Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268 (Print copies up to 2016) | e-ISSN: 2395-3454 | Vol. 21 | No. 5 (Suppl) | pp. 2201-2209 | 2022

Original Research Paper | https://doi.org/10.46488/NEPT.2022.v21i05.014 | Open Access Journal

# Future Predictions of Precipitation and Discharge Using CMIP5 Models in the Western Ghats Region, India

**Shilpa A. Veerabhadrannavar*† and B. Venkatesh****
*National Institute of Hydrology, Hard Rock Regional Centre, Visvesvaraya Nagar, Belagavi 590019, Karnataka, India
**National Institute of Hydrology, Hard Rock Regional Centre, Visvesvaraya Nagar, Belagavi 590019, Karnataka, India
†Corresponding author: Shilpa A. Veerabhadrannavar; shilpaveer56@gmail.com

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

*Received:* 15-04-2022
*Revised:* 31-05-2022
*Accepted:* 22-06-2022

**Key Words:**
Rainfall trend
Null hypothesis
Linear regression analysis
Ensemble
CORDEX-SA

## ABSTRACT

Climate change is expected to exacerbate the hydrological cycle globally and have a significant impact on water resources. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report states that observed and projected increases in both temperature and precipitation variability are the main reasons for projected climate change impacts on natural water resources. The examination of meteorological variables of the region, especially when agriculture is rainfall dependent, is very essential to formulate feasible adaptation strategies. As a result, using CORDEX-SA (Coordinated Regional Downscaling Experiment-South Asia) rainfall data (2021 to 2050), trend analysis was used to examine variations in rainfall data in the Kokkarne catchment of the Seetha river basin. Regression analysis was used to identify the season-wise rainfall trend. Annual, Summer, Monsoon, and Winter rainfall have depicted increasing trends with a rate of 2.46, 1.21, 2.77, and 0.009 mm per year respectively. The post-monsoon rainfall has projected a declining trend with a rate of -1.54 mm per year. Hence it is recommended that the designed strategies in the agricultural sector have to take the increasing, decreasing, and erratic nature of the trend of rainfall into consideration. Further considering the use of a Multi-Model Ensemble (MME) is reducing the SD and CV of rainfall data by 862 mm and 48.5% respectively. 87% of annual rainfall is contributed by monsoon season only with a Standard deviation of 424.4 mm and CV of 12%.

## INTRODUCTION

Water is a very essential component of all the biological processes taking place on the earth, and there is no substitute for it. Water constitutes a vital resource for sustaining life on earth (Earman & Dettinger 2011, Hossain 2015). Water is regarded as a source of energy and is used for a variety of purposes in the home, agriculture, and business. But Water is a limited natural resource (Deka et al. 2021, Hossain 2015). Rainfall is the major source of supply of water in any region. The water requirements of Plants are met by natural sources and irrigation. Crop output, particularly in rain-fed locations, is highly dependent on rainfall occurrence, hence it is critical to study the variation of rainfall (Bhatla et al. 2020) to predict the likelihood of rainfall patterns from the available historical records of hydrological data. The probability distribution helps in relating the severity of extreme events like droughts, floods, and severe storms to their number of occurrences which enables the prediction of their likelihood pattern throughout time. By fitting a frequency distribution to a hydrological dataset, the likelihood of patterns of random parameters can be estimated. In the present study, the hydrological data is analyzed, and the variability in the data under consideration is studied concerning the statistical parameters, to fit the distribution. A slight change in any of the climatic variables has an impact on crop growth phases, lowering yield stability and quality (Mahilange & Das 2018). Crop growth and crop yield are negatively influenced by changes in climatic variables (Acquah & Kyei 2012, Panda & Sahu 2019). Crop yields are primarily dependent on rainfall received during the monsoon season, while crops sown in the winter season are also reliant on soil moisture maintained from the preceding monsoon. As a result of these influencing factors, the shifting rainfall pattern and its influence on agriculture and water supplies have become a significant climatic issue.

**ORCID details of the authors:**

**S. A. Veerabhadrannavar**: https://orcid.org/0000-0002-1566-1640
**B. Venkatesh**: https://orcid.org/0000-0002-9352-5230

The agricultural output reflects the economic well-being of the country (Cheng & Hu 2012, Goswami & Paul 2010, Hussain & Taqi 2014). To avoid water resource difficulties, it is vital to properly manage current resources. So having an idea about the pattern of rainfall and its trend is crucial from the standpoint of agriculture. To deliver the needed amount of water to the crops for their growth, it is critical to have comprehensive knowledge of rainfall trends. Climate scientists will benefit from the trend analysis in their hunt for climate change implications and repercussions. The primary goal of a trend test is to determine if the values of a data series are increasing or decreasing. Trend analysis is primarily used to assess the direction of a trend and to quantify its magnitude. The key objectives of this study, with the above considerations, are, to assess the multi-model ensemble data, to analyze the seasonal trend of rainfall, and to assess discharge patterns. This form of analysis will aid in the evaluation of actions aimed at ensuring enough irrigation and food security.

## DATA USED AND METHODOLOGY

### Study Area

The study area under consideration is the Kokkarne catchment, belonging to the Seetha river basin. Seetha river originates in the Western Ghats of India in Karnataka, which travels towards the west and drains into the Arabian sea. The Kokkarne catchment is located between 13.25° N and 13.75° N latitudes and between 74.75° E and 75.25° E longitudes. The delineated catchment area of Kokkarne catchment is 385 $km^2$ with a 30-year average rainfall of 3915.61 mm during the historical period (1991-2020). The drainage net is composed of small streams that originate in the Western Ghats, which are dominated by the younger Greenstone lithoclan. The Western Ghats, an important morpho element that works as a water barrier for the west-flowing and east-flowing rivers of the southwestern section of the Indian peninsula, is formed by these metasediments and metavolcanics. The location map of the study area is shown in Fig. 1.

### Data

In this study, the rainfall dataset from the following five selected GCM (Global Climate Model) datasets (ACCESS1-0, GFDL-CM3, CNRM-CM5, MPI-ESM-LR, NorESM1-M) is obtained from http://cccr.tropmet.res.in. This CORDEX-SA data (Coordinated Regional Downscaling Experiment-South Asia) obtained for RCP 4.5 and the period of 2021-2050 is bias corrected before using as input to the Soil and Water Assessment Tool (SWAT) model. Table 1

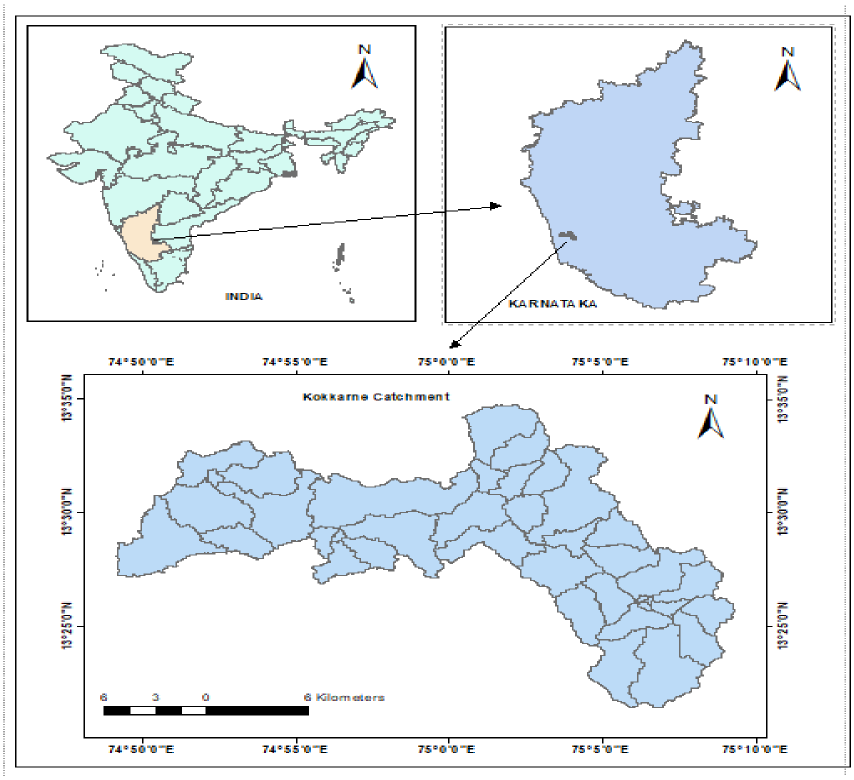


Fig. 1: Location map of the study area (Kokkarne catchment).

Table 1: Data source.

| Component | Source |
|---|---|
| Rainfall (Daily) | India Meteorological Department (IMD) |
| Temperature (Daily) | India Meteorological Department (IMD) |
| Discharge (Daily) | Water Resources Development Organisation (WRDO) |
| Digital Elevation Model (DEM) | Shuttle Radar Topography Mission (SRTM) |
| Soil map | Food and Agricultural Organization (FAO) |
| Land-use/land-cover maps (LULC) | Water Base Worldwide Dataset |

shows the data source for the study.

## SWAT Model

The Soil and Water Assessment Tool (SWAT) model is used to simulate river outflows (Neitsch et al. 2011). It is a physically based rainfall-runoff model which normally operates on a daily time frame and basin scale and accounts for regional heterogeneities by dividing the watershed into several hydrological response units (HRUs). Each HRU has its unique combination of soil, land use, and elevation. The model estimates the hydrology of each HRU based on the precipitation, surface runoff, evapotranspiration, percolation, and return flows in the catchment. The output of the SWAT model helps to analyze each subbasin discharge of the catchment.

## Representative Concentration Pathways

In the current study, RCP 4.5 scenario, which is a medium stabilization scenario is used. The IPCC Fifth Assessment Report (AR5) released in 2014 recommends RCP 4.5 as one of the representative concentration pathways (RCPs) in which radiative forcing is assumed not to overshoot beyond 4.5 W/$m^2$ by the end of 2100. Radiative forcing is the sum of the effects of greenhouse gases and other forcing components. RCP 4.5 takes into account long-term global greenhouse gas emissions in a global framework, as modeled by the Global Change Assessment Model, and adopts a cost-cutting method to attain the target radiative forcing (Thomson et al. 2011). RCPs can be used to highlight likely climate change impacts on watershed hydrology using GCM-predicted datasets (Hong et al. 2016; Mudbhatkal et al. 2017; Shrestha & Htut, 2016).

## Methodology

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

1. The regression analysis in this study was based on IMD (India Meteorological Department) rainfall data from the Kokkarne catchment for the baseline period 1991 to 2020. The Linear regression analysis was employed to discover trends in the rainfall data. One of the most basic approaches for calculating the trend of data in a time series is linear regression analysis. A parametric test that assumes normally distributed data is regression analysis. The linear relationship between time and the variable of interest is utilized to test the trend. The variables must be normally distributed, as well as be temporally and spatially independent, to apply this strategy correctly. The regression analysis can be done on the time series of rainfall data directly by using regression analysis with time as the independent variable and rainfall as the dependent variable, the trend in rainfall can be determined. The linear regression equation is expressed as:

$$y = mk + c \tag{1}$$

The dependent variable is y, while the independent variable is x. The slope of the line is m, and the intercept (value of y when x = 0) is c. The rate of increase or decline of the variable is represented by the slope. k denotes the length of time in years. The rainfall trend has been described by the slope line. If the slope line is positive, it indicates that rainfall is increasing. However, if the slope line is negative, it indicates that rainfall is decreasing. The dependent variable y in this study is rainfall, whereas the independent variable x is the year. The assumption of a normal distribution is required for linear regression. The null hypothesis in this study is that the slope of the line in the graph is zero, or that the rainfall data shows no trend.

The $R^2$ or square of the correlation value from the regression analysis was used to demonstrate the strength of the connection between the variables x and y. Which has a value ranging from 0.0 to 1.0. An $R^2$ score of 1.0 indicates that the connection is high and that all of the points are in a straight line. An $R^2$ value of 0.0, on the other hand, indicates that there is no connection and no linear relationship exists between x and y.

2. The multi-model ensemble data is analyzed with statistical parameters like standard deviation and Coefficient of variation.
3. The monthly distribution of rainfall in the catchment region is analyzed.
4. With the data inputs presented in Table 1, the SWAT model was used to simulate the Kokkarne catchment. The generated discharge output was used for the analysis.

## RESULTS AND DISCUSSION

### Trend Analysis

Fig. 2 and 3 show the trend of total annual and seasonal precipitation over the period under consideration. The rate of change in a linear regression model is determined by the slope of the regression line, which in the case of annual rainfall in the current study area is around 2.46 mm/year as shown in Fig. 3. The increasing trend of annual rainfall in the current study is matching with that of the increasing trend of precipitation as reported by Basappa et al. (2021) and Nandargi & Mulye (2014) in the study regions which belong to the Western Ghats. While the winter, spring, and summer seasons have shown an increasing trend in the study region, the post-monsoon season has shown a minor declining trend as presented in Fig. 2 and Table 2.

The rate of change is defined by the slope of the regression line, which in this case is roughly 1.21 mm/year, 2.77 $mm.year^{-1}$, -1.54 $mm.year^{-1}$, and 0.0093 $mm.year^{-1}$ for summer, monsoon, post-monsoon, and winter rainfall

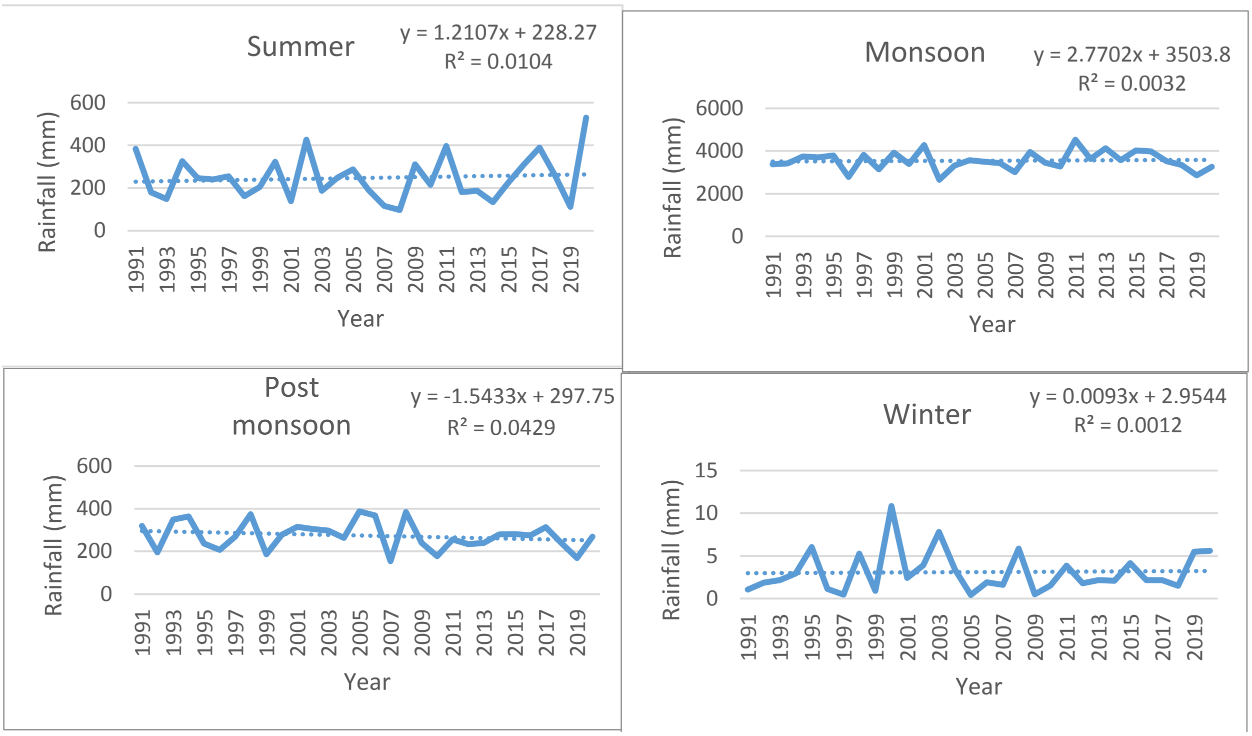


Fig. 2: Regression analysis of rainfall data (a) Summer, (b) Monsoon, (c) Post Monsoon (d) Winter

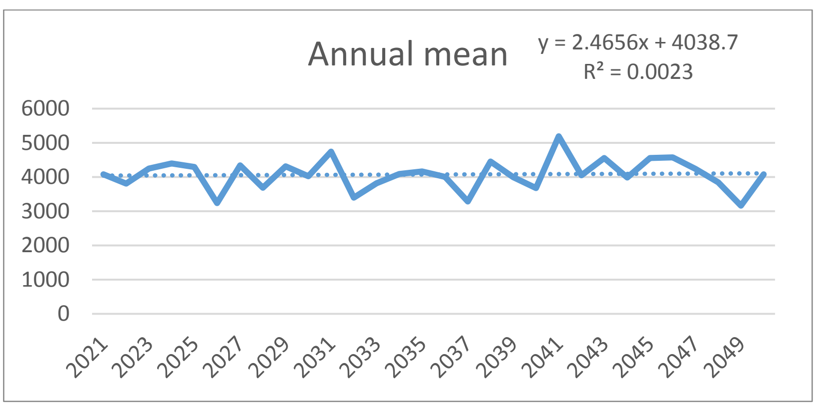


Fig. 3: Regression analysis of rainfall data (2021-2050) for Kokkarne catchment

Table 2: Regression analysis of rainfall data (a) Summer, (b) Monsoon, (c) Post Monsoon (d) Winter.

| Season | Regression Equation | $R^2$ |
|---|---|---|
| Summer | y = 1.21x + 228.27 | 0.0104 |
| Monsoon | y = 2.77x + 3503.8 | 0.0032 |
| Post monsoon | y = -1.54x + 297.75 | 0.0429 |
| Winter | y = 0.0093x + 2.95 | 0.0012 |
| Annual | y = 2.46x + 4038.7 | 0.0023 |

respectively, using a linear regression model (Fig. 2). The post-monsoon rainfall pattern was found to be fairly variable, while the winter trend was non-significant (Fig. 2). The post-monsoon rainfall season is showing a declining trend. 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, Jain & Kumar 2012, Kumar et al. 2010, Łupikasza et al. 2011, Malik & Kumar 2020, Radhakrishnan et al. 2017). The weather system being different in different seasons of the year is the prime factor leading to seasonal variation in precipitation as reported by Arora et al. (2006).

## GCM Uncertainty

Climate statistics for the near future are shown in Table 3 for the summer, monsoon, post-monsoon, and winter seasons and annual time scales. It is worth noting that the majority of the forecasts show a rise in mean annual rainfall when compared to the rainfall data of the baseline period (1777.7 mm). The ensemble means rainfall value for the catchment shows an increase of roughly 2299.2 mm. The annual rainfall projected by different GCM models ranges from 3555.7 mm (ACCESS1.0 GCM MODEL) to 4317.1 mm (MPI-ESM-LR GCM MODEL). During the monsoon season, all of the projections show similar variations.

As shown in Table 3, there are only minor variations in CV, which are 11 % and 12 % for the annual and monsoon seasons respectively, compared to 48.5 % and 58.9 % for the rainfall data of the baseline period, implying that variability will be reduced in the near future. Further, the CV of post-monsoon rainfall is 23.55 % which is higher than that of monsoon rainfall at 11.96%, implying that post-monsoon rainfall has more interannual variability than monsoon rainfall. Considering the above findings the use of Multi-Model

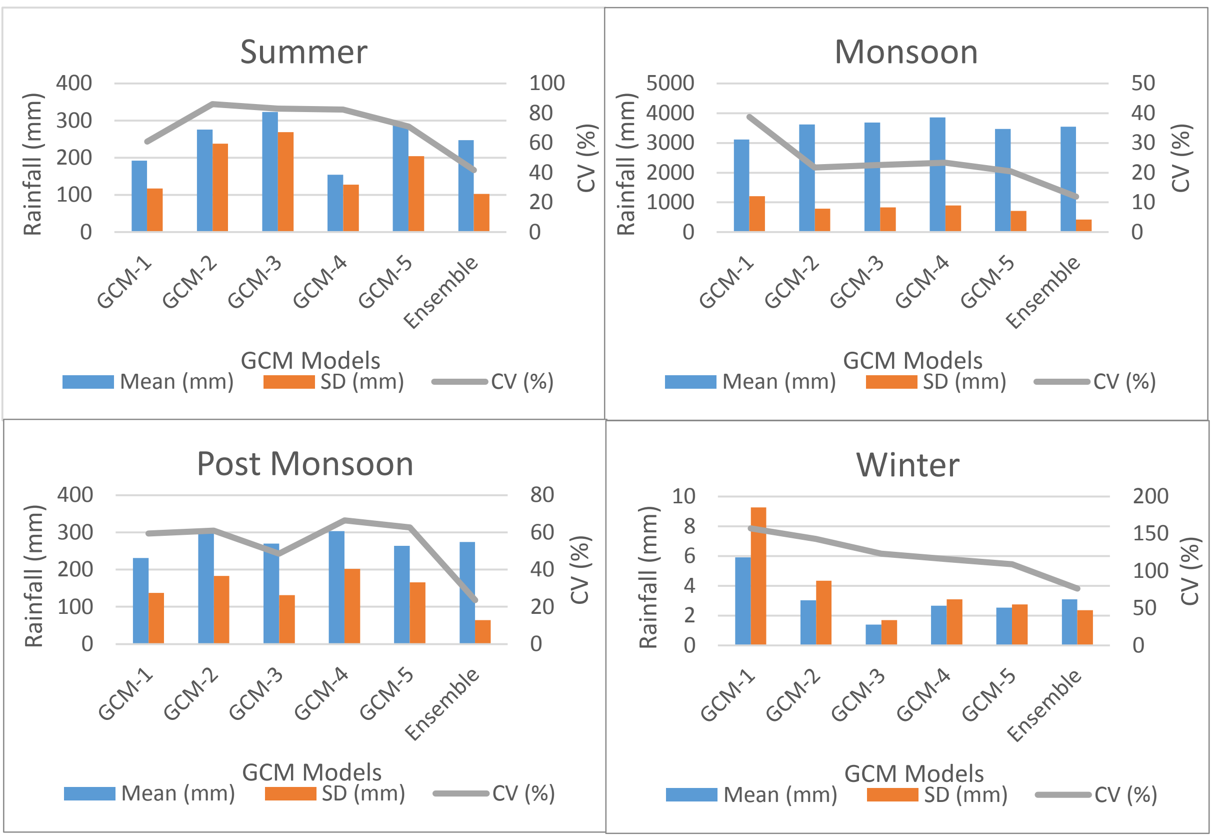


Fig. 4: Seasonal mean rainfall, standard deviation, and their corresponding CV.

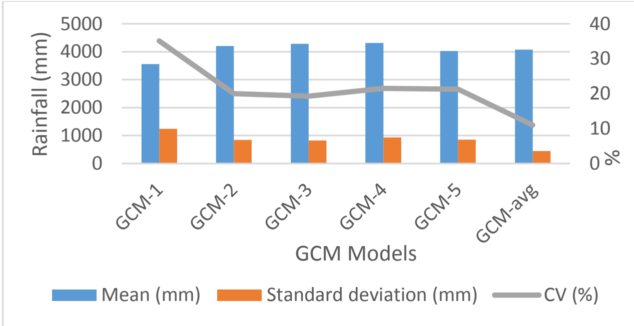


Fig. 5: Annual mean rainfall, standard deviation, and their corresponding CV.

Table 3: Climate statistics for near future bias-corrected GCM projections (2021-2050). The values in brackets represent the absolute change in the Bias corrected GCM data with reference period, i.e. IMD gridded data for the period (1991-2020).

| | | Mean (mm) | SD (mm) | CV (%) |
|---|---|---|---|---|
| IMD | Summer | 119.34 | 57.50 | 48.18 |
| | Monsoon | 1451.36 | 854.60 | 58.88 |
| | Post monsoon | 193.11 | 104.73 | 54.23 |
| | Winter | 4.62 | 5.73 | 123.94 |
| | Annual | 1777.69 | 861.95 | 48.49 |
| ACCESS1.0 | Summer | 192.3 (61.2) | 117.3 (104.1) | 61 (26.7) |
| | Monsoon | 3114.6 (114.6) | 1207.3 (41.3) | 38.8 (-34.2) |
| | Post monsoon | 231.2 (19.8) | 137.2 (31.1) | 59.4 (9.6) |
| | Winter | 5.9 (27.6) | 9.3 (62.3) | 157.3 (27) |
| | Annual | 3555.7 (100.1) | 1245 (44.5) | 35.1 (-27.7) |
| CNRM-CM5 | Summer | 276.1 (131.4) | 237.8 (313.6) | 86.2 (79) |
| | Monsoon | 3617.1 (149.3) | 785 (-8.2) | 21.8 (-63) |
| | Post monsoon | 300.5 (55.7) | 183.4 (75.2) | 61.1 (12.7) |
| | Winter | 3.1 (-33) | 4.4 (-23.3) | 143 (15.4) |
| | Annual | 4202.6 (136.5) | 839.1 (-2.7) | 20 (-58.8) |
| GFDL-CM3 | Summer | 323.6 (171.2) | 268.6 (367.2) | 83.1 (72.5) |
| | Monsoon | 3687.9 (154.1) | 832.2 (-2.7) | 22.6 (-61.7) |
| | Post monsoon | 270.2 (40) | 131.4 (25.5) | 48.7 (-10.2) |
| | Winter | 1.4 (-69.8) | 1.8 (-68.6) | 123.3 (-0.6) |
| | Annual | 4285.8 (141.1) | 826.3 (-4.2) | 19.3 (-60.2) |
| MPI-ESM-LR | Summer | 154.8 (29.8) | 127.5 (121.8) | 82.4 (71.1) |
| | Monsoon | 3851 (165.4) | 897.8 (5.1) | 23.4 (-60.3) |
| | Post monsoon | 303.4 (57.2) | 201.7 (92.6) | 66.5 (22.7) |
| | Winter | 2.7 (-41.7) | 3.1 (-46) | 115.9 (-6.5) |
| | Annual | 4317.1 (142.9) | 927.5 (7.7) | 21.5 (-55.7) |
| NorESM1-M | Summer | 288.7 (142) | 204.7 (256.1) | 70.9 (47.2) |
| | Monsoon | 3463.5 (138.7) | 709.4 (-17) | 20.5 (-65.2) |
| | Post monsoon | 264.1 (36.8) | 165.6 (58.2) | 62.8 (15.9) |
| | Winter | 2.6 (-43.8) | 2.8 (-51.2) | 108.8 (-12.3) |
| | Annual | 4023.8 (126.4) | 856.4 (-0.7) | 21.3 (-56.1) |
| Ensemble | Summer | 247 (107) | 102.9 (79) | 41.7 (-13.4) |
| | Monsoon | 3546.8 (144.4) | 424.4 (-50.3) | 12 (-79.6) |
| | Post monsoon | 273.8 (41.8) | 64.5 (-38.4) | 23.6 (-56.5) |
| | Winter | 3.1 (-33) | 2.4 (-58.1) | 76.4 (-38.4) |
| | Annual | 4076.9 (129.3) | 448 (-48) | 11 (-77.3) |

Ensemble (MME) data is encouraged as the process will reduce the uncertainties involved in individual GCM data (Ahmed et al. 2019, Colorado-Ruiz et al. 2018, Dai et al. 2001, Shiru et al. 2020, Wang et al. 2018).

The standard deviation of rainfall data projected by different GCM models under consideration varied from 826.3 mm (GFDL-CM3 GCM MODEL) to 1245 mm (ACCESS1.0 GCM MODEL), and the coefficient of variation varied from 19.3 mm (GFDL-CM3 GCM MODEL) to 35.1 mm (ACCESS1.0 GCM MODEL). Considering the ensemble of GCM values reduces the standard deviation of rainfall data for the period 2021-2050 to 448 mm, as shown in Fig. 5. Even the coefficient of variation is lowered to 11 %, along with the standard deviation. As a result, the rainfall variability of the projected data is reduced.

**Monthly Distribution of Average Precipitation (2021-2050)**

Kokkarne catchment receives annual precipitation ranging from 3201.82 mm to 5141.29 mm, with an average of 4069.38 mm. The highest monthly average precipitation is received during July (1230.73mm) (Krishnakumar et al. 2009), contributing 30.24 % to annual precipitation; August and September months with precipitation of 1018.39 mm and 387 mm ranked second and third, contributing 25.02 % and 9.51 % to annual precipitation, respectively. July is found to be the wettest month in the catchment as reported by other similar studies (Bhan et al. 2015, Singh & Mishra 2014, Zhang et al. 2019).

The monsoon season receives the highest precipitation of all the seasons, it is preferable to locate a feasible mechanism for storing extra precipitation in a reservoir, rather than letting it runoff or evaporate. A guideline for groundwater recharging might be constructed using this extra precipitation during the monsoon. With minimal extraction during the monsoon and by using groundwater recharging techniques, good groundwater can be conserved. It would be difficult to grow post-monsoon crops without additional irrigation since post-monsoon precipitation is more unpredictable and variable.

**Decadal Analysis of Rainfall and Discharge**

The box plot analysis of rainfall and discharge has been shown in Fig. 6. The rainfall is projected to decrease from 4164.64 mm in 2021-30 to 3999.02 mm in 2031-40 then projected to increase to 4157.16 mm in 2041-50. Similarly, the discharge output obtained from the simulation of the SWAT model was also analyzed and it was found that rainfall is projected to decrease from 218.40 $m^3.sec^{-1}$ in 2021-30 to 208.40 $m^3.sec^{-1}$ in 2031-40 and then projected to increase to 218.92 $m^3.sec^{-1}$ in 2041-50.

The increase in the discharge is correlated with an increase in the rainfall of the catchment as reported by studies like (Chiew et al. 1995, Fapeng et al. 2013; Miller & Russell 1992, Pfister et al. 2004, Van Steenbergen & Willems 2012).

## CONCLUSIONS

The purpose of this study was to use regression analysis of the rainfall data for the catchment to detect the annual and seasonal rainfall patterns. The rate of change of the rainfall was obtained by fitting the linear regression line, and the slope of the simple least-square regression expressed the trend. The current study used linear regression analysis, a significant parametric model that can be utilized to construct functional correlations between variables, to examine the rainfall trend for the study area. Furthermore, from 2021 to

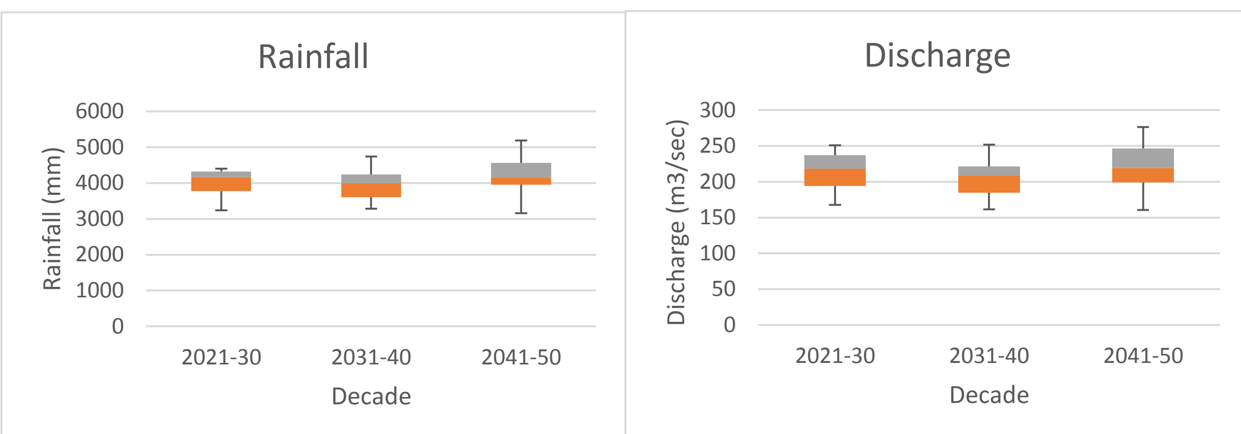


Fig. 6: Decadal analysis of 1) Rainfall 2) Discharge of Kokkarne catchment.

2050, the current study brings to light the impact of global climate change on rainfall and discharge patterns in the Kokkarne catchment.

Following are a few of the observations from the present research.

1. Except for the post-monsoon season, the trend m (the slope) in the equation y = mk + c of regression analysis revealed a positive trend for all three seasons.
2. Considering the Ensemble mean of rainfall data helps to reduce the uncertainty in the data.
3. The standard deviation of ensembled rainfall data has reduced to 448 mm.
4. CV of ensembled rainfall data has reduced to 11 mm.
5. July month is receiving the highest monthly average precipitation of 1230.73 mm.
6. The increase or decrease in the rainfall of the catchment is reflecting the increase or decrease in the discharge of the catchment.

Climate extreme events have an impact on farmers in the region and their agricultural activities with the increase in rainfall variability. The government may formulate climate-friendly water resource policies as a result of the findings of this study, which will promote self-sufficient and economical agricultural practices.

## ACKNOWLEDGMENTS

The authors thank the Indian Institute of Tropical Meteorology (IITM), Pune for making CORDEX-SA data available. The authors also gratefully acknowledge the climate data provided by the India Meteorological Department, New Delhi, and discharge data provided by WRDO, Bangalore. The authors acknowledge gratefully the National Institute of Hydrology, Belagavi, Karnataka, India for helping to acquire all the data used in this study.

## REFERENCES

Acquah, H. and Kyei, C. 2012. The effects of climatic variables and crop area on maize yield and variability in Ghana. Russ. J. Agric. Socio-Econ. Sci., 10(1): 10-13. https://doi.org/10.18551/rjoas.2012-10.02

Ahmed, K., Sachindra, D.A., Shahid, S., Demirel, M.C. and Chung, E. 2019. Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum and minimum temperature based on spatial assessment metrics. Hydrol. Earth Syst. Sci., 23(11): 4803-4824.

Arora, M., Singh, P., Goel, N. and Singh, R. 2006. Spatial distribution and seasonal variability of rainfall in a mountainous basin in the Himalayan region. Water Resour. Manag., 20(4): 489-508.

Basappa, V., Nayak, P. C., Thomas, T., Jain, S. and Tyagi, J. 2021. Spatio-temporal analysis of rainfall pattern in the Western Ghats region of India. Meteorol. Atmos. Phys., 133(4): 1089-1109. https://doi.org/10.1007/s00703-021-00796-z

Bhan, S., Devrani, A. and Sinha, V. 2015. An analysis of monthly rainfall and the meteorological conditions associated with cloudburst over the dry region of Leh (Ladakh), India. Mausam, 66(1): 107-122. https://doi.org/10.54302/mausam.v66i1.371

Bhatla, R., Singh, S., Verma, S., Tyagi, P., Maurya, A. and Pant, M. 2020. The study of rainfall variability during pre and post-monsoon seasons over all of India and its different regions in changing climate. J. Indian Geophys. Union, 24(3): 57-71.

Cheng, H. and Hu, Y. 2012. Improving China's water resources management for better adaptation to climate change. Clim. Change, 112(2): 253-282.

Cheung, W.H., Senay, G.B. and Singh, A. 2008. Trends and spatial distribution of annual and seasonal rainfall in Ethiopia. Int. J. Clim. Royal Meteorol. Soc., 28(13): 1723-1734.

Chiew, F.H.S., Whetton, P.H., McMahon, T.A. and Pittock, A.B. 1995. Simulation of the impacts of climate change on runoff and soil moisture in Australian catchments. J. Hydrol., 167(1): 121-147. https://doi.org/10.1016/0022-1694(94)02649-V

Colorado-Ruiz, G., Cavazos, T., Salinas, J.A., De Grau, P. and Ayala, R. 2018. Climate change projections from Coupled Model Intercomparison Project phase 5 multi-model weighted ensembles for Mexico, the North American monsoon, and the mid-summer drought region. Int. J. Clim., 38(15): 5699-5716.

Dai, A., Meehl, G.A., Washington, W.M., Wigley, T.M. and Arblaster, J.M. 2001. Ensemble simulation of twenty-first-century climate changes Business-as-usual versus CO 2 stabilization. Bull. Am. Meteor. Soc., 82(11): 2377-2388.

Deka, J.R., Bordoloi, M. and Sarma, P. 2021. Historical ponds of Darrang district: Identification and mapping, their ecological relevance for management planning. Int. J. Geoherit. Parks, 9(4): 496-508. https://doi.org/10.1016/j.ijgeop.2021.11.008

Earman, S. and Dettinger, M. 2011. Potential impacts of climate change on groundwater resources: A global review. J. Water Clim. Change, 2(4): 213-229.

Fapeng, U., Zhang, Y., Xu, Z., Teng, J., Liu, C., Liu, W. and Mpelasoka, F. 2013. The impact of climate change on runoff in the southeastern Tibetan Plateau. J. Hydrol., 505(1): 188-201. https://doi.org/10.1016/j.jhydrol.2013.09.052

Gedefaw, M., Yan, D., Wang, H., Qin, T., Girma, A., Abiyu, A. and Batsuren, D. 2018. Innovative trend analysis of annual and seasonal rainfall variability in Amhara regional state, Ethiopia. Atmosphere, 9(9): 326-336.

Goswami, A. and Paul, A. 2010. Assessment of trends and variability of post-monsoon rainfall for some selected districts of sub-Himalayan West Bengal, India. Ind. Geogr. J., 85(1): 37-44.

Hong, N.N., Xu, C.Y., Beldring, S., Tallaksen, L.M. and Jain, S.K. 2016. Water resources under climate change in Himalayan basins. Water Resour. Manag., 30(2): 843-859.

Hossain, M. 2015. Water: The most precious resource of our life. Glob. J. Adv. Res., 2(9): 1-11.

Hussain, M. and Lee, S. 2013. The regional and seasonal variability of extreme precipitation trends in Pakistan. Asia-Pacif. J. Atmos. Sci., 9(4): 421-441. https://doi.org/10.1038/s41598-019-41334-7

Hussain, M. and Taqi, M. 2014. Impact of agricultural credit on agricultural productivity in Pakistan: An empirical analysis. Int. J. Adv. Res. Manag, Social Sci., 3(4): 125-139.

Jain, S.K. and Kumar, V. 2012. Trend analysis of rainfall and temperature data for India. Curr. Sci., 102(1): 37-49.

Krishnakumar, K.N., Rao, G.P. and Gopakumar, C.S. 2009. Rainfall trends in the twentieth century over Kerala, India. Atmos. Environ., 43(11): 1940-1944. https://doi.org/10.1016/j.atmosenv.2008.12.053

Kumar, V., Jain, S.K. and Singh, Y. 2010. Analysis of long-term rainfall trends in India. Hydrol. Sci. J., 55(4): 484-496.

Łupikasza, E.B., Hänsel, S. and Matschullat, J. 2011. Regional and seasonal variability of extreme precipitation trends in southern Poland

and central-eastern Germany 1951-2006. Int. J. Climatol., 31(15): 2249–2271.

Mahilange, M. and Das, G.K. 2018. Estimating rainfall variability over five districts of the northern hill zone of Chhattisgarh state. J. Pharmac. Phytochem., 7(5): 3370-3374.

Malik, A. and Kumar, A. 2020. Spatio-temporal trend analysis of rainfall using parametric and non-parametric tests: A case study in Uttarakhand, India. Theoret. Appl. Climatol., 140(1): 183-207.

Miller, J.R. and Russell, G.L. 1992. The impact of global warming on river runoff. J. Geophys. Res. Atmos., 97(D3): 2757-2764. https://doi.org/10.1029/91JD01700

Mudbhatkal, A., Raikar, R., Venkatesh, B. and Mahesha, A. 2017). Impacts of climate change on varied river-flow regimes of southern India. J. Hydrol. Eng., 22(9): 1-13. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001556

Nandargi, S. and Mulye, S. 2014). Spatio-temporal rainfall variability over Goa, India. Int. J. Meteorol., 39(385): 99-121.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R. and Williams, J.R. 2011. Soil and Water Assessment Tool Theoretical Documentation Version 2009. Texas Water Resources Institute. https://oaktrust.library.tamu.edu/bitstream/handle/1969.1/128050/TR-406_SoilandWaterAssessmentToolTheoreticalDocumentation.pdf?sequence=1

Panda, A. and Sahu, N. 2019. Trend analysis of seasonal rainfall and temperature pattern in Kalahandi, Bolangir and Koraput districts of Odisha, India. Atmos. Sci. Lett., 20(10),1-10. https://doi.org/10.1002/asl.932

Pfister, L., Drogue, G., El Idrissi, A., Iffly, J.F., Poirier, C. and Hoffmann, L. 2004. Spatial variability of trends in the rainfall-runoff relationship: A mesoscale study in the Mosel basin. Clim. Change, 66(1): 67-87. https://doi.org/10.1023/b:clim.0000043160.26398.4c

Radhakrishnan, K., Sivaraman, I., Jena, S. K., Sarkar, S. and Adhikari, S. 2017. A climate trend analysis of temperature and rainfall in India. Clim. Change Environ. Sustain., 5(2): 146-153.

Shiru, M.S., Chung, E.S., Shahid, S. and Alias, N. 2020. GCM selection and temperature projection of Nigeria under different RCPs of the CMIP5 GCMs. Theoret. Appl. Climatal., 141(3): 1611-1627. https://doi.org/10.1007/s00704-020-03274-5

Shrestha, S. and Htut, A.Y. 2016.. Modeling the potential impacts of climate change on the hydrology of the Bago River Basin, Myanmar. Int. J. River Basin Manag. 14(3): 287-297.

Singh, S. and Mishra, A. 2014. Spatiotemporal analysis of the effects of forest covers on stream water quality in the Western Ghats of peninsular India. J. Hyrdol., 519(1): 214-224.

Thomson, A.M., Calvin, K.V., Smith, S.J., Kyle, G.P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A. and Clarke, L.E. 2011. RCP4. 5: A pathway for stabilization of radiative forcing by 2100. Climat. Change, 109(1): 77-94.

Van Steenbergen, N. and Willems, P. 2012. Method for testing the accuracy of rainfall-runoff models in predicting peak flow changes due to rainfall changes, in a climate-changing context. J. Hyrdrol., 414(1): 425-434. https://doi.org/10.1016/j.jhydrol.2011.11.017

Wang, B., Zheng, L., Ji, F., Clark, A. and Yu, Q. 2018. Using multi-model ensembles of CMIP5 global climate models to reproduce observed monthly rainfall and temperature with machine learning methods in Australia. Int. J. Climatol., 38(13): 4891-4902. https://doi.org/10.1002/joc.5705

Zhang, K., Wang, Q., Chao, L., Ye, J., Li, Z., Yu, Z., Yang, T. and Ju, Q. 2019. Ground observation-based analysis of soil moisture spatiotemporal variability across a humid to semi-humid transitional zone in China. J. Hydrol., 574(1): 903-914. https://doi.org/10.1016/j.jhydrol.2019.04.087