Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 5, May 2021:2574- 2573

Research Article

To study the impacts of climate change on precipitation of Barak river basin

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Abstract:
In the present study, impacts of climate change on precipitation and its projection for Barak river basin, Assam, India, has been studied. The study also attempted to compute the anticipated effects of climate change on precipitation of the study region based on the 5th IPCC assessment report. Here, statistical downscaling model(SDSM) is used as to downscale the course climatic variables derived from the CanESM2 dataset into finer resolution. Representative concentration pathways (RCPs) such as RCP 2.6, RCP 4.5 and RCP 8.5 are used for developing climate projections. Several statistical parameters are used to analyze the projected climate scenarios. The present study revealed that the study region is anticipated to have less precipitation in the future as observed in the all RCPs analysis. Compared to the observed precipitation for 2006-2013, the RCP2.6 shown better performance than other RCPs in simulating precipitation. Trend analysis indicated an increasing trend in observed precipitation (2078-2013) and a decreasing trends in simulated precipitation (2014-2100). Sen's slope test indicated a maximum change rate of precipitation as 0.02 mm/year (RCP8.5) and a minimum change rate as 0.006 mm/year (RCP2.6). The present study has also shown some evidence that the precipitation of the study area may seriously be affected due to changes in climate in the coming future. Findings of present study are expected to be useful in managing water and other resources of the region of Barak river basin.
Keywords: Climate; Change; Impacts; RCP; Trend.

1. Introduction

Significant variations in the occurrence of precipitation affects a region in many ways, specifically water resources of the region, causing flood and droughts. Changes in precipitation are mainly due to anthropological climate change. Climate change is not only affecting precipitation, but also other parameters such as temperature, humidity etc. Climate change caused significant changes in hydrologic cycles affecting the water resources which ultimately affects the demands of water for rapidly growing population, economic development, environment of a region. Water resources management is largely dependent on the occurrence and distribution of precipitation. Therefore, robust precipitation projections is essential for water resources management of a region both for present and future.

Though India receives both summer and winter rainfall, summer rainfall is crucial to decide water availability and food security of the region [1,2]. It is reported that almost 80% of the annual precipitation over the entire region of India occurs in the monsoon season[3,4]. As a result, flood during monsoon and drought during dry season have adversely affected the national economy as well as the life of millions of inhabitants. Most of the previous studies could not draw sufficient inferences on the effects of climate change over the India monsoon rainfall while some studies have been found to report the effects of climate change over the India monsoon rainfall [5–7]. Some literatures also reported about the increased mean Indian monsoon precipitation and its annual precipitation variation [5,8–10]. Climate model such as CMIP-5 models was often found to project an increased summer monsoon rainfall over the Indian region [11]. Similarly, IPCC AR4 models also reported an increased monsoon precipitation [13], and it also affected the monsoon circulation over the region[13,14]. Few CMIP-3 model's projected precipitation shown various types of monsoon rainfall trends to be occurred by 2100 under the SRES scenario [4]. Global monsoons analysis based on a coupled AOGCM suggested that the summer monsoon over the Indian region is expected to intensify in the coming future as it is anticipated that moisture content under various CO_2 forcings may be increased [16]. Analysis of RCP-4.5 scenario projected that global mean precipitation is expected to be increased by around 3.2% per 1º K of surface warming and also projected an increased yearly mean monsoon precipitation over Asian region [17,18]. It is also further reported that CMIP-5 models has better capability to represent rainfall due to its higher resolution in comparison to CMIP-3 models [19] and therefore CMIP-5 models produce better results in simulating monsoon rainfall. Although the mean rainfall error pattern is comparable both in CMIP-5 and CMIP-3, CMIP-5 model was reported to have less error pattern as compared to CMIP-3 model [20]. Several studies considered that black carbon aerosols has affected significantly on South Asian monsoons [21,22] and suggested that it could lead to substantial decrease in average monsoon rainfall. Several studies observed insignificant trend in the central Indian monsoon in last few decades [23] while an increasing trend was observed in many studies in terms of extreme events over central India[23,24]. Another significant region in India is the North-East region, often known as NE India where climate is different compared to other parts of India due to uniqueness in its climatic features. North-East region has two major river networks, namely Brahmaputra and Barak river. Several studies were already conducted to computationally analyze the changes in various climatic variables due to climate change and also attempted to compute the effects of changing climate on Brahmaputra river basin water resources [25–27]. Literatures related to effects of climate change on Barak river basin water resources are very scarce. Further, literatures on application of the climate models, known as the Representative Concentration Pathways (RCPs) in the Barak river basin are also not available. So, the present attempts to analyze the effects of climate change on precipitation of Barak river basin using different RCPs such as RCP2.6, RCP4.5, and RCP8.5. The RCPs scenarios derived from the CanESM2 dataset are available at a grid size of 2.8125° resolution which are too course in nature for hydrological analysis and thus a downscaling technique known as the statistical downscaling models (SDSM) is applied to convert the course resolution scenario into fine resolution for basin scale analysis.

2. Study region and data

Barak river basin is selected as the study region (Fig. 1) and the basin is located in Assam, India with a drainage area of 41,157 km^2 [28]. The basin receives an annual rainfall of about 2640 mm [29]. The dataset required in the present study are collected as daily total observed precipitation for two meteorological stations, i.e. Laxmipur and Dholai meterological stations. Besides these two stations, one more dataset is prepared by taking mean of these stations and named this dataset as Mean (D+L) station. Data of daily observed precipitation of the current climate are collected from the RMC, Guwahati. Subsequently, daily predictor variables of the same time period and region is obtained from NCEP reanalysis for validation and calibration of the downscaling model and also daily predictors are extracted from RCP2.6; RCP4.5; and RCP8.5 for simulation purposes from Canadian Earth System Model (CanESM2). Details of available predictor variables and RCPs are given in Table1-Table2.

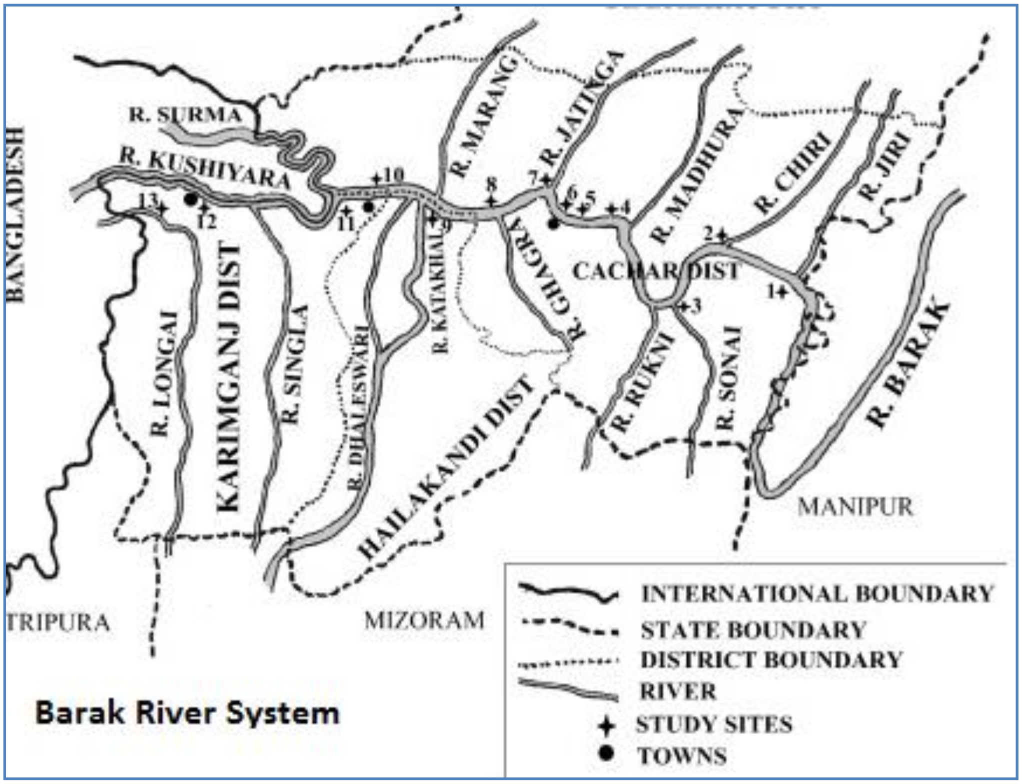

Fig. 1. Map of Barak river network.

Table 1. List of predictors obtained from NCEP Reanalysis and CanESM2 models.

Sl. No.	Predictors	Description of the variables	Sl. No.	Predictors	Description of the variables
1	mslpgl	Mean sea level Pressure	14	p8_fgl	850 hpa airflow strength
2	fgl	Surface airflow strength	15	p8_ugl	850 hpa zonal velocity
3	ugl	Surface zonal velocity	16	p8_vgl	850 hpa meridional velocity
4	vgl	Surface meridional velocity	17	p8_zgl	850 hpa vorticity
5	zgl	Surface Vorticity	18	p8_thgl	500 hpa wind direction
6	thgl	Surface wind direction	19	p8_zhgl	850 hpa divergence
7	zhgl	Surface divergence	20	p500gl	500 hpa geopotential height
8	p5_fgl	500 hpa airflow strength	21	p850gl	850 hpa geopotential height
9	p5_ugl	500 hpa zonal velocity	22	s500gl	Specific humidity at 500 hpa
10	p5_vgl	500 hpa meridional velocity	23	s850gl	Specific humidity at 850 hpa
11	p5_zgl	500 hpa vorticity	24	rcpgl	Near surface relative humidity
12	p5_thgl	500 hpa wind direction	25	shumgl	Surface specific humidity
13	p5_zhgl	Surface divergence	26	tempgl	Mean temperature at 2 m

Table 2. Summary of Representative Concentration Pathways (RCPs)

Sl. No.	Type of RCP	Features	Developed by
1	RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m² in 2100.	MESSAGE
2	RCP4.5	Stabilization without overshoot pathway to 4.5 W/m² at stabilization after 2100	GCAM
3	RCP2.6	Peak in radiative forcing at ~ 3 W/m² before 2100 and decline	IMAGE

3. Methodology

The methodology used for downscaling climatic variables is the Statistical Downscaling Model (SDSM) which has been successfully used for downscaling diverse climate variables [30–32]. Downscaling model is used to develop a linear relationship between global variables and local-scale variable such as precipitation, occurrence, and intensity at desired stations. Local scale parameters are then modeled using a stochastic weather generator. The present downscaling model is applied with a various number of global and local variables. The present model has facilities to adjust various features internally which include variance inflation and bias correction. This ability of the downscaling model help to avoid the issues of over or under estimation of statistical parameters of downscaled variables. The basic functions of SDSM and other relevant information may be found in [30,33–35].

4. Results and discussions

4.1 Selecting the relevant global variables

The selection of set of most relevant global variables with respect to local variables is a challenging task for a statistical downscaling methods [35]. This is due to the fact that the choice of global variables usually determine the features of the downscaled climate scenario.

A correlation analysis is applied to select the most correlated set of global variables from the available list of global variables as shown in fig. 2. A set of 10 most correlated global variables with respect to the local variable (Precipitation) are selected for analyzing the impacts of climate change in the study region (Table 3). Correlation analysis indicated that the correlation strength between global variables and local variable are mostly below 0.5 which may be due to combined effects of global and local variables [36]. Several studies also reported that that the correlations between the global variables and local variables such as precipitation were found to be quite low as compared to those for daily minimum and maximum temperatures [31].

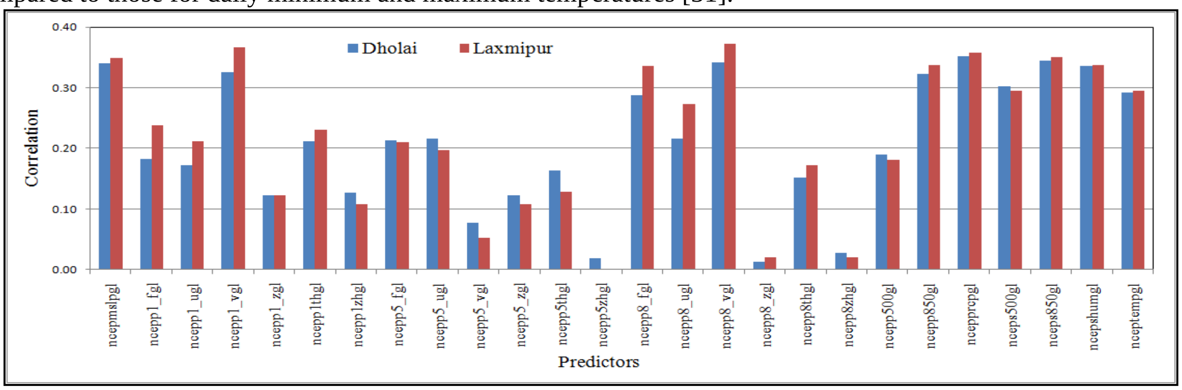

Fig. 2. Correlation analysis of NCEP predictors with the predictand

Table 3. List of 10 most selected correlated NCEP variables.

Sl. No.	Predictors	Description
1	mslpgl	Mean sea level Pressure
2	vgl	Surface meridional velocity
3	p8_fgl	850 hpa airflow strength
4	p8_vgl	850 hpa meridional velocity
5	p850gl	850 hpa geopotential height
6	s500gl	Specific humidity at 500 hpa
7	s850gl	Specific humidity at 850 hpa
8	rcpmgl	Near surface relative humidity
9	shumgl	Surface specific humidity
10	tempgl	Mean temperature at 2 m

4.2 Model calibration results

The SDSM is calibrated using 10 most correlated NCEP predictors variables and daily total precipitation of three different meteorological stations. The data considered for calibration of SDSM covers a period of 1978-1991 while data covering a period of 1992-2005 are used for validating the downscaling model. Various relevant parameters of the downscaling model are adjusted during the calibration process to achieve the best of the global and local climate variables. Model performance in the calibration process of the SDSM are assessed in terms of coefficient of correlation (R) and root mean square error (RMSE) and estimated as follows:

$$R = \frac{\sum_{i=1}^{n}(Obs_i - \overline{Obs}).(Pred_i - \overline{Pred})}{\sqrt{\sum_{i=1}^{n}(Obs_i - \overline{Obs})^2.\sum_{i=1}^{n}(Pred_i - \overline{Pred})^2.}} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{pred,i})^2}{n}} \quad (2)$$

Where, *Obs* = observed data value; *Pred* = predicted data value; Obs_i = mean observed data value and $Pred_i$ = predicted mean data. The best model achieved for different stations and RMSE of calibration data series are shown in table 4 and table 5.

The downscaling model was unable to capture the daily precipitation series appropriately. The differences in average of observed and simulated precipitation for Dhali, Laxmipur and Mean (D+L) are 0.50 mm per day; 0.28 mm per day; and 0.09 mm per day, while the RMSE for these stations are 17.11 mm per day; 19.27 mm per day; and 16.32 mm per day respectively. Although the downscaling model was showing little variation in average rainfall, but it was showing a higher value of RMSE and inversely the smaller value of R. This indicates that the performance of the downscaling model in downscaling rainfall time series is poor. This also indicates that the present downscaling model (SDSM) has a tendency to under estimate the quantity of rainfall in wet days and over estimate the quantity of rainfall in dry days.

Table 4: The calibration performance of the downscaling models

	Dholai			Laxmipur			Mean(D+L)		
Data	Mean	RMSE	R	Mean	RMSE	R	Mean	RMSE	R
Observed(mm)	7.29			8.67			7.98		
Simulated (mm)	7.79	17.11	0.205	8.95	19.27	0.212	8.07	16.32	0.257

4.3 Model validation results

To validate the downscaling model (SDSM), three data sets of precipitation corresponding to the three stations are generated for the period of 1992–2006 using NCEP predictors and observed rainfall data. Each generated data set contains a set of 20 ensembles. The RMSE and R of each ensemble is calculated and compared with the observed precipitation data and the ensembles having the lowest RMSE are selected for further analysis. The validation results of the model for all stations are provided in table 5.

Validation performance of the downscaling models is not found to be comparable with the performance of the models during calibration (table 4). The variation in the observed precipitation and simulated precipitation for Dholai, Laxmipur and Mean (D+L) stations are 0.57 mm per day, 0.59 mm per day and 0.10 mm per day while the corresponding RMSE of the stations are 17.88 mm per day, 18.58 mm per day and 16.39 mm per day respectively. The validation results shows significant variation as compared to the model calibration results.

Table 5: The performance of SDSM in simulating rainfall during the validation period

Data	Dholai			Laxmipur			Mean(D+L)		
	Mean	RMSE	R	Mean	RMSE	R	Mean	RMSE	R
Observed (mm)	7.93			8.10			8.00		
Simulated mm)	7.34	17.88	0.187	8.67	18.58	0.189	8.10	16.39	0.239

4.4 Projection of daily total rainfall with RCPs

The calibrated and validated downscaling model is used for projection of daily total precipitation of the study region. In this case, predictor variables of RCPs derived for the study area are used as input to the model. The RCP data covering a period of 95 years (2006-2100) are divided into two parts, namely validation data (2006-2013) and generation data (2014-2100). Prior to application of downscaling model in generation of precipitation scenarios, it is important to analyze the ability of the downscaling model performance. Initially, the precipitation scenarios for different RCPs for validation period (2006-2013) are generated for each site and compared with the corresponding observed precipitation data. Here , the performances of the downscaling model are measured in terms of RMSE, R and percentage errors of observed and simulated precipitation data (table 6).

The results indicate that RCP2.6 is better than other two RCPs in representing daily observed precipitation in all the stations while RCP8.5 is the worst. However, the differences are within a range of acceptable limit as their RMSE and R values are closer to each other. Hence, all the RCPs are used for generation of future precipitation scenarios for further analysis.

Table 6. RCP Validation during 2006-2013 time period

Station	RCPs	RMSE	R	Mean	Percentage Error
Dholai	Observed			7.22	
	RCP26	17.879	0.140	8.22	13.85
	RCP45	17.805	0.157	8.53	18.14
	RCP85	18.024	0.118	8.28	14.68
Laxmipur	Observed			7.83	
	RCP26	18.657	0.161	8.96	14.43
	RCP45	18.864	0.160	9.25	18.14
	RCP85	18.717	0.162	9.03	15.33
Mean(D+L)	Observed			7.53	
	RCP26	16.513	0.191	8.66	15.01
	RCP45	16.643	0.189	9.24	22.71
	RCP85	16.558	0.186	8.98	19.26

4.5 Trend analysis of the precipitation data

In the context of precipitation changes and its variability due to anticipated changing climate, it is important to determine the changes in trends of occurrence of precipitation, both in past and future. Reliable information of changing trends of rainfall is very crucial for water resources management, disaster management, hydrological planning of the region etc. Therefore, the anticipated changing trends of rainfall and its variations are assessed using Mann-Kendall trend test and Sen's slope estimator to identify and quantify the magnitudes of changes in the past and future precipitation. Detailed information of the proposed techniques may be found in literature [37–39].

The non-parametric Mann–Kendall test at 5% significance detected significant trend in precipitation both in past and future while the Sen's slope test estimated the magnitude of rate of changes of precipitation. Detailed results of trend analyses are given in table 7. During 1978-2013, an increasing trend was detected in Dholai and Mean (D+L) stations while a decreasing trend was detected in Laxmipur station. During 2014-2100, decreasing trends were observed in the RCPs simulated precipitation.

The rate of changes of precipitation were computed using Sen's slope esimtaor. The maximum and minimum rate of changes in precipitation were found as 0.019 mm/year (Dholai) and 0.003 mm/year in Mean (D+L) stations in observed precipitation. In simulated precipitation, the maximum and minimum rate of changes in precipitation were found as 0.02 mm/year in Mean (D+L) with RCP8.5 and 0.006 mm/year in Dholai and Laxmipur with RCP2.6. The Sen's slope test detected a considerable decreasing pattern in simulated precipitation during 2014-2100. The means of observed precipitation (1978-2013) and simulated precipitation were shown in Fig.3-Fig. 6 to support the findings of both Mann-Kendall and Sen's slope estimator.

Table 7. Mann-Kendall (MK) and Sen's slope tests results.

Station	Data	MK Trend	Sen Slope (mm/year)
Dholai	Observed	Increasing trend	0.019
	RCP2.6	Decreasing trend	-0.006
	RCP4.5	Decreasing trend	-0.014
	RCP8.5	Decreasing trend	-0.018
Laxmipur	Observed	Decreasing trend	-0.010
	RCP2.6	Decreasing trend	-0.003
	RCP4.5	Decreasing trend	-0.015
	RCP8.5	Decreasing trend	-0.015
Mean(D+L)	Observed	Increasing trend	0.003
	RCP2.6	Decreasing trend	-0.006
	RCP4.5	Decreasing trend	-0.016
	RCP8.5	Decreasing trend	-0.020

Fig. 3. Means precipitation (mm) of Dholai, Laxmipur and Mean (D+L) stations for 1978-2013.

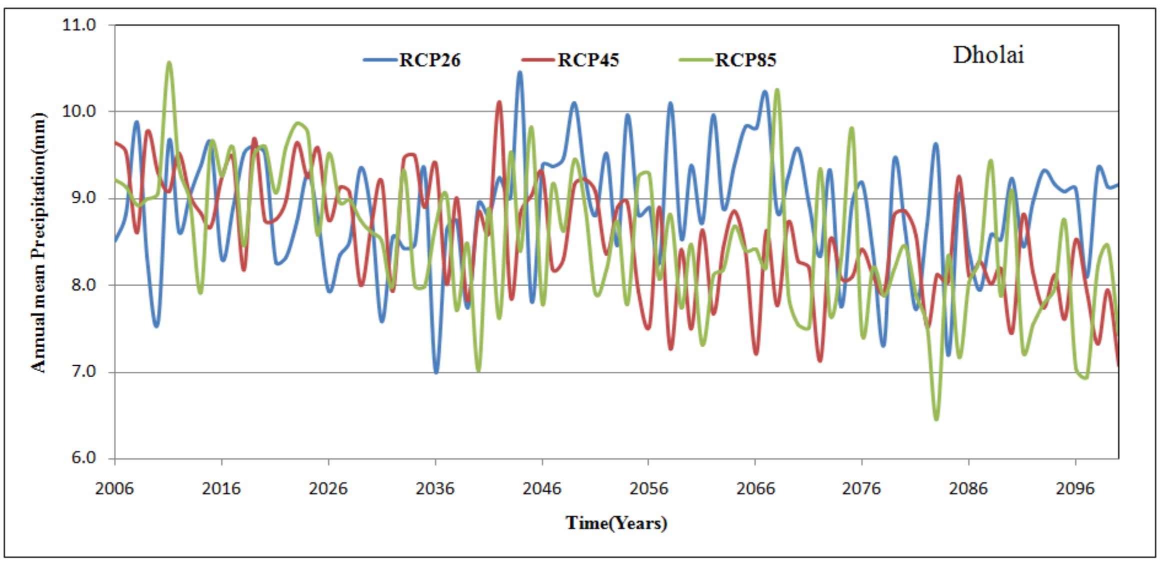

Fig. 4. Mean precipitation (mm) of all RCPs for Dholai station for the period of 2014-2100.

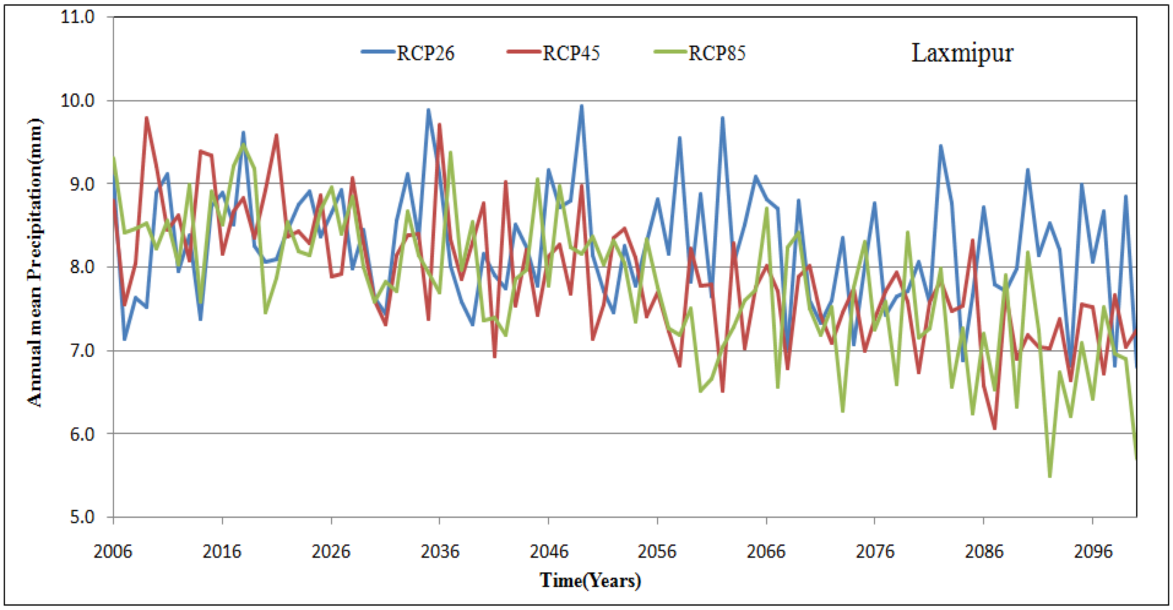

Fig. 5. Mean precipitation (mm) of all RCPs for Laxmipur station for the period of 2014-2100.

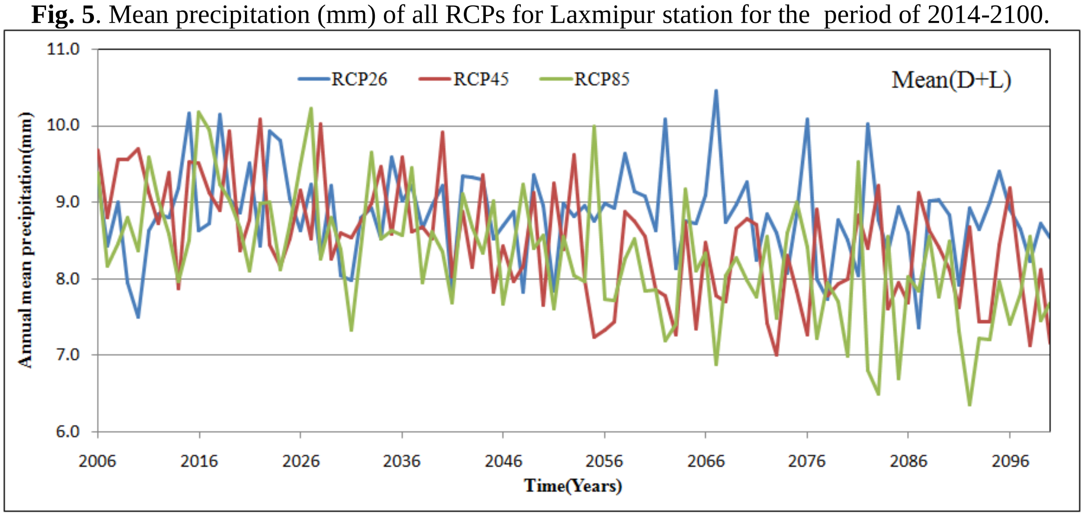

Fig. 6. Mean precipitation (mm) of all RCPs for Mean (D+L) station for the period of 2014-2100.

5. Conclusion and future scope

The future precipitation projection for Barak river basin was carried out using the CanESM2 dataset and Representative Concentration Pathways (RCPs), available in course grid size of 2.8125° resolution and this resolution is too course for basin level study. Therefore, the outputs of the global climate variables were downscaled to finer resolution for the study region using downscaling model (SDSM). Precipitation projections of the study region are carried out for RCP2.6, RCP4.5 and RCP8.5 after validating the RCPs with observed precipitation of 2006-2013.

Projected precipitation of the Barak basin have shown an increasing trend during RCP validation period of 2006-2013. The RCP2.6 has simulated precipitation better than other RCPs with minimum percentage errors in all the stations while the RCP4.5 has performed the worst. Whereas a decreasing trends in precipitation are observed during the period of 2014-2100. Trend analysis on the means of the observed and future precipitations are carried out using Mann-Kendall and Sen's slope tests. MK test indicated an increasing trend in Dholai and Mean (D+L) while a decreasing trend is observed in Laxmipur station. Decreasing trends are observed in the RCP simulated precipitation in all the station. Sen's slope test indicated a maximum decreasing rate of 0.02 mm/year (RCP8.5) and a minimum decreasing rate of 0.006mm/year in 2014-2100. Though, it is an indication that precipitation will decrease but instant events with higher magnitude and frequency are highly anticipated in future.

The present study revealed that the study region is anticipated to have decreasing precipitation trend in the coming future. In general, along with changing precipitation trends in the region due to climate change, climate change is also likely to affects the Barak basin water resource. Further, the anticipated changing climatic condition may affect various water related issues. Therefore, the results of the present study may be useful for future planning; mitigation; and adaptation of the water resource management to reduce the impact of climate change in the basin.

The present study covered the precipitation data of two individual meteorological stations without considering other important climatic variable such as temperature. The climate change information derived in the present study may be fine tuned using data of additional stations and including more climatic variables in the process.

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