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Uncertainty analysis of downscaled daily precipitation using climate scenarios of different story line

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Abstract: Analysis of the model errors and quantification of uncertainties in downscaled meteorological variables is valuable in identifying the most accurate and reliable downscaling model for climate change impact studies. Statistical Downscaling Model (SDSM) is used in simulating precipitation using HdCM3A2 and HdCM3B2 scenarios. Model errors and uncertainties associated with the downscaled results of daily precipitation are analyzed using various statistical techniques at 95% confidence intervals in the estimates of means and variances of both observed and downscaled data. The study has been carried out using 24 years of observed and downscaled daily precipitation data covering from 1978 to 2001 for the Barak river basin located in Assam, India. In the downscaling experiment, averaged daily mean precipitation of six meteorological stations and the large-scale predictors of the NCEP and HdCM3 scenarios have been used. The variability and uncertainty assessment results indicate that, in daily precipitation downscaling using HdCM3A2 scenario results are closer to the observed in most of the cases as compared to HdCM3B2 scenario at 95% confidence level. Further assessment of those models, in terms of skewness and average dry and wet spell length comparison between observed and downscaled daily precipitation also indicates that HdCM3A2 scenario results are closer to the observed data as compared to the results of the HdCM3B2 scenario. Overall, HdCM3A2 scenario may be considered better suited for application in simulating precipitation.

Key words: Uncertainty analysis; Model errors; Precipitation; Downscaling

1. Introduction

Reliability of downscaling results is an important issue in climate change impact studies due to the presence of model errors and uncertainties associated with the downscaled data. These errors and uncertainties result from the modeling concepts, assumptions and the data used. Analysis of the model errors and quantification of uncertainties in downscaled meteorological variables is valuable in identifying the most accurate and most reliable downscaling model which can be used in hydrologic modelling for climate change impact studies. Precipitation is one of the most important climatic variables in climate change impact studies and hydrological modeling (Yu et al., 2015; Ibrahim et al., 2015). Climate change significantly affects the temporal pattern and amount of annual precipitation at the regional level, which in turn would affect the regional water resources and future water availability (Saha, 2015). Its variability constitutes a significant source of uncertainty for hydrological modeling (Tao et al., 2009; Asante and Amuakwa-Mensah, 2014). Assessment of precipitation variability and other features are studied on regional scale prior to application in hydrologic modeling (Hasanean H and Almazroui, 2015; Yazid, 2015). However, precipitation is also subject to uncertainty due to measurement errors, systematic errors, stochastic error due to the random nature of rainfall, the irregular topography and model concepts or assumptions. Accurate simulation of the spatial distribution of rainfall with least errors may yield good inferences about the precipitation of a region. Precipitations data are sparse and do not often provide adequate spatial representation of rainfall. It requires understanding in the patterns of rainfall variability and the sources of uncertainty.

Various statistical downscaling methods such as multiple linear and non-linear regression and stochastic weather generators are used by many investigators due to easier and less costly to implement unlike the dynamical downscaling technique which are computationally demanding. Hence, statistical downscaling methods are mostly used in anticipated hydrologic impact studies under climate-change scenarios. One of the well-recognized statistical downscaling tools that implements a regression based method is the statistical downscaling model (SDSM) and it has been used successfully in downscaling climatic variables (Yar and Chatfield, 1990). However, downscaled climatic variables such as precipitation bears model errors and uncertainties and required to be quantified prior to its application in modelling task. In this study, observed daily mean precipitation of Barak river basin and corresponding observed large-scale atmospheric predictors from the National Centers

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for Environmental Prediction (NCEP) reanalysis data sets are used for calibration and validation of the downscaling models, and then the derived predictors of HdCM3A2 and HdCM3B2 scenarios are used in simulating daily precipitation for the current period (1978–2001). The objective of this study is to assess the model errors and uncertainties associated with the downscaled precipitation in the Barak river basin, Assam, India (Fig. 1) and attempts to provide some indication of how each downscaling model will affect the generation of future scenarios based on the GCM outputs. Different uncertainty assessments methods are used for assessing model uncertainty include analyzing the statistical properties of the model errors (Kaleris et al., 2001; Ang and Tang, 1975), confidence intervals for the estimates of means and variances of the model results (Wilby et al., 2002).

2. Materials and methods

This section describes the details of data and methods used in analyzing uncertainty of daily precipitation. Daily rainfall of Barak river basin and corresponding daily global data of HadCM3A2 and HdCM3B2 experiments were downloaded for analysis purpose.

2.1. Study area and data

The study area selected for the application of downscaling methods is the Barak river basin (Fig. 1); the Barak basin lies between east longitudes 91°10' to 95°7' and north latitudes 21°58' to 26°24'. The river has its origin at the Japvo mountain of Manipur hills, passes through the southern part of Assam and outfalls in the Bay of Bengal after merging with Brahmaputra by the name of Meghna. The drainage area of the river basin lying in India is 41,157 km2 out of which Assam shares 17.6 % (Ojha and Singh, 2004). The basin receives a mean annual rainfall of 2640 mm (Mirza et al., 2001). Precipitation from six meteorological stations, Laxmipur; Dholai; Imphal; Shillong; Agartala; and Kailashahar which are located in Barak river basin are selected for the study and one dataset is prepared by taking daily mean precipitation of these stations are prepared for the study purpose. Daily total precipitation records representing the current climate were collected from the Regional Meteorological Centre, Guwahati and prepared for downscaling experiments. At the same time, corresponding daily observed data of large-scale predictor variables representing the current climate condition of the region is derived from NCEP_1961-2001 reanalysis is downloaded from Canadian Climate Change Scenario Network for validation and calibration of the downscaling model. Corresponding daily observed large-scale predictors are extracted from HadCM3A2 and HdCM3B2 experiments for simulation purposes from the closest grid point (25 latitude X 93.75 longitude) to the study area are used as inputs in downscaling models.

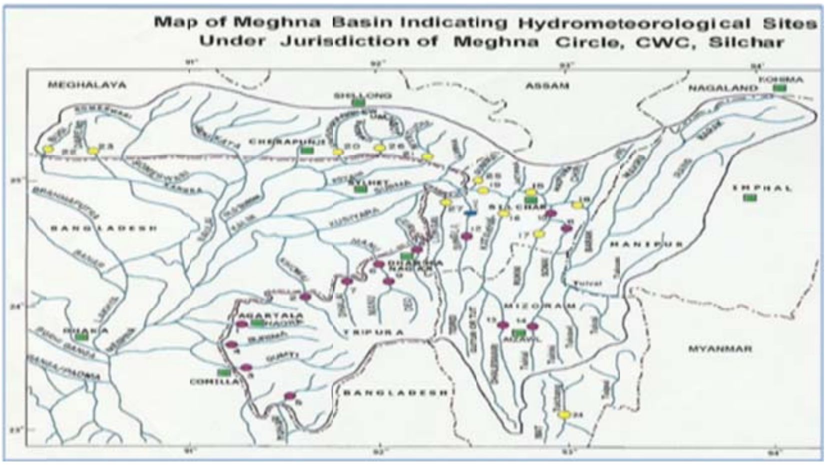

Fig. 1: Map of Barak river system

2.2. Statistical downscaling model (SDSM)

Statistical downscaling model (SDSM) is described as hybrid between a multivariate linear-regression method and a stochastic weather generator. SDSM has been used successfully by many in downscaling climate variables due to its facility for rapid generation of multiple, low-cost, single-site simulations of daily weather variables under present and future climate forcing (Wilby et al., 2000; Hassan et al., 2012). SDSM needs two types of daily data. The first type corresponds to local predictands of interest (e.g. temperature, precipitation) and the second type corresponds to the data of large-scale predictors (NCEP and GCM) of a grid box closest to the study area (Hashmi et al., 2010). The basic functions of SDSM are quality control and data transformation, screening of predictor variables, model calibration, weather generation, statistical analysis, graphing model output and scenario generation. Quality control and data transformation enables the identification of gross data errors, missing data codes and outliers and if required transform predictors and/or the predictand prior to model calibration. Screening of predictor variables operation is used in identifying empirical relationships between gridded predictors (such as mean sea level pressure) and single site predictands (such as station precipitation) and is central to all statistical downscaling methods. Large-scale relevant predictors are selected by the results of correlation analysis, partial correlation analysis and scatter plots and also based on the physical sensitivity between selected predictors and predictand. The Model Calibration is a three step operations between a user–specified predictand and a set of predictor variables. Firstly, selection of optimization techniques such as dual simplex algorithm and least square technique to computes the parameters of multiple linear regression equations; secondly selection of the model structure such as monthly, seasonal or annual sub–models and lastly selection of the process such as unconditional or conditional. In unconditional models a direct link is assumed between the predictors and predictand (e.g., local wind speeds may be a function of regional airflow indices). In conditional models, there is an intermediate process between regional forcing and local weather (e.g., local precipitation amounts depend on the occurrence of wet–days, which in turn depend on regional–scale predictors such as humidity and atmospheric pressure). Weather generation operation generates ensembles of synthetic daily weather series given observed (or NCEP re–analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series representing current climate conditions. Data analyses provides a means of interrogating both derived SDSM scenarios and observed climate data and produce the chosen statistics such as monthly/seasonal/annual means, maxima, minima, sums and variances. Graphical analysis is done in two ways of graphical analysis through the Compare Results screen and the Time Series Plot screen. The Compare Results screen enables the User to plot monthly statistics produced by the Analyze Data screen. The graphing option allows simultaneous comparison of two data sets and hence rapid assessment of downscaled versus observed, or current versus future climate scenarios. The Time Series Plot screen produce a time series plot of chosen data files in terms monthly, seasonal, annual or water year periods for statistics such as Sum, Mean, Maximum, Winter/Summer ratios, Partial Duration Series, Percentiles and Standardized Precipitation Index. Finally, the Generate Scenario operation is used to produces ensembles of synthetic daily weather series given atmospheric predictor variables supplied by a climate model (either for current or future climate experiments), rather than observed predictors.

2.3. Calibration and validation

In calibration and validation of downscaling model, averaged daily mean precipitation and 26 large-scale predictor variables derived from NCEP-1961-2001 reanalysis for 24 years data are prepared. To eliminate the irrelevant input variables, sensitivity analysis is performed using all 26 input variables. Sensitivity analysis is a method of extracting cause and effect relationship between inputs and outputs of the network and provides a measure of the relative importance among the predictors (input of the neural network) by calculating how the model output varies in response to variation of an input. The sensitivity results provide a measure of the relative importance of each input (predictor) in the particular input-output transformation. From the sensitivity analyses, twelve predictor variables were found be most relevant to the predictand (precipitation) and hence, selected for simulation of precipitation. The model is again calibrated with these twelve selected (most relevant) predictor variables adjusting several model parameters. The best performance of the statistical downscaling model is achieved with duplex optimization criteria at 12 variance inflation, 0.9 bias correction and 0.3mm/day threshold value. The performance of the model is analyzed in terms of RMSE and percentage mean error. The model validation results are achieved at a RMSE of 8.63 mm/day and percentage error of 5.87%. Further, daily precipitation has been simulated using HdCM3A2 and HdCM3B2 scenarios. Performances of the downscaling model in simulating daily precipitation were assessed in terms of RMSE and percentage mean error. The RMSE and percentage mean error of HdCM3A2 simulation are 11.14 mm/day and 15.51% while the RMSE and percentage mean error of HdCM3B2 simulation are 13.48 mm/day and 18.13%. These results indicate that HdCM3A2 simulation is closer to the observed precipitation as compared to that of HdCM3B2 simulation.

3. Uncertainty assessment in downscaled results

Model errors and uncertainties in downscaled daily precipitation are assessed in terms of means and variances of downscaled data. The uncertainty assessment are analyzed graphically for the 24 years of observed and downscaled daily precipitation using exploratory data analysis to examine several characteristics, such as normality, outliers and autocorrelation. On the basis of these preliminary analyses, either a parametric or nonparametric approach is employed in evaluating model errors with statistical significance tests at the 95% confidence level.

3.1. Exploratory data analysis

The exploratory data analysis plots of observed (1978–2001) daily precipitation at Barak river basin for the month of January are analyzed using various test for checking normality and outliers in the observed and downscaled daily precipitation. Precipitation data are often non normal and bears outlier data due to its extremity in occurrence from no rain to extreme events. Normality test using the Anderson-Darling test's p-value indicates that there is evidence that the data do not follow a normal distribution (Fig. 2). Outlier test by Grubbs technique provided the G statistic and p-value indicates the presence of outlier data in the data series (Fig. 3). Histogram plot indicates that the distribution is positively skewed (Fig. 4). Finally, the time series plots have clearly indicated the presence of outlier, non-normality and skewness in the data series (Fig. 5). From these test, it is concluded that daily precipitation data do not hold all the assumptions of parametric data analysis and contain some outliers in the data series. The exploratory data analyses of the downscaled and observed daily precipitation for all other months are assumed to support the same conclusions. Hence, uncertainty assessment in the estimates of means and variances of daily precipitation is assumed to be better suited for data analysis by non-parametric test.

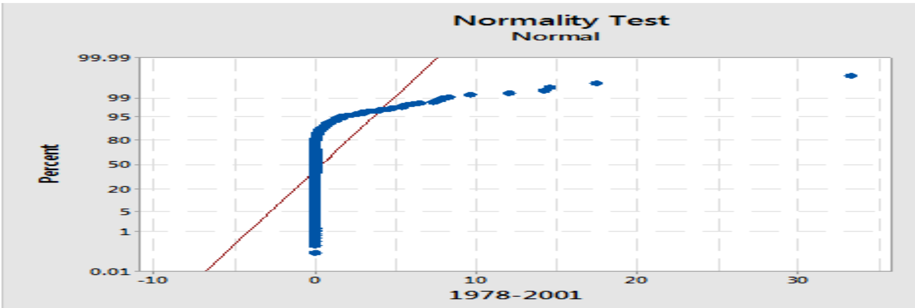

Fig. 2: Anderson-Darling normality test for January 1978-2001

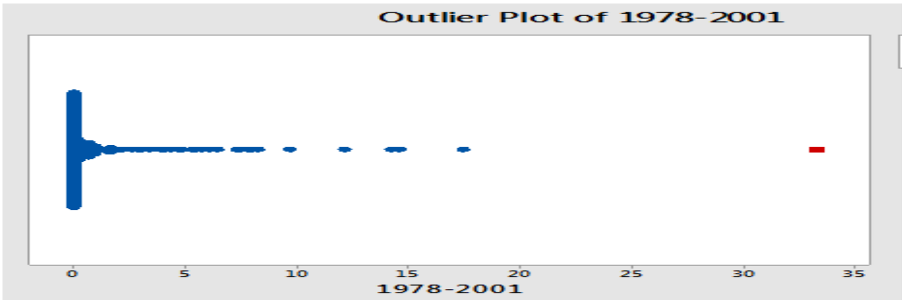

Fig. 3: Outlier test for observed precipitation for January 1978-2001

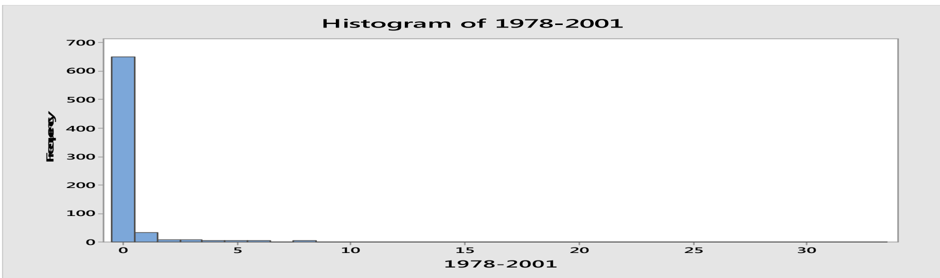

Fig. 4: Histogram plot for observed precipitation for January 1978-2001

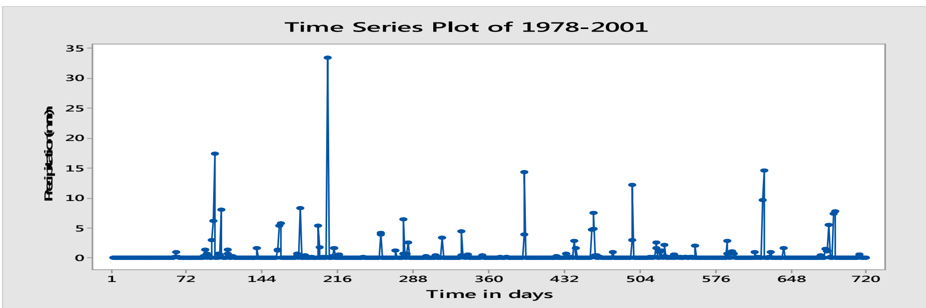

Fig. 5: Time series plot for observed precipitation for January 1978-2001

3.2. Model error evaluation in the estimates of means

Model errors in the estimates of means have been evaluated using the non-parametric Wilcoxon rank-sum method, also known as the Mann–Whitney test at the 95% confidence level. In terms of hypothesis testing, the p value is the level of significance for which the observed test statistic lies on the boundary between acceptance and rejection of the null hypothesis. A detailed description of the theory of Wilcoxon rank-sum test can be found in (Lehmann, 1975; Conover, 1980).

The absolute downscaling model errors (absolute values of the observed minus simulated data) in the estimates of mean daily precipitation for each month are shown in Fig. 6. These errors are tested at the 95% confidence level using the non-parametric Wilcoxon rank-sum test for daily precipitation. These test results of Wilcoxon rank sum test are shown in Table 1. In daily precipitation downscaling at the Barak river basin, absolute model errors of HdCM3A2 scenario in simulating precipitation are lower that of HdCM3B2 scenario (see Fig. 6). The statistical significance test results (p values in Table 1) of the model errors in daily precipitation downscaling reveal that, at 95% confidence level, the model errors are insignificant in almost all the months ($p<0.05$) except March and October. Overall, the general trend in daily precipitation downscaling for the current period using HdCM3B2 predictors has higher errors in March, May and July while HdCM3A2 has high error in October only. This indicates that HdCM3A2 scenario has better capability to simulate daily precipitation as compared to HdCM3B2 scenario.

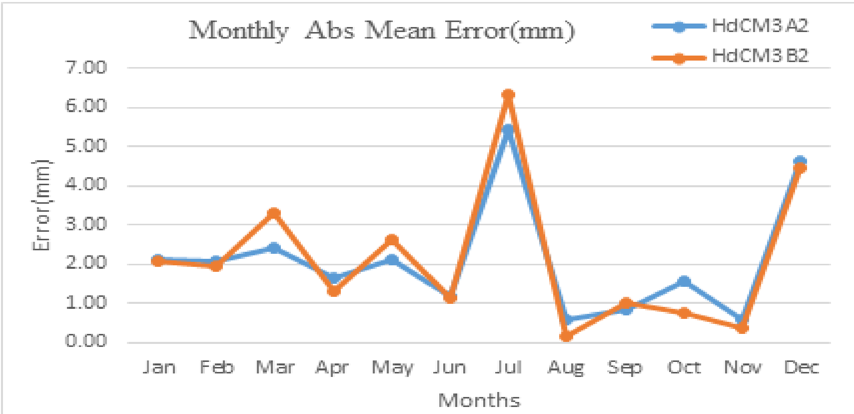

Fig. 6: Model error (absolute) in daily precipitation (1978-2001)

Table 1: Non-parametric Wilcoxon rank-sum test (p-values) results (1978-2001)

[redacted]	[redacted]	[redacted]
[redacted]	0.065	0.005
[redacted]	0.002	0.004
[redacted]	0.270	0.071
[redacted]	0.529	0.220
[redacted]	0.643	0.317
[redacted]	0.327	0.338
[redacted]	0.000	0.000
[redacted]	0.152	0.781
[redacted]	0.040	0.016
[redacted]	0.010	0.009
[redacted]	0.001	0.000
[redacted]	0.014	0.028

3.3. Model error evaluation in the estimates of variances

In case of continuous and not normally distributed data, Levene's test (Levene, 1960) is often used to test whether the two sample population variances are equal or not. Modified Levene's test method is employed here that considers the distances of the observations from their sample median rather than their sample mean. Using the sample median rather than the sample mean makes the test more robust when the underlying data follow a skewed distribution.

Comparative plots of the variances of the observed and downscaled daily precipitation for each month are shown in Fig. 7 for the Barak river basin. The equality of variances between observed and simulated daily precipitation has been tested statistically in each month at the 95% confidence level using the Levene test. The corresponding test results for daily precipitation are shown in Table 2. In the case of daily precipitation downscaling, the graphical comparison of variances is presented in Fig. 7, and shows that the HdCM3A2 simulation show variability that is closer to the observed data. But HdCM3B2 simulation does not represent variability close to the observed data, and rather high variability appears in most of months. In the case of the HdCM3A2 simulation, the variance test results (p-values) are all found to be below 0.05 only in May, June and November (Table 2), suggesting that the simulated and observed variances are statistically different. In the HdCM3B2 simulation, the p values are found to be below 0.05 May, June and November, indicating an equality of variances for those months. These test results indicate that the variability of the downscaled daily precipitation is more in case HaCM3B2 scenario than HdCM3A2 scenario at 95% confidence level.

3.4. Skewness of precipitation data

The performance of the downscaling models in daily precipitation downscaling further assessed using the skewness, which measures the asymmetry of a distribution around its mean, has been considered. A comparative plot of skewness of the observed and downscaled daily precipitation data is provided in Fig. 8 for the study area. The skewness statistics indicate that the observed daily precipitation data are significantly positively skewed. We consider a distribution significantly skewed while the absolute value of the skewness statistic is more than two times the standard error (SES) of the estimates of the skewness statistic. The SES can be estimated using (Tabachnick and Fidell, 1996):

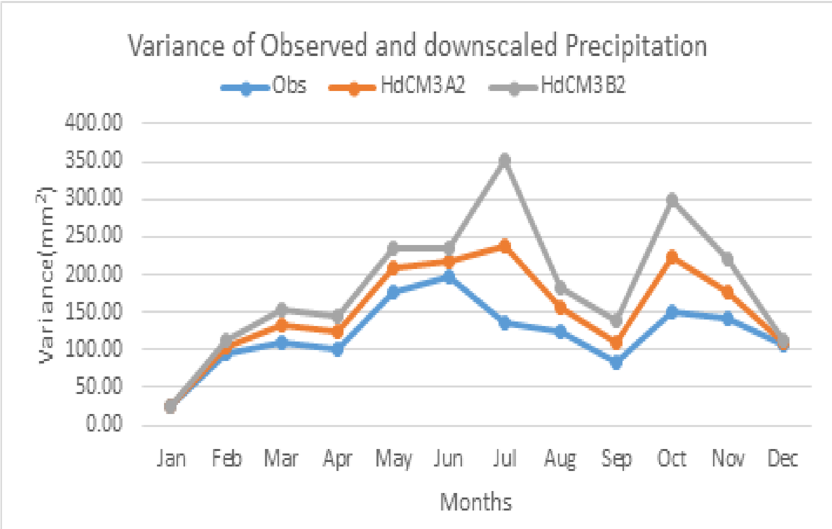

Fig. 7: Variance of daily precipitation downscaled (1978-2001)

Table 2: Test results (p values) of the Levene test for the equality of variances.

[redacted]	[redacted]	[redacted]
[redacted]	0.935	0.739
[redacted]	0.309	0.190
[redacted]	0.974	0.591
[redacted]	0.104	0.092
[redacted]	0.016	0.003
[redacted]	0.000	0.002
[redacted]	0.408	0.162
[redacted]	0.672	0.638
[redacted]	0.657	0.925
[redacted]	0.202	0.770
[redacted]	0.003	0.000
[redacted]	0.371	0.612

$$\boldsymbol{SES} = \sqrt{\frac{6}{N}} \qquad (1)$$

In our case, for example, if we consider 24 years of daily precipitation data in the month of January, the total number of data points would be N=24*31=744, and the SES for this example would be $\sqrt{\frac{6}{744}} = 0.09$. Two times the standard error of the skewness is 0.18, and the absolute value of skewness statistic of daily precipitation for January is 3.5 (Fig. 8) which is greater than 0.18, we can conclude that the distribution is significantly skewed. Similarly, it can be shown that the observed daily precipitation data are significantly and positively skewed in all other months. On computing the skewness of downscaled daily precipitation, we find that the skewness of all downscaled daily precipitation data is also significant and positively skewed in all months. However, if we consider the comparative plots of skewness in Fig. 8, then we find that the HdCM3A2 simulation skewness is closer to the observed data in most of the months and that of the HdCM3B2 simulation skewness are slightly higher from the observed data in all the months except September.

3.5. Dry and wet spell length of precipitation data

Analysis of dry and wet spell length in each month is an important indicator for performance assessment of the downscaling models in daily precipitation downscaling. Here, dry days is considered with a precipitation amount of less than 0.3 mm and dry-spell length in each month is the maximum number of consecutive dry days in a month. Days with a precipitation amount of 0.3 mm or more per days is considered as wet day.

Comparative plots of the average dry and wet spell length for each month of observed and downscaled precipitation data are provided in Fig. 9 and Fig. 10. Fig. 9 indicates that both the scenarios could reproduce dry spells closer to the observed data only in March, May, September and October.

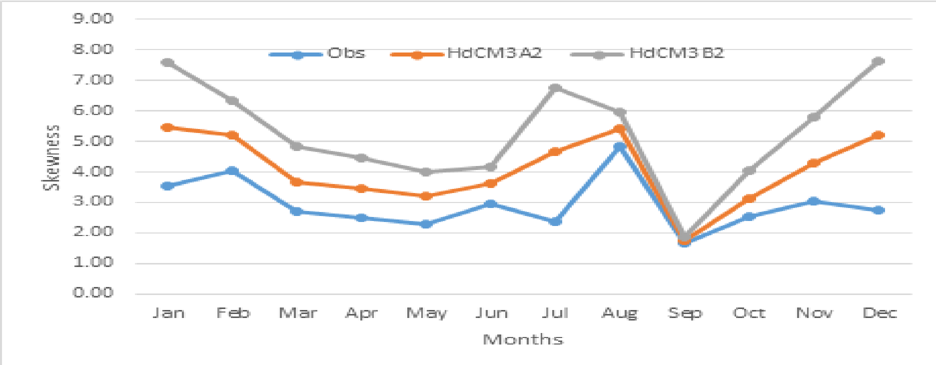

Fig. 8: Skewness in downscaled daily precipitation (1978-2001)

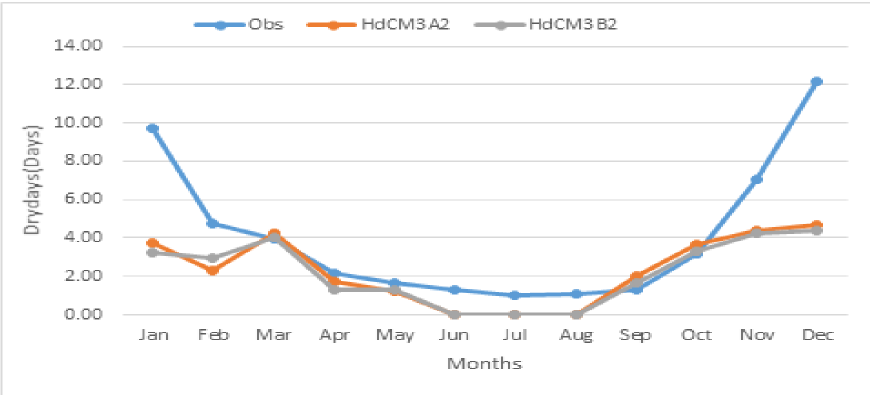

Fig. 9: Average dry-spell length in downscaled daily precipitation (1978-2001)

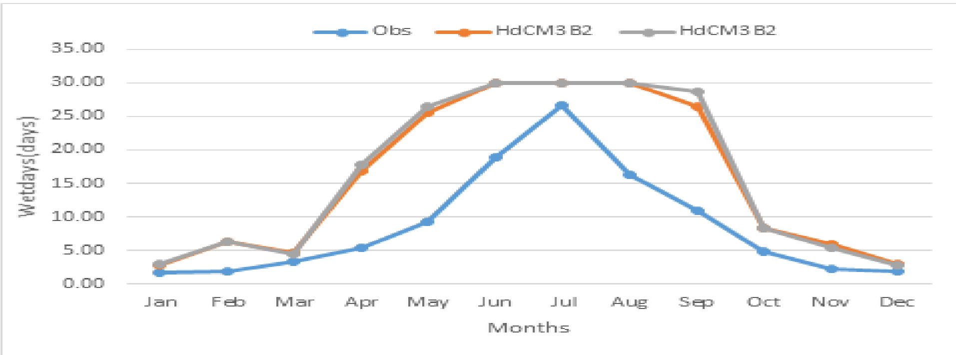

Fig. 10: Average wet-spell length in downscaled daily precipitation (1978-2001)

4. Summary and conclusions

GCMs under two different story lines, namely the HdCM3A2 and HdCM3B2 have been used in downscaling daily precipitation in Barak river basin and their downscaled results are compared by assessing errors and uncertainties for the current period 1978–2001. The uncertainty assessment results indicate that in daily precipitation downscaling, in terms of model errors (differences between observed and simulated mean values), both the GCMs has almost the same level of reproducibility in generating climate scenarios and the associated model error and uncertainties are comparable to each other while downscaled with the SDSM at the 95% confidence level. The SDSM produces errors significant in March, May, July and October in daily precipitation downscaling.

However, the variance comparison indicates different patterns unlike the model errors comparison for the mean estimates. The variance comparison with the observed data shows that, in daily precipitation downscaling with HdCM3A2 and HdCM3B2 are not close to the observed variability except Jan, Feb and Dec and significantly different from the observed variability at 95% confidence level.

Skewness test indicated that observed and downscaled precipitation is significantly skewed. Skewness of HdCM3A2 scenario result is closer to the observed skewness as compared to that of the HdCM3B2 in almost all the cases. It concludes that

HdCM3A2 simulation is better suited than HdCM3B2 simulation.

In case of dry and wet spell length assessment, HdCM3A2 simulation is slightly better than HdCM3B2 simulation in generation the dry and wet spell length features.

From the study, it is observed that HdCM3A2 scenario has better reproducibility in simulating daily precipitation than HdCM3B2 scenario in the present study area and the model used. This study also gives an idea about the performance of GMCs with different story line in simulation daily precipitation. However, this study is performed using only one downscaling model (SDSM) and two GCMs (HdCM3A2 and HdCM3B2 scenarios) with averaged mean precipitation of multiple meteorological stations. Attempts may be made using multiple models and GMCs of different generations.

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