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Effect of Climate Change on Rainfall Trend in Krishna River Sub-Basin, Andhra Pradesh using SDSM

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Abstract*—The frequent and irregular change in climatic condition, known as climate change significantly affects many hydrologic events like the precipitation rate, its frequency, runoff, and the water flow in the rivers stream. The significant change in theses hydrologic events, cause an adverse effect on the people around the world. So, it is necessary to study the changing pattern of these climatic events to reduce the future hydro-climatological hazards. The evolution of global general circulation models (GCMs), a boon for the climatic studies, which are capable to predict future climatic data based on the present datasets. This prediction helps us to plan for the significant adaptation actions for safe future. Though, it is unmanageable to use the raw data of GCMs at a local scale, due to its coarse resolution. Therefore, the main aims of the present study are to estimate the effect of climate change on rainfall pattern in 3 Coastal districts of Andhra Pradesh, India, under three Representative Concentration Pathways (RCPs) from Global Climate Model data of CanESM2. The estimation was done using the Statistical Downscaling Model (SDSM) in the study area. The goal behind using this model is evaluating the efficiency of SDSM to predict the future rainfall. The actual data of three districts, (namely Krishna, Guntur and Prakasam) which finally converted into 3 weather stations using Thiessen Polygon method. The method was used for a period of 51 years (1961 - 2012) and Global Climate Model data of CanESM2 under RCPs of RCP2.6, RCP4.5, and RCP8.5 for the period of 2006-2100. The period of 1961-1995 was used as the calibration period and 1996-2005 as validation. After the validation, rainfall was recorded individually for all the three scenarios of RCPs namely RCP2.6, RCP4.5, and RCP8.5. The results showed the values of R^2 and RMSE for themodel calibration and validation ranged from 0.69 to 0.86 and between 1.99 and 3.88, respectively for all three stations used in the study. The obtained future rainfall data from 2020-2100 was then correlated with the base period rainfall from 1961-1995. The trend shows that the overall volume of precipitation will increase in this region (three districts of Andhra Pradesh) of lower Krishna River for the period of 2020-2100 as compared to the base period due to the change in climate. The approximate predicted change up to the 21st century will be 19.51%, 18.50%, and 15.99% for Guntur, Krishna, and Prakasam districts respectively under the worst scenarios of RCP8.5. Therefore, it is concluded that the future pattern of rainfall in these three districts of Coastal Andhra Pradesh, under RCP4.5 and RCP8.5 constantly increasing, especially in the case of RCP8.5 due to the climate change.

***Keywords*— SDSM; Downscaling; Climate Change; Rainfall.**

1. INTRODUCTION

Andhra Pradesh, a Southern State of India, lies in the south eastern region of India, with Bay of Bengal on the east and shares boundaries with Telangana state in the north-west, Chhattisgarh state in the north, Odisha state (formerly known as Orissa) in the north-east, Karnataka state in the west and Tamil Nadu state in the south. Andhra Pradesh is the seventh largest state in India covering an area of approximately 162,970 Km^2. It has a coastline of 970 Km along the Bay of Bengal. The coastal plain, also known as the Andhra region, runs almost the entire length of the state and consists of 9 districts. Most of the rivers, in the state flow from west to east. The deltas formed by the most important of those rivers: the Godavari and the Krishna - make up the central part of the plains, an area of fertile alluvial soil. This geographical locality of the study area mainly Krishna and Guntur district are more vulnerable towards the climate change. Krishna district is highly affected by frequent cyclones and cloudburst during monsoon season, especially at low lying coastal areas. The climatic conditions of the districts are of extreme kind with hot summers and humid winters and may be classified as tropical. The period starting from April to June is the hottest.Cyclones generally occur in the month of May-June and October-November, with a primary peak in November and secondary peak in May. Cyclones affect the entire East Coast of Andhra Pradesh.

According to the State Disaster Management Department, about 44% of the AP state is vulnerable to tropical Cyclones and related disasters. The stretch between Nizampatnam in Guntur district and Machilipatnam in Krishna district are the most prone to storm surges. East and West Godavari districts, with vast stretches of paddy fields and irrigation, drainage canals bear the brunt of cyclones accompanied by strong winds up to 230 Km/h and pounding rains. In the aftermath of cyclones, these areas get flooded, leading to huge crop losses besides other damages.

As per the previous data, we can visualize that the frequency of these events is increasing year by year. As per the report of the Intergovernmental Panel on Climate Change (IPCC) 2013-AR5, the increase in temperature from the year 1990 to 2100 will be approximately 1.4°C to 5.8°C [2], [3]. The Intergovernmental Panel on Climate Change (IPCC) in his fifth assessment report (AR5) reported that the change in local precipitation and temperature due to climate change may increase the hazards like droughts and floods and their severity [4], [5]. General Circulation Model (GCM) models are capable to predict the expected change in climatic conditions for future [2], [6], [7], [8]. The GCM model results are created on a very larger grid scale (200 to 650 km) [11]. Due to this large grid, the results obtained are not precisely sufficient to be applied straight to study the change of different hydrological influences at the local scale. To overcome these scale parameters, we use downscaling which is capable to fill the rift among the local scaled climatic inputs and global scaled climatic parameters [12]-[14]. So, we can say that projection across different scales which is also known as Downscaling, is a procedure that relates local and regional - scale climate variables to the larger scale atmospheric components. In other words, we can say, Downscaling joins the gap between large and local scale climatic data.

In the last three decades, different downscaling methods have been explained, which were effective to overcome the differences between spatial and temporal local and coarse scale [11], [15]. Broadly, the downscaling method is classified into two types, namely statistical downscaling and Dynamical Downscaling [16], [17]. The present study concentrates on statistical downscaling method because it is reasonable, easy to handle and better to understand by the common people community. Also, the statistically downscaling procedures are much clearer than dynamical methods which are based on RCM (Regional Climate Model) to downscale outputs from GCMs [10], [18]. It has the capability to accurately represent local-scale information on climate change studies. The projection made by the statistical downscaling technique is by using long term historical data of precipitation or temperature to get a proper relationship with large scale variable [19], [20]. The Statistical Downscaling Model (SDSM) is one of the tools used for downscaling [11], [21]. SDSM is a regression-based model [13] and is widely accepted in the climatic studies to downscale different climatic parameters like rainfall and temperature to predict future modification in different hydrological situations. In this study, SDSM is chosen for analyzing three distinguished CanESM2 scenarios of RCP2.6, RCP4.5, and RCP8.5. The working of SDSM model is shown below by Fig-1.

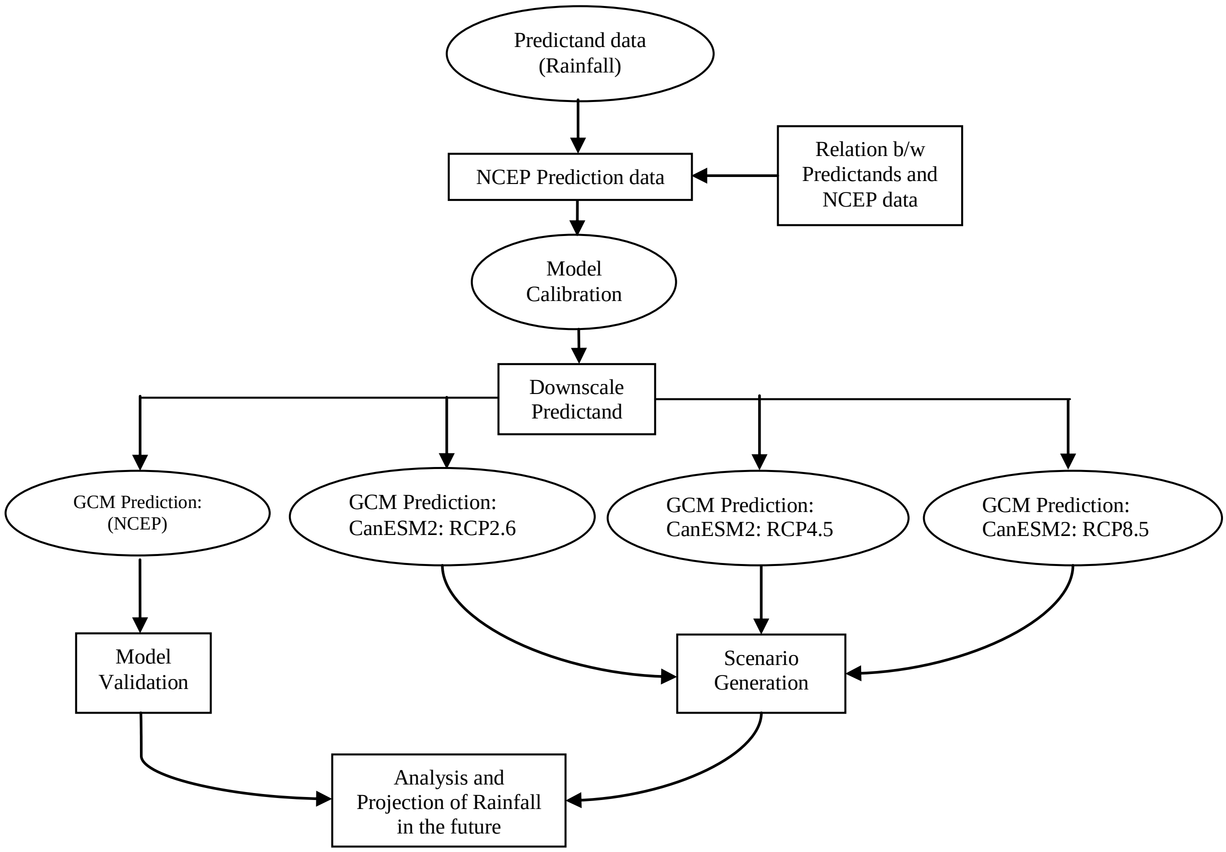


Fig-1: The working of SDSM [14]

2. MATERIALS AND METHODOLOGY

2.1 STUDY AREA AND DATA USED IN DOWNSCALING PROCESS:

2.1.1 Study Area

Study Area is Krishna, Guntur and Prakasam districts of AP, lies between $15.3485^0$and 16.6100^0 North latitudes and 79.5603^0 and 80.7214^0 East longitudes (Fig-2 (a) &Fig-2 (b)). The total area of the study area is about 17626 sq.km.

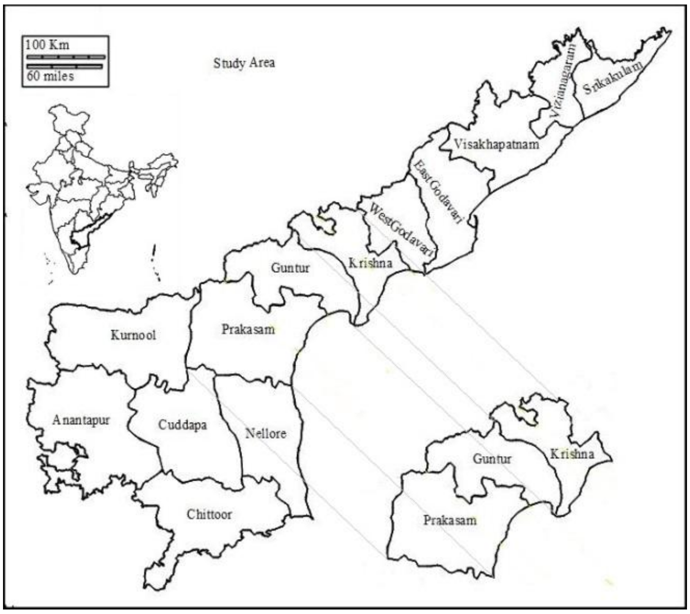


Fig-2(a): Study Area showing Krishna, Guntur and Prakasam districts

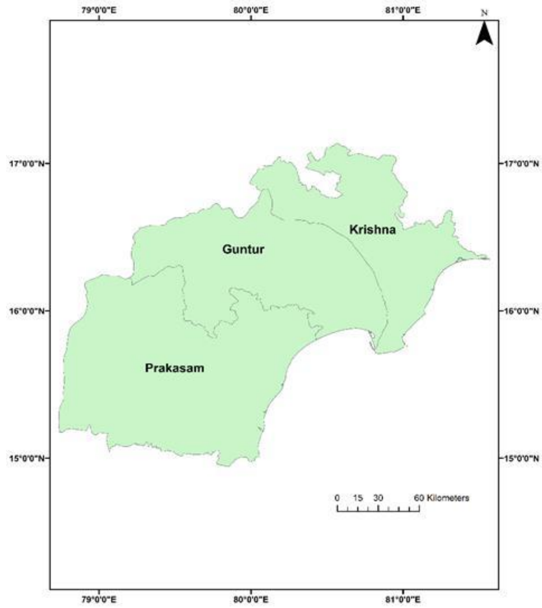


Fig-2(b): Study Area showing Latitudes and Longitudes

2.1.2 Data Used

Rainfall Pattern:

The Andhra Pradesh State receives precipitation in monsoon season, from June to September. Generally, the climate of Andhra Pradesh is humid with a high wind velocity during entire year. The annual normal rainfall of AP is 940 mm during the North-East Monsoon (October to December).

To study the fluctuations of mean monthly rainfall patterns, three rain gauge stations in Krishna, Guntur and Prakasam districts are considered as representatives of the study area. Fig-3 shows various rain gauge stations present in the study area.In all the mentioned stations, the maximum rainfall is observed during the monsoon season. Fig-4 (a) – (c) shows the maximum average monthly rainfall at the rain gauge stations in Krishna, Guntur and Prakasam districts respectively.

The Thiessen polygons method is applied to calculate average precipitation of the three districts (Krishna, Guntur and Prakasam) of AP State. The following equation is used.

$$P_{avg} := \frac{\sum_{i=1}^{n} \left(A_i \cdot P_i\right)}{\sum_{i=1}^{n} A_i} \quad \text{---} \quad Eq(1)$$

Where, P_{avg} is the areal average precipitation over the watershed, A_i is the area of polygon i and P_i is the precipitation for polygon i. The integer n is the number of polygons and gauges.

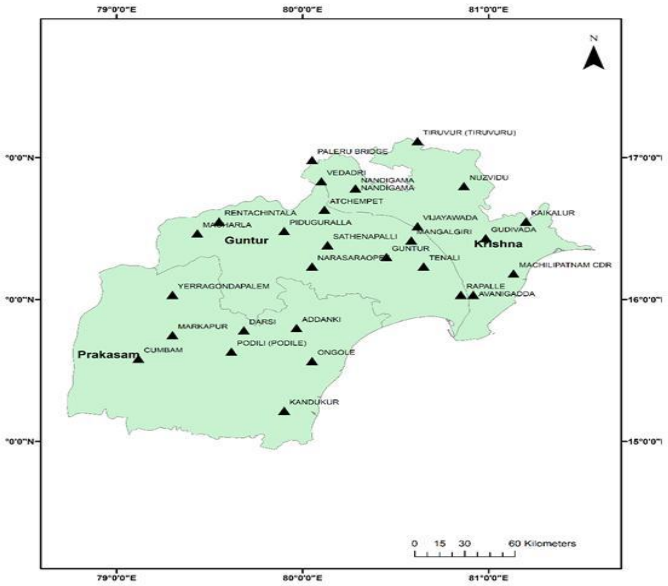


Fig-3: Rain gauge stations available in study area containing 3 districts of AP.
(*Black triangles indicate location of rain gauge stations*)

2.2 Climate Change Downscaling

Downscaling, or projection across different scales, is a procedure that links local and regional- scale climate variables to the larger scale atmospheric components. Downscaling joins the gap between large and local scale climatic data. The interpretation across scales is based on the assumption that similar atmospheric models produce similar climatic conditions. Now the basic question is that why we need downscaling? In a better way, we can answer this question that: GCM (General Circulation Models) outputs are of insufficient spatial and temporal resolution, causing an insufficient representation of orography and land surface characteristics, when the interoperation may not represent some of the features properly which may have important impacts on local climate. To overcome these faults, we have to find a way which fulfills the gap of connecting the information that the climate modeling society can currently provide and that is needed by the different researchers.

2.3 Statistical Downscaling Model (SDSM)

The SDSM is a medium, which is used to downscale the climatic components to a fine scale in different climate change studies. The SDSM is also considered as a hybrid model which combines the stochastic climate generator and the regression-based downscaling methods. In this model, the large-scale climatic variables are used to locate the local-scale weather for generating different climatic parameters [12]-[14]. Benefits of implementing SDSM in the downscaling process:

a) It has been extensively used in many catchments scales over a large range of different climatic situation around the globe by providing reliable results.
b) It is user-friendly and openly available software which can be downloaded from https://copublic.lboor.ac.uk/cocwd/sdsm
c) Different statistical analysis can be performed in SDSM to check the model validity.

2.3.1 Working of SDSM (Statistical Downscaling Model)

SDSM is used to downscale the different climatic parameters such as rainfall and temperature, from GCMs to the local scale. It covers the random probability distribution approach as well as Multiple Linear Regression (MLR). To proceed with the downscaling process in SDSM, firstly we need to develop a quantitative relationship between predicted (observed) and predictor (large scale parameter). In SDSM three models are integrated based on the timescale i.e. annual, seasonal and monthly sub- model. All these models are based on a regression equation. In the present study, the monthly model has been chosen. Besides, the sub-models may be conditional and/or unconditional based on the nature of the climatic parameter to be downscaled. As per the resource and SDSM manual, the conditional model is best suited for downscaling of rainfall event and is unconditionally appropriate for downscaling of temperature. Eq (2) provides the common description of a downscaling model as defined by Wilby et al., 1999.

$$R_t = F(XT) \quad \text{--} \quad \text{Eq (2)}$$

Where R_t is the local scale predictands or climatic parameters as observed data at single or multiple sites at time t, XT is the predictor data of large-scale atmospheric variables i.e. GCM and F are the methods used to establish the relationship between these two different spatial systems.

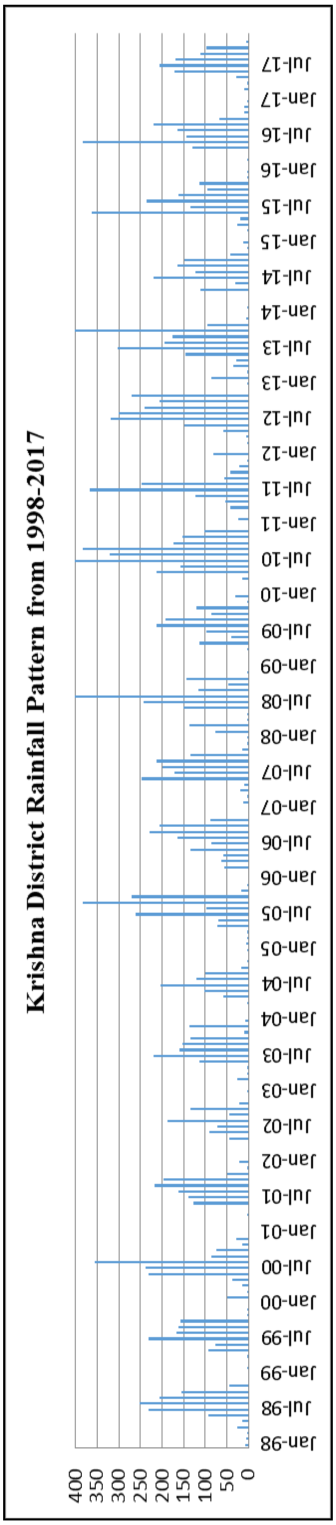


Fig-4(a): Monthly Rainfall from three rain gauge stations of Krishna District

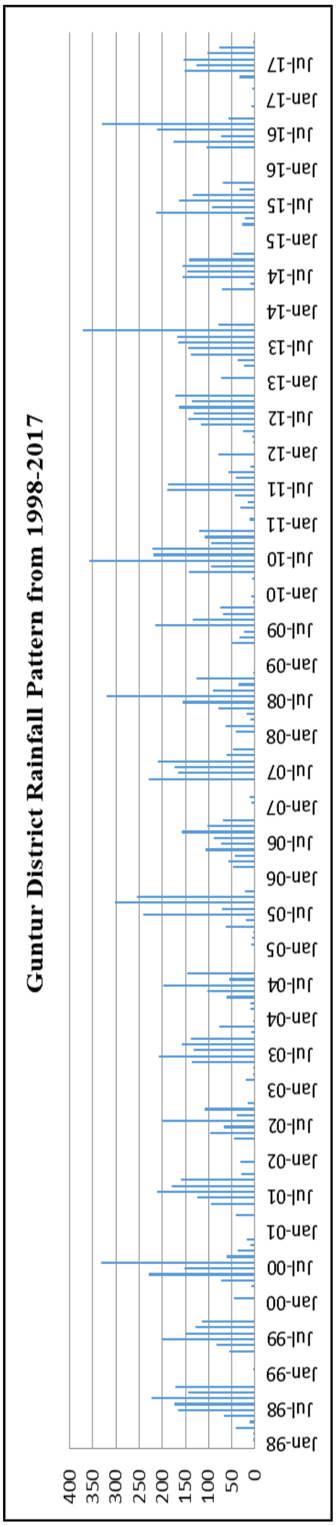


Fig-4(b): Monthly Rainfall from three rain gauge stations of Guntur District

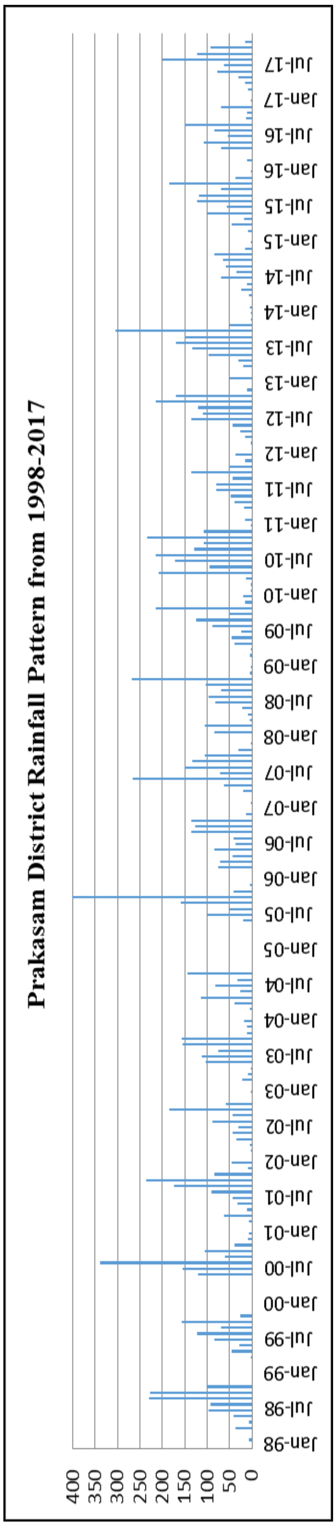


Fig-4(c): Monthly Rainfall from three rain gauge stations in Prakasam District

2.4 Selection of GCM Model:

Global Climate Change Model: CanESM2 predictors based on CMIP5 experiments is the second generation Canadian Earth System Model (CanESM2). It is the fourth generation coupled global climate model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma) of Environment and Climate Change Canada. CanESM2 represents the Canadian contribution to the IPCC Fifth Assessment Report (AR5). This CanESM2 model is a combination of CanCM4 model and Canadian Terrestrial Ecosystem Model (CTEM), which based on the terrestrial carbon cycle. The CTEM model explains the land-atmosphere carbon transaction phenomena. CanESM2 consists of three Scenarios: RCP2.6, RCP4.5, and RCP8.5. The Representative Concentration Pathways (RCPs) are four greenhouse gas concentration (not emissions) trajectories selected by the IPCC for its Fifth Assessment Report (AR5). The four RCPs, RCP2.6, RCP4.5, RCP6.0, and RCP8.5, are described after a reasonable range of radiative forcing values projected in the year 2100. RCPs represent a broad area of possible problems related to climate change like the effect of greenhouse gases, air pollutants, and their emissions, and different land use scenario. RCP8.5 considers the highest and RCP2.6 considers the lowest scenarios of greenhouse gases that have been recently reviewed by the study based on climatic research. The different RCP Scenarios considered in this study is RCP2.6, RCP4.5, and RCP8.5.

2.4.1 Data used in SDSM

The data used for the climate change downscaling contain daily rainfall data obtained from Indian Metrological Department. The predictor variables which contain the historical NCEP data with the specific scenarios (RCP2.6, RCP4.5, and RCP8.5) inside the spatial grid cell (2.8125^0 x 2.8125^0) of the large-scale climate change GCM-CanESM2 model.

The metrological stations used for downscaling is listed in Table-1.

Table-1: Metrological stations used for downscaling

Station Name	Longitude (degrees)	Latitude (degrees)	Period (year)
Krishna	80.7214 E	16.6100 N	1961-2012
Guntur	80.0088 E	16.3906 N	1961-2012
Prakasam	79.5603 E	15.3485 N	1961-2012

2.4.2 Model Calibration and Validation

SDSM performs two ways of model calibration based on the characteristics of climate data. They are known as conditional and unconditional methods. A conditional process is established for the precipitation and evaporation data analysis as they are based on the local scale predictors i.e. it is assumed that there is an indirect connection between the data and predictors. During the calibration process, the NCEP Re-analysis data set is used in accordance with the specified year period for each predictand. The historical data of predictands, i.e. precipitation are divided into two segments: the first segment is used for calibration of the model and the second part of the dataset is used for validation as an independent dataset.

In SDSM, there are two ways to optimize the model output, one is Ordinary Least Square (OLS) method and the other one is Dual Simplex (DS). In the present study, OLS is used because it is faster than DS [13], [22]. The root mean square error (RMSE) and coefficients of correlation (R^2) were used to compare the performance of historical and simulated data of the model during calibration and validation period. The model was calibrated for the period from 1961-1995 and this period is used as the base period. The model is then used to simulate the daily rainfall for the period of 1996-2005 with the help of NCEP and CanESM2 predictors. This is used for validation of the model. The description of R^2 and RMSE of rainfall data is shown in Table-2.

Table-2: R^2 and RMSE value during Calibration and Validation of Model

Station Name	Calibration			Validation		
	R^2	RMSE	Nash Coefficient, E	R^2	RMSE	Nash Coefficient, E
Krishna	0.82	3.88	0.80	0.83	3.31	0.82
Guntur	0.77	3.29	0.78	0.69	3.34	0.81
Prakasam	0.81	2.91	0.71	0.86	1.99	0.70

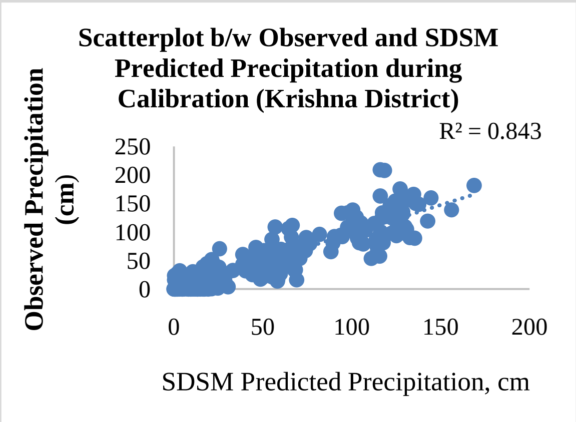
2.4.3 Calibration and Validation Analysis of SDSM

Coefficient of determination (R^2) and Root mean square Error (RMSE) for monthly precipitation at the three sub-basins namely Krishna, Guntur and Prakasam districts are given in Table-2. The values show that the model is capable of explaining monthly precipitation very well. The plot in Fig-5: (a-c) shows that there is good agreement between the observed and NCEP simulated precipitation throughout the year during the calibration and validation period and this is supported by the bar diagram as shown in Fig-6 (a-c). Season wise analysis of monthly precipitation data shows the satisfactory results. The RMSE value for calibration and validation period is less than the half of standard deviation value. As per the literature [23] it shows satisfactory handling of data for further analysis.

In the present study, for predicting the effect of climate change on precipitation trends, the CanESM2 GCM scenario, i.e. RCP2.6, RCP4.5, and RCP8.5 is used. The SDSM is used to find out the future rainfall for the period of 2005-2100 under various carbon emissions as mentioned earlier. The period from 1961-2000 is selected as the base period to visualize the changing pattern of rainfall. The selection of base period is based on suggestion made in different literature and these 40 years of data is sufficient to assess the transformation in climate. So, the prediction of future rainfall is based on the comparison of these two-time extents *i.e.* 1961-2000 and 2005-2100. After calibration and validation of SDSM, the model is used to downscale the large-scale predictor variables derived from the RCP2.6, RCP4.5, and RCP8.5 scenarios of CanESM2, with daily precipitation simulated for the following periods: historical (1961–2000), the 2020s (2005–2021), 2050s (2022–2051), 2080s (2052–2080) and 2100s (2081-2100). As mentioned above, the historical simulation (1961-2000) acts as a reference for future projection and changes. Predicted changes in annual mean precipitation during future periods (the 2020s, 2050s, 2080s, and 2100s) in the three basins namely Krishna, Guntur and Prakasam of AP are shown in Table 3. This shows a mixed pattern of positive or negative changes, with different trends in the 2020s and 2050s, and steady with the increases in the 2080s and 2100s. The trend shows that the overall amount of rainfall will increase significantly in all three basins of AP for the period of 2081-2100 as compared to the base period. There is a mixed trend in rainfall, under CanEsm2 scenarios of RCP2.6 and RCP4.5. In RCP2.6, we can see the mix trend of rainfall pattern i.e. sometimes the rainfall is increasing and in some decades it goes down. In RCP4.5 the trend is slightly higher than the base period for the 2020s and 2050s and in 2080s and 2100 it increases abruptly. The approximate predicted change up to the 21st century will be 19.5%, 18.5%, and 15.99% for Krishna, Guntur, and Prakasam basin respectively under the scenarios of RCP8.5. So, it can be predicted that the rainfall pattern in RCP8.5 is going to be increase significantly. The results of precipitation downscaling using SDSM are found satisfactory in nature. If we visualize the results on the seasonal basis, it can be seen that in JJAS (June-July-Aug-Sept) i.e. monsoon season there will be a large variation in rainfall under all the RCP scenarios, especially in Krishna, Guntur and Prakasam districts. In post-monsoon season i.e. ONV (Oct-Nov-Dec) it is seen that there may be significant precipitation at all three sub basins especially during RCP8.5. This indicates that the monsoon season may shift in future. The PBIAS bar diagram is shown in Fig-7.

Table-3: Projected future changes of a mean precipitation in the three basins of AP.

Scenario Variable	RCP2.6				RCP4.5				RCP8.5			
	2020s	2050s	2080s	2100s	2020s	2050s	2080s	2100s	2020s	2050s	2080s	2100s
Guntur ($\Delta P/P$ (%))	-1.69	-0.33	4.73	5.25	1.02	-1.78	7.07	8.59	5.82	5.38	9.27	19.51
Krishna ($\Delta P/P$ (%))	-0.22	1.25	-1.89	4.66	1.30	4.81	6.13	8.09	8.003	11.39	12.53	18.50
Prakasam ($\Delta P/P$ (%))	-1.08	2.70	1.53	5.05	1.05	2.80	5.17	10.7	4.32	9.18	10.85	15.99



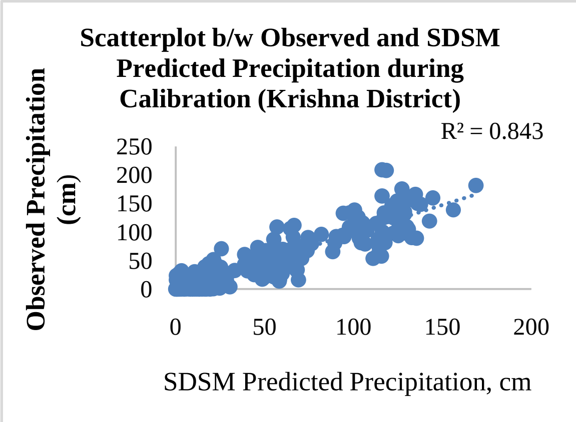
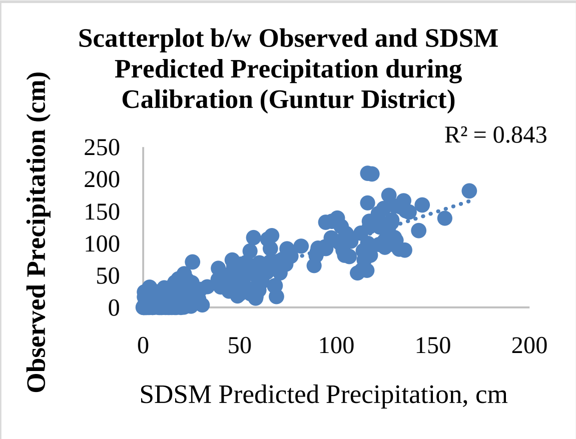


Fig-5(a)

Fig-5(b)



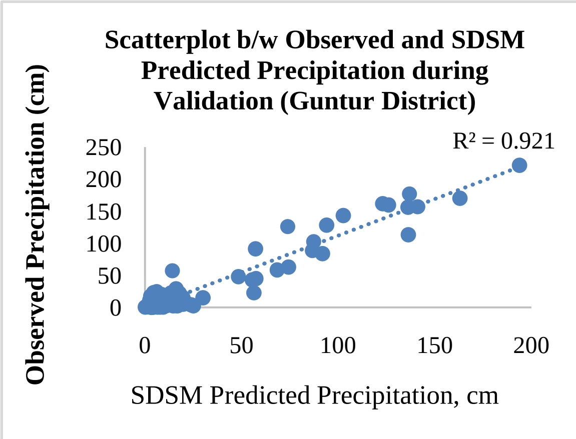
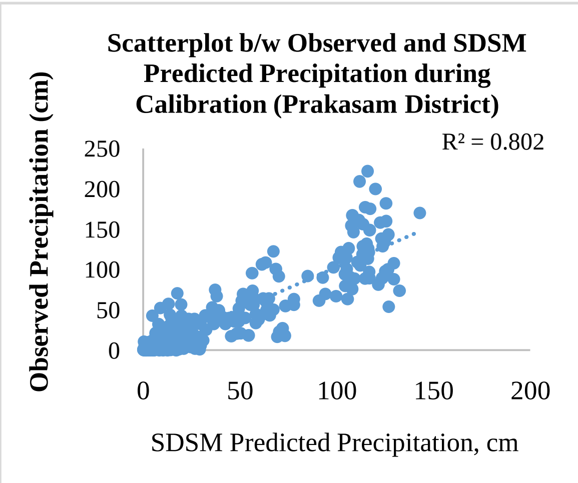


Fig-5(c)

Fig-5(d)



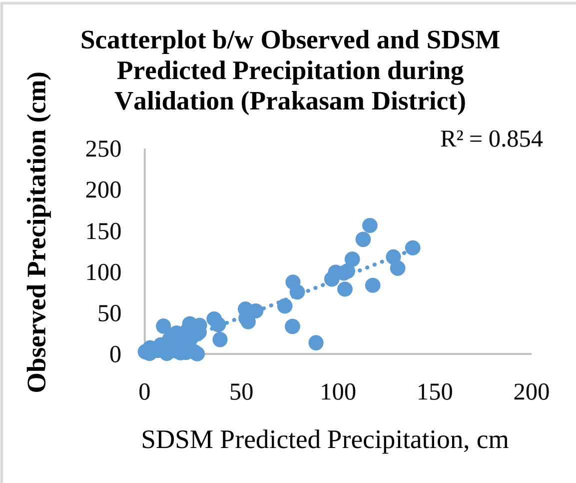


Fig-5(e)

Fig-5(f)

Fig-5 (a-f): Correlation between differentdatasets at 3 districts of AP

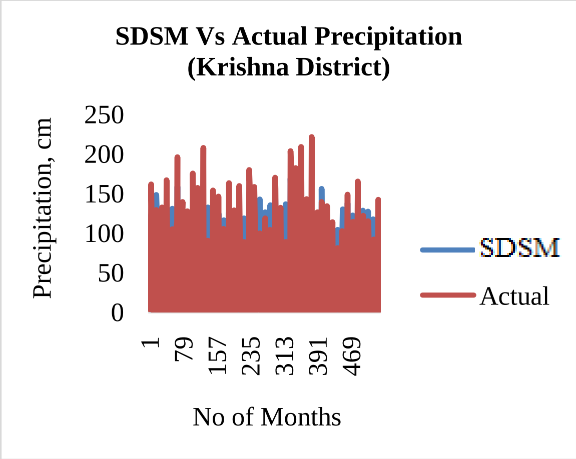


Fig-6(a): Plot between ANN and Actual Precipitation (Krishna)

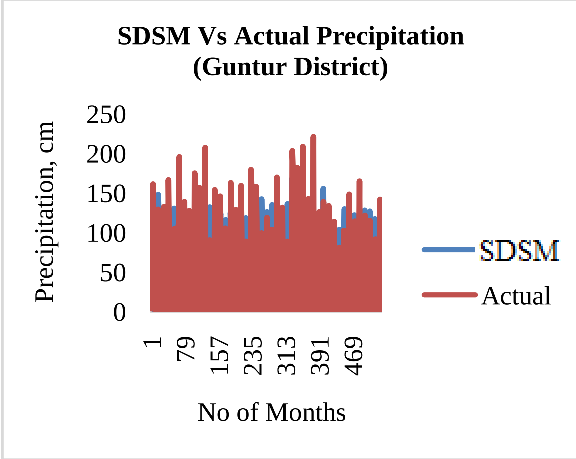


Fig-6(b): Plot between ANN and Actual Precipitation (Guntur)

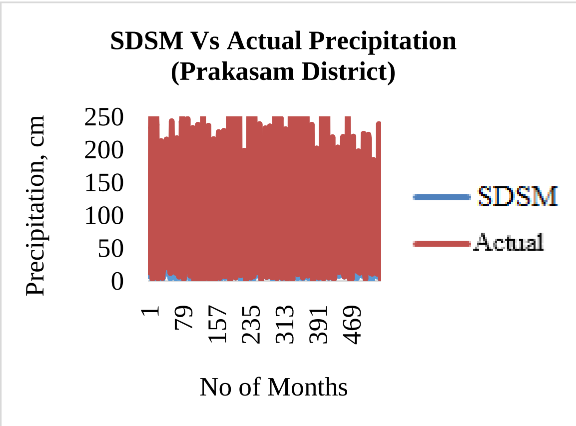


Fig-6(c): Plot between ANN and Actual Precipitation (Prakasam)

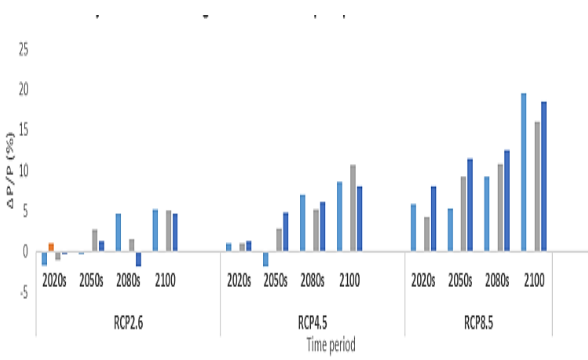


Fig-7: Showing PBIAS under different scenarios.

3. CONCLUSIONS

The present study attempted to forecast the rainfall pattern in three different basins: Krishna, Guntur and Prakasam. Nowadays SDSM is widely used for projecting the future trend of temperature and precipitation. In the present study, SDSM was applied to project the future change in Krishna, Guntur and Prakasamdistrictsusing the CanESM2 GCM having scenarios of RCP2.6, RCP4.5, and RCP8.5.

The ultimate purpose behind is to find out the projected change in precipitations in Krishna, Guntur and Prakasam districts. In this study, the historical data of three stations was used for the period of 1961-2000. This observed precipitation data is applied in the SDSM to choose the most effective predictors. The predictors or large scale parameters for model simulation are chosen based on the partial correlation (partial r) and p-values. The results show a reliable correlation between the modeled and observed results during the validation period. The result shows that the rainfall will increase under the entire RCP scenario especially in the case of RCP8.5. In RCP2.6, there is a little fall of rainfall in the 2020s and 2050s. The seasonal rainfall varies from one station to another, especially during the monsoon season where there will be very high rain, especially in RCP8.5 scenarios. In all the scenarios, it can visualize that the change in the rainfall is considerable after the 2050s. The changes in rainfall up to 2050s are not notable. However, in 2080, and 2100, the predictions are alarming in nature. The seasonal analysis of rainfall data also shows the shifting of monsoon trend up to September especially in case of RCP8.5. Besides, with the supposed rise of rainfall due to global climate change, the Krishna, Guntur and Prakasam districts of APwill continue to encounter vulnerability related to the flood.

Hence, based on the conclusions of this research, it is suggested that we should develop better mitigation measures to counter such heavy rainfall in the future. The policymakers and the local governments should focus on the better planning of water management in areas of Krishna, Guntur and Prakasam districtsespecially for water storage capacity and effective management of drainage system.

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