Incorporation of Long Term Climate Changes in Hydrological Modelling

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Abstract*: One of climate change's most important concerns at the moment is its impact on hydrology as it has direct links with agriculture, vegetation, and livelihood. This study tries to analyze potential future climate change in the Kumaradhara river basin. This study involved three steps: (1) acquiring and using general circulation model (GCM) to project future global climate scenarios; (2) establishing statistical relationships between GCM data and observed data using Statistical Downscaling Model (SDSM); (3) downscaling the second generation Canadian Earth system Model (CanESM2)GCM output based on the established statistical relationship. The statistical downscaling is carried out for three scenarios used in the fifth evaluation report of the recent Intergovernmental Panel on Climate Change (IPCC) viz., Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5. The statistical downscaling Model (SDSM) results showed that the mean annual daily precipitation is altered in the basin under all the scenarios but it will be different in different time periods depending on scenarios and the basin will experience the reduced precipitation levels in summer. Also the precipitation will marginally rise in all the time slices with reference to baseline data. We can conclude from the results that this region's climate will affect future farming as the availability of water is bound to change. This study should, however, be followed up by a larger study incorporating multiple CMIP5 models such that changes in hydrological-regimes can be examined appropriately.

Keywords: climate change impacts; general circulation model; CanESM2; RCPs; Statistical downscaling; SDSM

I. INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) has examined climate extremes and theirs impacts on environment. Variations in solar radiation received by earth, biotic processes and certain human activities are identified as preliminary causes for climate change. Simulation of interactions of drivers of climate is done using climate models including ocean, atmosphere, ice and land surface. Many climate models are used for impact assessment. Any rises in global temperature due to doubling of carbon dioxide (CO2) concentrations are predicted using General Circulation Models / Global Climate Models (GCM).

General Circulation Models (GCMs) use three dimensional grid and physical processes such as those in the atmosphere, land, surface and ocean are represented using numerical models. GCMs discretize the equations for energy transfer and fluid motion which are integrated overtime. Decision makers and planners use scenarios to analyze the situations in which results are uncertain. Long term consequences of climate change and the plausible climate pathways are predictable using GCM. The GCM which is described above simulate weather in different atmospheric layers and the resulting output is coarse, typically in the range of 2 to 5 degrees (~200 to 500 KM).

Users need climate data on scales smaller than the GCM grid. This can be obtained by downscaling the GCM. High resolution details can be derived from low resolution variables using the technique of downscaling. Statistical and dynamical downscaling are two types of downscaling techniques. Due to the high computational requirements dynamical downscaling is not preferred. Statistical downscaling technique is adopted in the present study.

Statistical Downscaling Model (SDSM) version 4.2 which is free software was used. It is a hybrid of regression based and stochastic weather generators where the correlation of Predictand (local scale variable) and Predictors (large scale atmospheric variables) are performed. The Canadian Climate Impacts and Scenario project (CCIS) has suggested Statistical Downscaling Model as an appropriate tool for downscaling.

The structure of this paper is as follows. In Section II the outline of study area and datasets obtained for the analysis is described. Section III outlines the methodology adopted in this study. The assessment of changes in climate comparing them with baseline period of downscaled CanESM2 GCM output and observed data is depicted in Section IV. The Summary and conclusions are outlined in the Section V. In our analysis we limit our focus by comparing the observed and modeled downscaled daily precipitation data for one GCM model considering single site data.

Research Objectives:

General objective - To assess the impact of climate change on Kumaradhara river basin.. Specific objectives are as follows.

* To establish the statistical/empirical relationship between atmospheric climate variables (Predictors) on a large scale and local climate variable (Predictand), i.e. precipitation using statistical downscaling

*Projecting future precipitation by applying the established statistical relationships and using GCM outputs for RCPs (Representative Concentration Pathways) 2.6, 4.5 and 8.5 scenarios

* To check capability of statistical downscaling model (SDSM)

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II. STUDYAREA & DATA SETS

Study area

Western Ghats or the ranges of Sahyadri form a mountain range along India's western coast. This range is situated along the western edge of the Deccan Plateau from north to south, separating the plateau from a narrow coastal plain along the Arabian Sea. The range starts near the Gujarat and Maharashtra border, south of the Tapti River, and runs through the states for a length of 1,600 KM.

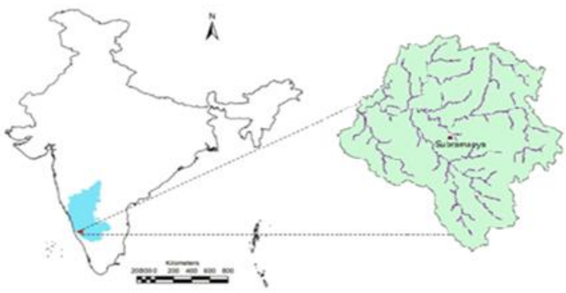

Figure 1- Location of Kumaradhara river basin

The river Kumaradhara originates in the central Western Ghats at an altitude of 1480 m in Kodagu and the river falls to 33 m in Uppinangadi, Puttur Taluk and joins the Netravathi River as shown in Figure 1.The river basin of Kumaradhara ranges from 12^{o}29'4 "to 12^{o}58'33" N and 75^{o}9'58 "to 75^{o}47'48" E having catchment area of 1780 sq KM. The basin of the river is spread over three districts: Hassan, Kodagu and Dakshina Kannada. The rain gauge station considered in this study is a village, Subramanya, which is located in Dakshina Kannada district in Karnataka state having co ordinates as 12 ° 39′ 49.71″ N, 75 ° 36′ 55.3″ E (12.66 N,75.61 E).

The Kumaradhara basin's climate is characterized by heavy rainfall and high humidity. The year is divided into four seasons according to the Indian Meteorological Department (IMD). Approximately 92% of the rainfall occurs during the monsoon season in the south-west and north-east, and the remaining 8% of the rainfall occurs in the remaining period. The river is located Western Ghats of Malnad region, with moderate hills & linear ridges having undulations in the topography. The precipitation in the basin ranges from 3250 mm to over 4250 mm per year.

Data used

Local scale data (Predictands): The daily precipitation record for rain gauge station located at Subramanya for the period 1961 to 2005 was obtained from the IMD.

Global scale Climate data (Predictors): The atmospheric reanalysis variables i.e., large-scale climate variables from the National Center for Environmental Prediction (NCEP) contains past global climate variables for validation and calibration of the SDSM. In this study we have used the Second generation Canadian Earth System Model i.e., CanESM2. The outputs of CanESM2 under three emission scenarios viz., Representative Concentration Pathway (RCP) 2.6, 4.5 & 8.5 of Intergovernmental Panel on Climate Change (IPCC) fifth assessment report. This data set has a grid spacing of 2.8° by 2.8°. Prior to statistical downscaling predictors are normalized as a final step.

III. METHODOLOGY

The downscaling of the meteorological variables obtained as output from the CanESM2 under IPCC assessment report (V) of emission scenarios for Representative Concentration Pathways (RCPs) 2.6, 4.5 and 8.5 is performed using SDSM 4.2. The CanESM2 output and the NCEP project reanalysis data provided the same set of 26 predictor variables as shown in Table 1. The model is validated for the baseline period along with the downscaled outputs of GCM. The changes in the mean precipitation in the study area between present and future scenarios are investigated.

Table 1 – The details of Predictor variables associated with CanESM2

SL. No	Predictors	Description of Predictors
1.	mslpgl.dat	Mean sea level pressure
2.	p1_fgl.dat	1000hpa Windspeed
3.	p1_ugl.dat	1000hpa Zonal wind component
4.	p1_vgl.dat	1000hpa Meridional wind component
5.	p1_zgl.dat	1000hpa Relative vorticity of wind
6.	p1thgl.dat	1000hpa Wind direction
7.	p1zhgl.dat	1000hpa Divergence of true wind
8.	p500gl.dat	500hpa Geopotential
9.	p5_fgl.dat	500hpa Wind speed
10.	p5_ugl.dat	500hpa zonal wind component
11.	p5_vgl.dat	500hpa Meridional wind component
12.	p5_zgl.dat	50 hpa Relative vorticity of wind
13.	p5thgl.dat	500hpa Wind direction
14.	p5zhgl.dat	500hpa Divergence of true wind
15.	p850gl.dat	850hpa Geopotential
16.	p8_fgl.dat	850hpa Wind speed
17.	p8_ugl.dat	850hpa Zonalwind component
18.	p8_vgl.dat	850hpa Meridionalwind component
19.	p8_zgl.dat	850hpa Relative vorticity of wind
20.	p8thgl.dat	850 hpa Wind direction
21.	p8zhgl.dat	850hpa Divergence of true wind
22.	prcpgl.dat	Total precipitation
23.	s500gl.dat	500hpa Specific humidity
24.	s850gl.dat	850hpa Specific humidity
25.	shumgl.dat	1000hpa Specific humidity
26.	tempgl.dat	Air temperature at 2m

Statistical Downscaling Model (SDSM)

Empirical relationships between GCM-climate variables and local climate are established by SDSM in a simplified way as shown in Equation 1.

$$R= Y(X) \tag{1}$$

Where R: the predictand (a local climate variable), Y: the predictor (a set of large climate variables), and X is the L-conditioned deterministic / stochastic function and is empirically estimated from historical observations.

Statistical downscaling has several advantages when compared to the use of raw GCM output resulting from the model's stochasticity.

The statistical downscaling of daily precipitation was carried out as follows. The facilities provided for the respective function by the SDSM 4.2 *Quality Control* function helps to check input data errors which provide general information such as mean value, maximum and minimum value, number of missing data, total number of values, etc. The *data transformation* operation provides the ability to transform either the predictor variable or predictand by choosing desired transformation form. We have used a fourth root transformation to the original series so as to convert it to a normal distribution. This normal distribution is then used for regression analysis. The SDSM option for *Screen variables* provides a sophisticated tool to determine the most suitable predictor variables. It has options to select a monthly, seasonal or annual correlation between predictand and predictor variables. It also provides partial correlation and scatter plot to determine which set of predictor variables to choose from. Selection of predictor variables forms a very important step in Statistical downscaling. Improving the output of SDSM's is achieved by selecting appropriate predictor variables and developing the predictor-predictand relationship. Therefore, predictor choice determines the character of the downscaled climate scenario.

The *Calibrate Model* uses an optimization algorithm (usually ordinary least squares) and calculates the multiple regression equation parameters after enabling each of the predictand and a set of likely predictors. The Monthly model type is selected to derive model parameters for individual month. 30 years of data (1961–1990) are used to calibrate the regression model from the 45 years of data representing the current climate, whereas 15 year data (1991–2005) are used for validation.

The *Weather generator* helps validate the model that has been calibrated. This operation generates synthetic daily weather data sets for the specified period using regression model weights or parameter file prepared during model calibration and NCEP reanalysis dataset large-scale atmospheric predictor variables. The record period to be synthesized and the number of ensembles can be changed as required. For the period from 1991 to 2005, synthetic daily series of rainfall were generated.

Synthetic daily weather data series were generated using GCM CanESM2 data using the *Scenario generator* operation of SDSM. After the model is validated, the same file parameter or regression weight used during the operation of weather generation is used to downscale future data. But this time, output of CanESM2 is used as large scale atmospheric predictor sets instead of using data from NCEP reanalysis. CanESM2 has three emission scenarios, namely 8.5, 4.5 and 2.6 Representative Concentration Pathways (RCPs). Ensembles of daily rainfall synthesized data were generated for each emission scenario for all variables and stations for the period 2006 to 2099, and the average of these ensembles was used for the specified period as final daily weather data. We repeated the same procedure to generate future rainfall data for all RCPs. On all downscaled precipitation values, *summary statistics* operation is performed. Once again, it is possible to compare the data statistics under baseline and future climate forcing by using the *Compare results* and *Time Series Analysis* operation.

IV. RESULTS AND DISCUSSION

Selection of predictor variables

Following the preliminary analysis (quality control, data transformation) of the all predictors, the predictors available from the NCEP reanalysis data were selected to be used to calculate the correlation coefficient (partial r). Checking the association of predictors and predictand, the final set of predictors are selected. The mean percentage of the variance and the mean standard error obtained as a result of the calibration of station is determined.

For the Subramanya station i.e., for Kumaradhara basin, the dominant predictor variables selected for precipitation were - mean sea level pressure, 1000 hPa zonal wind component, 850 hPa Wind speed, 850 hPa zonal wind component, 850hPa Geopotential, Total precipitation, 850 hPa Specific Humidity. They are shown in Table 2.

Table 2 - Predictor variables for Kumaradhara basin

Predictor-Variables	*Partial r-value*	*Partial p-value*
ncepmslpgl	-0.062	0.000
ncepp1_ugl	0.084	0.000
ncepp8_fgl	0.069	0.000
ncepp8_ugl	0.066	0.000
ncepp850gl	-0.067	0.000
nceprcpgl	0.091	0.000
nceps850gl	0.239	0.000

Calibration and Validation of SDSM

Model was calibrated based on the predictor variables generated from the NCEP dataset. The observed data sets of 1961-2005 (45 years) were divided into two periods. The initial 30 years (1961-1990) data was used for calibration while the remaining 15 years (1991-2005) data was validated. The explained variance E and mean standard error for daily precipitation obtained as a result is 26% and 0.287 respectively prior to bias correction. The adjustment of variance-inflation and bias-correction is also made during calibration. Variance inflation helps to control the value of variance in downscaled daily weather variables while bias correction compensates for the tendency of the downscaling model's to overestimate and underestimate the mean of precipitation, wet-days-percentage etc. While the default value of 12 produces about normal Variance Inflation (VI), there is no Bias Correction (BC; default value 1). Both the values viz. VI and BC were adjusted several times. The adjustments were done till VI and BC reach best statistical agreement between observed and simulated outputs for precipitation. Similar procedure to calibrate all variables is followed. The comparative graph between observed and downscaled modeled data for monthly mean of daily precipitation demonstrated good results that are shown in Figure 2, 3, 4, 5, 6 and 7. However, simulation has underestimated the mean dry-spell length in the basin. Improving this result was difficult as several attempts to increase the dry-spell length in simulation spontaneously affected the other variables that were well calibrated earlier.

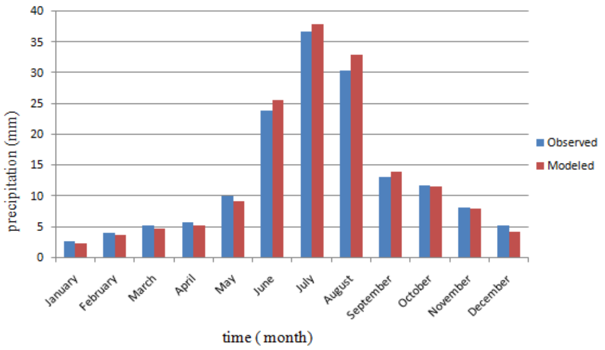

Figure 2- Comparison plots of average monthly precipitation during calibration period (1961-1990)

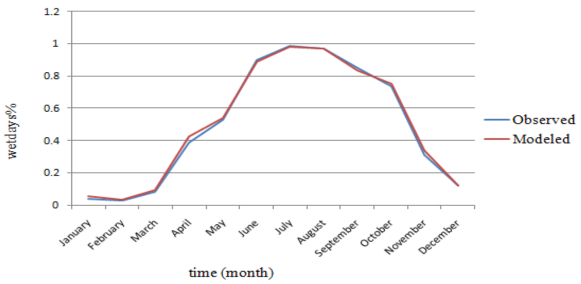

Figure 3- Comparison plots of percentage of average monthly wet days during calibration period (1961-1990)

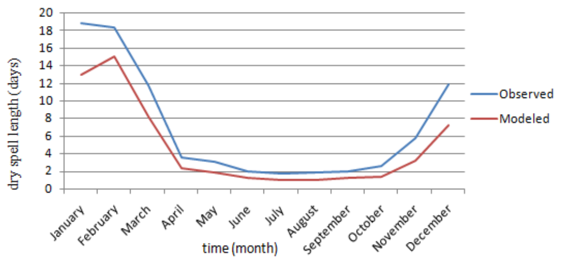

Figure 4- Comparison plots of average monthly dry spell lengths during calibration period (1961-1990)

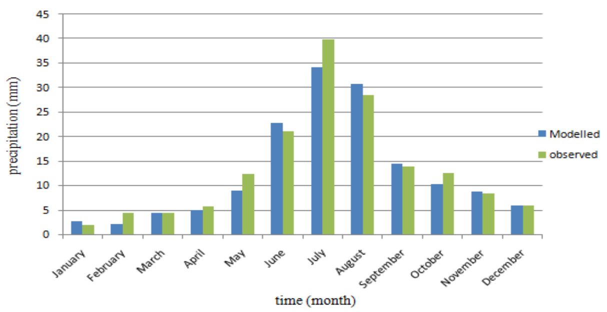

Figure 5- Comparison plots of average monthly precipitation during validation period (1991-2005)

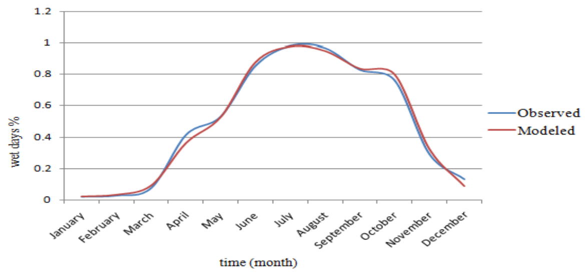

Figure 6- Comparison plots of percentage of average monthly wet days during validation period (1991-2005)

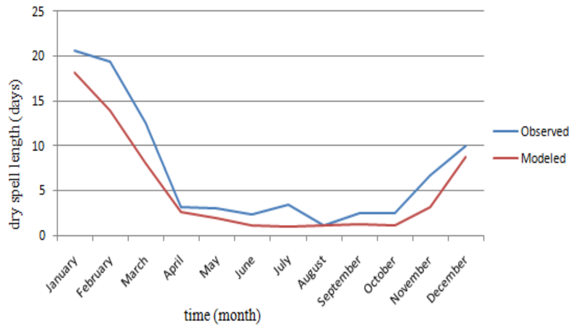

Figure 7- Comparison plots average dry spell lengths during validation period (1991-2005)

Projected Change in Climate Variables

Future climate variables at Kumaradhara basin were analyzed by considering future data into three time slices, i.e., 2006-2035, 2036-2065 and 2066-2095, which is considered hereafter as the 2020s, 2050s and 2080s. In order to analyze the climate changes of future climatic variables, the period 1976 to 2005 was considered as the baseline. The precipitation projection neither showed a consistent increase nor decrease. The model showed the reduction in mean daily precipitation under RCPs 4.5, 8.5 in 2020 compared to RCP 2.6 and an increase in precipitation under RCP 4.5 & RCP 8.5 in 2050s compared to RCP 2.6. Under RCP 2.6 & 8.5 scenarios, precipitation increases during 2080s compared to RCP 4.5. The mean annual precipitation minimally increased under RCP 2.6 during 2020s and 2080s, and marginal decrease in the middle of 2050s. Under the RCP 4.5, precipitation will decrease slightly in the 2020s and increase in the 2080s and 2050s. Similarly, RCP 8.5 projected the possibility of declining precipitation in the 2020s and increase in precipitation in 2050s and 2080s. For the three time slices, mean daily precipitation increased as compared to the baseline period. The observed increase was different in different months in which there will be some months of increased precipitation and others of decreased precipitation. The projections of monthly mean precipitation for the present and future periods under RCPs 2.6, 4.5& 8.5 are shown in Figure 8, 9 and 10. The change in wet days percentage at various time slices for each month for the basin are also shown in Figure 11, 12, and 13. The precipitation was projected at three time slices and under different scenarios was found to vary. The projected percent change in the future precipitation for Kumaradhara basin under three different scenarios at different time slices are depicted in Table 3.

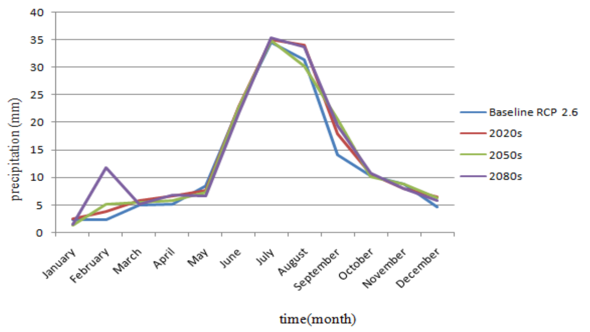

Figure 8 - Projected monthly mean precipitation for the present & future periods under RCP 2.6

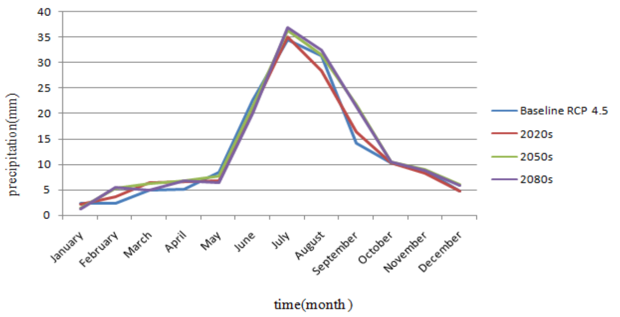

Figure 9 - Projected monthly mean precipitation for the present & future periods under RCP 4.5

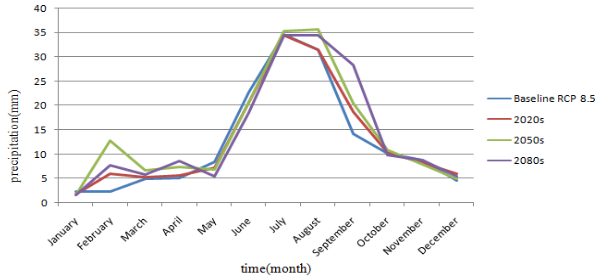

Figure 10 - Projected monthly mean precipitation for the present & future periods under RCP 8.5

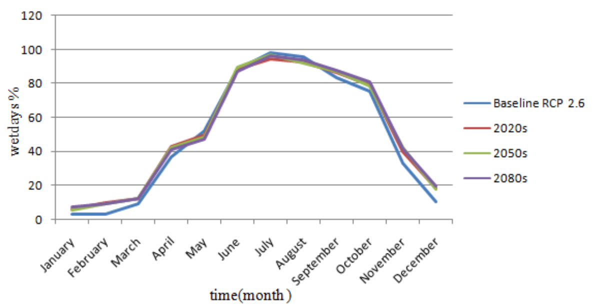

Figure 11 - Projected changes in percentage of wet days for the present & future periods under RCP 2.6

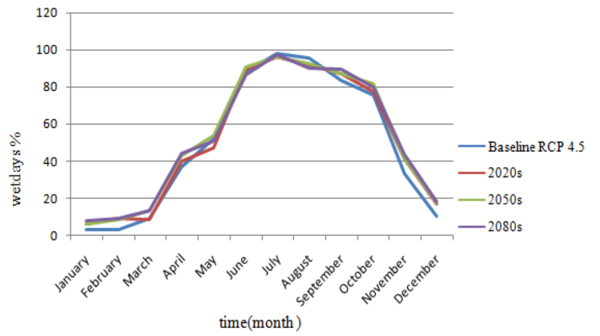

Figure 12 - Projected changes in percentage of wet days for the present & future periods under RCP 4.5

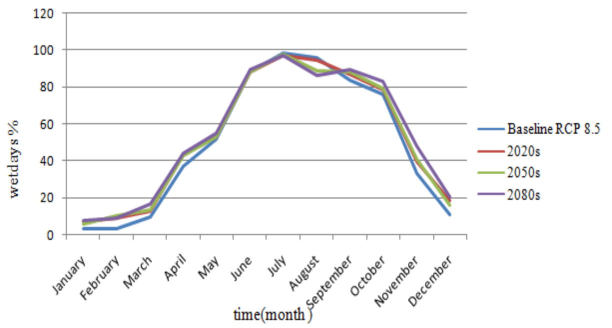

Figure 13 - Projected changes in percentage of wet days for the present & future periods under RCP 8.5

Table 3 - Projected percent change in the future precipitation at different time slices

RCP	2020 s	2050 s	2080 s
RCP 2.6	8.57945	6.479885	11.82114
RCP 4.5	0.279607	9.7814	7.682401
RCP 8.5	4.317885	14.12884	12.93334

V. CONCLUSIONS

The basin is predicted to experience reduced precipitation levels during summer. The future pattern of rainfall is altered due to climate change under all the scenarios and affects farming. The marginal rise in precipitation levels is seen with respect to baseline data. Statistical Downscaling Model (SDSM) is built on certain criteria; hence the real world may have significantly different results compared to the results of the study. SDSM can efficiently predict mean values and the trend of changes.But it is limited because special local weather events may not be captured by the model. Modeling the climate system is a theoretical approach which may not precisely happen as projected;

also variables related to human beings (e.g. GHGs emissions, burning of fossil fuel etc) are unpredictable.

VI. LIMITATIONS OF THE STUDY

The study on impacts of climate changes on Kumaradhara river basin is limited because it considers one GCM and analysis is carried out for a single site. Also several assumptions are involved in SDSM.

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