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Short Communication

Performance Study of Global Circulation Model HADCM3 Using SDSM for Temperature and Rainfall in North-Eastern Bangladesh

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Abstract

This paper describes application of a statistical downscaling model to study the performance of the global circulation model HADCM3 (Hadley centre coupled model, version 3) for the Sylhet and Moulvibazar districts (North-eastern region) of Bangladesh. Predictors of HADCM3 have been downscaled by statistical downscaling model (SDSM). Daily observed temperature and rainfall data from 1981 to 2006 was used to conduct the calibration and 2007 to 2011 was used for validation using SDSM. Percent of bias (PBIAS), Nash-Sutcliffe efficiency (NSE) and modified index of agreement are also used for the assessment of downscaled temperature and rainfall data. PBIAS of downscaled temperature is the least (-0.30%), NSE (0.80) and modified index of agreement (0.83) is the highest for daily maximum temperature at Sylhet station. Among five rainfall stations, PBIAS of downscaled rainfall is the least (1.31%), NSE (0.76) and modified index of agreement (0.79) is the highest at Kanairghat station. The downscaled temperature and rainfall data approximately agree with the observed data.

Keywords: Temperature; Rainfall; SDSM; Downscaling; Validation; PBIAS; NSE.

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1. Introduction

GCMs depict the climate using a three dimensional grid laid over the globe, typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans [1]. Their resolution is thus quite coarse, relative to the scale of the exposure units needed in most impact assessments [2]. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modeled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM-based simulations of the future climate [3]. While simpler models have also been used to provide globally- or regionally-averaged estimates of climate response, only GCMs, possibly in conjunction with nested regional models, have

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the potential to provide geographically and physically consistent estimates of regional climate change which are required in impact analyses [4].

One of the many GCM's developed in different institutions over the world over the last decade is the HadCM3 (Hadley centre coupled model, version 3) GCM. It has been used extensively for climate change detection, future prediction, and other climate sensitivity studies [5] and is one the models used in analyses of the present and future global climate, as summarized, for example, in of the various assessment reports of the Intergovernmental Panel on Climate Change (IPCC) [6]. The HadCM3-model has a spatial resolution of $2.5^0 \times 3.75^0$ (latitude by longitude) [7]. In spite of their coarse horizontal resolutions, GCM's have also been applied in many regional climate impact studies [8].

Downscaling is a technique by which large-scale properties of the free atmosphere are used to predict local meteorological conditions. Two fundamental approaches exist for the downscaling of large-scale GCM output onto a grid with a finer spatial resolution. These are dynamical downscaling and statistical downscaling [9].

Statistical Downscaling as epitomized, for example by the Statistical Downscaling Model (SDSM) is intended to bridge the gap between accessibility and sophistication [10]. SDSM can also be used as a stochastic weather generator or to fill in gaps in hydro-meteorological time series [11]. Research had been conducted on HADCM3 and statistical downscaling by many researchers in Bangladesh (*e.g.* Rahman and Mcbean [12], Mukherjee *et al.* [13], Hasib *et al.* [14] and Rajib and Rahman [15]). The objective of this study is to evaluate the performance of the global circulation model HADCM3 using SDSM at Sylhet and Moulvibazar districts in Bangladesh.

2. Theoretical Formulations and Methodology

2.1. *Climate data*

Monthly temperature and rainfall data covering the Sylhet ($24^0$53'40" latitude, $24^0$53'40" longitude) and the neighboring Moulvibazar ($24^0$18'31" latitude, $91^0$43'49" longitude) district have been collected from the Bangladesh Meteorological Department (BMD). The temperature and rainfall data cover a period of 30 years from 1981 to 2011. The study area is shown in Fig. 1. Rainfall stations Tajpur and Kanairghat are located in Sylhet district and Chandbagh, Sreemangal and Manu railway bridge are located in Moulvibazar district. The monthly mean of temperature and rainfall is shown in Fig. 2.

2.2. *SDSM model*

The downscaling processes is regression based process, such as temperature or wind speeds, there is a relationship between the predictand U_i and the chosen predictors X_{ij} :

$$U_i = Y_o + \sum_{j=1}^{n} Y_j X_{ij} + e_i \tag{1}$$

The predictor variables provide daily information concerning the large-scale state of the atmosphere. The predictand describes condition at the site scale (i.e. temperature, rainfall etc.). The model error e_i is assumed to follow a Gaussian distribution and is stochastically generated from normally distributed random numbers and added on a daily basis to the deterministic component. This white noise enables closer fit to the variance of the observed and downscaled distributions, but can degrade skill at replicating serial autocorrelation implicit to daily predictor variables [4].

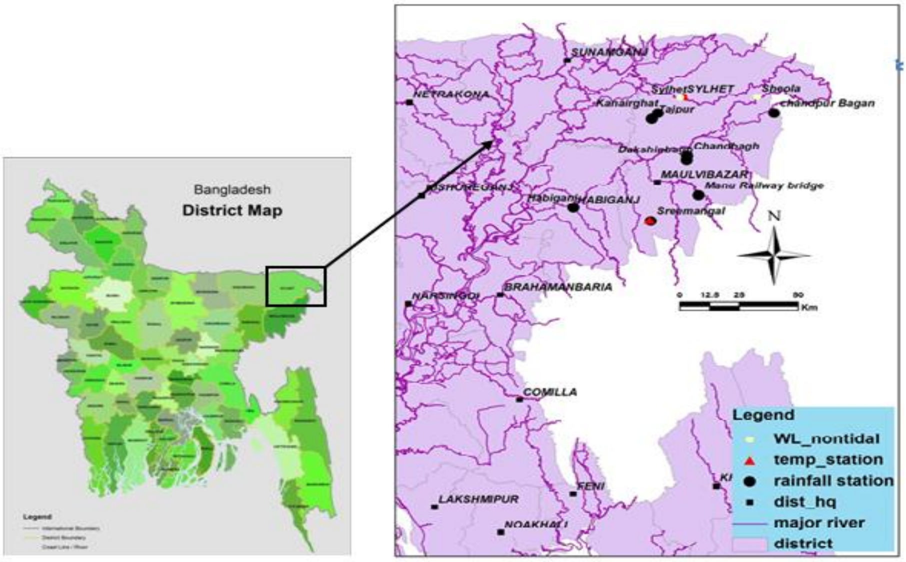

Fig. 1. Study area.

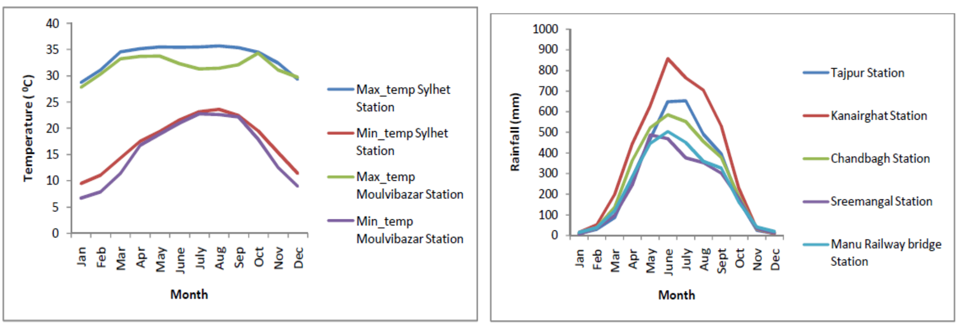

Fig. 2. Monthly mean temperature and rainfall of Sylhet and Moulvibazar districts.

Among various predictors of HADCM3, the selected predictors are near surface specific humidity (Shum), Mean sea level pressure (MSLP), Mean temperature (temp), 500 hPa geopotential height (p500), 850 hPa geopotential height (p850), Near surface relative humidity (Rhum), Relative humidity at 500 hPa (r500). These are selected through screening using statistical downscaling model (SDSM), will be discussed in the following section.

2.3. *Methodology*

Downscaling of climate change data was conducted using SDSM. Before downscaling process, quality control was ensured. The empirical relationship between gridded predictors (such as mean sea level pressure) and single site predictands (such as station precipitation) was then evaluated. After finding suitable predictor variables, calibration process was performed. By using calibration parameter obtained from calibration process, climate scenarios were produced with ensembles of synthetic daily weather series derived from atmospheric predictor variables [10].

2.3.1. *Calibration*

The calibration of downscaling models was based on solving multiple regression equations, by given daily weather data (the predictand) and regional–scale atmospheric (predictor) variables. To initiate the calibration process it is prerequisite to define calibration time period. The observed time period 1981 to 2006 was used to conduct the calibration of temperature and rainfall.

2.3.2. *Percent of bias (PBIAS)*

Percent of bias (PBIAS) [16] measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias. The percent of bias (PBIAS) defined as

$$PBIAS(\%) = \frac{\sum_{i=1}^{n}(O_i - S_i) * 100}{\sum_{i=1}^{n}(O_i)} \tag{2}$$

where PBIAS is the deviation of data being evaluated, expressed as a percentage.

2.3.3. *Nash-Sutcliffe efficiency (NSE)*

The Nash-Sutcliffe efficiency (NSE) [17] is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance.NSE indicates how well the plot of observed versus simulated data fits. NSE ranges between $-\infty$ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance. The Nash-Sutcliffe efficiency (NSE) is defined as:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \quad (3)$$

2.3.4. *Modified Index of agreement (d)*

The modified index of agreement [18] varies from 0.0 to 1.0, with higher values indicating better agreement between the model and observations. Here 0.0 and 1.0 represent no correlation and perfect fit, respectively. *d* is defined as :

$$d = 1.0 - \frac{\sum_{i=1}^{N}|O_i - S_i|}{\sum_{i=1}^{N}(|S_i - \bar{O}| + |O_i - \bar{O}|)} \quad (4)$$

where *n* is the number of compared values, O_i is observed data, $\bar{O}$ is observed mean S_i is simulated data, $\bar{S}$ is simulated mean.

3. Results and Discussion

Out of the different SRES scenario (IPCC Special Report on Emission Scenarios) A2 for temperature and precipitation was selected for their relevance with South Asia. Evaluation of HADCM3 GCM for temperature and precipitation were performed to see the fitness of this model data in respect of predictand (local temperature and rainfall) with the help of SDSM. The residuals from the downscaled data were examined against adequacy.

3.1. *Correlation of predictors*

Screening of predictors has been conducted using SDSM. Among various temperatures and rainfall stations the best correlated and partial correlated predictors and predictand of these stations are given in the Tables 1, 2, 3 and 4, respectively. Table 1 indicates correlation between predictor and predictand of maximum temperature at Sylhet station. The strongest correlation in each month is shown as data with asterisk, blanks represent insignificant relationships.

Table 1. Correlation between predictor and predictand of maximum temperature at Sylhet station.

Predictor	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Shum	0.498*	0.508*	0.351*	0.077	0.06	0.002	0.007	0.011	0.003	0.017	0.162	0.514*
MSLP	0.021	0.011	0.033	0.089	0.03	0.163	0.006	0.021	0.069	0.012	0.132	0.235
temp	0.020	0.016	0.131	0.002	0.002	0.113	0.212	0.167	0.173	0.184	0.152	0.048
p500	0.077	0.005	0.201	0.582*	0.589*	0.598*	0.583*	0.559*	0.443*	0.339*	0.466*	0.010
p850	0.184	0.218	0.103	0.028	0.169	0.152	0.117	0.067	0.026	0.203	0.158	0.135
Rhum	0.020	0.011	0.010	0.040	0.062	0.077	0.483	0.439	0.343	0.007		0.198
r500	0.003	0.023	0.011	0.018	0.380	0.001	0.006	0.011	0.085	0.113	0.011	0.030

Table 2 reports partial correlations between the selected predictors and predictand of maximum temperature at Sylhet station. These statistics help to identify the amount of explanatory power that is unique to each predictor. Data marked with asterisk show strongest partial correlation.

Table 2. Partial correlation between the predictor and predictand of maximum temperature at Sylhet station.

Predictor	Partial correlation
Shum	0.511*
MSLP	-0.003
Temp	-0.071
p500	0.523*
p850	0.420*
Rhum	0.200
r500	0.010

Table 3 illustrates the correlation between the predictor and predictand for the each month of Kanairghat rainfall station. The strongest correlation in each month is shown in red, blanks represent insignificant relationships. Table 4 reports partial correlations between the selected predictors and predictand. Data with asterisk show strongest partial correlation.

Table 3. Correlation between predictor and predictand of rainfall at Kanairghat station.

Predictor	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Shum	0.012	0.022	0.002	0.098	0.196	0.136	0.122	0.211	0.030	0.003	0.123	0.018
MSLP	0.010	0.013	0.582*	0.589*	0.449*	0.488*	0.498*	0.592*	0.443*	0.013	0.126	0.048
temp	0.022	0.001	0.067	0.200	0.050	0.131	0.005	0.120	0.137	0.130	0.200	0.105
p500	0.248*	0.308*	0.223	0.300	0.026	0.003	0.212	0.176	0.062	0.551*	0.314*	0.390*
p850	0.020	0.151	0.206	0.066	0.125	0.125	0.113	0.076	0.303	0.008	0.150	0.030
Rhum	0.001	0.003	0.010	0.082	0.021	0.026	0.038	0.309	0.113	0.202	0.012	0.015
r500	0.003	0.011	0.022	0.030	0.096	0.096	0.121	0.101	0.103	0.123	0.114	0.021

Table 4. Partial correlation between predictor and predictand of rainfall at Kanairghat station.

Predictor	Partial correlation
Shum	0.022
MSLP	0.081
Temp	0.426*
p500	0.526*
p850	0.323*
Rhum	0.144
r500	0.010

3.2. *Validation of downscaled temperature and rainfall*

The five years data of temperature and rainfall from 2007 to 2011 were used for model validation. Figs. 3a and 3b illustrate validation graph of downscaled temperature at Sylhet station for 2007 to 2011. Green line represents observed temperature and Red line represents downscaled temperature. From the visual inspection it is seen that downscaled data series is almost close to the observed series.

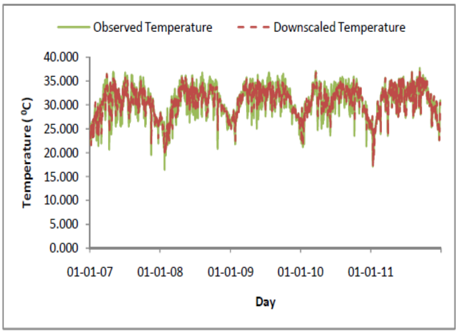

Fig. 3a. Validation of downscaled maximum temperature at Sylhet station, 2007-2011.

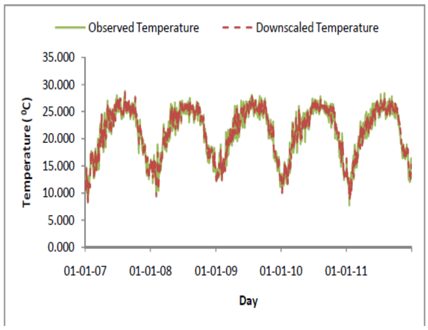

Fig. 3b. Validation of downscaled minimum temperature at Sylhet station, 2007-2011.

Figs. 4a and 4b provide the validation graph of downscaled rainfall of different stations at Sylhet districts for 2007 to 2011. Green line represents observed rainfall and red line represents downscaled rainfall. From the visual inspection it is seen that downscaled data series is agree with the observed series.

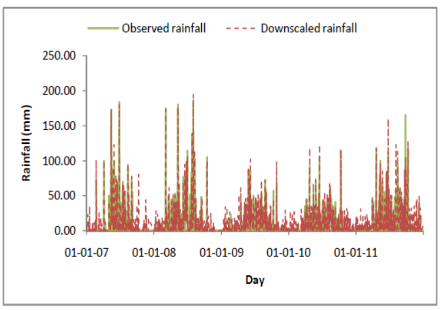

Fig. 4a. Validation of downscaled rainfall at Tajpur station.

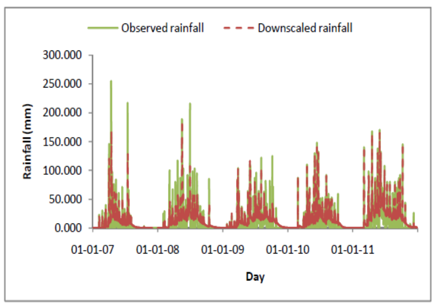

Fig. 4b. Validation of downscaled rainfall at Kanairghat station.

PBIAS for maximum temperature of Sylhet station, minimum temperature of Sylhet station, maximum temperature of Moulvibazar station and minimum temperature of Moulvibazar station are -0.30%, -0.47%, -0.46% and -1.53%, respectively. So there is slight overestimation of downscaled temperature. NSE for maximum temperature of Sylhet station, minimum temperature of Sylhet station, maximum temperature of Moulvibazar station and minimum temperature of Moulvibazar station are 0.80, 0.79, 0.79 and 0.76, respectively. Index of agreement for maximum temperature of Sylhet station, minimum temperature of Sylhet station, maximum temperature of Moulvibazar station and minimum temperature of Moulvibazar stations are 0.83, 0.80, 0.79 and 0.74 respectively. Among different variable NSE and index of agreement of maximum temperature at Sylhet station are the highest. So the downscaled maximum temperature at Sylhet station fitted well to the observed one.

PBIAS for Tajpur, Kanairghat, Chandbagh, Sreemangal and Manu railway bridge stations are -4.96%, 1.31%, -10.43%, -8.77% and -7.63%, respectively. The deviation of downscaled rainfall data from observed data is noticeable. Downscaled rainfall of Kanairghat is comparatively less biased (1.31%) than other rainfall stations. NSE for Tajpur, Kanairghat, Chandbagh, Sreemangal and Manu railway bridge stations are 0.73, 0.76, 0.65, 0.68 and 0.70, respectively. Index of agreement for Tajpur, Kanairghat, Chandbagh, Sreemangal and Manu railway bridge stations are 0.75, 0.79, 0.60, 0.63 and 0.69 respectively. Among different rainfall stations NSE and index of agreement for Kanairghat station are the highest. So the downscaled rainfall is fitted well to the observed one at Kanairghat station.

Figs. 5a, 5b, 5c and 5d illustrate normal probability plot (percent versus residuals) and residuals scatter plot (residuals versus fitted values) of maximum temperature at Sylhet station and rainfall at Kanairghat station respectively. The normal probability plot of the residuals shows that they follow normal distribution except little departure from normality at the tails due to the outliers. But there is no trend in the residuals scatter plot for both downscaled temperature and rainfall. So the residuals are mutually independent.

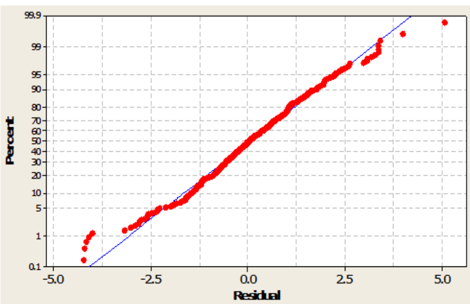

Fig. 5a. Percent versus Residual plot for normal probability of downscaled maximum temperature at Sylhet station.

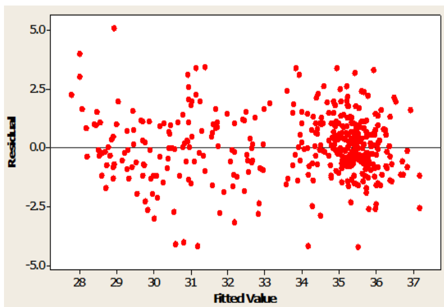

Fig. 5b. Residuals versus fitted value of downscaled maximum temperature at Sylhet station.

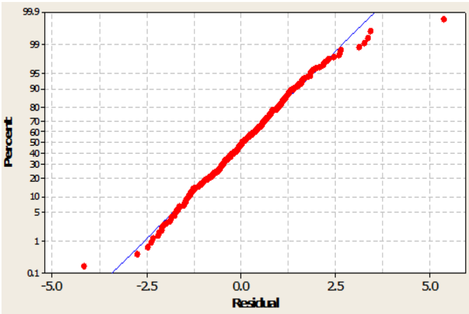

Fig. 5c. Percent versus Residual plot for normal probability of downscaled rainfall at Kanairghat station.

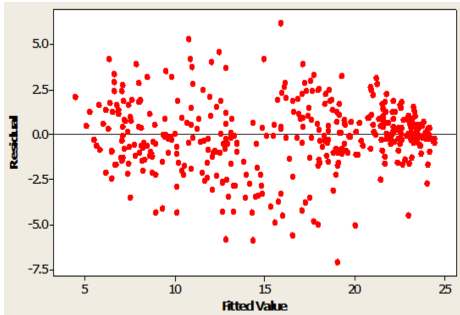

Fig. 5d. Residuals versus fitted value of downscaled rainfall at Kanairghat station.

4. Conclusions

Statistical downscaling of GCM (global circulation model) for temperature and rainfall data can easily be understood and adopted in order to minimize climate changes and its relevant impacts. There are some biases in downscaled temperature and rainfall. Such biases were comparatively less for downscaled temperature in comparison to rainfall. PBIAS (percent of BIAS) of downscaled daily maximum temperature at Sylhet station was the least (-0.30%). NSE (Nash-Sutcliffe model efficiency) and index of agreement of downscaled daily maximum temperature at Sylhet station was 0.80 and 0.83 respectively. As a result, the downscaled daily maximum temperature was fitted well to the observed data at Sylhet station. PBIAS (percent of BIAS) was the least (1.31%) of daily rainfall at Kanairghat station. NSE (Nash-Sutcliffe model efficiency) and index of agreement of downscaled daily rainfall at Kanairghat station was 0.76 and 0.79 respectively. Moreover, the agreement between downscaled daily rainfall and observed one was impressive at Kanairghat station. Finally, it was evident that performance of GCM model HADCM3 using SDSM was successively promising to temperature and rainfall data. It might be used effectively for estimation and prediction of missing temperature and rainfall values and investigation of long term temperature and rainfall changes.

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