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# Prediction of Precipitation in Saraikela-Kharsawan District of Jharkhand by Statistical Downscaling Method

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# Prediction of Precipitation in Saraikela-Kharsawan District of Jharkhand by Statistical Downscaling Method

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## Abstract

Over the years, changing climate has been a matter of concern which has led to drastic changes in various climatic factors like precipitation, temperature, humidity etc. The state of Jharkhand receives a lower amount of precipitation when compared with other states of India. So the objective of the study was to predict the future rainfall of a district receiving moderate to low rainfall. The second generation of the Canadian Earth System Model (CanESM2) was the chosen Global Climatic Model for the study. The historical precipitation data of the district Saraikela-Kharsawan that was used to downscale was chosen from the 15 years span of 1980-1995.
The prediction of the monthly average precipitation was based on two separate Representative Concentration Pathways i.e., RCP4.5 and RCP8.5 with an aim to find out the precipitation from 2080-2090 considering whether the emission of greenhouse gas $CO_2$ will be controlled or will not be controlled in the upcoming years. The study proves that there is an increase of 16.44% while considering RCP4.5 and a considerable increase of 24.10% while considering RCP8.5 until the year 2090. By this study, there is a future scope of prediction of river flow, groundwater recharge, sedimentation etc for that particular district of Saraikela-Kharsawan.

***Keywords:*** *Precipitation, downscale, global climate model, greenhouse, representative concentration pathway*

## 1. INTRODUCTION

Global warming has been a serious concern for the scientist and engineers over the years as it has led to various climate changing issues especially due to the increase of greenhouse gases. Intergovernmental panel on climate change (IPCC) 2013, reports that there might be a rise of 1.4°C to 5.8°C temperature from the year 1990 to 2100 [1]. And such changes might also affect the other environmental factors like precipitation, humidity, wind speed etc. It is also been predicted that there shall be an increase of rainfall in the upcoming years until 2100.
The study on climate changes is done by the help of General Circulation Models or Global Climate Models (GCMs). It is a typical climatic model commonly used for weather forecasting, understanding the climate and forecasting climate change on the earth. A computational grid is employed over the earth where the grid points shall be close enough to develop a relationship between all kinds of physical, chemical and biological mechanisms and hence can be simulated well enough for the weather and climatic studies. Various types of GCM models are available which can be very useful for the particular study. Amongst all of them CanESM2 model was used for the prediction of the future precipitation.
CanESM2 is the second generation of the Canadian Earth System Model. CanCM4, a physically coupled atmosphere-ocean model coupled to a terrestrial carbon model (CTEM) and CMOC - an ocean-carbon model are the main constituents of the CanESM2 Global Climate Model. Government of Canada sponsored website of Canadian climate data and scenarios provide all the necessary data related to CanESM2 of any region on the earth. 26 climatic parameters having historical data of the years 1976-2005 is also provided by CanESM2. It also provides the future climatic data of the years 2006-2100 under three scenarios of Representative Concentration Pathways (RCPs) i.e., RCP2.6, RCP4.5 and RCP8.5.

The Central Water commission (CWC), Ministry of Water Resources, River Development and Ganga Rejuvenation (now ministry of Jal Shakti) and the Indian Space Research Organization (ISRO) together on 3rd December 2008, initiated the memorandum of understanding on developing a platform which consists of web enabled Water Resource Information System which shall be popularly known as India-WRIS. This online platform India-WRIS provides essential surface water data on river monitoring, reservoirs, surface water quality, soil moisture, precipitation, minor irrigation tanks and evapotranspiration. It also provides groundwater data like the groundwater level and groundwater quality. And this data can be received from any available stations where the recording is done along with the suitable time step required by the user between any two possible dates from all the possible resources available.

The data available needs to be downscaled by taking information known at large scales for the predictions to be made at local scale. Downscaling can be done in two possible ways. Either by dynamical or statistical approach. Statistical Downscaling Model (SDSM) does the work in two steps. Firstly, a statistical relationship is developed between the large scale predictors and local variables. Secondly, the relationships developed, are applied to the output of the GCM experiments so as to simulate the future of local climatic characteristics.

When the rainfall of Limbang River Basin was statistically downscaled under transitional climate by Tahir et al. (2017), it was found out that there was an increase of 8.13% of rainfall as per RCP2.6 scenario, 14.7% increase of rainfall as per RCP4.5 scenario and drastic 40.6% increase of rainfall as per RCP8.5 scenario from 2071-2100 with 1976-2005 as the base period [2]. Pichuka et al. (2017) have done their work on Bhadra Reservoir Basin and predicted the basin to experience increased events of daily extreme high inflow during the future period of 2006-2035 when compared with a baseline period of 1971-2000 due to increase of threshold value [3]. The same analysis can also be done by using SUFI-2 algorithm in SWAT-CUP and some other GCMs like CNRM-CM5. In Krishna River Basin, the analysis on CNRM-CM5 gave a prediction of future rainfall to increase by 10% and 17% as per RCP4.5 and RCP8.5 scenarios respectively as claimed by Tirupathi et al. (2018) [4]. Sometimes, the amount of rainfall in the future years may decrease. Soundharajan et al. (2016) proved that by using CMIP5 GCM on Pong Reservoir of the Beas Reservoir Basin. The reservoir inflow runoff reduced due to the reductions of rainfall. But, the rise of temperature has also resulted in the melting of snow and glaciers in the same basin which in turn again increases the inflow and thereby complements the effect of reduction of rainfall and nullifies its effect [5]. Anandhi et al. (2008) downscaled precipitation for IPCC SRES Scenarios using support vector machine (SVM). Potential predictors were chosen as the NCEP variables which are correlated to the precipitation and are also realistically simulated by CGCM3 whereas the predictand is chosen as monthly Thiessen weighted precipitation for the river basin for downscaling precipitation. The projected increase in precipitation is least for COMMIT scenario whereas it is high for A2 scenario. [6]. Gaur et al. (2018) applied physical scaling towards downscaling climate model precipitation data. Future precipitation projections that were downscaled well indicate increase in mean and maximum precipitation intensity and a decrease in the number of dry days. Also an increase in the frequency of short (1-day), moderately long (2–4 day), and long (more than 5-day) precipitation events is projected [7]. Aziz et al. (2018) have represented their work on analysis of statistical correlation for downscaled precipitation data and have given the conclusion that no strong statistical correlation existed between observed data with the reanalysed GCM data. A highest value of 0.18 could be obtained as a correlation coefficient between the predictors and predictands of NCEP [8].

### 1.1 *Study Area*

From the formerly known princely states of Saraikela and Kharsawan, the district Saraikela – Kharsawan is one district of the state Jharkhand (India). It is one among all the 24 districts of the state situated between 85°30'14''E & 86°15'24''E longitudes and 22°29'26''N & 23°09'34''N latitudes covering an area of 2724.55 sq. kilometers approximately. Saraikela-Kharsawan is bordered by East

Singhbhum District (Jharkhand) in the East, West Singhbhum district (Jharkhand), Khunti district (Jharkhand) & Ranchi district (Jharkhand) in the west, Purulia district (West Bengal) in the north and Mayurbhanj district (Odisha) in the south. The district also has an elevation range of 209 meters to 178 meters. The district faces typical Indian climate comprising of five seasons namely – summer, monsoon, autumn, winter and spring. Being located in one of the drier parts of Jharkhand, Saraikela-Kharsawan district receives a moderate rainfall during the monsoon.

**Table 1:** About Saraikela-Kharsawan Geography and Demography

| | |
|---|---|
| **Location** | Saraikela – Kharsawan (District) |
| **Headquarters** | Saraikela |
| **Division** | Kolhan |
| **Area** | 2724.55 sq. kilometers |
| **Average annual precipitation** | 1350 mm |
| **Rainfall Station** | Saraikela |
| **Popular Rivers** | Subarnarekha, Kharkai, Korkori |
| **Popular Dams & Reservoirs** | Chandil Dam & Reservoirs |
| **Population** | 10,65,056 |

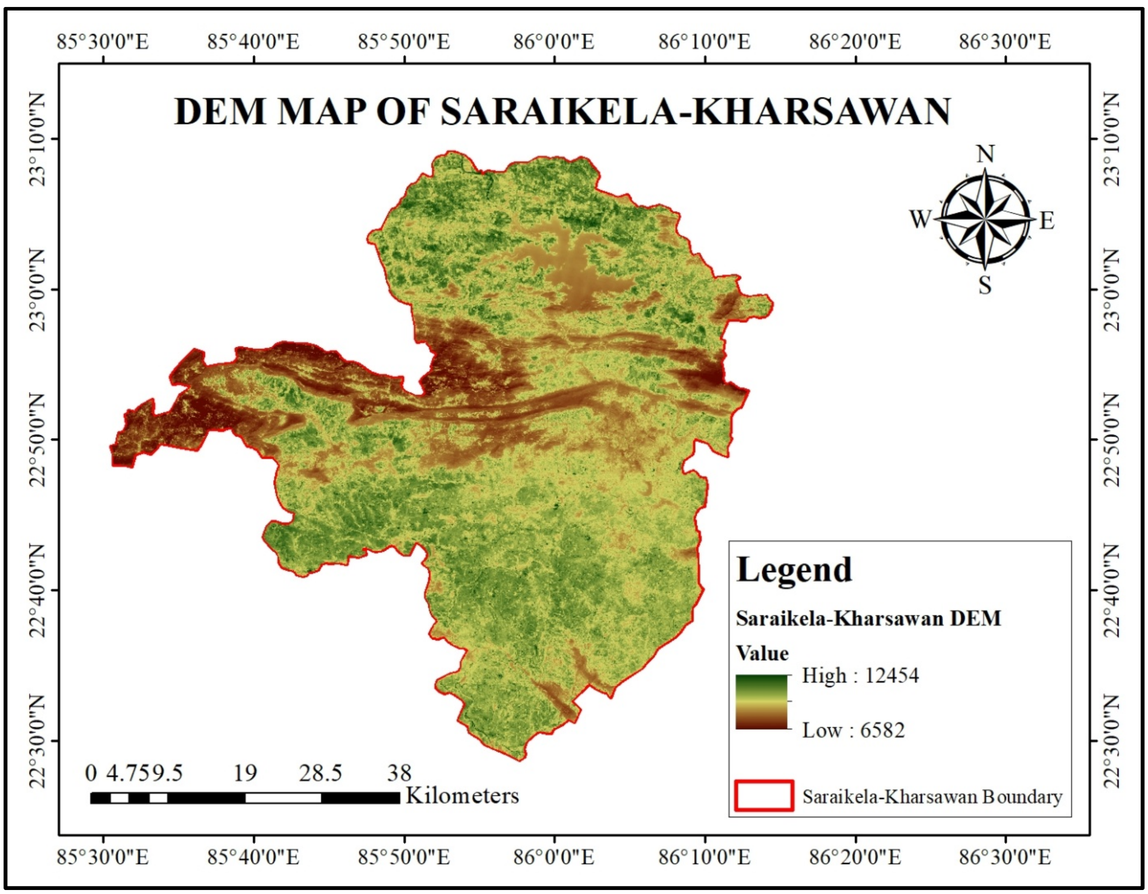



**Fig 1:** DEM Map of District Saraikela-Kharsawan

## 2. METHODOLOGY

Downscaling refers to the process of prediction of climate at local scales with reference to the available large scale information. Statistical Downscaling Model (SDSM) is a well known tool for making predictions and downscale climate data. Ordinary Least Square method is used for downscaling the data. The very initial step includes the screening of the variables to find the best suited ones from the available variables of NCEP-NCAR (1961-2005). This is analyzed for the P-value and Partial r value and the screened values are ensured to have zero or minimum P-value and maximum partial correlation (r) value. For this particular study, the chosen predictor variables for calibration after the screening were "ncepp500gl" and "nceprcpgl" out of all the available 26 predictor variables. The scenario was generated as per CanESM2 and the precipitation for a period of 15 years (1980-1995) of District Saraikela-Kharsawan was modelled. The modelled past data was used to predict the monthly average precipitation for the district for 11 future years i.e, 2080-2090 in a span of 15 years with each year taken as the central value of the span.

### *2.1 Screening of the Predictor Variables*

As per the Multiple Linear Regression (MLR), the most relevant atmospheric parameters are chosen based on the P-value and partial correlation (r) value. The parameters of the predictors must have a high partial correlation and a minimum P-value and then only can be chosen for the calibration. The chosen parameters for calibration after the screening were "ncepp500gl" and "nceprcpgl" out of all the available 26 parameters of the predictor.

### *2.2 Calibration of Data*

The historical data that has been used for the calibration of precipitation of the district in the study is 1980-1995. Regression equation and Chow Test was fed to calculate for the calibration providing a conditional process as the sub-model. The calibration of the model was done for monthly output. Also, 20 histograms were created in this calibration process. The Ordinary Least Square (OLS) method was used to optimize the model instead of the other available method i.e., the Dual Simplex (DS) method as the latter is a slower method. The R-squared, Root Mean Square Error (RMSE) and Chow Test results were calculated for both the conditional and unconditional statistics with the autoregression applied. And this was done for all the 12 months from 1980 to 1995.

### *2.3 Future Prediction of Precipitation*

The prediction was made for the years 2080-2090 as per two scenarios of Representative Concentration Pathway of CanESM2 i.e., RCP4.5 and RCP8.5. The modelled data of the monthly averages was the input parameter and individually for each future year, monthly average precipitation was predicted as per both RCP4.5 and RCP8.5. This prediction was done by estimating the values for a period of 15 future years with the central year being the desired year whose prediction is to be done and such process was repeated 11 times for 11 years from 2080-2090. The trend is analysed from the historical data of 1980-1995 which is the base for the quantitative analysis and prediction of the future trends. Simultaneously the data for the future precipitation is also formulated. Firstly, the prediction is done for the RCP4.5 scenario of CanESM2 where the emission is somehow controlled. Secondly, the prediction was made for the RCP8.5 scenario of CanESM2 where there is no control on emission.

## 4. RESULTS AND DISCUSSIONS

The results of the R-squared, RMSE and the Chow Test for both conditional and unconditional statistics are shown in Table 2. The predictor parameters so screened to be perfect for these tests are "ncepp500g"l and "nceprcpgl". All these values are from the historical data of 1980-1995.

**Table 2:** Results of $R^2$, RMSE and Chow Test for Model Validation

| UNCONDITIONAL STATISTICS | | | |
|---|---|---|---|
| **Month** | **RSquared** | **RMSE** | **Chow** |
| January | 0.127 | 0.252 | 2.8520 |
| February | 0.150 | 0.302 | 0.6823 |
| March | 0.198 | 0.309 | 2.7133 |
| April | 0.192 | 0.363 | 1.9127 |
| May | 0.116 | 0.446 | 2.1072 |
| June | 0.132 | 0.413 | 1.6450 |
| July | 0.112 | 0.312 | 0.5762 |
| August | 0.067 | 0.335 | 0.8653 |
| September | 0.224 | 0.415 | 1.3606 |
| October | 0.204 | 0.398 | 1.7429 |
| November | 0.239 | 0.204 | 2.0726 |
| December | 0.193 | 0.180 | 1.6604 |
| Mean | 0.163 | 0.327 | 1.6825 |
| **CONDITIONAL STATISTICS** | | | |
| **Month** | **RSquared** | **RMSE** | **Chow** |
| January | 0.021 | 0.243 | 1.5304 |
| February | 0.015 | 0.321 | 1.4811 |
| March | 0.011 | 0.295 | 2.6388 |
| April | 0.008 | 0.317 | 1.3135 |
| May | 0.017 | 0.333 | 0.4238 |
| June | 0.001 | 0.436 | 2.7703 |
| July | 0.005 | 0.400 | 2.6327 |
| August | 0.002 | 0.385 | 3.7849 |
| September | 0.005 | 0.427 | 0.7838 |
| October | 0.004 | 0.349 | 0.2410 |
| November | 0.029 | 0.483 | 0.2809 |
| December | 0.286 | 0.330 | 0.0000 |
| Mean | 0.034 | 0.360 | 1.4901 |

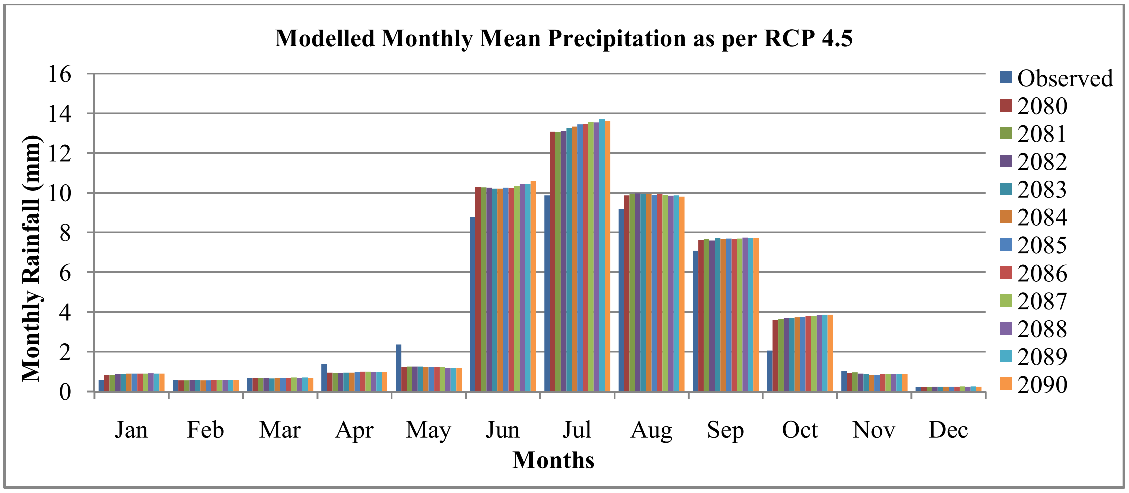
The results of the prediction was based on two different Representative Concentration Pathways (RCPs) of CanESM2 i.e., RCP4.5 and RCP8.5. The historical data of 1980-1995 is modelled to find the future data of 2080-2090 and it is the predicted monthly mean precipitation for every single year between 2080-2090. It has been seen that there is an overall rise of 16.44% of precipitation as per the RCP4.5 scenario and an abrupt overall rise of 24.10% for the precipitation as per RCP8.5 until the year 2090. It was also interesting to find out that, despite of an overall rise of precipitation as per both the scenarios, the observed precipitation of April and May month has always been higher than the modelled precipitation of the same two months be it any year or any scenario. These results are shown and well represented in Table 3 (a) and 3 (b). Also a comparison showing the rise of the monthly average precipitation for each month is represented in the form of bar graphs.

**Table 3 (a):** Modelled Monthly Mean Precipitation as per RCP4.5

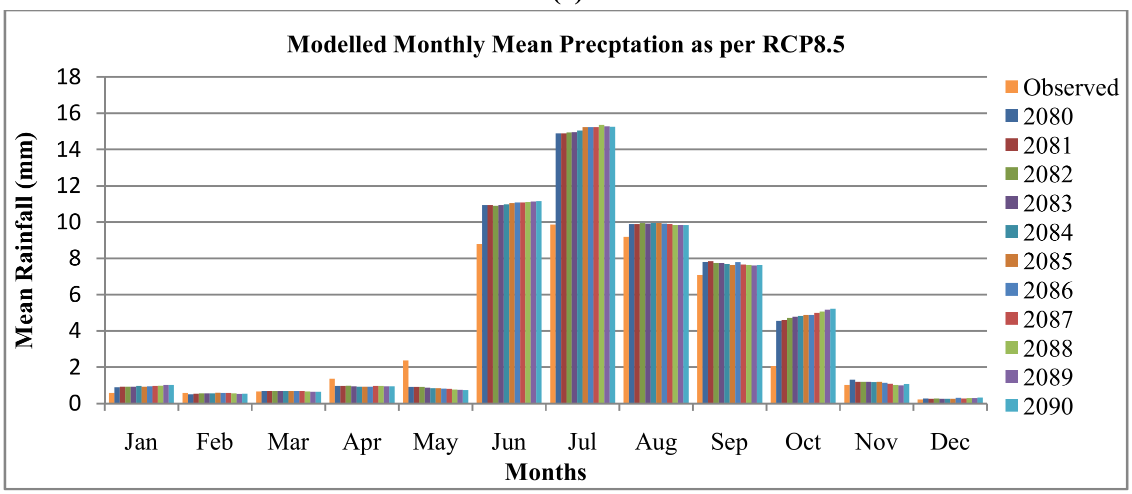
| Month | Observed | 2080 | 2081 | 2082 | 2083 | 2084 | 2085 | 2086 | 2087 | 2088 | 2089 | 2090 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jan | 0.581804 | 0.836 | 0.835 | 0.865 | 0.875 | 0.893 | 0.888 | 0.889 | 0.898 | 0.909 | 0.892 | 0.888 |
| Feb | 0.575793 | 0.555 | 0.563 | 0.576 | 0.578 | 0.568 | 0.568 | 0.572 | 0.575 | 0.573 | 0.573 | 0.579 |
| Mar | 0.669501 | 0.665 | 0.672 | 0.663 | 0.658 | 0.683 | 0.679 | 0.681 | 0.691 | 0.683 | 0.692 | 0.681 |
| Apr | 1.37541 | 0.939 | 0.92 | 0.928 | 0.942 | 0.939 | 0.979 | 1.003 | 1.001 | 0.986 | 0.979 | 0.992 |
| May | 2.37237 | 1.238 | 1.251 | 1.259 | 1.259 | 1.215 | 1.216 | 1.212 | 1.206 | 1.173 | 1.176 | 1.164 |
| Jun | 8.7921 | 10.29 | 10.27 | 10.25 | 10.2 | 10.21 | 10.25 | 10.24 | 10.35 | 10.43 | 10.45 | 10.6 |
| Jul | 9.87225 | 13.07 | 13.06 | 13.11 | 13.25 | 13.33 | 13.44 | 13.47 | 13.57 | 13.55 | 13.69 | 13.61 |
| Aug | 9.18276 | 9.867 | 9.955 | 9.966 | 9.941 | 9.943 | 9.882 | 9.927 | 9.89 | 9.859 | 9.868 | 9.81 |
| Sep | 7.07944 | 7.622 | 7.672 | 7.591 | 7.721 | 7.68 | 7.695 | 7.66 | 7.693 | 7.745 | 7.722 | 7.739 |
| Oct | 2.06525 | 3.595 | 3.633 | 3.681 | 3.689 | 3.733 | 3.739 | 3.797 | 3.793 | 3.854 | 3.871 | 3.864 |
| Nov | 1.03091 | 0.922 | 0.952 | 0.894 | 0.878 | 0.841 | 0.832 | 0.861 | 0.868 | 0.887 | 0.88 | 0.866 |
| Dec | 0.233011 | 0.228 | 0.228 | 0.241 | 0.246 | 0.24 | 0.238 | 0.245 | 0.253 | 0.239 | 0.264 | 0.237 |
| **Annual** | **43.8306** | **49.83** | **50.01** | **50.02** | **50.24** | **50.28** | **50.41** | **50.56** | **50.79** | **50.88** | **51.06** | **51.04** |

**Table 3 (b):** Modelled Monthly Mean Precipitation as per RCP8.5

| Month | Observed | 2080 | 2081 | 2082 | 2083 | 2084 | 2085 | 2086 | 2087 | 2088 | 2089 | 2090 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Jan | 0.581804 | 0.903 | 0.925 | 0.925 | 0.935 | 0.955 | 0.93 | 0.953 | 0.963 | 0.976 | 1.029 | 1.023 |
| Feb | 0.575793 | 0.521 | 0.554 | 0.557 | 0.561 | 0.572 | 0.592 | 0.587 | 0.577 | 0.563 | 0.538 | 0.542 |
| Mar | 0.669501 | 0.675 | 0.682 | 0.678 | 0.675 | 0.681 | 0.675 | 0.679 | 0.677 | 0.668 | 0.647 | 0.654 |
| Apr | 1.37541 | 0.967 | 0.968 | 0.975 | 0.94 | 0.934 | 0.926 | 0.929 | 0.961 | 0.968 | 0.947 | 0.94 |
| May | 2.37237 | 0.91 | 0.92 | 0.908 | 0.886 | 0.853 | 0.85 | 0.83 | 0.813 | 0.783 | 0.76 | 0.74 |
| Jun | 8.7921 | 10.93 | 10.94 | 10.91 | 10.93 | 10.97 | 11.05 | 11.08 | 11.09 | 11.11 | 11.13 | 11.14 |
| Jul | 9.87225 | 14.88 | 14.89 | 14.93 | 14.96 | 15.04 | 15.25 | 15.24 | 15.25 | 15.36 | 15.29 | 15.26 |
| Aug | 9.18276 | 9.887 | 9.884 | 9.932 | 9.919 | 9.955 | 9.961 | 9.914 | 9.906 | 9.853 | 9.846 | 9.825 |
| Sep | 7.07944 | 7.797 | 7.824 | 7.743 | 7.738 | 7.683 | 7.65 | 7.775 | 7.664 | 7.64 | 7.622 | 7.632 |
| Oct | 2.06525 | 4.565 | 4.6 | 4.713 | 4.798 | 4.829 | 4.876 | 4.873 | 5.003 | 5.077 | 5.18 | 5.219 |
| Nov | 1.03091 | 1.326 | 1.198 | 1.19 | 1.187 | 1.18 | 1.189 | 1.149 | 1.092 | 1.028 | 0.991 | 1.081 |
| Dec | 0.233011 | 0.282 | 0.272 | 0.28 | 0.272 | 0.27 | 0.267 | 0.315 | 0.288 | 0.299 | 0.303 | 0.335 |
| **Annual** | **43.8306** | **53.65** | **53.65** | **53.74** | **53.80** | **53.92** | **54.22** | **54.32** | **53.99** | **54.32** | **54.28** | **54.39** |




**(a)**




**(b)**

**Fig. 2: (a)** Comparison Showing the Observed and Modelled Monthly Mean Rainfall as per RCP4.5 **(b)** Comparison Showing the Observed and Modelled Monthly Mean Rainfall as per RCP8.5

## 4. CONCLUSIONS

The precipitation of the district Saraikela-Kharsawan has been downscaled and a prediction of the future precipitation has been done. The historical data of 1980-1995 has been the base for the quantitative approach applied in SDSM to predict the precipitation of the district for the future years of 2080-2090 under two different scenarios i.e., RCP4.5 and RCP8.5 of the CanESM2 model. It has been seen that there is an overall increase of rainfall for both the scenarios with RCP8.5 scenario resulting in the highest precipitation. Also, the precipitation of April and May, which was observed to be higher, has somehow shown a decrease of monthly mean precipitation be it any year or any scenario. So, for Saraikela-Kharsawan District, there will be less precipitation in summers in the future as per both RCP4.5 and RCP8.5 scenarios, but there will be an overall increase in precipitation in other seasons and also annually, year by year the precipitation will increase. The outcomes of this study could be helpful for the analysis of climate change effects on various other water resources of the district like the flow of Subarnarekha River and the capacity and sedimentation of Chandil Dam & Reservoir all being part of the same district.

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