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An Assessment of Future Predictions of Rainfall Using GCM Projections in the Western Ghats Region of India

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ABSTRACT

The present study has been taken up to quantify the possible impacts of climate change on the climate variables using the outputs of the global climate model dataset over the Sagar and Kokkarne catchments. The baseline period considered is 30 years (1991-2020), and the daily rainfall dataset is used. The rainfall dataset for the future period is derived from five selected GCMs (Global Circulation Model) datasets under the (Representative Concentration Pathway) RCP 4.5 scenario for the period (2021-2050). The mean, standard deviation, and coefficient of variation of yearly rainfall are determined to check the rainfall variability using statistical analysis. The ensemble rainfall mean values of the five GCMs suggest that the uncertainty in the projected results is reduced by considering the cluster of GCMs. The minimum rainfall for the future period has shown an increasing trend (42.3 % 10.5 %) whereas maximum rainfall has shown decreasing trend (52.44 %, 15.28 %) for Sagar and Kokkarne catchments respectively. The future predicted results show that the percentage change in Ensemble mean annual rainfall for the period 2021-2050 with reference to rainfall data of the baseline period (1991-2020) is depicting an increasing trend of 2.52 % and 4.12 % for Sagar and Kokkarne catchments respectively. Monsoon arrival is earlier in the Kokkarne catchment as compared to the Sagar catchment. The highest positive percentage change in mean annual rainfall of 24.89 %, 10.25 % is projected by MPI-ESM-LR GCM, and the Highest negative percentage change in mean annual rainfall of -28.49 %, -9.19 % is projected by ACCESS1.0 GCM for Sagar and Kokkarne catchments respectively. This analysis will provide useful information for water resources planning engineers, research scientists, and farmers to assess the water availability in the region and create storage if essential.

INTRODUCTION

Climate change has posed threat to development all over the world. Climate change is projected to induce a reduction in the availability of surface water in the future (Pachauri et al. 2014). Climate change caused by humans is believed to be the greatest threat to the earth and the environmental system. According to the IPCC, humans are responsible for more than half of the average temperature increase between 1951 and 2010 (Pachauri et al. 2014). The temperature rises, although not as noticeable as changes found in the hydrological process but will result in global warming. The water cycle and land ecosystem processes are changing as a result of global warming.

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The temperature rises and rainfall variation, which are considered to be the main component of the climate system, can have a negative impact on agriculture, forestry, economy, human health, and well-being (Kotir 2011, Mahato 2014, Thornton et al. 2014). According to future climate estimates, moist and mid-latitude regions will be going to witness an increase in rainfall frequency, whilst the sub-tropical, dry zone would be facing the opposite climatic situation. Rainfall variability is directly linked to the occurrence of events of floods and droughts. Floods will cause the overflow of water over the land surface, on the other hand, droughts can reduce the amount of water available, in the sources such as lakes and dams. Due to human overpopulation and their activities, the demand for water usage is increasing (Cassils 2004, Wang et al. 2018). Rainfall pattern trends have a significant impact on smallholder farmers, due to their reliance on water resources from natural sources for agricultural production and community sustenance, Particularly the farmers who are relying on rain-fed agriculture will be the hardest hit.

With its complicated geographical characteristics, Various parts of India suffer from natural disasters, such as floods and long dry seasons (Pareek & Trivedi 2011, Rasul 2015), and climate variations are becoming more common as a result of climate change (Jolly et al. 2015), putting Indian geographical region at risk. High rainfall magnitude can be assessed in terms of water availability, agricultural development, food security, and the economics of the country. The amount of water available is determined by rainfall rates (García-Ruiz et al. 2011, Sharma 2000) and the land-use changes in the region. Historical climate fluctuation should\ be evaluated to anticipate future climate variations and manage the available water resources for agriculture and other purposes in the best possible way and be ready with contingency plans as there is always uncertainty associated with the rainfall received in the catchment. Hence the primary goal of this research is to identify rainfall changes during the future period of (2021-2050) with reference to the baseline period of (1991-2020). This will encourage the development of ecologically friendly, long-term technologies and innovation for self-sufficiency in agriculture and food security.

STUDY AREA

The study area under consideration is composed of two river catchments, Sagar catchment, and Kokkarne catchments, belonging to Varada river and Seetha river respectively. Both the Varada river and Seetha river originate in the Western ghats of India in Karnataka (Fig. 1).

MATERIALS AND METHODS

The various steps followed in the present study are as follows:

1. IMD gridded rainfall data for the baseline period (1991-2020) of Sagar catchment and Kokkarne catchment is used in the present study.
2. The rainfall dataset is obtained from the following five selected global climate models (GCMs) (Table 1) under the RCP 4.5 scenario for the future period of (2021-2050) which is downscaled for the South Asia region.
3. The downscaled rainfall dataset is further bias-corrected, and then statistical factors are used to investigate the variation in distribution across the study area. The rainfall dataset acquired for the catchments is statistically analyzed to see whether there are any significant differences in the rainfall dataset. Also included are the graphs demonstrating the percentage change in rainfall statistical parameters for the study period of 2021-2050, as well as graphs depicting the effect of bias correction in the raw GCM dataset. The mean, median, standard deviation, kurtosis, skewness, minimum, maximum, and range are all used in this study to calculate the metric.
4. The standard deviation is a measure of dispersion. A low number implies that the data is clustered closely around the mean. A large number implies that the dataset is widely distributed on both sides of the mean. A high standard deviation denotes large year-to-year fluctuations, whereas a low standard deviation denotes smaller fluctuations. In other words, high-standard-deviation rainfall is deemed to be more volatile than low-standard-deviation rainfall.
5. The skewness and kurtosis are calculated to see if the annual rainfall dataset followed a normal distribution. Skewness is a metric for symmetry, or more specifically, the lack of it. If the dataset appears the same to the left and right of the center point, it is considered to be symmetric. A normal distribution has zero skewness, and any symmetric dataset should have skewness close to zero. Negative skewness values indicate that the dataset is skewed to the left, whereas positive skewness values show that the dataset is biased to the right. Kurtosis is a metric for how peaked or flat a dataset is in comparison to a normal distribution. To put it another way, a dataset with a high kurtosis has a noticeable peak near the mean, a rapid drop, and heavy tails. The low kurtosis dataset features a flat top near the mean instead of a high peak. The kurtosis of the standard normal distribution is zero. A peaked distribution has positive kurtosis, while a flat distribution has negative kurtosis.

RESULTS AND DISCUSSION

Statistical Analysis of Climate Projections for the Near Future (2021-2050)

The GCM model projecting the lowest mean annual rainfall for the Sagar catchment is the ACCESS1.0 GCM model, with a corresponding lowest mean value of 1271.29 mm, according to Table 2. The corresponding dataset is skewed right, with the standard deviation correlating the lowest annual rainfall

Table 1: List of CMIP5 GCMs used in the present study. (Source: http://cccr.tropmet.res.in)

GCM code	1	2	3	4	5
GCMs	ACCESS1.0	CNRM-CM5	GFDL-CM3	MPI-ESM-LR	NorESM1-M
Horizontal grid spacing (lon x lat)	1.875 x 1.25	1.4 x 1.4	2.5 x 2.0	1.9 x 1.9	x 1.9

being 414.83 mm. However, the maximum annual rainfall projected by the MPI-ESM-LR GCM model has a standard deviation of 472.05 mm, indicating that the maximum rainfall is greatly distributed or that the maximum rainfall pattern in the MPI-ESM-LR GCM model is inconsistent, as indicated by the highest range value. This conclusion is supported once more by the coefficient of variation statistics. The larger CV value signifies larger dispersion (Thangjai et al. 2020, Yosboonruang et al. 2019). The variation in CV values implies that the rainfall in the study area is highly variable.

For the period under consideration, the ACCESS1.0 GCM model projects the lowest and highest mean annual rainfall of 3555.61 mm, and 6197.29 mm respectively, and the corresponding standard deviation of 1244.91 mm for the Kokkarne catchment, as shown in Table 3. The ACCESS1.0 GCM model rainfall dataset is skewed to the right side. The high standard deviation figure is directly linked to the wide range of rainfall. The difference between the maximum and minimum annual rainfall is represented by the rainfall range. The standard deviation and range represent the unpredictability of annual rainfall and thus how dependable the rainfall is in terms of persistence.

Table 2 and Table 3 show that, except for the ACCESS1.0 GCM model, the coefficient of variation for all global circulation models is lower for both catchments, indicating smaller variability from the mean, and comparable observations are made for the rainfall data projected by this GCM. The low coefficient of variability reported for the aforementioned global circulation models indicates that they are more reliable than the ACCESS1.0 GCM model in terms of rainfall. The CV indicates the degree of precision with which the treatments are compared and is a good indicator of the reliability of the experiment. It is also stated that the larger the CV value, the poorer the reliability of the experiment.

The mean annual rainfall of 1822.47 mm and the associated standard deviation of 200.67 mm is expected for the Sagar catchment, whereas the mean annual rainfall of 4076.94 mm and the related standard deviation of 447.96 mm is projected for the Kokkarne catchment. The highest median rainfall values are projected for the Sagar and Kokkarne catchments, with 2277.05 and 4463.12 mm (as projected by the MPI-ESM-LR GCM model) respectively. Tables 2 and 3 show that rainfall datasets for both catchments are positively skewed as projected by the ACCESS1.0 GCM model, CNRM-CM5 GCM model, GFDL-CM3 GCM model, and negatively skewed as projected by the MPI-ESM-LR GCM model, NORESM1-M GCM model.

Table 2: Statistical summary of annual rainfall over Sagar catchment.

GCM	ACCESS1.0	CNRM-CM5	GFDL-CM3	MPI-ESM-LR	NorESM1-M	Ensemble
Mean [mm]	1271.29	1541.47	2106.05	2220.15	1973.36	1822.47
Min [mm]	480.51	965.93	1200.46	1372.94	832.98	1442.61
Max [mm]	2238.05	2302.34	2982.49	3008.17	2942.97	2153.71
Median [mm]	1218.49	1492.66	2011.40	2277.05	1961.86	1831.21
Std Dev [mm]	414.83	342.75	420.86	472.05	413.02	200.67
CV [%]	32.63	22.24	19.98	21.26	20.93	11.01
Kurtosis [mm]	-0.42	-0.29	-0.07	-0.90	1.20	-0.62
Skewness [mm]	0.17	0.47	0.32	-0.20	-0.12	-0.12

Table 3: Statistical summary of annual rainfall over Kokkarne catchment.

GCM	ACCESS1.0	CNRM-CM5	GFDL-CM3	MPI-ESM-LR	NorESM1-M	Ensemble
Mean [mm]	3555.61	4202.54	4285.76	4317.04	4023.73	4076.94
Min [mm]	1483.08	2580.02	2547.21	2568.25	1588.61	3161.08
Max [mm]	6197.29	5813.67	5912.52	5843.10	5778.03	5191.50
Median [mm]	3366.61	4008.59	4127.59	4463.12	4169.99	4076.55
Std Dev [mm]	1244.91	839.03	826.27	927.43	856.34	447.96
CV (%)	35.01	19.96	19.28	21.48	21.28	10.99
Kurtosis [mm]	-0.59	-0.69	-0.70	-0.96	1.03	0.40
Skewness [mm]	0.29	0.23	0.14	-0.18	-0.42	-0.07

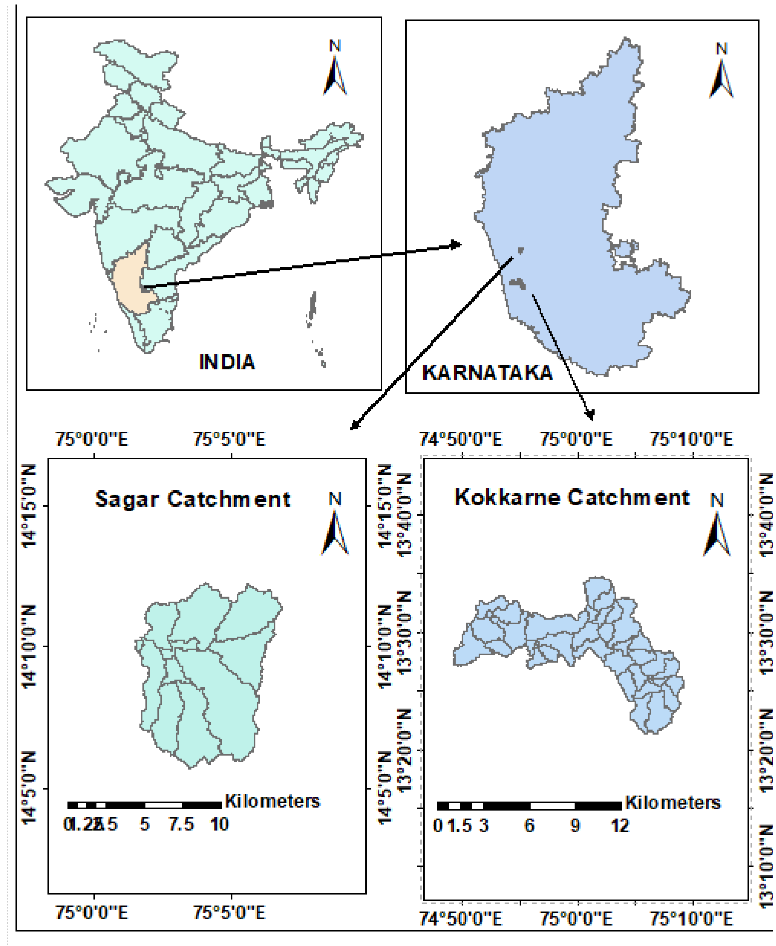

Fig. 1: Study areas (Sagar and Kokkarne catchments).

The standard deviation is one way of summarizing the spread of a probability distribution. It has to do with the level of uncertainty involved in projecting the value of a random variable. High levels indicate a greater degree of uncertainty than low values. Tables 2 and 3 clearly showed that the standard deviation values of the Kokkarne catchment are higher than the standard deviation values of the Sagar catchment. Because of the relationship between the standard deviation and the mean values, the deviation from the normal distribution cannot be ignored. This is backed up by the coefficients of variation of rainfall dataset projected by GCM models under consideration, which range from 19-33 and 19-36 for the Sagar and Kokkarne catchments, respectively. This demonstrates that rainfall values in the Kokkarne catchment are significantly different from the rainfall of the Sagar catchment. The fact that the CV values are so high indicates that the rainfall is highly unpredictable and unreliable, which can be ascribed to the length of the dataset set used or the quality of the dataset.

The smaller the coefficient of variation of rainfall dataset projected in a GCM, the lower the variability and the more reliable the projected rainfall of that particular GCM model. Tables 2 and 3 show that the rainfall variability projected by the GFDL-CM3 GCM model for both the catchments is the lowest of all the GCMs and so can be considered reliable.

According to the findings of statistical analysis tests, there are substantial discrepancies in the statistical characteristics of the rainfall dataset for the Sagar and Kokkarne catchments over the research period.

Evaluation of Climate Projections for the Near Future (2021–2050)

Fig. 3 also shows that rainfall in both the catchments is underestimated throughout the monsoon season. It can be seen that rainfall in the monsoon season is indicating delayed commencement of the monsoon season for Sagar catchment and a slightly early start of monsoon season in Kokkarne catchment.

The bias correction method is unable to rectify the beginning of monsoon as projected by many GCMs, and this may be the case for subsequent seasons when analyzing future estimates. The so-called climate change may be to blame for the change in rainfall season. This kind of natural variability in the precipitation trends being underestimated by the GCMs is also reported by (Mahmood et al. 2018, Pervez & Henebry 2014, Singh et al. 2019, Tolika et al. 2006, Van Haren et al. 2013) During the winter season, underestimation of rainfall datasets may be seen in both catchments as a modest corrective shift in the quantity of rainfall received compared to the rainfall dataset of the baseline period (1991-2020).

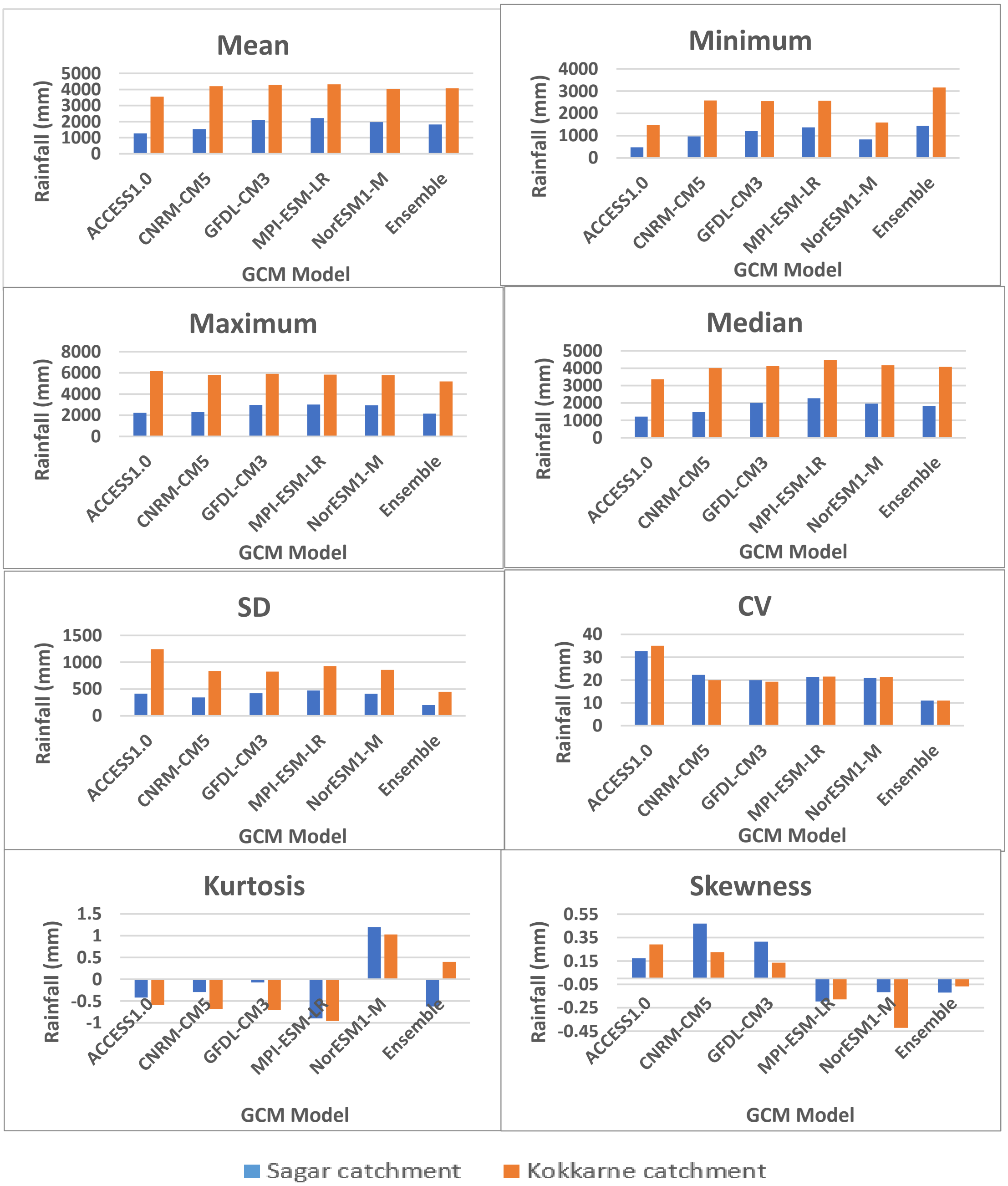

Fig. 2: Parameters of statistical analysis of rainfall dataset
Note: Std. Dev= standard deviation, CV=Coefficient of variation

Nevertheless, there are considerable sources of uncertainties in the results, related mainly to the climate model projections' ability to describe the probability of occurrence of extreme events. Further, due to the nature of extreme events, there is only a limited dataset available and the inherent natural or internal variability adds uncertainty to the analysis of the results. GCM bias might also be blamed for the uncertainties (Fig. 3). For locations with the GCM dataset, bias correction approaches can be employed in climate change studies. Using an ensemble of climate projections, as in this work, can provide an estimate of the internal variability uncertainty of the GCM model. The choice of the bias-correction method, on the other hand, influences the total uncertainty in the outcome, and the method should only be adopted after a thorough examination of other options. To deal with significant biases, such as those due to erroneous timing and location of stationary synoptic scale rainfall fields like the monsoon, improvements in climate model post-processing approaches are still needed. There have been advancements in analyzing the influence of climate change at the regional scale, but further methods for reducing the uncertainties associated with GCM datasets and scaling procedures need to be investigated.

Seasonal Uncertainty

Table 4 shows the absolute difference in mean monthly rainfall between the GCM projections and the mean monthly rainfall in the baseline scenario for the Sagar catchment. The Ensemble mean of all the projections show an increase in rainfall contribution during monsoon (+4.59%), Post monsoon (+17.91%) winter (+1.52%) whereas a decrease in rainfall contribution during summer (-47.41%) is projected. The rainfall data values for the baseline period (1991-2020), as shown in Fig. 4 and Table 4, are significantly low in the monsoon, post-monsoon, and winter seasons, and high in the summer season which can be attributed to the effect produced by climate change. When compared to the reference dataset, all GCMs are unanimously depicting decreasing trend in the percentage contribution during the summer season for the future period (2021-2020).

The Ensemble mean of all the projections shows an increase in rainfall contribution during monsoon (+4.69 %) and summer (+16 %), and a decrease in rainfall contribution during Post monsoon (-6.39 %), winter (-50.76 %) for the Kokkarne catchment. As shown in Fig. 4 and Table 5, the observed rainfall data values are comparatively low in monsoon and summer seasons, and substantially high in post-monsoon and winter seasons, which can be attributed to the effect of climate change. In comparison to the reference rainfall dataset for the baseline period, the overall percentage contribution to the winter season for the future period (2021-2020) is decreasing as projected by all the GCMs under consideration.

This kind of seasonal variation in precipitation in different regions has also been reported by (Cheung et al. 2008, Gedefaw et al. 2018, Hussain & Lee 2013) The weather system being different in a different season of a year is the prime factor leading to seasonal variation in precipitation as reported by (Arora et al. 2006).

GCM Uncertainty

Uncertainties are inherent in any modeling system, and proper assessment of uncertainties is a major research task. Although uncertainties cannot be eliminated, evaluating and comprehending their impact on model prediction is critical (Rupa & Mujumdar 2019). Though the climate models for the research region are carefully chosen, the measurement of uncertainty in climate change impacts on climatic variables such as rainfall and temperature is required because GCM simulations are mostly based on initial boundary conditions. Rainfall and temperature are the most important input variables in hydrological modeling, hence uncertainty in these variables is important in climate change effect studies on streamflow.

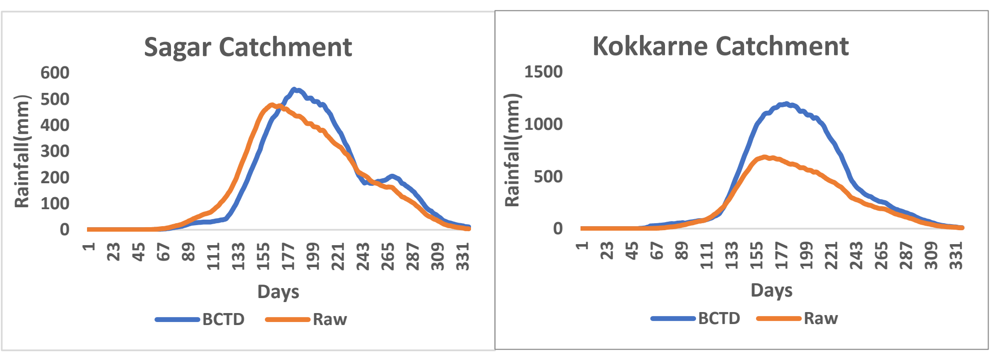

Fig. 3: Mean annual rainfall cycle over the future period (2021-2050) using a 30-day moving average of the Sagar and Kokkarne catchments.

The model uncertainty in climate change impact on the mean percentage change of mean, minimum and maximum annual rainfall in the Sagar catchment (Table 6) for RCP 4.5 indicate an increasing trend (+2.52%), an increasing trend (+42.30 %), and a decreasing trend (-52.44%) with respect to the corresponding mean, minimum and maximum annual rainfall of baseline period (1991-2020) respectively. reduction in maximum rainfall falls in line with a research report by (Al-Ansari et al. 2014, Modarres et al. 2018, Rana et al. 2014).

In the case of the Kokkarne catchment, the model uncertainty in climate change impact on the mean percentage change of mean, minimum and maximum annual rainfall (Table 7) for RCP 4.5 shows an increasing trend (+4.12 %), an increasing trend (10.50 %) and a decreasing trend (-15.28 %) with respect to the mean, minimum and maximum annual rainfall of baseline period (1991-2020) respectively. It is worth noting that most of the estimates show a decrease in mean annual rainfall when compared to the rainfall data of the baseline period of 1777.69 mm for the Sagar catchment. However, most predictions show a rise in mean annual rainfall for the baseline period of 3915.61 mm for the Kokkarne catchment.

CONCLUSIONS

The current study examines the impact of global climate change on rainfall datasets from the Sagar and Kokkarne catchments from 2021 to 2050 (a 30-year period). The present statistical analysis of the rainfall dataset provides a clear picture of variations in the rainfall dataset with respect to various statistical parameters. The mean, standard deviation, and coefficient of variation of the annual rainfall dataset are calculated to check the rainfall variability. The rainfall pattern is observed to be slightly scattered based on the computed results. The purpose of this research is to determine the rainfall variability and GCM uncertainty in the projected rainfall data of the present studied areas.

Following conclusions can be made from the present study.

Table 4: Percentage changes of rainfall in near future bias corrected dataset (2021–2050) over the monsoon months as compared to baseline dataset (1991–2020) for Sagar catchment.

Season	Monsoon	Post-monsoon	Winter	Summer
Ensemble	16.64(4.59)	17.29(17.91)	0.07(1.52)	-18.86(-47.41)
ACCESS1.0	-105.73(-29.14)	-15.39(-15.94)	2.4(51.95)	-19.97(-50.2)
CNRM-CM5	-53.77(-14.82)	23.42(24.25)	-2.13(-46.1)	-20.52(-51.58)
GFDL-CM3	83.01(22.88)	20.32(21.04)	-1.63(-35.28)	-13.14(-33.03)
MPI-ESM-LR	110.75(30.52)	39.35(40.75)	0.33(7.14)	-26.74(-67.22)
NorESM1-M	48.94(13.49)	18.74(19.41)	1.4(30.3)	-13.92(-34.99)

Note: Values in the parentheses represent the relative change from IMD data for the baseline period (1991-2020).

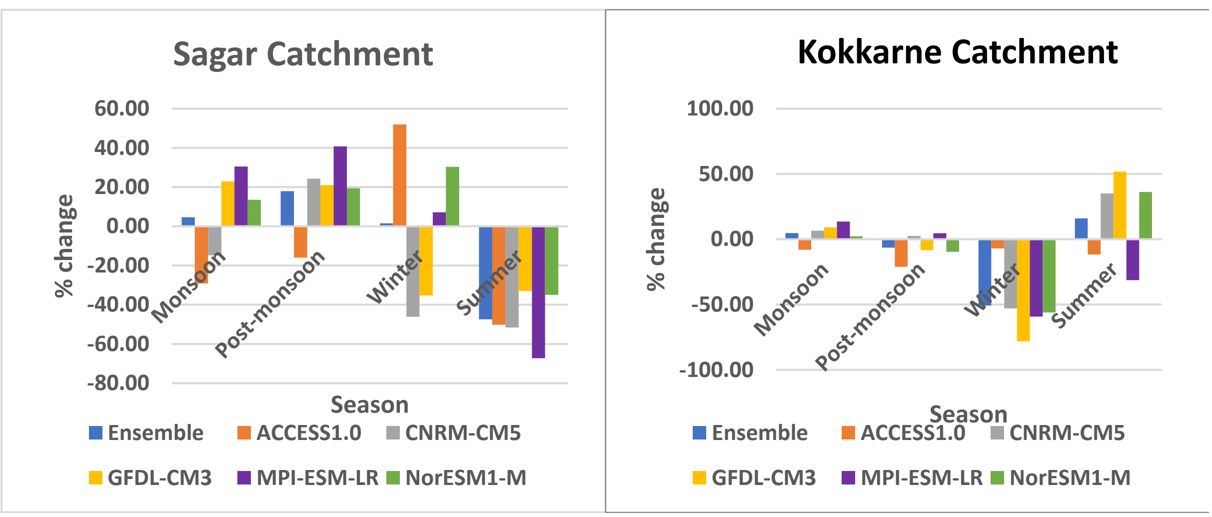

Fig. 4: Percentage changes of rainfall in near future bias corrected dataset (2021–2050) over the monsoon months as compared to the baseline dataset (1991–2020).

1. The mean annual rainfall in the Kokkarne catchment is more than Sagar catchment by 123.70 %.
2. Although the standard deviation values of ensemble rainfall data of Kokkarne catchment are higher than that of Sagar catchment, the coefficient of variation value of Kokkarne catchment is lower than that of Sagar catchment. This essentially means that the ensemble rainfall dataset of the Kokkarne catchment has lesser variability.
3. According to the RCP 4.5 scenario, by 2050, mean annual rainfall is expected to be highly variable, with an increasing trend in rainfall for the Sagar catchment (+2.52 %) and Kokkarne catchment (+4.12%).
4. The mean annual rainfall data of the Sagar catchment is slightly more negatively skewed than the rainfall data of the Kokkarne catchment.
5. It is preferable to use the ensemble mean for subsequent analysis since it reduces the standard deviation and coefficient of variation, making the rainfall data more dependable.
6. The raw rainfall data from both the catchments are underestimated. The underestimation of the case of the Kokkarne catchment is more than that of the Sagar catchment.
7. Ensemble means rainfall data of GCMs used in this analysis predict that monsoon rainfall from 2021 to 2050 in both

Table 5: Percentage changes of rainfall in the near future bias corrected dataset (2021–2050) over the monsoon months as compared to baseline dataset (1991-2020) for Kokkarne catchment.

Season	Monsoon	Post-monsoon	Winter	Summer
Ensemble	39.87(4.69)	-9.64(-6.39)	-3.34(-50.76)	10.38(16)
ACCESS1.0	-68.01(-8)	-31.97(-21.18)	-0.46(-6.99)	-7.55(-11.64)
CNRM-CM5	55.38(6.52)	3.83(2.54)	-3.49(-53.04)	22.74(35.06)
GFDL-CM3	77.53(9.12)	-12.61(-8.35)	-5.15(-78.27)	33.55(51.73)
MPI-ESM-LR	115.02(13.53)	6.97(4.62)	-3.9(-59.27)	-20.3(-31.3)
NorESM1-M	19.41(2.28)	-14.43(-9.56)	-3.69(-56.08)	23.47(36.19)

Note: Values in the parentheses represent the relative change from IMD data for the baseline period (1991-2020).

Table 6: Percentage changes in the mean, minimum and maximum annual rainfall (mm) over the study area for Sagar catchment during 2021-2050 with reference to the baseline period of 1991-2020.

GCM	Mean	Minimum	Maximum
ACCESS1.0	-506.41 (-28.49)	-533.26 (-52.6)	-2290.62 (-50.58)
CNRM-CM5	-236.22 (-13.29)	328.36 (18.47)	442.46 (24.89)
GFDL-CM3	328.36 (18.47)	186.69 (18.42)	-1546.17 (-34.14)
MPI-ESM-LR	442.46 (24.89)	359.17 (35.43)	-1520.5 (-33.58)
NorESM1-M	195.66 (11.01)	-180.78 (-17.83)	-1585.69 (-35.01)
Ensemble	44.78 (2.52)	428.84 (42.3)	-2374.96 (-52.44)

Note: Values in the parentheses represent the relative change from IMD data for the baseline period (1991-2020).

Table 7: Percentage changes in the mean, minimum and maximum annual rainfall (mm) over the study area for Kokkarne catchment during 2021-2050 with reference to the baseline period of 1991-2020.

GCM model	Mean	Minimum	Maximum
ACCESS1.0	-360 (-9.19)	-1377.55 (-48.16)	69.56 (1.14)
CNRM-CM5	286.93 (7.33)	-280.61 (-9.81)	-314.06 (-5.13)
GFDL-CM3	370.15 (9.45)	-313.42 (-10.96)	-215.21 (-3.51)
MPI-ESM-LR	401.43 (10.25)	-292.38 (-10.22)	-284.63 (-4.65)
NorESM1-M	108.12 (2.76)	-1272.02 (-44.47)	-349.7 (-5.71)
Ensemble	161.33 (4.12)	300.46 (10.5)	-936.23 (-15.28)

Note: Values in the parentheses represent the relative change from IMD data for the baseline period (1991-2020).

the catchments will be higher than monsoon rainfall data of the baseline period (1991-2020).

8. For Sagar and Kokkarne catchments, GFDL-CM3 GCM with the lowest CV of 19.98, 19.28 is projecting 2106.05 mm, 4285.76 mm of mean annual rainfall which is more than the ensemble mean annual rainfall by 15.56 %, 5.12 % respectively.
9. For Sagar and Kokkarne catchments, ACCESS1.0 GCM with the highest CV of 32.63, 35.01 is projecting 1271.29 mm, 3555.61 mm of mean annual rainfall which is less than the ensemble mean annual rainfall by 30.24 %, 12.78 % respectively.

To prove the conjecture of the scientists, more than one statistical procedure is required to measure changes in hydrological datasets such as rainfall. This endeavor is a little step in that direction.

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