Climate Change Impact Assessment on the Precipitation over the Ghataprabha Sub-Basin, India under Future Climate Change Scenarios

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Abstract

The present study has been taken up to quantify the possible impacts of the climate change on the climate variables using the outputs of global climate models datasets over the Ghataprabha Sub-basin. The climate variables (precipitation, maximum and minimum temperature) data from the five selected global climate model dataset were downscaled using change factor method under four representative concentration pathway (RCP 2.6, 4.5, 6.0, and 8.5) scenarios for future periods near-century (2010-2039), mid-century (2040-2069), and end-century (2070-2099). The downscaled results of all the five models were ensembled using multi-model ensembling method to reduce the uncertainty in the projected results and the percentage change in the climate variables were shown with respect to the historical/baseline period (1961-1990) using spatial plots and histograms. The future projected results shows that percentage change in the annual mean precipitation with respect to the historical (1961-1990), is decreasing for most of the grids in the study area during the near-century while during mid and end centuries it shows an increasing trend across all the four RCP scenarios. The average daily minimum and maximum temperature with respect to the historical (1961-1990) values were showing an increasing trend in the study area during the near, mid, and end centuries across all the four RCP scenarios. Further, study also analysed the percentage change in 100-year return level over the study area.

1. Introduction

Water is a fundamental entity for the development of industries, irrigation activities, and economic growth. However, due to increased population and industrialization water has become inadequate to our growing demand, and also it has become a scanty resource. The changing climate does have more effect on water resources and their quality. The Surface temperature of the earth is increasing gradually and will likely to impact the availability of water and its demand across the world. The rise in the mean surface temperature by 4.4°C by end of this century (Krishnan et al., 2020) will give away uncertainties on predictions of extreme events and for implication of strategies on varied zones of India (Yaduvanshi et al., 2020). Further, the study by Wang et al. 2021 show anthropogenic activity is the dominant cause of observed warming, since the mid-20th century. In view of this, global warming and its effects on human societies, regional availability of water, agricultural productivity, etc. have drawn considerable attention.

Climate change is the global scenarios and is affecting the Indian sub-continent regions due to changes in the patterns of precipitation, temperature and frequency of extreme events (Basheer and Pandey 2021, Dash et al., 2021, and Dhimal et al., 2021). Extreme events can have major impacts on humans and ecosystems leading to disasters such as floods and landslides (Tuel and Martius 2021). Government in the developing nations haven't been able to effectively address challenges posed by climate change. And, to date very few researchers have analyzed the climate change impacts on hydrological cycle, water use and livelihood at regional level in an integrated manner (Patil and Laddimath, 2021). Thus, it makes sense and urgent need to develop necessary basin level adaption strategies. Regional scale assessment helps to understand the implications of changing climate with sensitive cardinal variables such as precipitation and probable effects on natural resources so that policy makers can develop the strategies for suitable mitigation and adoption plans to combat the calamities such as floods and droughts. On such study by Chandole et al. (2019) to assess the climate change impacts used sensitive hydro-meteorological parameters namely, precipitation and temperature via trend detection to bring in the policy for watershed management. Thereby, investigations of regional and global climatic changes and variability and their impacts at regional scale assessment have received considerable attention in recent years. Statistical downscaling in spite having limitations (Tukimat et al., 2019) is found effective by many researchers owing to its less complications and computational efforts in comparison with downscaling (Laddimath and Patil, 2019). This technique finds it's predominate applications on the themes of water resources in response to hydrological modeling for regional assessments of changing climate (Gupta and Jain, 2018; Bhatta et al., 2019; Rajashekhar et al., 2020; Pandey et al., 2021).

For the present study Ghataprabha river sub-basin, was selected as a study area, as it has a semi-arid condition, receives a major portion of rainfall during ISMR, and vulnerable to change in the climate. It is observed from the literature, there is a lack of study regarding the regional scale climate change impacts assessment over the Ghataprabha Sub-basin. This study attempts to deliver the information about the future climate change impacts on the climate variables like precipitation, maximum and minimum in the Ghataprabha sub-basin, under different climate change scenarios. Reddy et al. (2021) projected an increasing trend in the annual mean rainfall and temperature under future scenarios during the study period. The study also incorporates ensembling of GCMs as the climatic models developed by various organizations across the globe failed miserably in capturing the reality as they ignore the fundamental and intrinsic processes which dominate the climate.

2. Material And Methods

2.1 Study Area

The Ghataprabha River sub-basin (K3), of Krishna basin, India was selected as a study area. The sub-basin has a predominantly semi-arid condition. River catchment lies approximately between $15^{\circ} 45'$ and $16^{\circ} 25'N$ latitudes and $74^{\circ} 00'$ and $75^{\circ} 55'S$ longitude (Fig. 1). The total area of river catchment is 8829km^2 out of which 77.2% lies in Karnataka and the rest 22.8% lies in Maharashtra. Except for hillocks and valleys, most of the catchment area is flat to gently undulating. Hiranyakeshi, Markandeya, and Tamraparni are the principal tributaries of the Ghataprabha River (Biggs et al., 2007). The sub-basin is more vulnerable to change in the climate, prone to the variable rainfall distribution and the warmer weather conditions as well. According to the national water development agency (NWDA) of India, the majority of the sub-basin area is covered by agricultural activities (63.7%) and forest area of 12.6%, any changes in the climate will have profound effects on the water security and socio-economic development.

2.2 Observe Data

In this study, high-resolution precipitation ($0.25^{\circ} \times 0.25^{\circ}$) data obtained from the India Meteorological Department (IMD), Pune, and $1^{\circ} \times 1^{\circ}$ gridded temperature data downloaded from the SWAT website were used for the study area. Other observed data like solar radiation, relative humidity, and windspeed were downloaded from NCEP/NCAR reanalysis 1 datasets (Kalnay et al. 1996). However, all the data's are regridded to IMD 0.25° precipitation grid location by 2D linear interpolation technique to make it consistent with IMD precipitation grids.

2.3 Climate Models

According to current research, GCMs are the robust and credible tools used in climate change impact assessment studies. GCMs are available at coarse resolution and are not suitable to use for the sub-basin scale studies. This mismatching of scale can be resolved using the downscaling techniques (Fowler et al. 2007). There are two kinds of downscaling techniques namely dynamical downscaling and Empirical downscaling. Dynamical downscaling is a nesting of regional climate models (RCMs) within GCM data and derives the local climate information using complex algorithms. RCMs need a high computational cost in building a downscaling model (Haas and Pinto, 2012). Empirical downscaling techniques derive the statistical relationship between global-scale climate variables (Predictors) and local-scale climate variables (Predictand) (Sachindra et al. 2014). An empirical downscaling technique requires less computational cost when comparing with a dynamical downscaling technique and these techniques are simple and easy to apply and more extensively used in climate change impact assessment study. Hence for the current study, a Change Factor (CF) method which is a kind of empirical downscaling technique is applied to downscale the GCM outputs, which is an empirical downscaling method (Fowler et al. 2007; Sunyer et al. 2012; Mugume et al. 2013). Recently, Reddy et al. (2021) studied the performance of ten CMIP5, GCM models and Change Factor downscaling method over the Ghataprabha river sub-basin, India, and for the current study the selected GCM models were based on their results. Particularly, five GCMs (BCC-CSM1.1 (m), MIROC-ESM, MIROC-ESM-CHEM, MIROC5, and NorESM1-M), which are relatively well performing and have daily simulations under four future scenarios, that is a moderate (RCP 4.5) and a high future (RCP 8.5) scenario are considered for the two future time slices 2010-2039 and 2070-2099 and 1961-1990 as a control period. In the RCP4.5 and RCP 8.5, the radiative forcing level reaches the 4.5 W/m^2 and 8.5 W/m^2 , by 2100. In comparison to the previous special report on emission scenarios (SRES), impacts caused by land cover changes were considered by the RCPs (Moss et al., 2010; Joorabian et al., 2017). Multi-Model Ensembling (MME) of all five GCMs was done to minimize the uncertainty in the GCMs projections.

2.4 Downscaling Method

In the present study, a simple and most straightforward means of obtaining high spatial resolution scenarios by applying coarse-scale climate change projections to a high resolution observed climate baseline called Change Factor Method (Hay et al., 2000; Kilsby et al., 2007; Akhtar et al., 2008; Anandhi et al., 2011; Treasa et al., 2017; Ba et al., 2018). The Change Factor (CF) method is classified into Additive CF and Multiplicative CF described in detail below:

2.4.1 Additive CF method:

An additive CF method is the arithmetic difference between the future and historical projections of a GCM computed by using equation 1. This method, typically used for temperature, solar radiation, wind speed, and relative humidity.

$$D_f = D_0 + \left[\left(\overline{GCM_f} \right) - \left(\overline{GCM_h} \right) \right] \quad [1]$$

2.4.2 Multiplicative CF method:

The multiplicative CF is the ratio between future and historical projections of a GCM computed by following equation 2. This method, typically used for precipitation, as precipitation will not be a negative range.

$$D_f = D_0 \times \frac{\overline{GCM_f}}{\overline{GCM_h}} \quad [2]$$

Where, D_f is downscaled future variable, D_0 is observed historical data, $\overline{GCM_f}$ is GCM future climate scenario and $\overline{GCM_h}$ the values from a GCM historical respectively. In the present study, the multiplicative change factor method is used to downscale the precipitation and additive change factor method is used to downscale the other climate variables under future climate change scenarios over the Ghataprabha sub-basin.

2.5 Ensembling of downscaled results

Further a Multi-Model Ensembling (MME) of change factor downscaled results of all five GCMs were done to minimize the uncertainty in the GCMs projections. These ensemble results were then used as input to the SWAT model to evaluate the water balance components. Example (Time-period: 2010-2039; Scenario: RCP 4.5) of ensemble averaging of multiple GCMs is shown in Table 1.

Table 1. Multi-model Ensembling

Sl. No.	Model-1	Model-2	Model-3	Model-4	Model-5	Ensemble average
Day-1	X1	X2	X3	X4	X5	(X1+X2+X3+X4+X5)/5
"	"	"	"	"	"	"
"	"	"	"	"	"	"
Day-n	Xn	Xn	Xn	Xn	Xn	(Xn+Xn+Xn+Xn+Xn)/5

3. Results And Discussion

3.1 Climate Change Impacts on Climate Variables over the Study Area

The ensembled results were then used to display the percentage change in the climate variables with respect to the historical values. The assessment of possible future changes in climate variables is necessary for studying the influences of changing climate on hydrology and water resource management. This assessment will help in studying the effects of climate change on streamflow, agriculture, floods, droughts, long-term water availability, and quality in river catchments. The percentage change in the climate variables is assessed by using the below equation (Eq. 3),

The formula used to calculate percentage change (%Δ):

$$\% \Delta = \frac{[F_t - H_t]}{H_t} \times 100 \quad (3)$$

From Eq. (3), where, H_t represents the historical period, F_t represents the future period. The historical period is considered from 1961 to 1990.

The 100 – year daily rainfall return level with respect to the historical period (1960-1990). The 100-year daily rainfall return level is calculated from the annual maximum daily rainfall series. In detail, the annual maximum series of daily rainfall is fitted with the empirical distribution and the rainfall quantile which has 0.01 [$p=1/T=1/100$] exceedance probability is considered as the 100-year return level of daily rainfall.

The percentage change in the climate variables under four RCPs for the three future time slices is displayed in terms of spatial plots and histograms in the subsequent section of this chapter. The spatial plot shows the grid-wise variation of the climate variables over the study area. A histogram plot gives the information about the number of grids falling within the specified range as defined to portray the average sub-basin conditions with respect to the historical values.

3.2 Precipitation

The percentage change in mean annual precipitation with respect to the historical value is analysed using equation 3. Fig. 2 shows the annual mean precipitation over the sub-basin (1961-1990). It is observed from the spatial plot (Fig. 2) that during the historical period the sub-basin has recorded in the range of 500 to 1500 mm of rainfall and only a few grids in the upstream has recorded in the range of 2000 to around 5000 mm of rainfall. The 100-year return level of maximum rainfall recorded in a day (in mm) over the subbasin during 1961-1990 is also analysed (Fig. 3)

The Spatial maps (top 3 panels) and histograms (bottom 3 panels) of the percentage change in mean annual precipitation estimated from ensemble average under RCP 2.6, 4.5, 6.0, and 8.5 scenarios are shown in Figs. 4, 5, 6 and 7 respectively.

From the spatial and histogram plots (figs. 4, 5, 6 and 7), it is observed that the percentage change in mean annual precipitation with respect to the historical observed (1961-1990) values, is decreasing for most of the grids in the study area during the near-century (2010-2039), while during mid (2040-2069), and end (2070-2099) centuries it shows an increasing trend across all the four RCP scenarios. Particularly, from the histogram percentage variation in the mean annual precipitation is varying from -2.5% to 7%, -1.5% to 15%, 1% to 10%, and 1.5% to 18% under RCP 2.6, 4.5, 6.0, and 8.5 scenarios across all three time slices respectively.

The overall percentage change in mean annual precipitation is varying from -3% to 18 % for the grids in the sub-basin under four scenarios. Percentage change in 100-year annual daily maximum rainfall return level projected from ensemble average under RCP 2.6, 4.5, 6.0, and 8.5 scenarios are plotted in Figs. 8, 9, 10, and 11 respectively

The percentage change in 100-year return level of daily rainfall is varying from -15% to 35% for the grids in the sub-basin under different scenarios. However, the average percentage change in 100-year return level of daily rainfall of the entire sub-basin is mostly positive for all three future time periods and four scenarios. Note that the maximum percentage increase in 100-year return level of daily rainfall is higher than the maximum percentage increase in the annual mean rainfall.

3.3 Rainfall along the river network

River networks are important elements of the landscape because they serve as ecological corridors for living things and play a significant role in shaping the hydrological response of catchments (Garbin et al., 2019). The natural flow regime of rivers is determined by climate, vegetation, and landscape properties, and it is dependent on their ecological integrity (LeRoy et al., 1997; Botter et al., 2013; Garbin et al., 2019). The change in the rainfall amount may change the flow regime along the river network. The change in the annual mean rainfall is analyzed for the grids lying over the river network as shown in fig. 12. Changes in annual mean rainfall along the river network estimated from ensemble average under RCP 2.6, 4.5, 6.0, and 8.5 scenarios are plotted in Figs. 13, 14, 15, and 16 respectively. The average change (%) in monthly precipitation over the sub-basin based on ensemble average of projections with respect to observed values is analyzed (Table 2).

Table 2. Average change (%) over the sub-basin in monthly precipitation based on the ensemble average of projections from five GCMs

Scenarios	Time	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
RCP 2.6	2010-2039	5.12	-20.34	-21.83	-28.84	-16.00	-2.38	-3.07	6.22	7.76	-10.47	-2.68	15.61
	2040-2069	-22.08	-4.29	-1.67	-17.91	12.90	20.16	0.16	-3.37	-0.71	-11.09	-2.78	13.59
	2070-2099	0.54	-16.98	31.12	-3.64	27.56	31.63	-2.19	-6.28	-7.09	-21.93	-13.18	11.23
RCP 4.5	2010-2039	11.50	-23.37	-19.03	-19.99	-20.25	4.75	-2.90	6.81	7.47	-9.10	5.73	-0.88
	2040-2069	-13.26	-1.85	32.16	-17.46	5.52	24.25	-1.00	1.26	-0.76	3.54	-3.38	-15.55
	2070-2099	-7.09	-21.06	31.99	-6.45	42.90	40.23	3.49	-4.11	-6.76	-10.76	-2.40	25.69
RCP 6.0	2010-2039	21.62	-8.20	-28.58	-14.93	-19.22	5.84	-0.38	7.92	3.93	5.64	14.00	18.48
	2040-2069	-9.61	-5.52	-16.20	-21.52	-1.24	19.98	-2.06	-1.75	2.86	-7.52	-0.84	25.18
	2070-2099	11.23	-0.17	35.82	-4.22	26.31	29.34	-4.55	-4.22	-4.47	-14.50	16.25	20.66
RCP 8.5	2010-2039	12.07	-16.37	-20.32	-32.63	-19.10	4.69	2.90	3.68	8.55	8.98	8.96	7.34
	2040-2069	-17.59	3.58	-11.53	-19.46	-12.59	11.65	4.28	2.87	9.05	-8.50	6.68	26.29
	2070-2099	-12.94	-24.48	14.67	-6.44	35.38	41.52	2.36	4.34	6.28	-2.50	2.76	20.22

3.4 UNCERTAINTY QUANTIFICATION

3.4.1 GCM and Scenario Uncertainty

In any modeling method, uncertainties are inherent and a major science challenge is the accurate quantification of uncertainties. Although the uncertainties cannot be removed completely, quantifying them and understanding their effect on model prediction is essential (Rupa and Mujumdar 2019). Though the climate models are carefully chosen for the study region, as the GCM simulations are affected largely based on initial and boundary conditions, hence the quantification of uncertainty in climate change impacts on climate variables and streamflow is carried out and presented using box and whisker plots (Fig. 17). Box plots are used to display the distributions of numeric data values, especially when comparing them across multiple groups. They are designed to provide high-level information of a dataset at a glance, i.e., the shape of the distribution, its central value, and its variability. The ends of the box are known as the lower (Q1) and upper (Q2) quartiles and the area of the box span the inter-quartile range. The vertical line (red line) in the box plot indicates the median (Fig. 17). The two lines outside the box are the whiskers, which are extending from the box represents the highest and lowest value from the datasets. The skewed left, indicates the most of the data are on the right side of the plot (i.e., towards upper quartile), symmetric indicates that, the median is in the middle of the box plot, and skewed right indicates the most of the data are on the left side of the plot (i.e., towards lower quartile).

It is not possible to predict exactly which RCP scenario is likely to occur in the future. And also it is very difficult to present the uncertainty for each IMD grid in sub-basin, the uncertainty in climate change impacts on climate variables is quantified in this section based on the sub-basin average value. Hence the GCM + scenario uncertainty in climate change impact on average annual mean precipitation was presented using box plot corresponds to the downscaled outputs from the five climate models under four climate change scenarios for each time slices (2010-2039, 2040-2069, and 2070-2099).

GCM + Scenario uncertainty in the downscaled results of precipitation obtained from the five GCMs under four RCP scenarios for three time slices are analysed with respect to the average values of historical period in terms of maximum, mean and minimum percentage change (Table 3). The mean percentage change in the precipitation is 1.06%, 3.04%, and 6.39% under future time series 2010-2039,

2040-2069 and 2070-2099 respectively. Fig.18 shows boxplot of the GCM and Scenario uncertainty in climate change impact on average annual mean precipitation over the sub-basin. It can be observed that precipitation is projected to increase during the period 2070-2099 is more than the other two times slices over the study area.

Table 3. Changes in the average annual mean precipitation (mm) over study area (GCM + scenario uncertainty).

Period	Min.	Mean	Max.	Min. % change	Mean % change	Max. % Change
2010-2039	995.82	1062.72	1205.59	-5.30	1.06	14.65
2040-2069	1006.55	1083.56	1181.14	-4.28	3.04	12.32
2070-2099	967.47	1118.73	1381.77	-8.00	6.39	31.40

Min. = Minimum; Max. = Maximum; The average annual mean precipitation over the sub-basin during 1961-1990 is 1051.55 mm, ('+' sign indicates the Increase, and '-' sign indicates the Decrease).

3.4.2 GCM Uncertainties

Further, for all four RCP scenarios, the GCM uncertainties (model uncertainty) in climate change impacts on average annual mean precipitation over the sub-basin under four RCP scenarios (2.6, 4.5, 6.0, 8.5) for three-time windows (2010-2039, 2040-2069, 2070-2099) are plotted as box-plot in Fig. 19 and the minimum, mean, and maximum percentage change in the climate variables with respect to the historical values (1961-1990) are tabulated in the Table 4.

The model uncertainty in climate change impact on mean percentage change of an average annual mean precipitation (Table 4) for RCP 2.6 shows decreasing trend (-1.49 %) in the near century (2010-2039), and increasing trend of 2.3%, and 2.12% under the mid (2040-2069), and far century (2070-2099) respectively. The projections for RCP 4.5, 6.0, and 8.5 show an increasing trend of 0.02%, 2.75%, and 2.97%, under near century 4.53%, 1.88%, and 3.47 under mid century, and 8.04%, 3.64%, and 11.76% under far century respectively.

Since, Precipitation, being dominant input variable to the hydrological modeling, uncertainty in these variables play a major role in climate change impact studies on streamflow. From the analysis, it is observed that the GCM uncertainty in precipitation is more (except near-century), the uncertainty in streamflow is also more.

Table 4. Changes in the average annual mean precipitation (mm) over the study area (GCM uncertainty).

Scenarios	Period	Min.	Mean	Max.	Min. % change	Mean % change	Max. % Change
RCP 2.6	2010-2039	995.82	1035.91	1101.12	-5.30	-1.49	4.71
	2040-2069	1038.81	1075.69	1097.66	-1.21	2.30	4.38
	2070-2099	999.43	1073.80	1185.36	-4.96	2.12	12.72
RCP 4.5	2010-2039	1008.66	1051.73	1078.72	-4.08	0.02	2.58
	2040-2069	1006.55	1099.20	1171.48	-4.28	4.53	11.41
	2070-2099	1033.10	1136.08	1294.04	-1.75	8.04	23.06
RCP 6.0	2010-2039	1032.96	1080.44	1154.63	-1.77	2.75	9.80
	2040-2069	1016.35	1071.30	1123.59	-3.35	1.88	6.85
	2070-2099	967.47	1089.86	1225.43	-8.00	3.64	16.54
RCP 8.5	2010-2039	1021.98	1082.81	1205.59	-2.81	2.97	14.65
	2040-2069	1048.83	1088.03	1181.14	-0.26	3.47	12.32
	2070-2099	1040.02	1175.18	1381.77	-1.10	11.76	31.40

4. Conclusion

Understanding the impact of climate change on Ghataprabha sub-basin, India requires robust projections of sensitive climate variables such as Precipitation. Similarly, studies on assessing the impact of climate change on watershed regions of Krishna basin (Ghataprabha is the sub-basin of Krishna basin), have also found precipitation to be key determinants (Chanapathi and Thatikonda, 2020; Uday Kumar and Jayakumar, 2020; Chanapathi et al., 2018). Downscaling the climate variables as an output from the GCMs under four Representative Concentration Pathways (RCPs) using statistical downscaling for this work. Precipitation data for the study area is downscaled from the simulations of five GCMs in the four RCP 2.6, 4.5, 6.0 and 8.5 scenarios and the impacts of climate change on precipitation are analyzed by calculating the percentage change in the climate variables with respect to the historical period.

A Change Factor method owing to its merits is employed to downscale the precipitation for all the five selected GCM outputs, under different scenarios for three future periods namely, 2010-2039, 2040-2069, 2070-2099 (near, mid and far century respectively). The ensembled results were then used to display the percentage change in the climate variables with respect to the historical values. The percentage change in the climate variables under four scenarios for the three future time slices is displayed in terms of spatial plots and histograms.

Our analysis indicates that the percentage change in mean annual precipitation with respect to the historical observed (1961-1990) values decreases for most of the grids in the study area during the near century (2010-2039), while during mid (2040-2069), and end (2070-2099) centuries it shows an increasing trend across all the four RCP scenarios. Particularly, from the histogram plots, the percentage change in the mean annual precipitation is varying from -2.5% to 7%, -1.5% to 15%, 1% to 10%, and 1.5% to 18% under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 scenarios across all three time slices respectively. The percentage change in 100-year return level of daily rainfall is varying from -15% to 35% for the grids in the sub-basin under different scenarios.

Chanapathi and Thatikonda, (2020) reported that there were higher levels of uncertainty in climatic variables in their work on "Evaluation of sustainability of river Krishna under present and future climate scenarios". Therefore, for this work, a multi-model ensemble average will help in addressing the underlying uncertainties by employing a set of climate models and scenarios by taking a simple arithmetic average. The ensembled results were then used to display the percentage change in the climate variables with respect to the historical values. The assessment of possible future changes in climate variables is essential for studying the influences of changing climate on hydrology and water resource management. This assessment will help in studying the effects of climate change on stream flow, agriculture, floods, droughts, long-term water availability, and quality in river catchments. For policy framing purposes, the projections provided in this study based on the ensemble average across GCMs and Scenarios may be used as guidelines.

Declarations

Ethical approval: Not applicable.

Consent to participate: We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

Consent to publish: The authors agree to publish this article in the Environmental Science and Pollution Research.

Authors Contributions:

Mr. Nagendra Reddy : performed the analytic calculations and performed the numerical simulations and took the lead in writing the manuscript.

Dr. Nagraj S. Patil : Verified the analytical methods and supervised the findings of this work.

Dr. Rajashekhar S. Laddimath : helped to supervise the project and aided in interpreting the results and worked on the manuscript

All authors discussed the results and contributed to the final manuscript.

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Figures

Figure 1

Location map of the study area.

Figure 2

Annual mean precipitation (in mm) over the study area (1961-1990).

Figure 3

100-year return level of maximum rainfall recorded in a day (in mm) over the sub-basin during 1961-1990.

Figure 4

Spatial plots (top 3 panels) and histograms (bottom 3 panels) of percentage change in annual mean precipitation for RCP 2.6 scenario projected from ensemble average. Red line in the histogram indicates the mean percentage change.

Figure 5

Spatial plots (top 3 panels) and histograms (bottom 3 panels) of percentage change in annual mean precipitation for RCP 4.5 projected from ensemble average. Red line in the histogram indicates the mean percentage change.

Figure 6

Spatial plots (top 3 panels) and histograms (bottom 3 panels) of percentage change in annual mean precipitation for RCP 6.0 scenario projected from ensemble average. Red line in the histogram indicates the mean percentage change.

Figure 7

Spatial plots (top 3 panels) and histograms (bottom 3 panels) of percentage change in annual mean precipitation for RCP 8.5 scenario projected from ensemble average. Red line in the histogram indicates the mean percentage change.

Figure 8

Spatial maps (top 4 panels) and histograms (bottom 4 panels) of percentage change in 100-year annual daily maximum rainfall return level projected from ensemble average in RCP 2.6 scenario. Red line in the histogram indicates mean percentage change.

Figure 9

Spatial maps (top 4 panels) and histograms (bottom 4 panels) of percentage change in 100-year annual daily maximum rainfall return level projected from ensemble average in RCP 4.5 scenario. Red line in the histogram indicates mean percentage change.

Figure 10

Spatial maps (top 4 panels) and histograms (bottom 4 panels) of percentage change in 100-year annual daily maximum rainfall return level projected from ensemble average in RCP 6.0 scenario. Red line in the histogram indicates mean percentage change.

Figure 11

Spatial maps (top 4 panels) and histograms (bottom 4 panels) of percentage change in 100-year annual daily maximum rainfall return level projected from ensemble average in RCP 8.5 scenario. Red line in the histogram indicates mean percentage change.

Figure 12

Grids along the river network

Figure 13

Changes in the annual mean precipitation along the river network projected from ensemble average under RCP 2.6 scenario.

Figure 14

Changes in the annual mean precipitation along the river network projected from ensemble average under RCP 4.5 scenario.

Figure 15

Changes in the annual mean precipitation along the river network projected from ensemble average under RCP 6.0 scenario.

Figure 16

Changes in the annual mean precipitation along the river network projected from ensemble average under RCP 8.5 scenario.

Skewed left

Symmetric

Skewed right

Figure 17

Shapes of Box and Whisker Plots

Figure 18

GCM + scenario uncertainty in climate change impact on the average annual mean precipitation over study area. The solid horizontal line indicates the historical value.

Figure 19

GCM uncertainty in climate change impact on average annual mean precipitation over study area for all four RCP scenarios. The solid horizontal line indicates the historical value.

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