

# A Study of Climate Change Impact on Precipitation of Sheonath River Basin

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## Abstract

**Objectives:** Climate change impact assessment on precipitation data. **Methods/Statistical analysis:** This study is done for estimating the impact of climate change on the precipitation of Jondhara station, in the Seonath river basin, Chhattisgarh, India under A2 and B2 scenario of the HadCM3 GCM model. Statistical Downscaling Model (SDSM) was applied in this work. Selection of predictor variables is the most important steps in the statistical downscaling processes because it mostly affects the quality of the generated scenarios. Linear scaling method was used for the bias correction of the downscaled data in the study. **Findings:** The values of  $R^2$  and NSE were 0.78 and 0.78 respectively, for the calibration period (1980-1991) and for the validation period (1992-2001) are 0.70 and 0.69 respectively. These parameters show the good applicability of the model performance. The change in mean annual precipitation during the period 2020-2049, 2050-2079 and 2080-2099 are -0.28%, -0.61%, and -2.39% respectively for A2 Scenario in comparison to the baseline period. Similarly, the values are increased 0.22%, 2.22%, and 2.00% respectively for the B2 scenario. **Application/Improvements:** This paper elaborates the effect of climate change on the precipitation of the Seonath river basin.

**Keywords:** Bias Correction, Climate Change, General Circulation Model, Statistical Downscaling Model (SDSM)

## 1. Introduction

Climate change is one of the most serious topics both globally and locally. The survival and growth of the society are closely linked with the concept of climate change. Climate change is a multidimensional aspect with many dimensions such as global temperature, precipitation, pressure etc. These are all interconnected at some level. In this paper, the precipitation variable is analyzed. The globally averaged combined land and ocean temperature data as calculated by a linear trend, show a warming of 0.85 [0.65 to 1.06] °C, over the period 1880–2012<sup>1</sup>. The constant rise of temperature is of grave concern and is indicative of global warming and poses constant threats of flooding at a global scale. On one hand, there might be flooding on another hand there is the possibility of severe droughts. As per IPCC fifth report, there is high confidence for droughts during the last millennium of greater

magnitude and longer duration than those observed since the beginning of the 20th century in many regions. India has experienced an increase of 0.42°C, 0.92°C and 0.09°C in annual mean temperature, mean maximum temperature and mean minimum temperature respectively over the last 100 years<sup>2</sup>. India is a populous country with strained resources and agriculture being a major GDP component, is poised for imminent risk. Assessment of precipitation trends, its prediction and modeling is a very important task. Growth, both social and economic, greatly depends upon prevailing climatic conditions.

Chhattisgarh is a fast-growing state with ample water resources. Average rainfall in the state is about 1400 mm annually, much of that confined to monsoon. There is a great temporal and spatial variation in rainfall due to which there is the constant threat of droughts<sup>3</sup>. Rice is abundantly grown in the state which happens to be a water intensive crop, thus proper water resource plan-

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ning is imperative to the state. The effect of local climate on water resources is immense and needs attention<sup>4</sup>. Therefore, future predictions of precipitation must be analyzed. Some researchers had done the climate change impact study using statistical downscaling technique in the Mahanadi river basin<sup>5</sup>. Temporal and spatial variability of precipitation regime in the Seonath river basin is conducted by researchers<sup>6</sup>.

Global Circulation Model (GCM) is extremely useful in modeling climatic changes. It involves simulation of Earth's climate using and representing complex physical, chemical and biological interactions in form of mathematical equations. Based on different emission scenarios different projections are made. The scenarios are based on different social, political, environmental and economic scenarios. For India A2 and B2 scenarios are considered. The model used is HadCM3 (*Hadley Centre Coupled Model, version 3*), developed at Hadley Centre, United Kingdom<sup>7</sup>. Couple model implies it uses both surface and oceanic circulation. GCM, however, provides data for large spatial distribution. Thus, it is necessary to down-scale the data. There are two methods of downscaling, dynamic and statistical<sup>5</sup>. The tool employed here is SDSM 4.2.9 which uses linear regression for downscaling<sup>8</sup>.

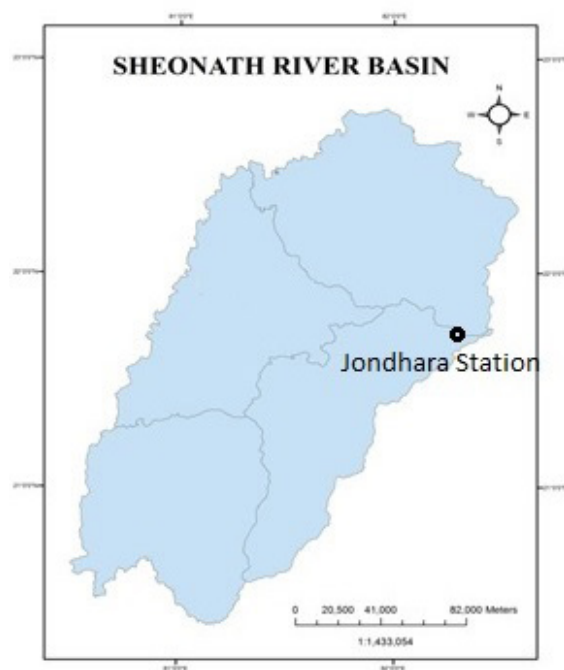


Figure 1. Sheonath river basin.

## 2. Study Area

The Seonath river basin is the longest tributary of the Mahanadi basin rises in village Kotgai, district Durg (Chhattisgarh) and drains three districts of Chhattisgarh namely Durg, Rajandgaon, and Bilaspur. The Seonath river originates near village Panabaras in the Rajnandgaon district. The Basin is located between latitude 20° 16' N to 22° 41' N and Longitude 80° 25' E to 82° 35' E. The drainage area of the Seonath River basin is 30,560 Square kilometers<sup>6</sup>. The river traverses a length of 380 kilometers. The mean annual rainfall in the basin varies from 1005 mm to 1255 mm. Seonath river basin comprises 25% of the catchment of the Mahanadi basin. Jondhara station is taken as a representative of Seonath river basin in this study. The study area is shown in Figure 1.

## 3. Data Availability

### 3.1 Observed Data (Predictand)

The observed (historical) data is obtained from the local authority i.e., Water Resource Department, Chhattisgarh state, for the period of 1980-2010 of the Jondhara station. This was used for the calibration and validation.

### 3.2 Large Scale Variable (Predictor)

The reanalysis data and experiment data for the BOX 22X\_26Y (78.75E 22.50N) is collected from the below source. **Source:** <http://www.ccsn.ec.gc.ca/?page=pred-hadcm3> **HadCM3 Predictors: A2 and B2 Experiments**

The predictor variables are supplied on a grid box by grid-box basis. By defining the box under consideration, a condensed file is downloaded, which contains three directories:

- a) **NCEP\_1961-2001:** This directory contains 41 years of daily observed predictor data, derived from the NCEP reanalyses, normalized over the complete 1961-1990 period. These data were interpolated to the same grid as HadCM3 (2.5 latitude x 3.75 longitude) before the normalization was implemented.
- b) **H3A2\_1961-2099:** This directory contains 139 years of daily GCM predictor data, derived from the HadCM3 A2 experiment, normalized over the 1961-1990 period.

c) **H3B2\_1961-2099**: This directory contains 139 years of daily GCM predictor data, derived from the HadCM3 B2 experiment, normalized over the 1961-1990 period.

## 4. Methodology

For our study, we have used Statistical Downscaling Model (SDSM, developed by Wilby in 2002) 4.2 for downscaling precipitation data. The SDSM 4.2 is a windows-based decision support tool which is used to access the impacts of global climate change. It can be downloaded from <http://co-public.lboro.ac.uk/cocwd/SDSM/main.html>.

SDSM can perform by adopting step by step the following seven function,

### 4.1 Quality Control and Data Transformation

There are elaborate operations under quality control in SDSM. The data sets can be checked for missing values and quality of data can be determined. If required various transformations such as logarithmic, exponential etc can be provided if required.

### 4.2 Selection of Predictor Variable

Screen Variables operation available in SDSM helps the user in selecting appropriate predictor variable for the available 26 variables. The variables are selected based on correlation analysis, partial correlation analysis, and the confidence interval. The correlation factor and P values explain the strength of the relationship between the predictor and predict and variables. Higher correlation value represents more association and smaller P values describe a better chance for the association between the variables.

### 4.3 Model Calibration

The Calibrate Model operation generates the calibration file for the user given period and predictor variables. Other options provided in this operation are an unconditional or unconditional process, model structure-monthly, seasonal or annual. We have used unconditional process and monthly sub-model.

### 4.4 Model Validation

The same operation in SDSM under calibration is used for generation of validation files. For the available data sets, the values are divided amongst calibration and validation ranges. The same settings as in calibration are

applied. The out file generated is used to calculate statistical parameters.

### 4.5 Weather Generation

Calibration of data returns parametric files containing information about the observed data set and predictor variables ascertained previously. The operation returns simulated values for the set time range. The weather generation enables verification of calibration and validation model using independently observed daily time series data.

### 4.6 Data Analysis

The generated files contain downscaled scenarios of observed ranges which can be compared with available observed data. For this analysis, various tools like MS Excel, R program can be used. In the present study, R has been used owing to its versatility. Statistical parameters such as R-Squared ( $R^2$ ), Standard Error in Estimation (SEE) are determined which are used to access the quality of calibration model and suitably validates it.

### 4.7 Graphical Analysis

The results are compared graphically by the comparative plotting of simulated values and observed values. This can be done both by SDSM and Excel. The plotted curves should rest as close as possible.

### 4.8 Scenario Generation

The scenario generator gives ensembles of downscaled data both for future and present time spans. Future scenarios are divided into four series.

Base Series: 31 years span as per available observed data (1980-2010)

20s Series: 2010-2049

50s Series: 2050-2079

80s Series: 2080-2099

Also, the difference between base series and other three series are also calculated which gives an idea about changes in future. This difference is also analyzed on a seasonal basis and annual basis.

## 5. Bias Correction

Bias is a systematic error i.e., raised due to the inaccuracy in the system. To eliminate the biases from the time series data of downscaled data, linear scaling method is adopted

in the study. It is widely used method due to its simplicity<sup>9</sup>. The method is shown by the following equation:

$$P_{mod\ a,b} = P_{raw-scen\ a,b} * \frac{\overline{P_{Obs,b}}}{\overline{P_{raw,b}}} \tag{2}$$

Where  $P_{mod\ a,b}$  is bias modified value of a<sup>th</sup> day of b<sup>th</sup> month,  $P_{raw-scen\ a,b}$  is the raw precipitation of scenario of a<sup>th</sup> day of b<sup>th</sup> month,  $\overline{P_{Obs,b}}$  is mean of the observed value of precipitation of b<sup>th</sup> month and  $\overline{P_{raw,b}}$  is the mean of raw precipitation of b<sup>th</sup> month. The length of the period (30 years) is advocated by the IPCC to use as a baseline period. The period 1980-2010 is considered as a baseline period from the usable information.

## 6. Results and Discussion

### 6.1 Calibration and Validation

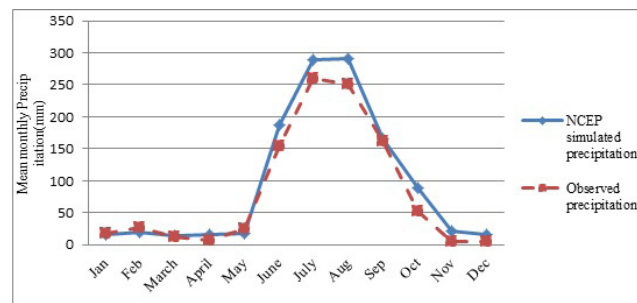
Suitable predictors for Jondhara station was selected and it is shown below in Table 1.

After screening of the potential predictors, simulated mean monthly precipitation was determined by using output of NCEP/NCAR. Observed and simulated mean monthly precipitation were plotted on the monthly scale during calibration period (1980-1991) and validation period (1992-2001) as shown in Figures 2 and 3 respectively. The R<sup>2</sup> value i.e., coefficient of determination is shown in Figures 4 and 5 for the calibration period and the validation period respectively. The performance of the model was assessed by the statistical parameters which is shown in Table 2. Variance is more in the observed precipitation data than NCEP, A2, and B2 data. This shows that SDSM model does not catch the entire range of variation of observed data. It helps to predict average precipitation better than the extreme events. Therefore, monthly precipitation data can be predicted good. Performance of the model was further assessed by the statistical parameters such as R<sup>2</sup> (coefficient of determination), NSE (Nash-Sutcliffe efficiency), and RMSE (root-mean-square error).

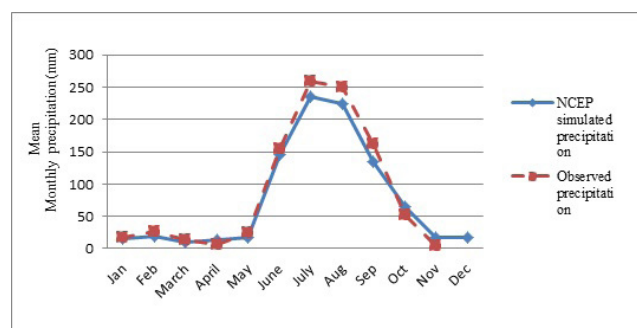
**Table 1.** Selected predictor for calibration of SDSM

Potential Predictor	Explanation	Potential Predictor	Explanation
ncepp_uas	Surface zonal velocity	ncepp8_uas	850-hPa zonal velocity
ncepp_zas	Surface vorticity	ncepp8_zas	850-hPa vorticity
ncepp_zhas	Surface divergence	ncepp5_fas	500-hPa airflow strength
ncepp5_vas	500-hPa meridional velocity	ncepr850as	Relative humidity at 850 hPa

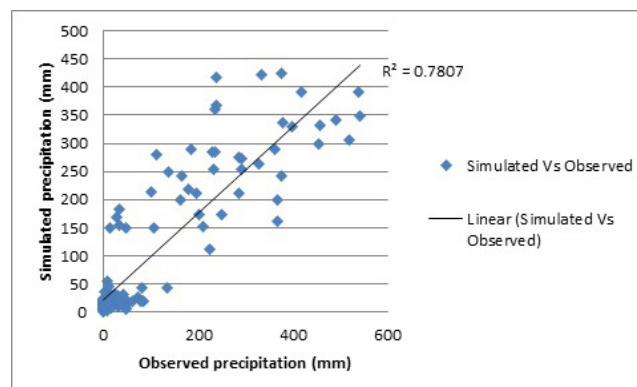
For calibration period (1980-1991) the value of R<sup>2</sup>, NSE and RMSE of 0.78, 0.78 and 67.03 and for the validation period (1992-2001), these values are 0.70, 0.69 and 73.88 respectively.



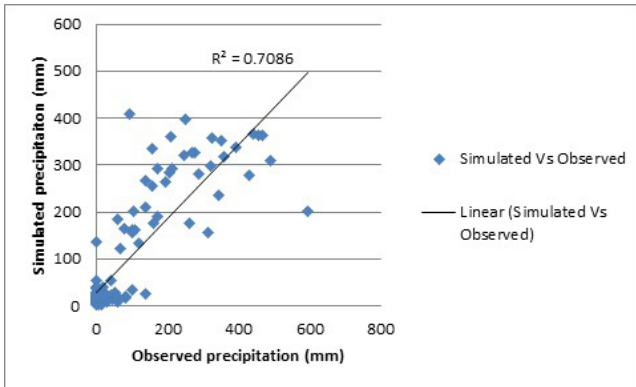
**Figure 2.** Mean monthly precipitation for the calibration period (1980-1991).



**Figure 3.** Mean monthly precipitation for the validation period (1992-2001).



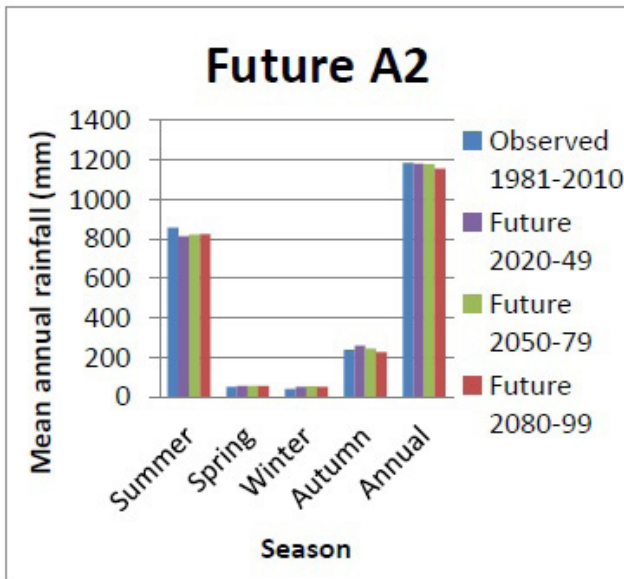
**Figure 4.** Coefficient of determination (R<sup>2</sup>) graph for the Calibration period (1980-1991)



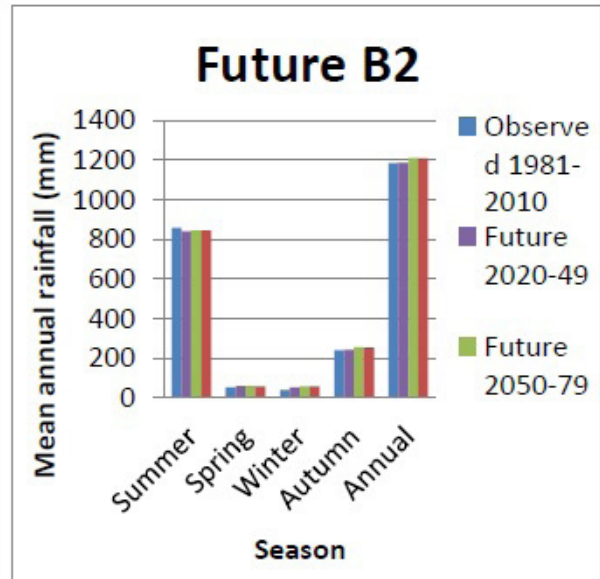
**Figure 5.** Coefficient of determination ( $R^2$ ) graph for the Validation period(1992-2001).

### 6.2 Future Projection of Precipitation Data

Precipitation at Jondhara station is generated under the climate scenario A2 and B2 of HadCM3 GCM model till the year 2099. The generated future projections were compared with the baseline period i.e., 1980-2010 and the percentage change in the amount of precipitation on seasonal scale, like winter (December – February), spring (March – May), Summer (June – August), autumn (September – November) and annual scale is computed. The respective changes are shown in Figures 6 and 7 for A2 and B2 Scenario respectively and the values of percentage change in precipitation is tabulated for A2 and B2 scenario in Tables 3 and 4 respectively.



**Figure 6.** Mean rainfall Seasonal and annual mean rainfall for future projected rainfall for A2 scenario.



**Figure 7.** Seasonal and annual mean rainfall for future projected rainfall for B2 scenario.

**Table 2.** Performance of downscaling model during calibration and validation

Statistics	Calibration (1980-1991)		Validation (1992-2001)	
	Observations	Model(NCEP/NCAR)	Observation	Model(NCEP/NCAR)
$\mu$	101.63	99.66	99.17	100.12
$\Sigma$	143.57	125.29	139.61	125.30
Cv	1.41	1.25	1.47	1.25
$R^2$	0.78		0.70	
NSE	0.78		0.69	
RMSE	67.03		73.88	
RE_ $\mu$	-0.019		0.09	
RE_ $\sigma$	-0.127		-0.06	

**Table 3.** Percentage change in seasonal and annual precipitation at Jondhara station for A2 scenario

Summer	Spring	Winter	Autumn	Annual	Period
-5.15	12.07	28.24	9.84	-0.28	2020-49
-4.04	13.06	32.68	3.26	-0.61	2050-79
-3.82	7.38	29.71	-4.69	-2.39	2080-99

**Table 4.** Percentage change in seasonal and annual precipitation at Jondhara Station for B2 scenario

Summer	Spring	Winter	Autumn	Annual	Period
-1.91	12.09	23.96	1.43	0.22	2020-49
-1.50	11.38	38.87	7.57	2.22	2050-79
-1.26	7.73	42.19	5.84	2.00	2080-99

## 7. Conclusion

SDSM is an effective tool for statistical downscaling of GCM outputs. The variable selected in this study to downscale the GCM output of HadCM3 is precipitation for Kawardha station lying in Seonath river basin under A2 and B2 scenarios. Depending on the data availability, monthly data of 22 years were selected into account where in 12 years (1980-1991) of data was used for calibration and 10 years (1992-2001) for validation period. Marginal changes in the annual mean precipitation are observed, which accounted for -0.28%, -0.61% and 2.39% for the 2020s, 2050s, and 2080s respectively under A2 scenario and 0.22%, 2.22%, and 2.00% for the 2020s, 2050s, and 2080s respectively under the B2 scenario. Seasonal variation is more visible during spring and winter season.

## 8. Acknowledgments

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