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Application of Statistical Downscaling Model for Prediction of Future Rainfall in Bhudhabalanga River Basin, Odisha (India)

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Abstract: The impact of climate change in the hydrology sector, often require fine scale spatial resolution climate information for studying present as well as future scenario. Global climate Models (GCMs) assess climate change scenarios on coarse partial resolution. There are different techniques to downscale to downscale coarser grid scale data to finer scale as coarse resolution of GCMs data cannot be used directly to asses climate impact for a particular area. Therefore downscaling of Global climate Models (GCMs) output is important to estimate regional climate change impacts. Precipitation is one of the important climate variables that is used as inputs in hydrologic models in many water resources studies. In this present study, Statistical Downscaling Model (SDSM) has been adopted to downscale daily precipitation to generate future climate outputs for Budhabalanga river basin in Odisha. Multiple linear regression (MLR) technique is used in SDSM. The daily precipitation data (1961-2001) representing Budhabalanga river catchment area has been used as input of the SDSM Model. The model has been calibrated and validated with large-scale National Central for Environmental Prediction (NCEP) reanalysis data for the period 1961-1990 and 1991-2001 respectively. The prediction of future daily precipitation for the period 2025s, 2050s and 2080s for the study area has been carried out corresponding to Hadley Centre Coupled Model version 3 (HadCM3 A2 and B2). The study results show that during the calibration and validation, confirm the SDSM model acceptability in regards to its downscaling performance for daily and annual rainfall. The results of the downscaled daily precipitation for future period indicates an increasing trend for the period 2025s and 2050s where as decrease in trend for the period 2080s for mean daily precipitation.

Keywords: Climate change, Global climate model, Scenario generation, Statistical downscaling, Precipitation, Budhabalanga basin

I. INTRODUCTION

1.1 General:

In recent year the major challenge for water resources management is the issue of climate change and need to provide environmental sustainable development. Climate is a complex system, and is very difficult to quantify its' variables.

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Many studies have focused the effects of Global Climate Models (GCMs) and climate change on precipitation variability in different parts of the world. A proper assessment of precipitation in future is needed with past experience for water resources planning. Global Circulation Models (GCMs) tools are available to simulate the present and future changes in climate at global scale. The numerical coupled models represents various earth systems including the earth surface, atmosphere, oceans are useful for the study of climate change and variability (Hewitson and Crane 1996; Wilby and Wigley 1997; Prudhomme et al.2003; Crawford et al.2007). These Models are coarser-grid resolution and more accuracy at large spatial scales (Bardossy 1997; Ojha et al. 2010; Hassan and Harun 2012; Mishra et al. 2014). Downscaling offers fine scale data from coarse grids GCMs. For example, the Hadley Centre's HadCM3 model has resolved at a spatial resolution of 2.50 latitude by 3.750 longitude whereas a spatial resolution of 0.1250 latitude and longitude is required for hydrologic simulations of monthly flow in Mountainous catchments (Salath'e, 2003). Hence, various downscale approaches are developed to bridge the gap between the resolution of climate models and regional and local scale process, and tested by many hydrologists and climatologists. (Giorgi and Mearns, 1991; Wilbey et al., 2007; Bardossy et al., 1997). The downscale methods include Multiple linear regression, Canonical correlation analysis, Support vector machines and Artificial neural networks (Lall et al. 2001; Ghosh and Majumdar 2006; Raje and Mujumdar 2009; Kanna and Ghosh 2010; Raje and Mujumdar 2011; Hashmi and Shamseldin 2011; Kodra et al., 2012).

In the present study, statistical downscaling model (SDSM) tools (Wilby et al., 2007) which employ the multiple liner regression approach to downscale GCMs outputs from global scale to local scale for assessment the future climate scenario on hydrological process of the Budhabalanga river catchment located in Odisha. The tool process through data quality control, data transformation, screening of the predictor variables, model calibration and validation, weather generation, scenario generation, statistical analysis and its representation of climate data (Wilby and Dawson 2007).

1.2 STUDY AREA

The Budhabalanga river rises at an elevation of about 800m of south of Similipal village in Mayurbhanj district, Odisha, India and flows for a length of 196 km to join the Bay of Bengal.

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The catchment area of Budhabalanga basin is about 4741 km^2 lies between 21^0 28' N to 22^0 20' N latitude and 86^0 20' E to 87^0 4' E longitude. Average annual rainfall in Budhabalanga basin is in order of 1580 mm. About 90% rainfall is received during June to October due to the influence of the South-West monsoon. Annual average runoff is 3.45 BCM. The temperature starts rising from February and peak reached in the month of May touching to 40^0 C. The location map of the study area is shown Fig.1.1.

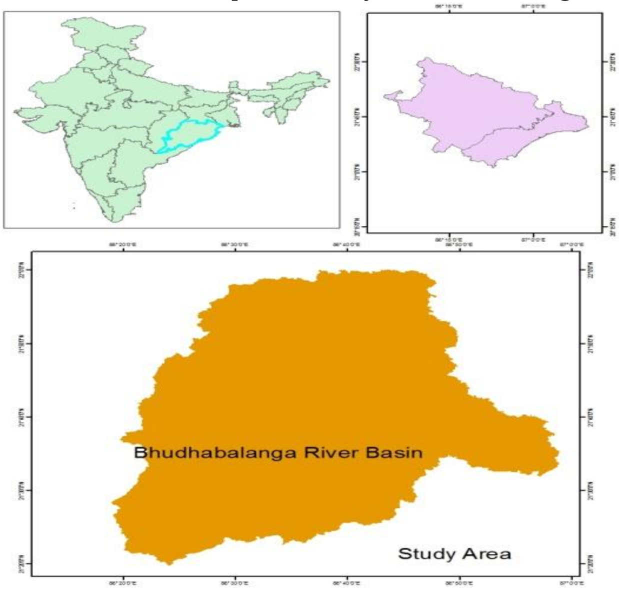

Figure 1.1 Location map of Study Area

1.3 Data Used

1.3.1 Meteorological Data: The daily precipitation data for the periods 1961-2001were collected from India Meteorological Department (IMD), Pune. The daily precipitation data were converted to monthly, seasonal and annual time scale for analysis.

1.3.2 NCEP reanalysis Data: National Centre of Environmental Prediction (NCEP) of 2.5^0 latitude X 2.5^0 longitude grid- scale re-analysis data are obtained from Canadian Climate Impacts Scenarios (CCIS) website for the period of 41 years (1961-2001).

1.3.3 GCM Data: The large-scale Hadley Center's GCM (HadCM3) for (HadCM3) A2 and B2 future scenarios data of 3.75^0 latitude X 3.75^0 longitude grid-scale for the period of 139 years (1961-2099) are obtained from Canadian Climate Impacts Scenarios (CCIS) website) (http://www.cics.uvic.ca/scenarios/sdsm/select.cgi). HadCM3 has been chosen because of it's wider acceptance in climate change impact. The daily predictor variables from HadCM3 are used for SDSM Model.

II. METHODOLOGY

1.4.1 Downscaling Process: The Statistical Downscale Model (SDSM) is a multiple regression-based tool for generating future scenarios to Predict the climate change impact in future. This model can capture the inter-annual variability better than other statistical downscaling approach e.g weather generators. The model requires two types of daily data e.g local observed data (Precipitation) known as 'Predictand' and larger-scale data different atmospherics variables known as 'Predictors' (NCEP reanalysis data and GCM Data). SDSM tool are uses statistical relation between predictor and predictand. During downscaling process, appropriate predictors selection is one of the most important and time consuming steps. The suitable predictor variable are selected through correlation, partial correlation analysis and scatter plots. Weights assigned to each predictor in calibration stage are tested against observed datasets during validation stage. Weights of predictors and predictand are estimated by using ordinary least-square method. The NCEP reanalysis data for the period 1961-2001 was used to identify the predictor. The study has been carried out using SDSM tool version 4.2.9.The methodology adopted for downscaling of climate variables at local stage summarised as shown in Figure 1.2

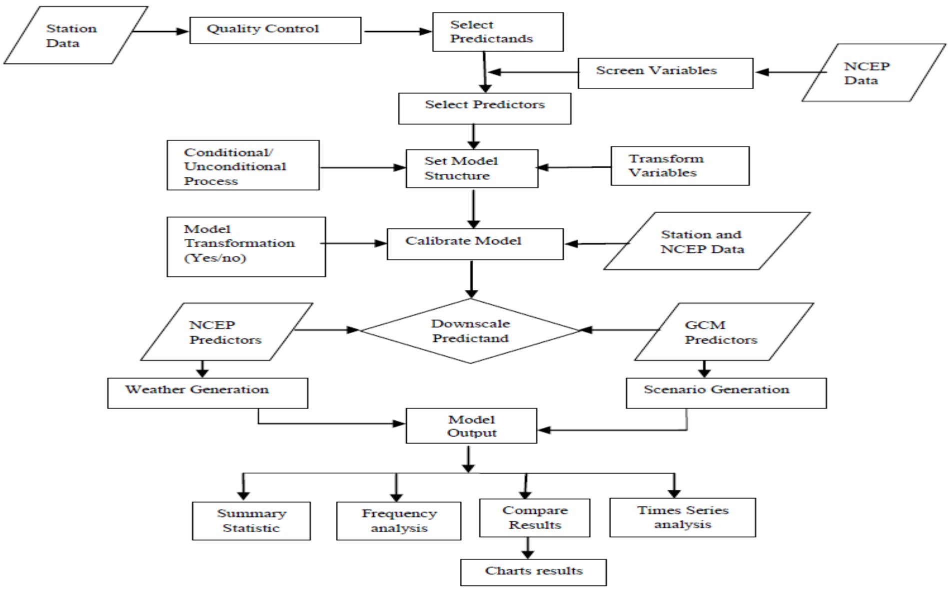

Fig.1.2 SDSM scenario generation for HadCM3 model (scenario A2 and B2)

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1.4.2 Calibration and Validation of SDSM: For model calibration empirical relationships, here multiple linear regression, were identified between gridded predictors and predictands observed precipitation. The observed daily data of large-scale predictor variables representing the present climate condition (1961-1990) derived from NCEP reanalysis dataset was used to investigate the percentage of variance explained by predictand-predictor. NCEP reanalysis data for the period 1961-1990 and 1991-2001 are used for model calibration and validation respectively.

1.4.3 Model evaluation criteria: The model performance was evaluated by the coefficient of determination (R^2), Nash-Sutcliffe Coefficient (NSE), root mean square error (RMSE), relative error (RE). In general, R^2 value used as an indicator of the strength of relationship between the observed and simulated values. NSE indicates, how precisely the plot of observed verses simulated values fits the line. For evaluation purpose, higher value of R^2 and NSE and lower values of RMSE and RE preferred.

1.4.4 Generation of Scenarios based on HadCM3 predictors: The Calibrated SDSM is applied to generate the two future scenario HadCM3 A2 and HadCM3 B2. The scenario generator operation in SDSM produced ensembles of synthetic daily weather series for given atmospheric predictor variables from HadCM3 experiments. Daily time series datasets were synthesized using independent predictors withheld from model calibration for each scenario. Thus, the time series of the present and future climate conditions were produced from the mean assembles. The study assumes that the predictor and predictand remain valid for future conditions. Forty (40) ensembles were considered for simulating each scenario for a period of 139 years (1961-2099). Four periods namely current period (1961-2001), 2025s (2011-2040), 2050s (2041-2070) and 2080s (2071-2099) were used for pattern and trend analysis.

III. RESULTS AND DISCUSSIONS

1.5.1 Predictors selection: The predictors selection of variables is the most significant and time consuming step in statistical downscaling model. All suitable predictors are usually significantly associated with predictands (Wilby et al., 2007). A list of predictor variable (NCEP and GCM) of grid box Bhudhabalng river basin is presented in Table 1.1. During initial screening process, all twenty six large-scale predictor variables have been considered. The predictor variables are selected based on correlation and partial correlation analysis of observed data NCEP predictors for the period 1961-2001 in SDSM. Variables with higher correlation coefficients between predictand (precipitation) and predictors (NCEP) are chosen for model formulation for scenario generation. These statistics analysis help to identify the amount of explanatory power that is unique to each predictor. A 5% significance level ($p<0.05$) is used to test the significance of predictor-predictand correlation.

Table. 1.1 Name and description of all NCEP and GCM Predictors

S. No.	Name	Description	Unit
1	mslp	Mean sea level pressure	Pa
2	p_f	Surface air flow	m/s
3	p_u	Surface zonal velocity	m/s
4	p_v	Surface meridoneal velocity	m/s
5	p_z	Surface verticity	s^{-1}
6	p_th	Surface wind direction	degree
7	p_zh	Surface Divergence	s^{-1}
8	rhum	Near surface relative humidity	%
9	shum	Surface specific humidity	g/kg
10	temp	Mean temperature at 2 m	C^0
11	p500	500hPa Geopotential height	m
12	p5_f	500hPa Airflow strength	m/s
13	p5_u	500hpa Surface zonal velocity	m/s
14	p5_v	500hpa Surface meridoneal velocity	m/s
15	p5_z	500hPa Surface vorticity	s^{-1}
16	p5_th	500hPa Surface wind direction	degree
17	p5_zh	500hPa Surface divergence	s^{-1}
18	r500	Relative humidity at 500hPa	%
19	p850	850hPa geopotential height	m
20	p8_f	850 hPa Surface air flow strength	m/s
21	p8_u	850hPa Surface zonal velocity	m/s
22	p8_v	850hPa Surface meridoneal velocity	m/s
23	p8_z	850hPa Surface vorticity	s^{-1}
24	p8th	850hPa Surface wind direction	degree
25	p8zh	850hPa Surface divergence	s^{-1}
26	r850	Relative humidity at 850hPa	%

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1.5.2 Model Calibration and Validation Results: The model calibration process formulates based on multiple regression between the predictand (observed precipitation) and selected NCEP predictors (Table 1.2) In the statistical model, during model calibration the event threshold 0.5mm rainfall has been considered as the predictand-predictor relationship is governing by wet-dry occurrence. It was found that seven out of twenty six predictors namely mslp, rhum, shum, p5_z, p8_z, r500, r850 were useful for downscaling precipitation.

Table.1.2 Selected NCEP predictors with correlation coefficient, partial correlation and p value

S. No.	Selected predictor	Correlation coefficients	Partial correlation	P value
1	ncepmslpas	-0.307	-0.063	0.0001
2	ncepp5_zas	0.366	0.187	0.0011
3	ncepp8_zas	0.361	0.159	0.0003
4	ncepr500	0.336	0.076	0.0017
5	ncepr850	0.371	0.070	0.0010
6	ncephrum	0.350	-0.027	0.0024
7	ncepshum	0.352	-0.035	0.0001

Calibration (1961-1990) and validation (1991-2001) result of the model is represented in Table 1.3. It can be observed that the SDSM models shows a good agreement between the observed and computed mean daily precipitation, Standard deviation and variance with correlation coefficient of 0.9 and 0.86 during calibration and validation respectively. The coefficient of determination (R^2), Nash-Sutcliffe Coefficient (NSE), root mean square error (RMSE), relative error(RE), values are shown in Table 1.4.

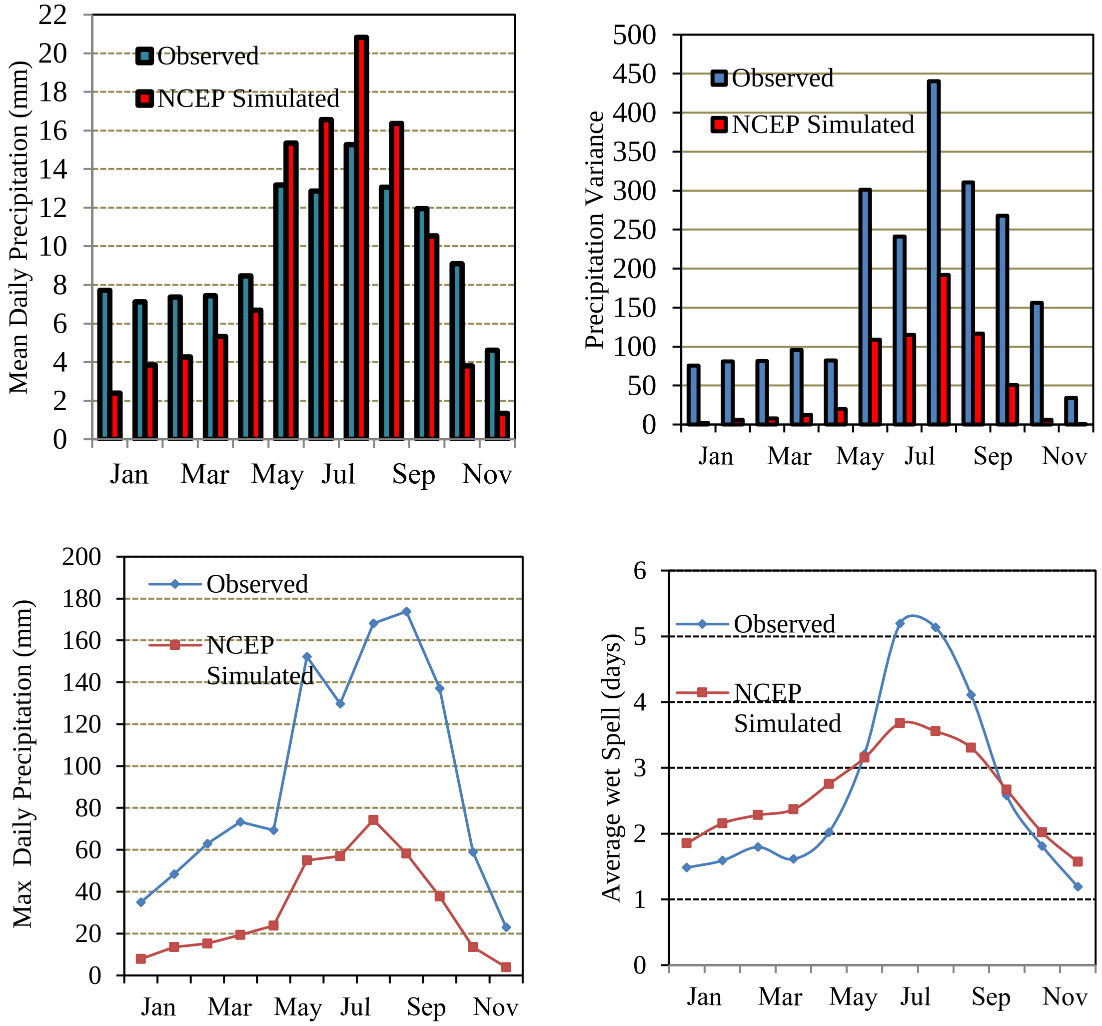

Fig.1.3 Calibration output of SDSM model downscaling (1961-1990) for daily precipitation

Table:1.3 Comparison between daily precipitation (Observed) and daily precipitation (Simulated) during SDSM model calibration and validation stages

Type	Period	Mean	SD	Variance	Correlation, r
Model Calibration	Observed Precipitation Data-1961-190	11.533	16.24	264.00	0.90
	Computed Precipitation Data-1961-190	9.708	10.16	103.15	
Model Validation	Observed Precipitation Data-1991-01	11.584	18.69	349.38	0.86
	Computed Precipitation Data-1991-01	9.806	10.28	103.59	

Table1.4 SDSM Model Performance parameters with NCEP predictors during calibration and validation stages

Performance Criteria	Precipitation	
	Calibrate (1961-1990)	Validation (1991-2001)
Coefficient of determination (R^2)	0.816	0.74
Nash-Sutcliffe Coefficient (NSE)	81.49	73.29
Root mean square error (RMSE)	63.38	79.02
Relative error (RE)	0.030	0.004

Calibrate result of observed and computed data of the SDSM model for mean daily precipitation, precipitation variance, maximum daily precipitation and average wet-spells is shown in Figure 1.3. There is a good agreement between observed and simulated mean daily precipitation. The observed variance and maximum daily precipitation are larger for the months (May to October). However, there is under-estimation for wet-spell length. The validation result of the SDSM models for the period 1991-2001 between observed and simulated mean daily precipitation, variance, maximum daily precipitation and wet-spell length is shown in Figure 1.4.

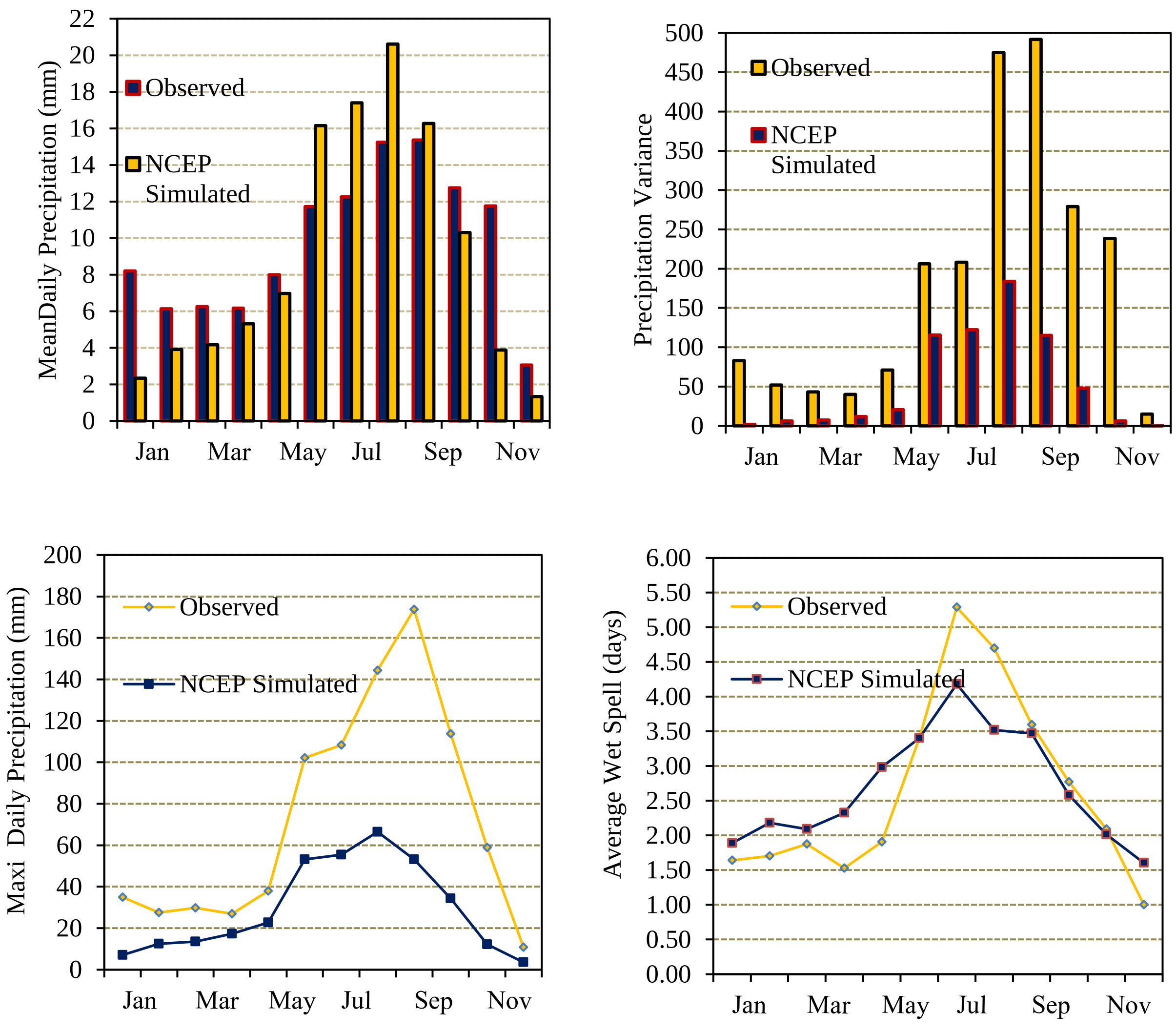

Fig.1.4 Validation output of SDSM model downscaling (1991-2001) for daily precipitation

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1.5.3 Future Scenario Generation: The HadCM3 predictors variables derived from NCEP dataset using Multiple Linear Regression models between the predict and large-scale predictors are used to generate the future downscaled data for A2 and B2 scenarios. The downscale process has been carried out for the scenario of the current and future time periods, namely present period (1961-2001), 2025s (2011-2040), 2050s (2041-2070) and 2080s (2071-2099). The result of the downscaled mean daily rainfall for different periods is shown in Fig. 1.5 for A2 scenario. The figure exhibits that the mean daily rainfall does not show a constant increase or decrease in rainfall trend for the scenario of the current and future time periods. From January to July and October to December an increase of daily rainfall is noticed for all three future time periods where as in the month of August and September, the rainfall decreases significantly for the period 2025s, 2050s and 2080s compare to present period (1961-2001). The result of the downscaled mean daily rainfall for different periods is shown in Fig.1.6 for B2 scenario.

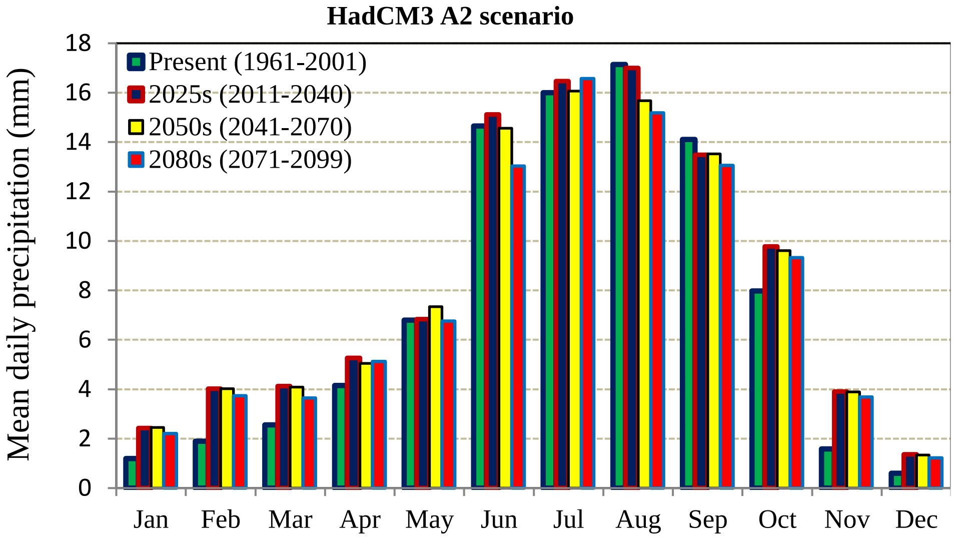

Fig. 1.5 Trend of mean daily precipitation for different period corresponding to HadCM3 A2 scenario

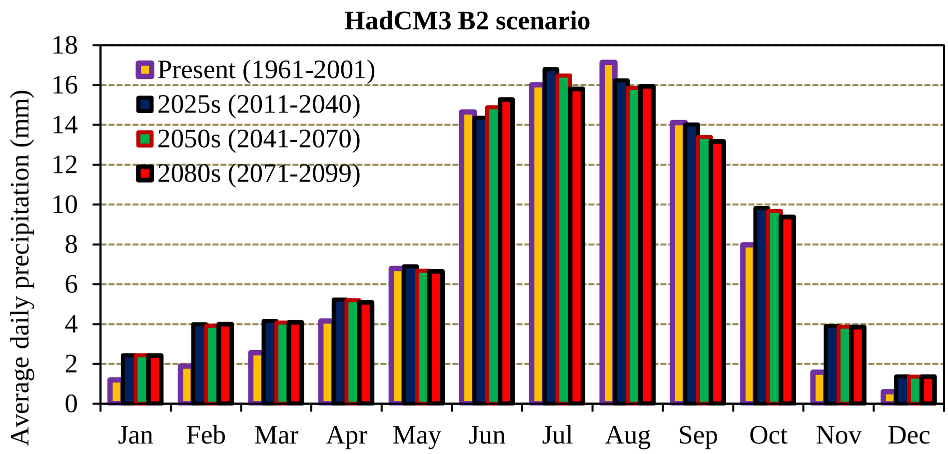

Fig. 1.6 Trend of mean daily precipitation for different period corresponding to HadCM3 B2 scenario

Table.1.5 Annual average precipitation for present and downscaled precipitation corresponding to HadCM3 A2 and B2 scenario

Period	HadCM3 A2 scenario	HadCM3 B2 scenario
	Annual average precipitation (mm)	
Present (1961-2001)	1583.30	
2025s (2011-2040)	1781.73	1748.19
2050s (2041-2070)	1672.42	1708.61
2080s (2071-2099)	1569.60	1650.57

The annual precipitation corresponding to future emission for HadCM3 A2 and B2 scenario is shown in Table 1.5.The result shows that there is an increase in trend of annual precipitation for future for the period 2025s and 2050s for both A2 and B2 scenario compared to present scenario. In the 2025s, the simulated rainfall is 1782mm and 1749mm for A2 and B2 scenarios respectively, and increase by 199mm and 265mm for A2 and B2 scenario. In B2 scenario, the annual rainfall decrease a value of 33mm more compare to A2. Similarly for 2050s, 2080s, the annual mean precipitations are 1672mm, 1570mm for A2 and 1709mm and 1651mm for B2 respectively. Decrease by 110mm, 212mm, 40mm, 98mm respectively for A2 and B2 scenario compare to the 2025s future annual average rainfall. The annual rainfall comparison for both A2 and B2 scenario with present annual rainfall shown in figure1.7.

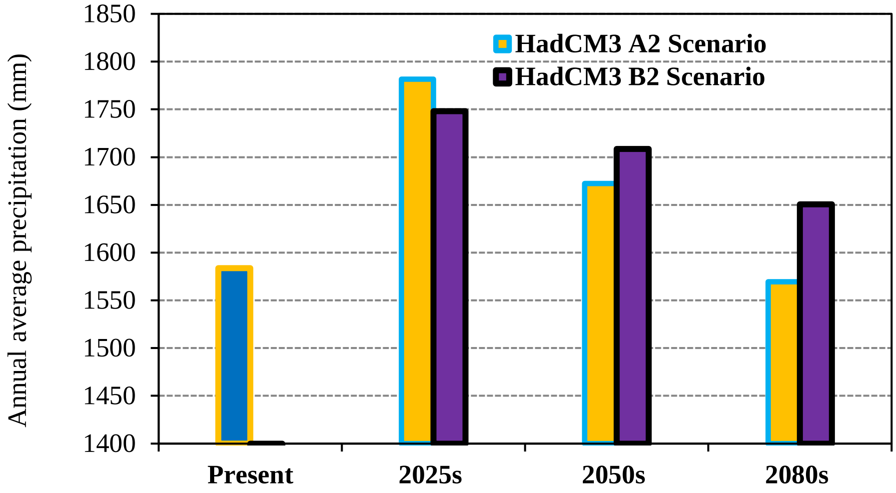

Fig.1.7 Future annual rainfall comparison for both A2 and B2 scenario with present annual rainfall.

IV. CONCLUSION

The main fundamental of SDSM is the relationship between predictand (rainfall) GCMs predictor (HadCM3 A2/B2). GCMs variables selection is the most important factor in the study of climate change, which will affects in the results of climate assessment. Many studies such as Hashmi et al. (2009) and Wilby and Wigly (1997) have considered more than five (05) GCMs variables in their SDSM analysis. Mishra et.al (2014) has considered seven (07) variables in their studies. The selection of GCMs variables are difficult and tricky. In this study, seven (07) of GCMs variables has been considered. The model calibration and validation has been performed using NCEP reanalysis data for duration 1961-1990 and 1991-2001 respectively and the results indicate that the model can be applied in Budhabalangaa river basin to downscale climate change at different temporal and spatial scale. Daily precipitation for the study area has been predicated for the periods 2025s (2011-2040), 2050s (2041-2070) and 2080s (2071-2099). The study shows that an increase in rainfall in the study area for the period 2025s and 2050s. As a results the Budhabalangaa Basin will be wetter in future.

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