3.79	-0.43 to 6.39
Spring	0.12 to 2.23	-0.28 to 2.92	0.06 to 3.71	-0.39 to 3.41	-0.09 to 3.21	-0.39 to 5.04
Summer	0.02 to 3.21	0.05 to 3.27	0.11 to 2.78	0.06 to 4.97	0.09 to 4.75	0.13 to 7.79
Autumn	-0.25 to 2.58	-0.34 to 3.1	0.04 to 2.57	-0.65 to 3.03	-0.64 to 3.25	-0.06 to 4.83

Changes in annual mean maximum temperature

Yearly maximum temperature will be raised in the range of 0.1^{o}C to 2.3^{o}C for 2030s, 0.3^{o}C to 3.2^{o}C for 2050s and 0.2^{o}C to 5.2^{o}C2080s respectively with respect to the base period.

RAINFALL PROJECTIONS

As like temperature projection, the change of monthly rainfall, percentage changes of seasonal rainfall and yearly mean rainfall were projectedfor the future time periods of the 2030s (2021 to 2040), 2050s (2041 to 2060) and 2080s (2071 to 2090) with respect to baseline (1986 to 2005) for RCP4.5 and RCP8.5 scenarios of 22 stations.

Changes in monthly rainfall

The rainfall prediction is very much difficult because no similarities is followed by the projection and for different station the changing pattern are different but in case of different scenarios (RCP4.5 &RCP8.5) changing pattern are similar for a selected station. Between 22 selected stations the range of sum of rainfall change is -180 mm to 250mm. Table 5 shows the monthly rainfall ranges of 2030s; 2050s and 2080s for different scenarios RCP4.5 and RCP8.5.

Table 4: Ranges of monthly rainfall changes in mm of 30s; 50s and 80s for RCP 4.5 and 8.5

Time period	RCP4.5	RCP8.5
2030s	-74 to 98	-70 to 92
2050s	-110 to 140	-100 to 130
2080s	-180 to 250	-100 to 220

Percentage Changes of seasonal rainfall

Analysing the results, it is found that the percent changes of sum of seasonal rainfall vary between -48 to +98%. The variation of rainfall changes is higher in summer and autumn compared to winter and spring. Table 6 shows the seasonal rainfall ranges of 2030s; 2050s and 2080s for different scenarios RCP4.5 and 8.5.

Table 5 Ranges of seasonal rainfall changes (in %) of 30s; 50s and 80s for RCP 4.5 and RCP8.5

Season	Winter		Spring		Summer		Autumn	
Time Period	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
2030s	-5 to 18	-2 to 25	-2 to 12	-5 to 16	-20 to 38	-30 to 62	-6 to 40	-4 to 42
2050s	-3 to 20	-3 to 26	-1 to 14	-10 to 20	-30 to 42	-40 to 78	-5 to 62	-5 to 62
2080s	-4 to 22	-5 to 29	-2 to 16	-12 to 42	-40 to 50	-48 to 98	-4 to 80	-6 to 82

Changes in (%) mean annual Rainfall

Yearly mean rainfall varies in different stations from -7.6% to 15% for 2030s -13.1% to 31.8% for 2050s and -17.1% to 42.6% for 2080s respectively. In the projections, the rainfall will be increased for most of the stations except Bogra, Tingri and Agartala.

CONCLUSIONS

The main purpose of this study was to estimate the future scenarios of maximum temperature and rainfall for the GBM basins. At first, we have selected a representative GCM for the GBM basins and downscaled that GCM to study the spatial and temporal change of climate parameter (rainfall and maximum temperature) in local scale.Calibration and validation of 22 gauge stations are made and are evaluated by statistical parameters R^2,NSE and PBIAS.The statistical parameters indicate good agreement between observed and model simulated data.In case of maximum temperature projection, it is found that the range of monthly maximum temperature change is -1.1°C to 8.3°Cbut for 17 stations maximum temperature changes are in the range of 0.5°C to 3°C.The range of maximum temperature change in winter, spring, summer, autumn are -0.54°C to 6.39°C; 0.39°C to 5.04°C; 0.02°C to 7.79°C and -0.65°C to 4.83°C respectively. The changes in yearly mean maximum temperatureare0.1°C to 2.3°C for 2030s, 0.3°C to 3.2°C for 2050s and 0.2°C to 5.2°C 2080s with respect to base period. Here it is observed that yearly mean maximum temperature will be increased gradually with time period.Among 22 selected stations the range of sum of monthly rainfall change is -180mm to 250 mm but 16 stations it is about -50 to +50 mm. The seasonal rainfall % change varies between -48% to +98%. The variation of rainfall changes is higher in summer and autumn compared to winter and spring. Yearly mean rainfall varies in different station from -7.6% to 15% for 2030s -13.1% to 31.8% for 2050s and -17.1% to 42.6% for2080s. Statistical downscaling scenarios can be applied to the climate change impact assessment to inform strategic decision- making and policy.

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