STATISTICAL DOWNSCALING OF GCM OUTPUT AND SIMULATION OF RAINFALL SCENARIOS FOR BRAHMANI BASIN

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Abstract

The change in climate threats the abundance of usable water across the globe. Most of the river basins are unable to cope up with the impact of climate change. Hence, assessing the future scenario has become the need of today. General Circulation Model(GCM) provide information at a course grid resolution. Downscaling can help in getting the information at a local scale level from GCM data which will help the researchers to work on a regional level. Statistical downscaling method is preferred over dynamic downscaling method due to its less complex calculations. Statistical downscaling model (SDSM) is widely used in prediction of future climate scenarios. Here Brahmani-Baitarani river basin is selected as a case study for the downscaling of precipitation in the monthly time scale. SDSM version 4.2 is used as the model and precipitation is taken as the predictand parameter. Predictors are chosen from the NCEP global variables like air temperature, geopotential height, specific humidity, zonal and meridional wind velocities, precipitable water and surface pressure data. The outcome of the study shows that the mean rainfall will increase in this river basin in the 2040s. Increase in dry spell and decrease in wet spell also observed in the results.

Keywords*: Climate Change, GCMs, Statistical downscaling model* (*SDSM*)*, Brahmani- Baitarani River system .*

1. Introduction

Climate change has adverse impact on the surface of earth starting from forest ecosystem to flood plain of rivers. Surface hydrology, forestry, floods, soil erosion, land use changes, ground water, environment, living beings and their ecosystems; all are affected by the climate change. Its adverse effect on water resources threats the abundance of usable water availability. Water is the basis of lifeline on earth. Population explosion associated with various anthropogenic activities like per capita use, industrialization and others require more water in coming decades. Therefore, a proper assessment of past and prediction of probable future precipitation and the resulting run off over time is necessary for hydrologist (Anandhi et al., 2008).

General circulation models (GCMs) are considered as the most effective tools to simulate climatic conditions on earth. They provide information at a coarse grid resolution (usually 1º to 2º). But data at a finer grid is required to work on a smaller study area like a smaller catchment. To manage the gap between the lower resolution and higher resolution downscaling is used. It tries to link between the GCM information and information needed by the hydrologists (Walsh, 2011).

Downscaling methods can be broadly classified into two groups; dynamical and statistical. Statistical downscaling method is preferred to dynamic downscaling method because of less computational work. Again it is classified into three subgroups; regression methods, weather generators and weather typing schemes. All the methods deal with the basic concept that regional climates (predictand) are the function of the large scale atmospheric state (predictor). This relationship between predictor and predictand can be deterministic or probabilistic function.

SDSM (statistical downscaling model) is the most commonly used model for this purpose. SDSM combinely uses a conceptual water balance model and a mass-balance water quality model to investigate climate change impact assessment (Wilby et al 2006). Many authors have compared SDSM with other statistical downscaling models. Harpham and Wilby (2005) concluded that SDSM yields better daily precipitation quantiles and inter-site correlation when compared with artificial neural networks(ANNs). Khan et al (2006) also concluded that SDSM is very efficient in reproducing various statistical parameters of data set in the downscaled results with a confidence level of 95%.

The present work focuses on the application of SDSM to the Brahmani-Baitarani river basin in India to simulate the future scenarios of the precipitation and other parameters.

2. Study area

Brahmani and Baitarani river basin is situated in the central-east India between latitude 20° 28' to 23° 35' N and longitude 83° 52' to 87° 30' E. The basin extends over the states of Odisha, Jharkhand and Chhattishgarh draining an area of 51, 822 Sq.km which is 1.7% of total geographical area of the country. Major part of its catchment area is situated in the state of Odisha. Both the rivers are seasonal in nature. They are rejuvenated at the onset of monsoon as they are fed by rain. At the time of summer, their discharge is significantly decreased. Though 90% of the basin receives an average annual rainfall of between 1400 to 1600 mm, some places like dhenkanal and jashpur district are drought prone areas. Two hydro-observation stations Jenapur and Gomlai are taken for this study. Jenapur station has a drainage area of 33,955 km^2 and Gomlai has a drainage area of 21,950 km^2. Figure 1 shows a schematic diagram of the Brahmani and Baitarani river system.

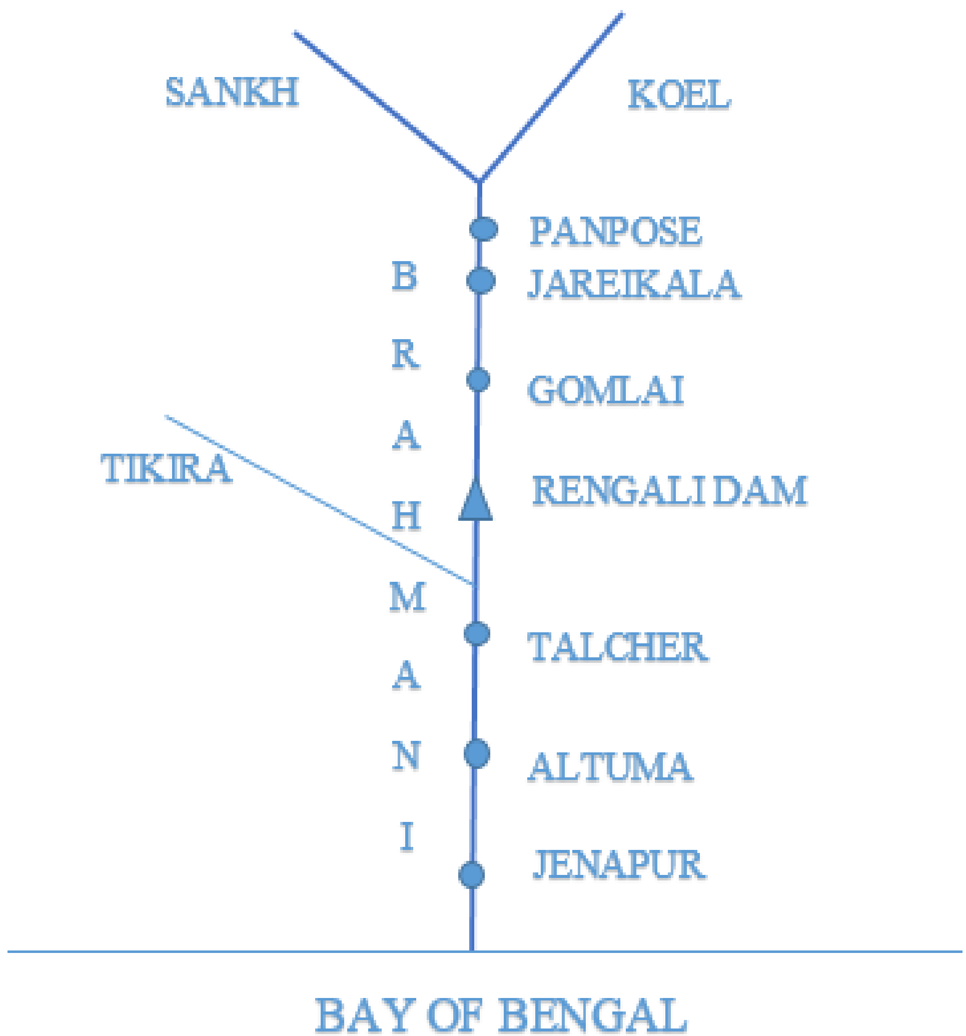


Fig 1. Schematic diagram of Brahmani-Baitarani river basin

3. Data

The observed large scale predictors have been derived from the NCEP reanalysis data sets that contain 41 years of daily observed predictor data normalized over the period 1961-1990. These data has been interpolated into the grid size of 2.5 latitude *3.75 longitude before the normalization is implemented. The HadCM3 (Hadley center for climate and prediction and research, UK) model output both for A2 and B2 scenario are directly downloaded from website http://climate-scenarios.canada.ca. The long term meteorological data from the period 1981-2016 is obtained from the central water commission (CWC) India on daily basis at the Gomlai and Jenapur in the state of Odisha. A total 36 years of data are taken as baseline period, out of which 25 years is used for calibration and 11 years is needed for validation of the model.

4. Methodology

4.1 SDSM

Among the handful models that are available for downscaling, the SDSM is very popularly used. Statistical downscaling model (SDSM) is a statistical weather generator based on linear multiple regression. It is used to predict the climate parameters such as the precipitation or temperature in long time duration. It uses large scale atmospheric variables to condition the local scale weather generators. It also uses stochastic techniques in variance of daily time series. In fact, it is the combination of transfer function and stochastic weather generator methods.

4.2 Multiple linear regressions

Multiple linear regressions are used to explain the relationship between one continuous dependent variable (predictand) with one or more than one independent variables (GCM outputs). For a given data set, a linear regression model assumes a linear relationship between the variables. The equation used for the multiple linear regressions is written as:

$$(y/x) = a + b_1x_1 + b_2x_2 + \ldots\ \ldots\ b_n\, x_n. \qquad (1)$$

where, y is the dependent predictant variable with respect to x, $x_1, x_2, x_3 \ldots x_n$ the independent predictor variables, a, b_1, $b_2 \ldots b_n$ the intercepts or parameters of the equation. Figure 2 shows the flow chart of climate scenario generation in SDSM.

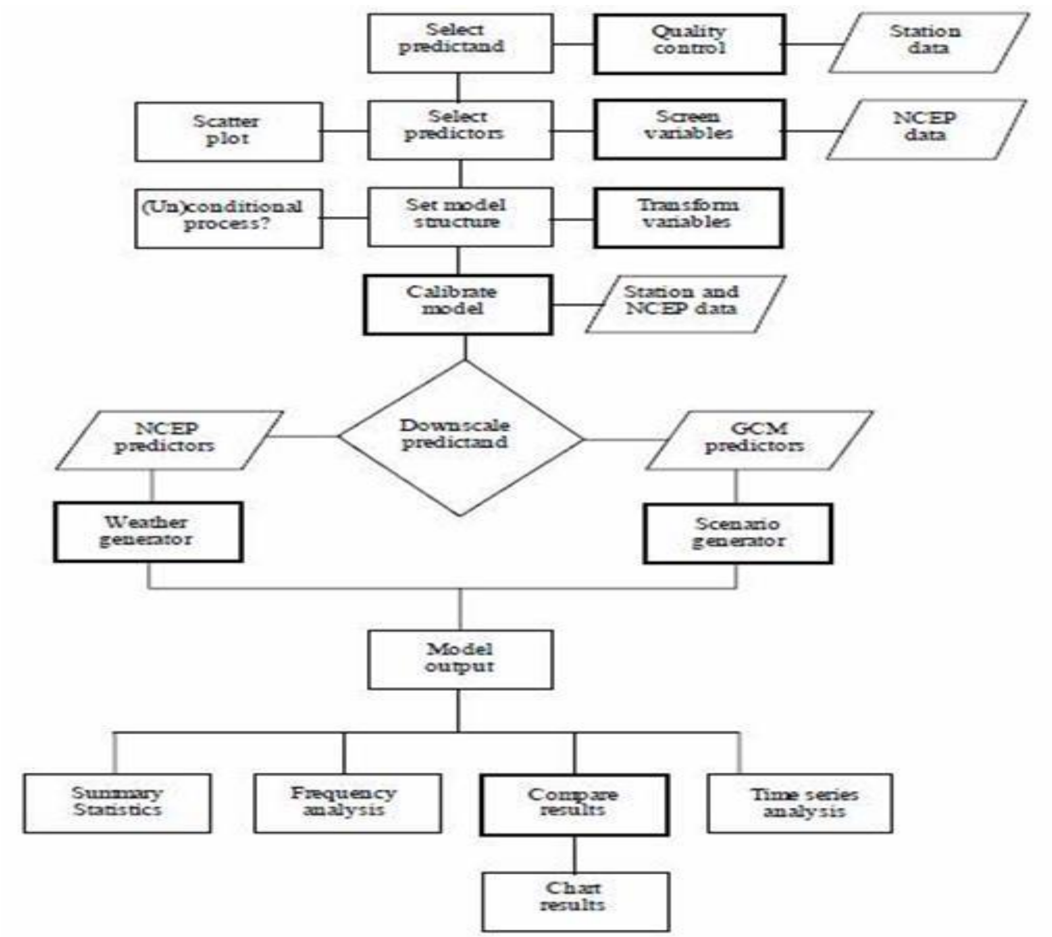


Fig 2. Climate scenario generation in SDSM (source: SDSM user manual)

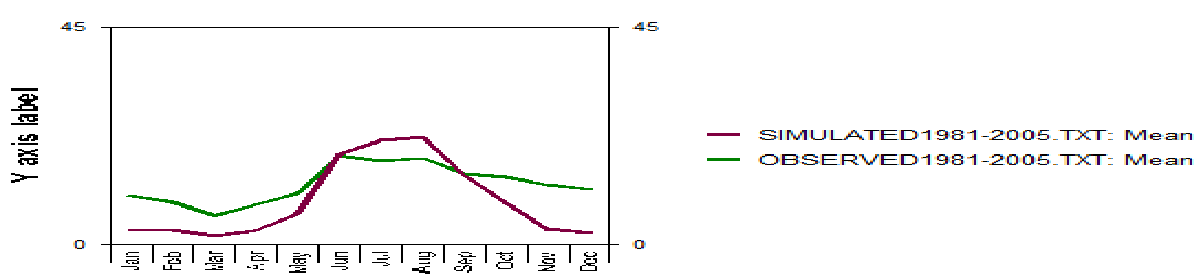
5. Results and discussion

Any error in the observed data may result the model to fail in the prediction of future climate scenario. Hence, before the simulations, the observed data are subjected to quality control in order to check for any missing data codes or gross data errors. For selecting a set of predictors, it is necessary to access the effect of predictors on the precipitation at that particular station. A correlation matrix is generated among the large scale global predictors and user specified predictand. Predictors are selected based on the highest correlation value. Partial r, p values and scatter plots are also considered in screening of the predictors. Predictor variables selected for each station after the screening test are given in Table1.

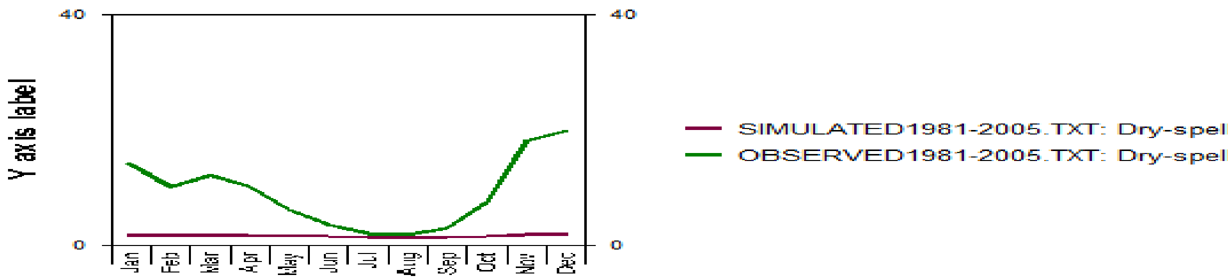
Table 1: Predictors selected for each station and their correlation values.

Station name	NCEP codes	Predictor variable	Correlation value	Partial r	P value
Jenapur	shumas	Surface specific humidity	0.265	0.056	0.0000
Jenapur	rhumas	Near surface relative humidity	0.229	0.011	0.2729
Jenapur	r850as	Relative humidity at 850hpa	0.212	-0.015	0.1412
Jenapur	p5thas	500hpa wind direction	0.177	0.018	0.0703
Jenapur	p-uas	Surface zonal velocity	0.174	-0.001	0.5632
Gomlai	shumas	Surface specific humidity	0.323	-0.092	0.0000
Gomlai	r850as	Relative humidity at 850hpa	0.277	0.021	0.0274
Gomlai	rhumas	Near surface relative humidity	0.287	-0.029	0.0023

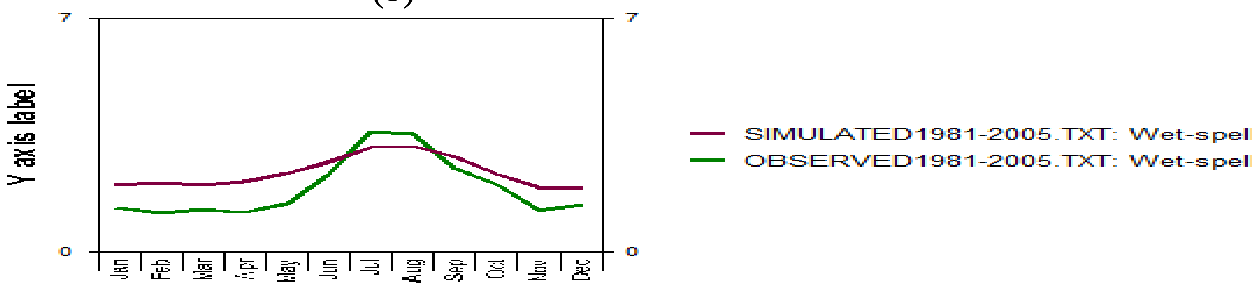
For calibration of the model 25 years of precipitation data (collected from CWC), between 1980 to 2005 is considered. A multiple linear regression is established between the NCEP variables and precipitation at that particular station. The intercepts of the regression equation are calculated by the forced entry method. Synthetic daily weather series is created by weather generation using the observed predictors. When a calibrated model is selected, SDSM automatically relates all necessary predictors to regression model weights. In the present study, monthly time scale is taken for analysis and no conditional factors are added. An ensemble size of 20 is used for the analysis. Results of model calibration for Gomlai station are shown in Figure 3.



(a)



(b)



(c)

Figure 3: Model calibration for (a)mean precipitaion (b)dryspell (c) wetspell of each month

Remaining 11 years data (2006-2016) is used for validation of the model. The statistical plot between observed and simulated value is plotted to compare the model output. Wet spell and dry spell curves are drawn to represent to number of consecutive rainy and non rainy days respectively. Figure 4 shows the plot for validation of the model.

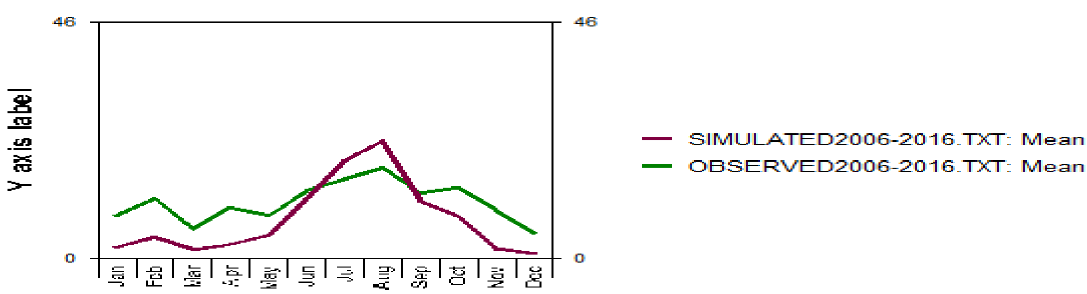


Figure 4: Validation of the model.

It is quite clear from Figure 4 that the model operates efficiently for calibration and validation. Hence future scenario is generated using this calibrated model. Scenario A2 experiment results show a very heterogeneous world with continuously increasing global population and regionally oriented economic growth that is more fragmented and slower than in other experiments; while that of B2 scenario experiment represents a world in which the emphasis is on local solutions to economic, social, and environmental sustainability, with continuously increasing population (lower than A2) and intermediate economic development. Both the scenarios are considered for the present study.

Outcome of climate model HadCM3 is used for scenario generation for six decades (2030 -2090) in two subgroups as 2030-2060 and 2060-2090. This GCM outputs are normalized to 360 days, 12 months with 30 days of each duration. Results are presented in Table 2 and Table 3.

Table 2: Simulated future precipitation for A2 and B2 scenarios at Jenapur station.

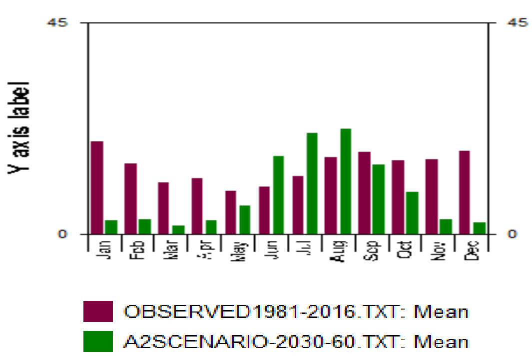
Months	Observed values 1981-2016	Predicted Values 2030-2060		Predicted Values 2060-2090	
		A2	B2	A2	B2
January	15.218	2.465	2.431	2.416	2.440
February	16.126	4.894	4.864	4.907	4.858
March	11.978	4.211	4.293	4.213	4.266
April	12.219	6.787	6.733	6.798	6.736
May	10.165	12.441	12.455	12.475	12.524
June	12.459	19.477	19.548	19.249	19.361
July	13.828	20.513	20.361	20.447	20.561
August	15.225	22.139	21.972	22.093	21.966
September	15.670	18.176	17.777	17.901	18.042
October	15.742	16.768	16.925	16.901	16.963
November	16.787	6.376	6.432	6.401	6.323
December	14.468	1.809	1.809	1.812	1.807
Annual total	169.615	136.056	135.6	135.613	135.847

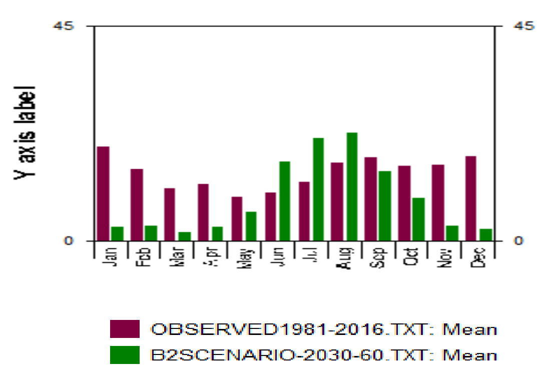
Table 3: Simulated future precipitation for A2 and B2 scenarios at Gomlai station

Months	Observed vale 1981-2016	Predicted 2030- A2	Values 2060 B2	Predicted 2060- A2	Values 2090 B2
January	19.742	2.969	2.980	2.966	2.933
February	15.15	3.220	3.159	3.187	3.143
March	10.96	1.843	1.855	1.871	1.844
April	11.88	3.045	3.043	3.041	3.033
May	9.29	6.065	6.1081	6.145	6.197
June	10.03	16.630	16.533	16.654	16.454
July	12.295	21.510	21.532	21.201	21.446
August	16.436	22.650	22.380	22.490	22.288
September	17.537	14.708	14.765	14.612	14.896
October	15.758	9.062	9.047	9.040	9.049
November	15.940	3.286	3.236	3.294	3.262
December	17.83	2.571	2.584	2.589	2.577
Annual total	172.848	107.559	107.221	107.093	110.384

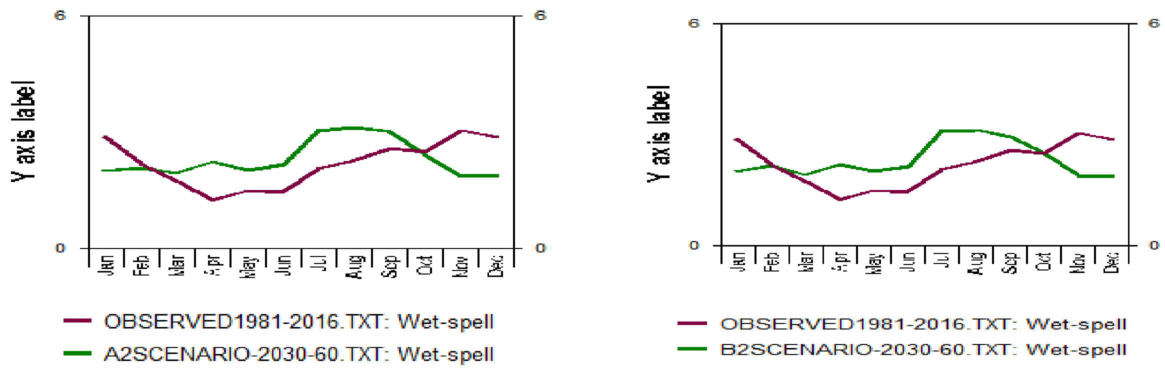
Monthly mean presentation of present and that of the period values from 2030 to 2060 at Gomlai station are represented graphically in Figure 5 which gives a clarification of change in rainfall scenarios.

(A)Mean precipitation





(B)Wet spell



(C)Dry spell

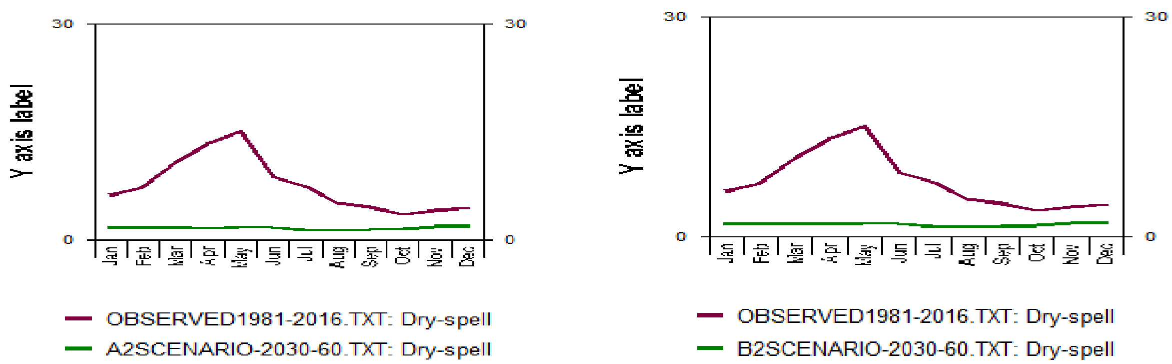


Figure 5: Comparisons between present scenario of precipitation and that of 2030-2060.

6. Conclusions

Based on the present study on the statistical downscaling of GCM outputs and simulation of rainfall scenarios for Brahmni – Baitarani River basins in Odisha the following conclusions can be drawn

- The dry spell is expected to increase and wet spell to decrease indicating the number of rainy days to be fewer in each year.
- Monthly mean precipitation is expected to increase in the rainy days (June, July and August).

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