Statistical downscaling of rainfall under climate change in different sub-basin of Uttarakhand, India 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, it's 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 Uttarakhand one of the hilly state of 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 model was calibrated and validated using the NCEP and historical rainfall data. The results showed the values of R2 and RMSE for the model calibration and validation ranged from 0.84 – 0.92 and between 1.99 and 3.66, respectively for all three stations used in the study. The obtained future rainfall data from 2005 – 2100 was then correlated with the base period rainfall from 1961 – 2000. The trend shows that the overall volume of precipitation will increase in this region of all three basins of Uttarakhand for the period of 2051 –2100 as compared to the base period due to the change in climate. The approximate predicted change up to the 21st century will be 19.5%, 18.5%, and 15.99% for Jyosimath, Tehri, and Uttarkashi basin respectively under the worst scenarios of RCP8.5. Therefore, it is concluded that the future pattern of rainfall in Uttarakhand catchment under RCP4.5 and RCP8.5 constantly increasing, especially in the case of RCP8.5 due to the climate change. The selection of the study region is based on the concentration of flash flood events and cloudburst in that region.

Keywords— SDSM, Downscaling, Climate change.

I. Introduction

Uttarakhand, a Himalayan state of India, with more than 80 percent hill area[1]. The state is covered with forest and, located at high altitude. The most of the parts of the state have deep glacier mass. This geographical locality makes Uttarakhand more vulnerable towards the climate change. Uttarakhand is highly affected by frequent flash flood and cloudburst during monsoon season, especially at high altitude area. If we see the historical 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. We conclude the discussion as 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~~s~~ local-scale information on climate change studies. The projection made by the statistical~~ly~~ downscaling technique is by using long term ~~based on~~ historical data of precipitation or temperature to get a proper relationship with large-scales variable[19], [20]. The s~~S~~tatistical 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 ~~by~~ analyzing three distinguished CanESM2 scenarios of RCP2.6, RCP4.5, and RCP8.5. The working of SDSM model is shown below by figure 1.

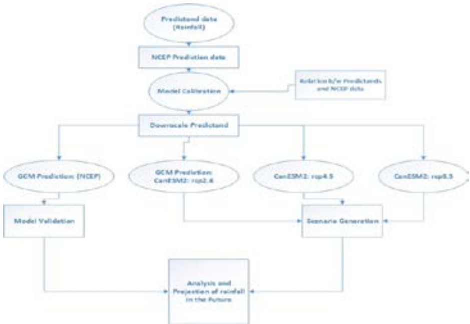


Fig. 1: The working of SDSM[14]

II. *Methodology*

Study area and Data used in downscaling process

A. Study area

Uttarakhand, a hilly state of India, located in the great Himalayas; lies between $28^0$43’ and $31^0$27’North latitudes and $77^0$34’ and $81^0$02’ East longitudes (Fig.2). The s~~S~~tate is spread in about 53,483sq.km of the geographical area. Out of the total geographical area, mountains and hills cover about 46,035 sq.km of the area. Along with the natural beauty, the state is also famous for cloudburst, landslide, and flash flood.

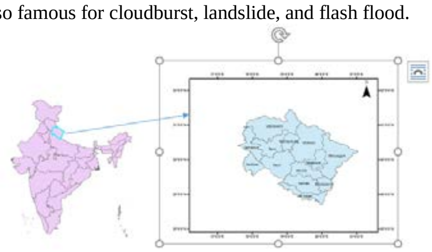
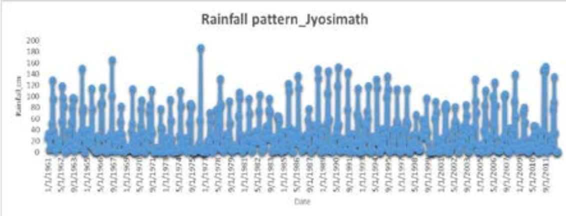


Fig.2: Location map of Study area.

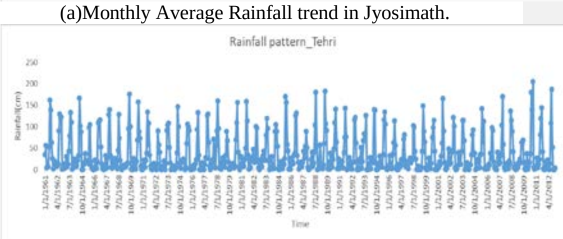
B. Data used:

Rainfall pattern

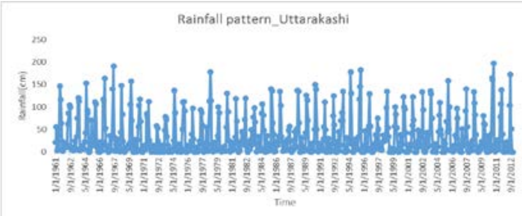
The Uttarakhand state receive~~encounter~~s massive precipitation in form of flash flood due its ~~to the~~ location at high altitude especially from June to August. Generally, the climate of ~~the~~ Uttarakhand is cold i.e. the average temperature is varying from 2^0c-8^0c, with a high wind velocity during the year. In the state, normal annual rainfall is about 1800 mm. To study the fluctuations of mean monthly rainfall patterns, three rain gauge stations at Uttarkashi, Jyosimath and Tehri are considered as representatives of the state. In all the mentioned stations the maximum rainfall is observed during the monsoon season. Fig: 3 (a-c) show the maximum average monthly rainfall at the rain gauge station~~s~~ of Uttarkashi, Jyosimath, and Tehri respectively. The average (July-August) rainfall in Uttarkashi, Jyosimath, and Tehri is ~~and which are~~ 560, 381, and 580 mm ~~in July-August,~~ respectively.



(a)Monthly Average Rainfall trend in Jyosimath.



(b)Monthly Average Rainfall trend in Tehri.



(c)Monthly Average Rainfall trend in Tehri.

Fig.3: (a-c): Mean monthly rainfall from three rain gauge stations in Uttarakhand.

The Thiessen polygons method~~:~~ is applied to calculate average precipitation ~~of all rain gauge station in Uttarakhand~~ at the

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three locations (~~@~~ Uttarkashi, Jyosimath and Tehri) of the state. The following equation is used.

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

Where, Pavg is the areal average precipitation over the watershed, Ai is the area of polygon i and Pi is the precipitation for polygon i. The integer n is the number of polygons and gauges. The location of rain gauges and the method describe above are shown in Figure 4 (a-b)

(a)

(b)

Fig.4 (a-b): Location map of rain gauges in Uttarakhand and Thiessen polygons method.

C. 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.

D. 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:

i. It has been extensively used in many catchments scales over a large range of different climatic situation around the globe by providing reliable results.

ii. It is user-friendly and openly available software which can be downloaded from https://copublic.lboor.ac.uk/cocwd/SDSM/.

iii. Different statistical analysis can be performed in SDSM to check the model validity.

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 ~~is~~ appropriate for downscaling of temperature. Equation 2 provides ~~is~~ the common description of a downscaling model as defined by Wilby et al., 1999.

$$Rt = F(XT) \quad \text{……………………… (2)}$$

Where Rt 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 is the methods used to establish the relationship between these two different spatial systems.

Selection of GCM Model:

Global climate change Model: CanESM2 predictors based~~:~~ on CMIP5 experiments is the~~: The~~ second generation Canadian

Earth System Model (CanESM2). It is ~~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 Scenario: 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 consider the highest and RCP2.6 consider the lowest scenarios of greenhouse gases that have been recently reviewed by the study based on climatic research. The different RCP Scenarios in this study is RCP2.6, RCP4.5, and RCP8.5.

STRUCTURE OF PREDICTOR/ LARGE SCALE DATASET FILES

A series of the graded daily value of long-term datasets are extracted into a single column text file per grid cell (box). This grid is uniform along the longitude with the horizontal resolution of 2.8125° and nearly uniform along the latitude of roughly 2.8125°.

Selection and screening of Predictor Variables for Downscaling process in case of Precipitation

Choosing a predictor is a major measure in the downscaling method since, it reflects the main output i.e. nature of the generated scenarios. In the SDSM, it is a cyclic process which lasts until we get the optimized objective function. The selection of large-scale predictors is a two-step process: firstly, we performed a correlation analysis between the NCEP reanalysis historical data with the past precipitation data to screen all the 26 predictor variables (NCEP Re-Analysis) for predictand data. Then the predictors having highest correlation are selected for further processing. Two statistical parameters namely, partial r and p-values are applied to describe the robustness of the association between the large-scale predictor and predictand. In general terms, the high value of correlation i.e. partial r shows a better degree of agreement between these two data and smaller p-values represent a valid possibility for an association between these variables i.e. between predictor and predictand. In the present study, we selected the most relevant predictors for the different catchments of Uttarakhand based the partial r and p-value and which is shown in in Table 2. The default value of significance level which is $p < 0.05$ is used to analyze the importance of predictor-predictand process. It was apparent that the partial correlations (partial r) among a set of predictor variables and each individual predictand were not great for analysis of daily precipitation data, which was supported by many researchers in their work.

Different Data used in SDSM

The data used for the climate change downscaling contain daily rainfall data obtained from Indian Metrological Department as predictand variables at a regional scale of Uttarakhand. The predictor variables which contains the historical NCEP data with the specific scenarios (RCP2.6, RCP4.4, and RCP8.5) inside the spatial grid cell ($2.8^0 * 2.8^0$) of the large-scale climate change GCM-CanESM2 model.

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

Table 1: ~~Metrological~~Meteorological stations used for downscaling

Station Name	Longitude(degree)	Latitude(degree)	Period(year)
Uttarkashi	78.44	30.72	1961-2012
Jyosimath	79.55	30.56	1961-2012
Tehri Garhwal	78.48	30.33	1961-2012

Table2: Partial r and P-Value of correlation of large scale predictor variables and predictands

Predictor / Predictand	850 hPa meridonial velocity(ncepp8_vgl)	Total precipitation(nceprcpgl)	Specific humidity at 500hPa(nceps500gl)	Surface specific humidity(ncepshumgl)	Ncep1_zgl	Ncep850gl	Ncep1_vgl
Partial r and P-Value	Partial r/ P-Value	Partial r/ P-Value	Partial r/ P-Value	Partial r/ P-Value	Partial r/ P-Value	Partial r/ P-Value	Partial r/ P-Value
Uttarkashi_ Precipitation	0.56/.012	NA	0.36/0.011	0.41/0.04	0.22/0.04	0.51/0.00	0.29/0.00
Jyosimath_ Precipitation	NA	NA	0.64/0.021	0.32/0.03)	0.43/0.001	0.34/0.01	0.228/0.00
Tehri_ Precipitation	.43/.031	.34/0.01	0.56/0.014	0.31/0.01	0.32/0.01	0.37/0.00	NA

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E. 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-Reanalysis 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) was 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 3.

Table3: R^2 and RMSE value during Calibration and validation of Model

	Calibration			validation		
Stations	R^2	RMSE	St deviation	R^2	RMSE	St deviation
Jyosimath	0.77	3.69	12.70	0.69	3.34	15.90
Tehri	0.82	2.88	21.01	0.83	3.31	20.10
Uttarkashi	0.81	2.91	22.21	0.86	1.99	25.20

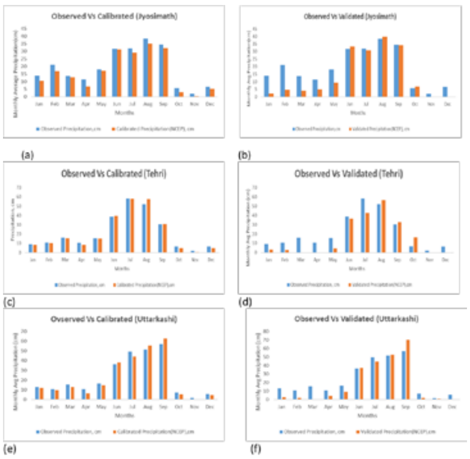


Fig. 5:(a-f) Showing observed, calibrated and validated precipitation at different basin of Uttarakhand.

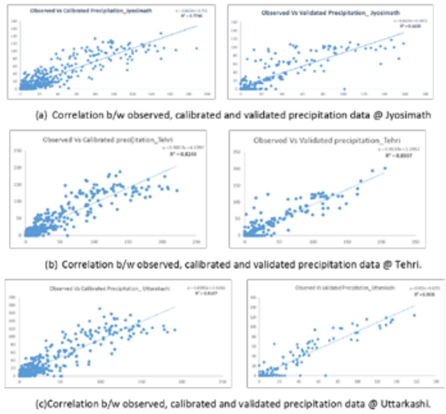


Fig.6 (a-c): Correlation between different data set

Calibration and validation analysis of SDSM

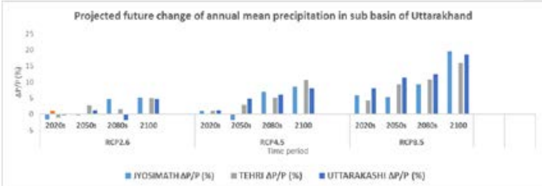
Coefficient of determination (R^2) and Root mean square Error (RMSE~~SE~~) for monthly precipitation at the three sub-basins ~~in the study area~~ of Uttarakhand are given in Table 6. The values ~~, which~~ shows that the model is capable of explaining monthly precipitation very well. The plot in Figure 6 (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 Figure 5 (a-f). 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. A ~~and as~~s per the literature ~~review~~[23] it shows satisfactory handling of data for further analysis.

III. RESULTS

In the present study, for predicting the effect of climate change on precipitation trends, the ~~for~~ CanESM2 GCM scenario, i.e. RCP2.6, RCP4.5, and RCP8.5 is used. T~~All these scenarios are displayed in t~~he SDSM is used to find out the future rainfall for the ~~time~~ period~~span~~ 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 ~~review available~~ and this 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 Jyosimath, Tehri, and Uttarkashi of Uttarakhand are shown in Table ~~:~~4. This ~~given below, which~~ 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 ~~this region of~~ all three basins of Uttarakhand for the period of 2081 –2100 as compared to the base period ~~due to the change in climate~~. While 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 Jyosimath, Tehri, and Uttarkashi basin respectively under the scenarios of RCP8.5. So, it can be predicted that frequency of flash flood and cloudburst 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 ~~we found that While~~ in JJAS (June-July-Aug-Sept) i.e. monsoon season there will be a large variation in rainfall ~~pattern~~ under all the RCP scenarios, especially in Tehri and Uttarkashi watershed. In post-monsoon season i.e. ONV (Oct-Nov-Dec) it is seen that ~~we also found~~ there may be significant precipitation at all three sub basins especially during RCP8.5. This indicates that the~~, which may show the shifting of~~ monsoon season may shift in future. The PBIAS bar diagram is shown in Figure 7.

Table 4: Projected future changes of a. mean precipitation in the three basins of Uttarakhand

Scenario	RCP2.6					RCP4.5				RCP8.5			
variable	2020s	2050s	2080s	2100		2020s	2050s	2080s	2100	2020s	2050s	2080s	2100
Jyosimath(ΔP/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
Uttarkashi (ΔP/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
Tehri (ΔP/P (%))	-1.080	2.70	1.53	5.05		1.05	2.80	5.17	10.7	4.32	9.18	10.85	15.99



IV. CONCLUSION

Uttarakhand is a~~the~~ hilly state of India, facing severe ~~so much~~ destruction due to landslides, cloudburst and flash flood. The present study attempted to forecast the rainfall pattern in three different basins of Uttarakhand. 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 rainfall in the different sub-basins of Uttarakhand using the~~, for~~ ~~GCM~~ CanESM2 GCM having scenarios of RCP2.6, RCP4.5, and RCP8.5. The ultimate purpose behind is to find out the projected change in precipitation in different sub-catchments of Uttarakhand ~~is to see the impact of climate change on flood vulnerability~~. In this study, the historical data of three stations was used for~~rom~~ the period of 1961-2000. This observed precipitation data is applied in the SDSM to choose the most effective predictors. ~~to which are capable to measure the future change.~~ 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 ~~of SDSM predicted~~ that the rainfall will ~~be~~ increased under all the 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 Uttarakhand will 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 ~~trends~~ in the future. The policymakers and the local governments should focus on the better planning of water management in hilly areas of Uttarakhand, especially for water storage capacity and effective management of drainage system.

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