

Assessing the Evolution of Rainfall Trends in India through Historical Analysis, Forecasting, and Comparison with the CMIP-6 SSP585 Scenario

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Abstract

Rainfall is a fundamental driver of the Earth's water cycle and human activity, necessitating the study of its trends to assess climate change impacts and formulate robust adaptation strategies. Accordingly, this study analyses rainfall trends in India across six Homogenous Regions (HRs) and thirty-four Meteorological Subdivisions (MSDs) from 1901 to 2022. Using Mann-Kendall (MK) Test and Innovative Trend Analysis (ITA), the study examines annual, seasonal, and monthly rainfall patterns in India. Annual results reveal significant rainfall decrease in the Northeast HR with significant negative trends in seven MSDs. Also, nine MSDs exhibited significant positive trends. Seasonally, the Northeast HR and its subdivisions exhibited negative rainfall trends, whereas Coastal Andhra Pradesh and Punjab exhibited positive trends. ERA5 reanalysis data reveal that these variations are driven by fluctuations in convective precipitation, increased low-cloud cover, and inadequate vertical moisture divergence. The study further utilizes an Artificial Neural Networks-Multilayer Perceptron (ANN-MLP) to forecast rainfall up to 2050, predicting an overall annual decrease. Comparison with CMIP-6 SSP585 projections indicates that all HRs and 28 MSDs will experience rainfall reductions surpassing the worst-case scenario. These findings, signalling significant impacts on agriculture and water resources, provide critical insights for policy-making in irrigation, water management, and climate research.

Keywords: Rainfall Trend Analysis, Mann-Kendall Test, Innovative Trend Analysis, Climate Change, Rainfall Forecasting, CMIP-6 Rainfall Projection.

1. Introduction

Climate change is anticipated to result in a widespread rise in extreme events and climate variability, imposing a significant challenge on the environment, society, and the economy (Hall et al., 2014). The projected climate variability suggests a reduction in renewable surface water and groundwater resources across many subtropical regions, heightening competition for water (Pachauri et al., 2015). Climate change, a continuous process, has historically been shaped by natural factors and, more recently, by human activities (Goudie, 2018). The impacts of changing climate manifest through alterations in rainfall and temperature, which are fundamental elements of the climate. According to Subash & Sikka, 2014, the variability in these fundamental parameters significantly influence the radiation balance, thereby influencing entire hydrological cycle. The potential outcomes of this influence include low agricultural productivity, an elevated risk of famines, loss of livelihood, reduced soil moisture, accelerated melting of glaciers, and decreased river flows (Jain et al., 2013). Therefore, it is crucial to analyse the fluctuations of these elements of climate to acquire a deeper understanding of climate change, its evolving patterns, and the impact of such changes on the geography of a region. Intergovernmental Panel on Climate Change (IPCC) also emphasizes the need for immediate attention to be given to studies aimed at detecting the effects of climate change and its impact on different sectors. Among the various elements of climate, rainfall plays a crucial role in shaping the environmental conditions of a region (Modarres and Silva, 2007; Kumar & Gautam, 2014; Singh et al., 2021). The environment, terrestrial ecosystems, oceanic ecosystems, biodiversity, and agriculture are all governed by rainfall patterns, and alterations in the rainfall regimes lead to imbalances within the respective ecosystems (Almeida et al., 2017). The anomalies in rainfall contribute to a rising occurrence of droughts and floods. This, along with diminishing rainfall in rainfed regions and the depletion of groundwater resources, has led to crop failures, livelihood losses, and the occurrence of extreme weather events (Guhathakurta et al., 2015). To tackle the issues emerging from escalating variability in rainfall patterns, water resource management has garnered significant attention in recent times. However, the successful implementation of any planning program heavily relies on the availability of water (Bisht et al., 2018). Rainfall is one of the most significant components of the hydrological cycle, and it plays a crucial role in redistributing water across the Earth's surface, counteracting concentration patterns dictated by the topography. Furthermore, the rainfall dynamics directly influence the resource balance on Earth's surface (Patowary et al., 2017; Banerjee et al., 2020).

Recently, a considerable amount of research has been devoted to examining both historical and contemporary climate change. The emphasis includes efforts to enhance and broaden datasets, alongside the application of more advanced data analysis techniques on a global scale (Kale & Nagesh Kumar, 2018; N. Kumar et al., 2019).

Trend analysis is a frequently employed approach to assess variations in the fundamental hydro-meteorological elements across predetermined spatial and temporal scales (Meena et al., 2015; Sanikhani et al., 2018). The analysis has been applied to detect rainfall trends as an indication of climate change both at global and national levels. At the global level, rainfall trend analysis has been carried out, including Díaz et al., 2021; Ratan & Venugopal, 2013; Ray et al., 2021 and Fazal et al., 2023, and at the national level for Italy (Caloiero et al., 2018), Ethiopia (Worku et al., 2019), Brazil (Almeida et al., 2017), Morocco (Khomsi et al., 2016), Bangladesh (Das et al., 2021), among others. Rainfall trend analysis has also been carried out for India (Ahmed et al., 2022; Mondal et al., 2015; Mooley & Parthasarathy, 1984; Praveen et al., 2020; Saini & Sahu, 2021; Subash & Sikka, 2014; Thapliyal & Kulshrestha, 1991), and various smaller regions of the country (N. Kumar et al., 2019; Saikh et al., 2023; Shahfahad et al., 2022, 2023; A. Kumar et al., 2023; Nath et al., 2023; Rana et al., 2012). Rainfall irregularities in India are due to inherent uncertainties. For instance, stronger northeasterly winds can restrict the influx of cooler air, leading to reduced winter rainfall nationwide. Furthermore, heightened cloud cover can amplify the concentration of solar radiation in the atmosphere, potentially disrupting rainfall patterns and complicating water management and allocation strategies. (Som & Dey, 2022).

Methodologically, parametric and non-parametric techniques have been utilized for trend analysis. According to Som & Dey, 2022, parametric and non-parametric techniques are the most popular and widely employed tools for trend analysis in hydrology, climatology, and meteorology. Non-parametric techniques are favored over parametric techniques due to their applicability to non-normally distributed data with missing values and their reduced sensitivity to outliers (Pattanayak & Kumar, 2013; Hamed & Ramachandra Rao, 1998). Additionally, they rely on fewer assumptions and are widely applicable, even in discrete data sets (N. Kumar et al., 2019). Various non-parametric techniques that have been adopted for trend analysis include the Regression Curve (Mudelsee, 2019; Sun & Fang, 2018), Mann-Kendall (MK) Test (Douglas et al., 2000; Gajbhiye et al., 2016; Jain et al., 2013; Panda & Sahu, 2019, 2019; R. Singh et al., 2021), Sens's Slope (Caloiero et al., 2018), Modified MK Test (Praveen et al., 2020; Saini & Sahu, 2021; Tripathi & Govindaraju, 2009), and the Kendall Rank Coefficient (Yücel et al., 2022). The MK Test, a widely recognized non-parametric technique, is employed for trend analysis in hydrology, climatology, and meteorology. Researchers have applied this method to examine variations in rainfall at various regional and global scales (Cailas et al., 1986; Demaree and Nicolis, 1990; Lettenmaier et al., 1994; Douglas et al., 2000; N. Singh & Sontakke, 2002; Huth & Pokorná, 2004; Abdul-Aziz & Burn, 2006; V. Kumar & Jain, 2011; Gajbhiye et al., 2016; Panda & Sahu, 2019). Nevertheless, climatologists have observed uncertainties associated with the application of the MK Test in time series data extended over a longer time scale (Mohapatra et al., 2021; Mondal et al., 2015). To address these uncertainties, homogeneity tests have been developed and are utilized to avert misleading results (Hamed & Ramachandra Rao, 1998). Homogeneity tests determine the presence (heterogeneity) or absence (homogeneity) of breakpoints in extensive data series. These tests play a crucial role in accurately applying trend analysis techniques to data that has exhibited different trends before and after the identified breakpoint. Examining trend patterns before and after breakpoints leads to more accurate results compared to applying trend detection techniques to continuous datasets as a whole (Zarenistanak et al., 2014). Frequently employed homogeneity tests encompass the Pettitt Test, Standard Normalized Homogeneity Test (SNHT), and Buishand Range Test, which are extensively utilized to detect break years (Alexandersson & Moberg, 1997; Buishand, 1982; Pettitt, 1979). Innovative Trend Analysis (ITA), introduced by Şen 2012, is another non-parametric trend analysis technique that presents a wider applicability in comparison to traditional non-parametric tests. It successfully addresses issues associated with autocorrelation and large sample sizes in temporal datasets (Machiwal et al., 2019).

The present study aims to conduct a comprehensive and spatio-temporally extensive rainfall trend analysis in India, i.e., spatially covering the entire Indian landmass resolved into six homogenous rainfall regions (HRs) and thirty-four meteorological subdivisions (MSDs), and temporally covering 122 years (1901-2022) resolved into monthly, seasonal, and annual series. The study also delves into the comparative assessment of the MK Test, Sens's Slope, and ITA as methods of trend analysis in the context of India. It must be noted that the homogeneity tests are integrated with the MK Test to improve its precision. Additionally, climatic predictions, such as rainfall forecasting, play a pivotal role in the realm of sustainable development strategies of the Anthropocene. The integration of trend analysis with future forecasting offers planners and policymakers a holistic perspective on the evolving climate and anticipated conditions in the years ahead. Climate predictions utilizing conventional forecasting methods, such as deterministic models and statistical models, which are frequently employed for this purpose, encounter limitations and yield less reliable results (Chakraverty & Gupta, 2008). The prediction models such as AutoRegressive Moving Average (ARMA), AutoRegressive Integrated Moving Average (ARIMA), and Seasonal AutoRegressive Integrated Moving Average (SARIMA) have inherent limitations in reliance on past values for regression and incorporating past errors in training variables

(Darji et al., 2015). The application of machine learning (ML) and deep learning (DL) as alternative approaches for has gained prominence (Immerzeel, 2008), for these models can handle large and complex datasets without requiring excessive information and can also perform well with time series data of non-stationary characteristics (Hossain et al., 2020). In this study, an advanced machine learning approach, specifically the Artificial Neural Network - Multilayer Perceptron (ANN-MLP), is utilized for rainfall forecasting. This machine learning algorithm, delves into the intricate patterns of rainfall data using neural networks, offering a more adaptable and potentially nuanced forecast. Moreover, the model-derived forecasts were compared with rainfall projections sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP-6) SSP585 (Shared Socioeconomic Pathway) that depicts the extreme climate change scenario. This integration enables us to validate our models against a broader spectrum of data and assess their performance in the context of climate model projections, further refining our understanding and confidence in the forecasted rainfall patterns. The valuable insights derived from this comparative evaluation and rainfall forecasting are poised to offer significant benefits to policymakers, scientists, hydrologists, and geologists. Armed with comprehensive data, they can formulate and execute more efficient water management strategies. The importance of this research is underscored by its potential to enhance informed decision-making processes within the realm of water resource management.

2. Materials and Methods

2.1. Study Area and Data Sources

India covers an extensive region with diverse geography, ranging from 8.4°N to 37.6°N latitude and 68.7°E to 97.25°E longitude, spanning 2.9 million km². This leads to high spatial variation in climatic conditions across the country. The India Meteorological Department (IMD) manages a network of 306 rainfall monitoring stations, with at least one station in each state, to collect climatic data (Ahmed et al., 2022). Annual precipitation in the region ranges from 160mm to 1800mm across different regions (Mondal et al., 2015). To study these spatial and temporal differences in rainfall, India is divided into six broader homogeneous rainfall regions (HRs), which include the Central Northeast Region, Hilly Region, Northeast Region, Northwest Region, South Peninsular Region, and West Central Region (**Fig. 1**). IMD has also divided India into thirty-six meteorological sub-divisions (MSDs) based on agricultural and topological factors (Guhathakurta et al., 2015). India broadly experiences the summer (March – May), monsoon (June – September), post-monsoon (October – December), and winter (January – February) seasons (Subash & Sikka, 2014). For this study, 122 years (1901 – 2022) of annual rainfall data was obtained from the Climatic Research Unit (CRU), University of East Anglia (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/pre/) followed by downscaling and averaging for six HRs and thirty-four MSDs of India. The dataset is continuous, with no missing values over the analysis period.

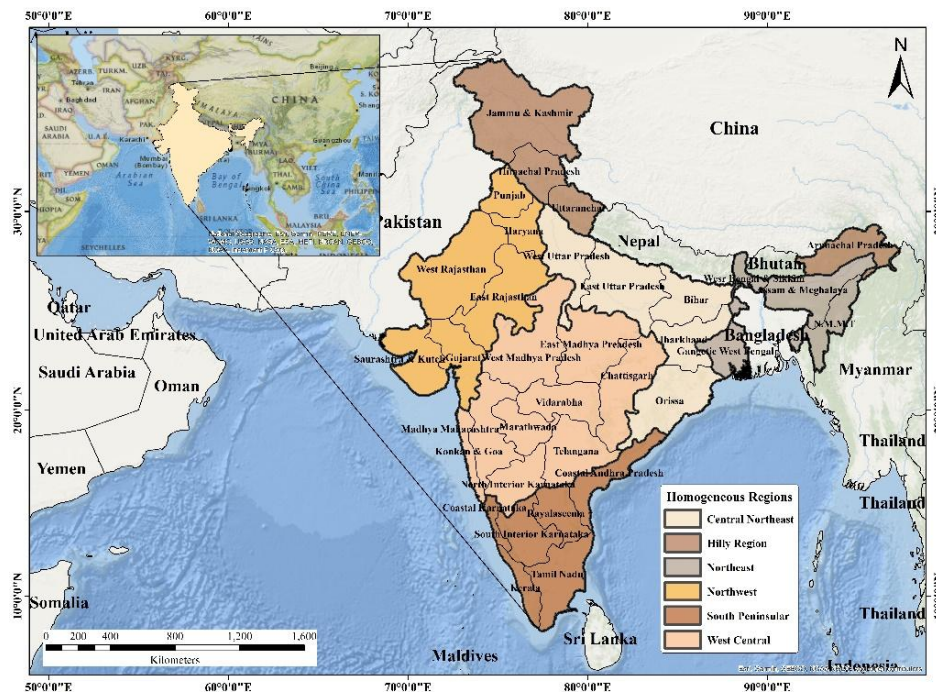


Fig. 1. Map of the study area representing homogeneous regions and meteorological sub-divisions of India

3. Methods

The detailed methodological flowchart of the study is given in **Fig. 2**. As depicted in the flowchart, this study examines monthly, seasonal, and annual rainfall trends over a span of 122 years (1901 – 2022) in India, employing non-parametric approaches including the MK Test, Sen's Slope, and ITA. Moreover, the study aims to forecast future rainfall by employing ANN-MLP model, and comparative assessment of the forecasts with CMIP-6 projections for India.

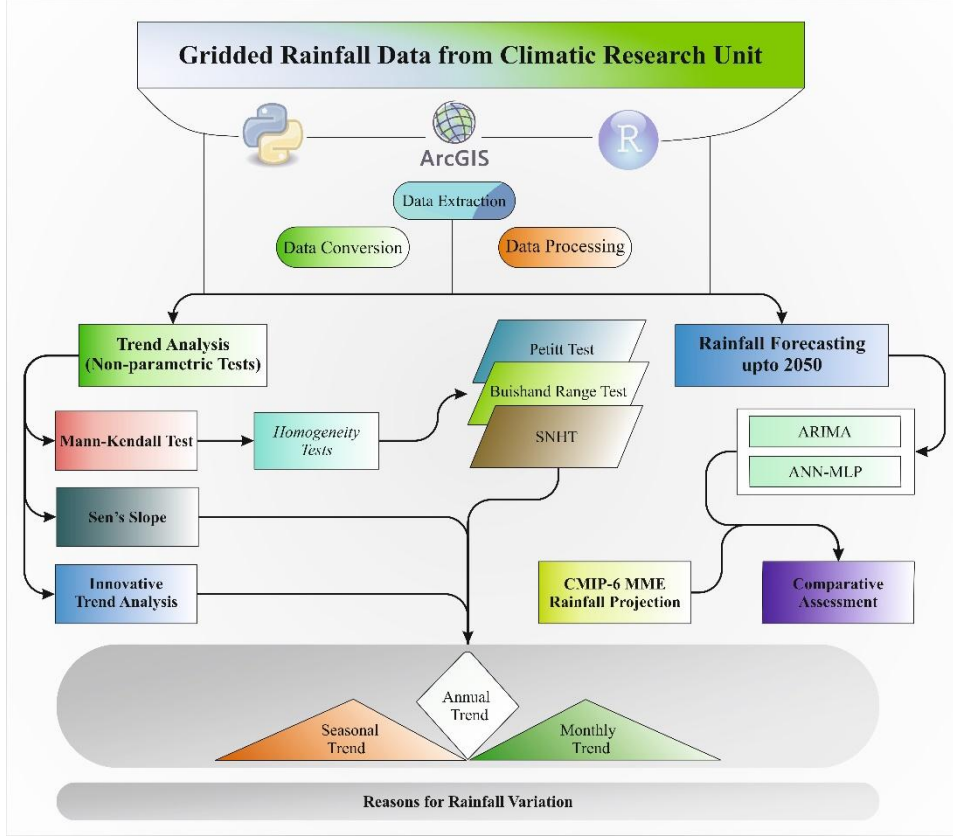


Fig. 2. Methodological flowchart

3.1. Mann Kendall (MK) Test

MK Test is a non-parametric test widely used for the identification of statistically significant trend in hydro-climatic variables such as temperature, precipitation, evapotranspiration and stream flow (Rahaman et al., 2023; Saini & Sahu, 2021). The test was initially suggested by Mann, 1945, and since then, it has been widely employed worldwide (Jain et al., 2013; Malik & Kumar, 2020). The test applies hypothesis testing to establish the null hypothesis (H_0) or alternate hypothesis (H_a) which indicate the absence or presence of trend (increasing/decreasing) in the time series data (Kendall, 1975; Mann, 1945). MK Test has following two advantages over other tests (Rahaman et al., 2023):

1. It is not necessary for the data to be regularly distributed.
2. It is relatively less sensitive to heterogeneity in the time series data.

The MK Test statistic (S) is defined as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (1)$$

Where, n is the maximum allowed number of observations, which is 10. Meanwhile, j has a bigger value than i . The j^{th} and i^{th} observations are denoted by letters x_j and x_i , respectively. The expression given below is used to calculate the sign (sgn) function:

$$sgn(x_j - x_i) = \begin{cases} +1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases} \quad (2)$$

When the number of observations surpasses ten ($n > 10$), S can be assumed to have a roughly normal distribution. The mean of S in this situation is zero, indicated by $E(S) = 0$ (Kendall, 1975). The variance of the S is defined in this context as follows:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t-1)(2t+5)}{18} \quad (3)$$

Where, n and m are the total number of observations and number of tied rank groups, with each group having t_i tied observations.

The Z-statistics can be determined using the following equation:

$$Z = \begin{cases} \frac{S-1}{\sqrt{var(s)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{var(s)}} & \text{if } S < 0 \end{cases} \quad (4)$$

A positive value of Z indicates an increasing trend, with a higher value of Z indicating a more significant trend. Conversely, a negative value of Z indicates a decreasing trend, where a higher absolute negative value implies a more significant trend. In this analysis, $\alpha = 0.05$ indicating 95% confidence level was used.

The accuracy of the Mann-Kendall (MK) test for detecting trends has recently been questioned. This is because time series data often exhibits autocorrelation, where data points close together in time are correlated with each other (Sonali & Nagesh Kumar, 2013). This violates an assumption of the MK test that requires independent data points. There are a few approaches that have been used to adjust for autocorrelation before applying the MK test (Mondal et al., 2015). These include ‘pre-whitening’ the data to reduce autocorrelation and using a modified version of the MK test designed for autocorrelated data (Von Storch, 1999). However, these adjustment methods don't always fully eliminate autocorrelation and can sometimes introduce new problems. Even removing portion of the autocorrelation may generate a new type of autocorrelation that did not previously exist, or components of a trend may be eliminated which can lead to under or overestimation (Kale & Nagesh Kumar, 2018).

In the current study, pre-whitening of the full data set was not applied. This decision was based on two factors:

1. The data set was longer than the recommended minimum length of 50 data points for the MK test, making the test more robust to autocorrelation issues.
2. The data exhibited a slope value larger than the 0.01 guideline, again suggesting that autocorrelation is less likely to severely impact the results (Bayazit & Önöz, 2007).

3.2. Sen's Slope Estimator

The Slope (β) estimator by Sen, a straightforward non-parametric technique, is employed to assess the magnitude and pace of variations within a time series dataset (Fathian et al., 2016; Habte et al., 2021). Sen's method proves resilient against significant outliers. It is derived from the approach outlined by Sen, 1968 as depicted in equation (5):

$$\beta = median \frac{x_i - x_j}{i - j} \quad (5)$$

Where, x_i is the data value at time t_i , and x_j is the data value at time t_j , and $i > j$. The positive and negative values of the slope suggest increasing and decreasing trend in the dataset, respectively.

3.3. Changepoint Detection using the Homogeneity Tests

A changepoint is a feature of a large, fluctuating, and dynamic dataset. It refers to points where there are evident and abrupt changes or breaks, resulting in peaks or depressions (Gallagher et al., 2013). In the case of a time series data spread over the interval of years, the changepoint is also referred to as the break year. In many circumstances, the presence of heterogeneity in the time series influences the detected monotonic trend and therefore it is recommended to implement changepoint detection before applying trend analysis techniques (Shen et al., 2018). Various techniques are available for change detection, and in the present study, the following widely recognized methodologies were employed:

3.3.1. Buishand Range Test

The Buishand range test, alternatively known as the Cumulative Deviation test (Buishand, 1982), is computed using adjusted biased sums or cumulative deviations from the mean. Breaks in the middle of the time series can be detected by this test (Bickici Arian & Kahya, 2019).

$$R_0^* = 0 \text{ and } R_m^* = \sum_{t=1}^m (P_t - P_{mean}) \quad (6)$$

$$R_m^{**} = R_m^* / \sigma \quad (7)$$

Where, $m = 1, 2, 3, \dots, n$.

$$S = \text{Max}|R_m^{**}| - \text{Min}|R_m^{**}|, 0 \leq m \leq n \quad (8)$$

3.3.2. Standard Normal Homogeneity Test (SNHT)

The Alexanderson test, also referred to as the standard normal homogeneity test, is utilized for identifying abrupt shifts or the existence of changepoints within time series data sets related to climate and hydrology (Alexandersson & Moberg, 1997). This approach is adaptable and easy to apply. The changepoint is detected by the following equation:

$$T_s = \max T_m, 1 \leq m < n \quad (9)$$

Changepoint refers to the point when T_s gets its maximum value in the data series. The T_m is derived using equation (10):

$$T_m = \bar{m}z_1 + (n - m)\bar{z}_1, m = 1, 2, \dots, n$$

$$\bar{z}_1 = \frac{1}{m} \sum_{i=1}^n \frac{M_i - \bar{M}}{s} \quad (10)$$

Where, $\bar{m}$ and s represent mean and standard deviation of the sampled data.

3.3.3. Pettitt Test

This non-parametric technique, proposed by Pettitt, 1979, locates the point of change on a monthly or annual scale in a time series. This test proves particularly beneficial in scenarios where hypothesis testing concerning the positioning of a changepoint is unnecessary. Its application has been extensive in identifying alterations observed within climatic and hydrological data series (Kabbilawsh et al., 2020)

When data has a time length of t and a shift occurs after m years, the resulting test statistics are calculated as per equation (4).

$$U_{t,m} = \sum_{i=1}^m \sum_{j=i+1}^t \text{sgn}(K_i - K_j) \quad (11)$$

Where, sgn is calculated by the following formula:

$$sgn(K_i - K_j) = \begin{pmatrix} 1 & \text{if } (K_i - K_j) > 1 \\ 0 & \text{if } (K_i - K_j) = 0 \\ -1 & \text{if } (K_i - K_j) < -1 \end{pmatrix} \quad (12)$$

All random variables from 1 to n are used to generate the test statistic $|U_{t,m}|$. Most of the distinct change points are identified in a location where the test statistic $|U_{t,m}|$'s magnitude is greatest.

$$Z_T = \text{Max}_{1 \leq t \leq m} |U_{t,m}| \quad (13)$$

The probability of a year shift is estimated when the absolute value of $|U_{t,m}|$ reaches its maximum according to:

$$P = 1 - \exp\left(\frac{-6Z_T^2}{K^2 + K^3}\right) \quad (14)$$

If the computed p-value is lower than the significance level α , the null hypothesis is deemed rejected.

3.4. Innovative Trend Analysis (ITA)

ITA approach, along with the MK Test and Sen's Slope, stand out among the common non-parametric trend analysis techniques for the extraction of the most accurate rainfall trend results (Ahmadi et al., 2017). In this study, a comparative assessment was conducted using ITA alongside two other techniques to validate the results obtained from the previously described methods.

First proposed by Şen, 2012, this graphical non-parametric technique of trend detection is more feasible because it can easily handle auto-correlated data and outliers. ITA offers a significant advantage over the MK test and other parametric and non-parametric statistical tests by eliminating the need for assumptions such as non-linearity, serial correlation, or specific sample sizes. It can recognise monotonic and sub-trends in time series datasets, as well as identify distinct combinations of trends in distinct time series data periods (Pour et al., 2020). To execute ITA, the original series is first divided into two sub-series with an equal number of observations. When there are an odd number of observations, the first entry is normally dropped (Sen, 2012). The series are then sorted in ascending order and plotted against each other in a Cartesian coordinate system, with the first half plotted on the X-axis and the second half plotted on the Y-axis (Wu and Qian, 2017). Finally, a straight line with the scatter plot reflecting monotonic trend or no trend, and the data plot is interpreted with reference to this monotonic trend line. If the scatter point concentration is above the 45° line (1:1), the time series shows an increasing trend, and if the scatter point concentration is below the 1:1 line, the time series shows a declining trend (Cui et al., 2017). If the scatter points are concentrated along the trend line, it shows that there is no trend in the dataset. In addition to this the slope of the data series was calculated using equation (15).

$$s = \frac{1}{n} \sum_{i=1}^n \frac{10(\bar{y} - \bar{x})}{n} \quad (15)$$

Where, s is a trend indicator with positive values representing a rising trend and negative values representing a declining trend. The y and x values are the averages of the first (x_i) and second (y_i) halves of the series, respectively. Moreover, n indicates the number of data points. The value of s is scaled by a factor of 10 prior to its comparison with the MK test.

3.5. Method for Detecting the Rainfall Changes

Data from the European Centre for Medium Range Weather Forecasts (ECMWF), ERA-5 (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=overview>) were used to assess changes in rainfall patterns, winter and summer precipitation, and moisture divergence between 1940 and 2022. The data was obtained at a resolution of $0.25^\circ \times 0.25^\circ$ for the atmosphere and $0.50^\circ \times 0.50^\circ$ for ocean waves and was collected on a monthly basis. ERA5 is the latest iteration of the ECMWF reanalysis, providing comprehensive data on global climate and weather patterns spanning the last 80 years. Data is accessible starting from the year 1940. ERA5 supersedes the ERA-Interim reanalysis. The convective precipitation, convective rainfall rate, low cloud cover, mean convective precipitation rate, mean total precipitation rate, and mean vertically integrated moisture divergence were extracted from the ERA5 dataset in the netCDF format. To identify the change point in the data series, Pettit test was applied in the

Python 3 environment and a notable change in the yearly average rainfall was observed after the year 1956 (**Fig. 3**). The change in circulation between two timeframes, before and after, is assessed by subtracting the circulation data from 1940-1956 from the data from 1957-2022 using the ECMWF ERA5 reanalysis data. All spatial maps were prepared on GrADS.

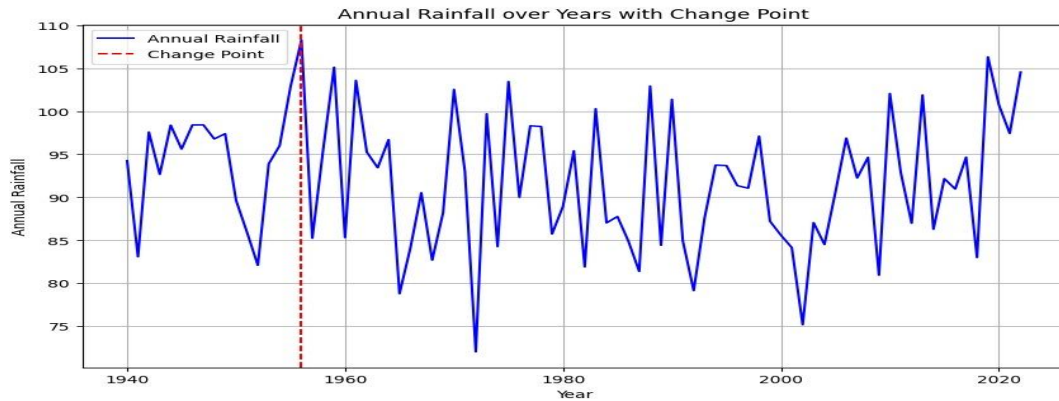


Fig. 3. Pettitt test for the change point detection of mean annual rainfall in India (1940-2022)

3.6. Rainfall Forecasting and Comparison with CMIP-6 SSP585 Projections

In this study, the rainfall forecasting was employed to project annual rainfall up to 2050, which is 28 years into the future from the present. The widely used approaches for rainfall forecasting are numerical and statistical methods, with the former having limited success in properly forecasting weather factors. Statistical approaches, on the other hand, treat rainfall time series as stochastic and are commonly employed for long-term rainfall forecasting (Shrivastava et al. 2012). In that context, several probabilistic and deterministic approaches like ARIMA and SARIMA (Kudnar et al., 2022; Ray et al., 2021) have been widely used to climate forecasting. However, these techniques have several drawbacks, including serial correlation and bias in forecasting non-linear hydro-climatic variables (Canchala et al., 2020). Moreover, these models are found to be inefficient as the duration of forecast period increases. Such shortcomings can be effectively addressed through the application of advanced artificial intelligence techniques (Saha et al., 2018).

The ANN-MLP is a widely used soft computing ML technique that is used to solve real-world problems (Pal & Talukdar, 2020). It is a distributed parallel information processing system organised by its architecture, which consists of connecting nodes, its method of determining connection weights, and its activation function, which is comparable to that of the human brain (Chakraverty & Gupta, 2008; Rahaman et al., 2023). The ANN-MLP structure is made up of three layers: input, hidden, and output. Neurons are the processing units of the neural network, or nodes (Mandal & Jothiprakash, 2012).

MLP is one of the most often used ANN architectures which is based on the back propagation algorithm (Sumi et al., 2012). Back-propagation rules spread errors across neural networks and allow hidden units to be changed. Non-linear processing elements (PEs) and huge interconnection are two important characteristics of multilayer perceptron. While former exhibits smooth non-linearity, the latter reflects any element of a specific layer and feeds all layer elements (Pal & Talukdar, 2020).

In this study, the entire rainfall datasets were divided into training and test datasets. The data was then normalized, and an ANN-MLP was used to forecast annual rainfall. The ANN-MLP model was repeated on the same datasets, adjusting the model parameters such as seed, momentum, learning rate and custom lag lengths till the optimal forecasting model was generated. Furthermore, Root Mean Square Error (RMSE) and mean absolute error (MAE) methodologies were used to assess the effectiveness of ANN-MLP for forecasting. The model parameters were fixed after the best ANN-MLP model was found and applied to rainfall data to forecast rainfall in India up to 2050 using *nnfor* and *forecast* packages in R.

The rainfall forecasts derived for 2050 using the ANN-MLP model were compared with the annual rainfall projections of the multi-model ensemble (MME) of three CMIP-6 GCMs i.e., CanESM5, BCC-CSM2-MR, and IITM-ESM. These three models were selected to develop the ensemble because these have been recommended

to be the best GCMs by several research studies including Hemanandhini & Rajkumar, 2023; Thakur & Manekar, 2023. Downscaled and bias-corrected NASA Earth Exchange Global Daily Downscaled Rainfall Projections (NEX-GDDP-CMIP6) datasets (r1i1p1f1 realization) for the year 2050 were downloaded from the NASA Center for Climate Simulation (<https://ds.nccs.nasa.gov/thredds/catalog/AMES/NEX/GDDP-CMIP6/catalog.html>) and pre-processed to yield the annual rainfall for the Indian territory. The 2050 rainfall for all the HRs and MSDs of India was calculated, tabulated, and mapped. The results from ANN-MLP were juxtaposed with the business-as-usual scenario of GCM projections, namely the SSP585 (Shared Socioeconomic Pathway), to assess the trajectory of rainfall in India under a worst-case scenario. The aim is to assess the congruence of Indian rainfall patterns with the implications of severe prospective climate change.

4. Results

4.1. Descriptive Statistics of Annual Rainfall

Across a span of 122 years, the annual rainfall patterns in India exhibit significant departure from the normal rainfall (**Fig. 4**) in certain HRs and MSDs, whereas in others, a consistent and unchanging level of rainfall persists. Descriptive analysis of the annual rainfall (**Fig. 5** and **Fig. 6**) was carried out in India for all six HRs and thirty-four MSDs by applying measures of central tendency and dispersion such as the mean, standard deviation, minimum, maximum, skewness and excess kurtosis.

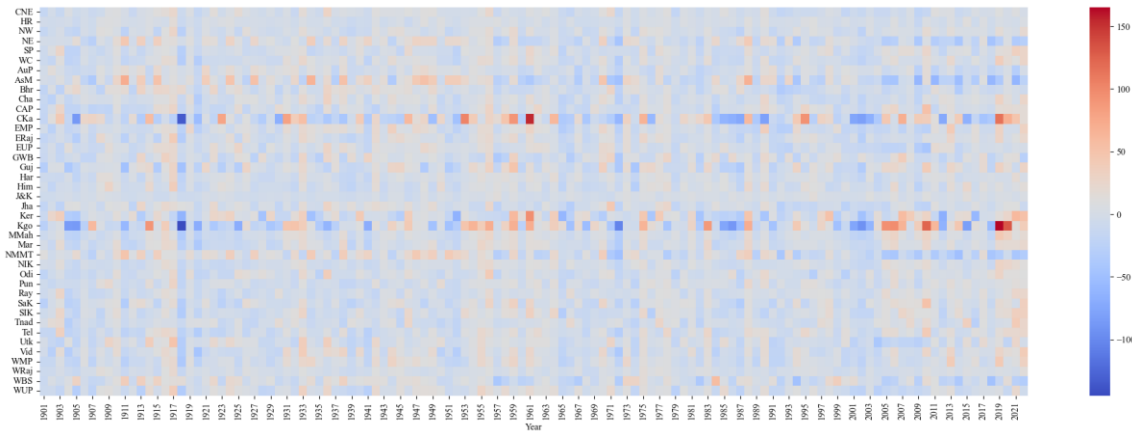


Fig. 4. Over the years departure of rainfall from the normal rainfall in HRs and MSDs of India

The findings for HRs suggest that the Northeast HR received the maximum average annual rainfall over the 122-year period, with a value of 1925 mm followed by the South Peninsular and Central Northeast HR, with values of 1037 mm and 989 mm respectively. The Northwest HR is the most rainfall-deficient region in India, with an annual average rainfall value of less than 500 mm. Among the MSDs, Coastal Karnataka received maximum rainfall with a value of 2696 mm, followed by the Konkan Goa and Assam Meghalaya with values of 2584 mm and 2337 mm respectively. The Western Rajasthan and Saurashtra Kutch MSDs receive the least amount of rainfall, with values of 307 mm and 436 mm respectively. The Jammu and Kashmir MSD also received very little amount rainfall of around 307 mm. Over the 122-year period, the minimum average rainfall was experienced by the Northwest HR (212 mm), where the MSDs of Western Rajasthan and Saurashtra Kutch also saw the lowest minimum average rainfall, with values of 83 mm and 109 mm, respectively.

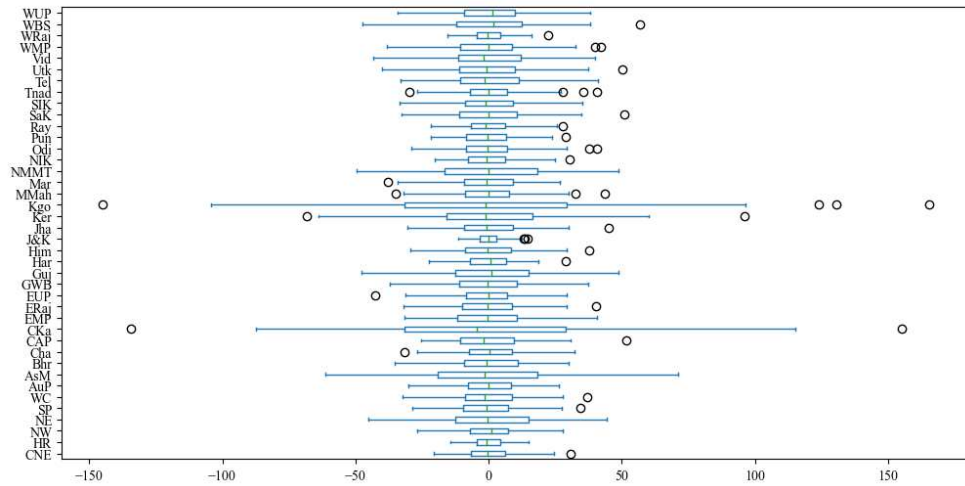


Fig. 5. Descriptive statistics of annual rainfall for HRs and MSDs in India

The greatest variation in rainfall, as indicated by the standard deviation, was noted in the MSDs of Konkan Goa (507 mm) followed by Coastal Karnataka (468 mm) and Assam Meghalaya (285 mm), while the lowest variability was seen in Jammu and Kashmir (50 mm), Western Rajasthan (67 mm), and Rayalaseema (98 mm) MSDs. Among the HRs the Northeast HR exhibited highly variable rainfall, with a standard deviation of 197 mm, while the lowest standard deviation was observed in the Hilly Region HR, at 55 mm.

The skewness in MSDs across India ranged from -0.02 to +0.58, while for HRs, it spanned from -0.10 to +0.33. Negative skewness was found in the MSDs of Western Uttar Pradesh (-0.02), Marathwada (-0.02), Haryana (-0.06), NMT (-0.09), West Bengal Sikkim (-0.11), Gujarat (-0.17), Eastern Uttar Pradesh (-0.19) and Arunachal Pradesh (-0.15), while the rest exhibited positive skewness. Among the HRs, the Northwest and Northeast HRs showed negative skewness of -0.10 and -0.12 respectively, while the others were positively skewed. A comparison of different homogeneous monsoon regions also revealed symmetry in rainfall distribution, with positive excess kurtosis in the West Coast (0.1) and Central Northeast (0.2) respectively.

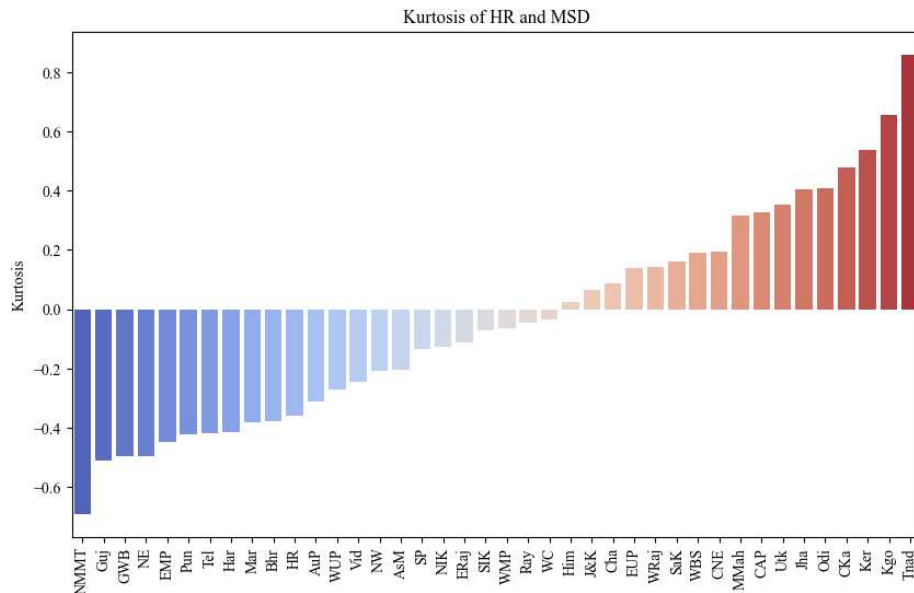


Fig. 6. Kurtosis of annual rainfall for HRs and MSDs in India

Closer observation of the West Coast HR showed asymmetry, as the MSDs within the west coast HR such as Eastern Madhya Pradesh, Marathwada, North Interior Karnataka, Vidarbha and Western Madhya Pradesh exhibited negative skewness ranging from -0.02 to -0.41, while the MSDs of Konkan Goa, Madhya Pradesh, Maharashtra and Chhattisgarh displayed positive skewness from 0.14 to 0.73. Meanwhile, a positive excess

kurtosis indicating a heavy tail and leptokurtic curve was seen in the MSDs of Tamil Nadu, Konkan Goa, Orissa, and Kerala.

Rainfall with a comparatively lower amount was observed in the Northwest HR, which contributed 6.8% to the total annual average rainfall of India. The MSDs of Western Rajasthan and Saurashtra contributed the least in this region, with percentages of 7.5% and 13.8% respectively. The MSD of Gujarat contributed the most at 25.2%. The West Central region is another rain-deficient area of India, with most of its area lying in the rain shadow zone, contributing just 13.3% to the country's total annual rainfall. The North Interior Karnataka MSD contributed the least at 5.8% compared to all other meteorological subdivisions. Telangana and West Madhya Pradesh MSDs also contributed small percentages of 8.7% each. On the other hand, the Northeast HR had the highest contribution at 27.5%, with the West Bengal Sikkim and NMMT subdivisions (MSDs) contributing 25.9% and 25.4% respectively. The Gangetic West Bengal MSD contributed the least within the Northeast HR. The Central Northeast and South Peninsular HRs contributed 14.1% and 14.8% respectively. The contributions of its subregions (MSDs) were Orissa (23.4%), Western Uttar Pradesh (16.2%), Rayalaseema (7.2%) and Coastal Karnataka (33.6%).

4.2. Mann Kendall (MK) Test and Sen's Slope for Annual, Seasonal, and Monthly Rainfall

The MK Test and Sens's Slope were calculated for all 40 regions of India, comprising six HRs and thirty-four MSDs. **Table S1** displays the z-scores of all the MK Test results, where bold values indicate a higher rate of trend change at a significance level of 0.05.

Results for the annual data reveal that only the Northeast HR showed a significant monotonic negative trend (z-score > -2) out of the six HR, while the other five displayed insignificant changes with a slight increasing trend (z-score of 2.00), mainly in the South Peninsular HR. The MSDs within the Northeast region (HR) all exhibited significantly decreasing rainfall trends. The MSDs of Arunachal Pradesh, Assam Meghalaya, Bihar, Eastern Uttar Pradesh, Jharkhand, NMMT, and West Bengal Sikkim demonstrated highly negative z-values. In contrast, the MSDs of Coastal Andhra Pradesh, Jammu & Kashmir, Konkan Goa, Madhya Maharashtra, Marathwada, Odisha, Punjab, Rayalaseema, Telangana showed strongly positive z-values, denoting increasing rainfall trends.

The winter season across India exhibited a decreasing rainfall trend, where in the HRs only the South Peninsular HR showed significant decreasing pattern of rainfall, rest all HRs showed insignificant decreasing trend. In the MSDs, the Rayalaseema, South Interior Karnataka, Konkan Goa and Tamil Nadu showed significantly decreasing patterns. In the pre-monsoon season, the MSDs of Eastern Rajasthan, Eastern Uttar Pradesh, Jammu & Kashmir, Odisha, Western Uttar Pradesh, Haryana, Bihar and Rayalaseema saw significant increases, while only NMMT had a significant decrease. For the monsoon season, the Central Northeast and Northeast HRs exhibited significant negative trends, while in the MSDs the Arunachal Pradesh, Assam Meghalaya, Bihar, Eastern Uttar Pradesh, Jharkhand, NMMT and West Bengal Sikkim also showed significant decreasing rainfall patterns. In contrast, the MSDs of Coastal Andhra Pradesh, Jammu & Kashmir, Konkan Goa, Madhya Maharashtra, Marathwada, Punjab, Rayalaseema, Telangana and South Interior Karnataka showed very high increasing monsoonal rainfall trends.

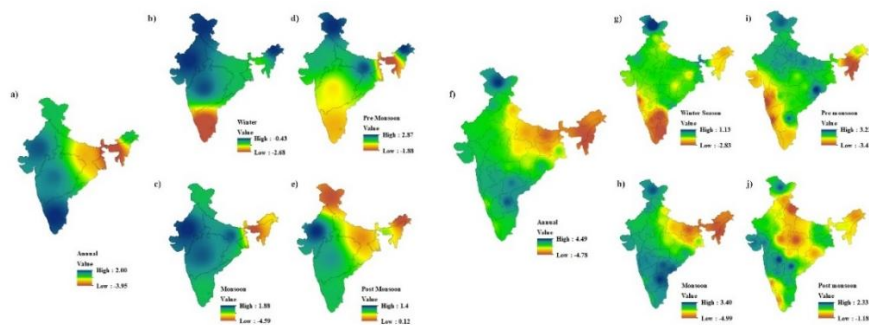


Fig. 7. z-score of annual, winter, pre-monsoon, monsoon and post-monsoon rainfall trend in India: (a-e) HRs of India, and (f-j) MSDs of India

The months of May, June, August and November exhibited maximum variations in across different regions. In May, significant positive trends were noticed in the Central Northeast region followed by the Hilly region and

Northwest HRs and also in the MSDs of Bihar, Chhattisgarh, Gangetic West Bengal, Haryana, Himachal Pradesh, Jharkhand, Odisha and Western Uttar Pradesh. The month of June showed significant negative trends in the Northeast HR along with the MSDs of Arunachal Pradesh, Assam, Meghalaya, Coastal Karnataka, NMMT, Kerala and West Bengal Sikkim. Significant positive trends were noticed in Haryana, Himachal Pradesh, Jammu and Kashmir, Punjab and Rayalaseema during this month. Conversely, in the month of August significant negative trends were observed in the Central Northeast and Northeast HRs and also in MSDs of Assam Meghalaya, Bihar, East UP, Jharkhand, NMMT, Uttarakhand and West Bengal Sikkim, while positive trends were observed in the month of August only in the MSDs of Konkan Goa, Madhya Maharashtra, Marathwada, Rayalaseema, Telangana and Western Madhya Pradesh. The month of November showed significant positive trends in the Hilly regions and Northwest HRs while in MSDs of Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir and Punjab. The spatial mapping of annual and seasonal MK Test results are given in **Fig. 7** and monthly MK Test results are depicted in **Fig. 8**.

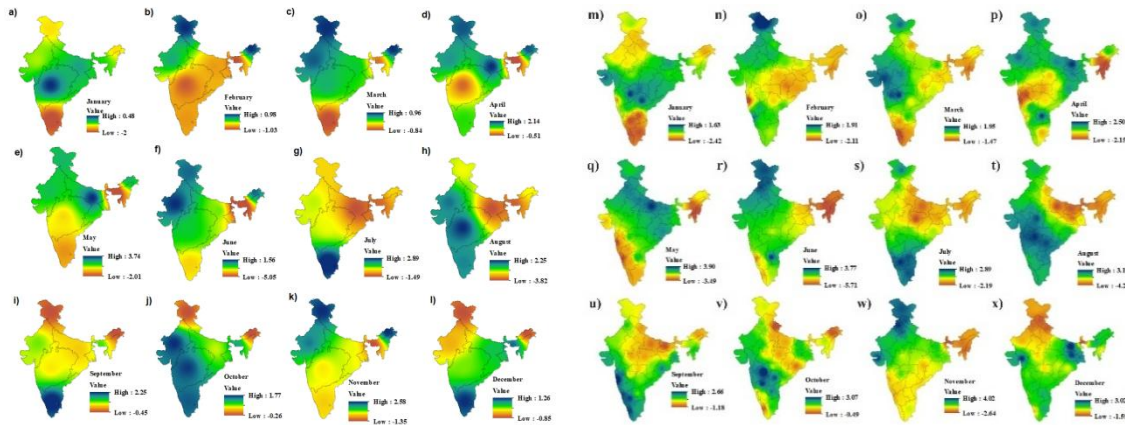


Fig. 8. z-score of monthly rainfall trend in India: (a-l) HRs of India, and (m-x) MSDs of India

4.3. Changepoint Detection and Trend Analysis for Annual, Seasonal, and Monthly Rainfall

Several researchers, while validating MK Test results, have claimed that the MK Test without changepoint detection is not the most suitable procedure for accurate trend detection. Therefore, it is recommended conducting a changepoint detection test when dealing with long temporal data scales. Hence, changepoint detection tests such as Pettitt's test, Buishand's range test and SNHT were implemented before applying the MK Test for detecting abrupt shifts in the rainfall data across all six HRs and thirty-four MSDs at annual, monthly and seasonal scales. To validate the integrity of the break years generated from the changepoint tests, h-value instead of p-value was used as a metric. The h-value gives the output as 'True' or 'False' and indicates if the data homogeneity is sufficient enough in order to call a year as 'break year'. Hence, these sudden changepoints imply that the rainfall datasets did not exhibit monotonic trends. The years of transition for nearly all HRs and MSDs were observed post-1950s across all three temporal scales. Detailed values of all transition years are provided in **Table S2**.

A break year in annual rainfall was identified for the Northeast HR. Before this year, there was an insignificant positive trend. After it, there was an insignificant negative trend. This break marks a shift from increasing precipitation to decreasing precipitation annually, with a peak occurring around the break itself. Identifying this turning point helps validate changes in regional rainfall patterns. The pre changepoint z values for all the HRs and MSDs is given in **Table S3**. For the winter season, the Tamil Nadu MSD and South Peninsular HR showed insignificant decreasing pre-changepoint trends but insignificant positive trends post-changepoint. In the pre-monsoon season, two HRs and eight MSDs displayed insignificant trends pre- and post-changepoint, but Odisha MSD showed an insignificant positive pre-changepoint trend followed by a significant increase post-changepoint. In the monsoon season, two HRs and 12 MSDs exhibited insignificant pre-changepoint trends. However, the Northeast HR and the MSD of Assam Meghalaya, and NMMT showed significant decreasing trends post-break year (**Table 1**), indicating monsoon rainfall has significantly declined in the North-eastern region of India over the past 70 years. In the post-monsoon season, only Jammu Kashmir MSD showed an insignificant positive pre-changepoint trend followed by an insignificant negative post-changepoint trend. The months of May, June and August exhibited the greatest number of break years. In May, the Central Northeast HR displayed an insignificant decreasing pre-changepoint trend but an insignificant positive trend post-

change point. Furthermore, eleven MSDs and one HR showed insignificant trends pre- and post-change point in the month of May. Three HR and twelve MSDs showed insignificant trend in both pre and post-change points. The graphical representation of MK Test results for the HRs is depicted in **Fig. 9**, and for the MSDs in **Fig. S1**.

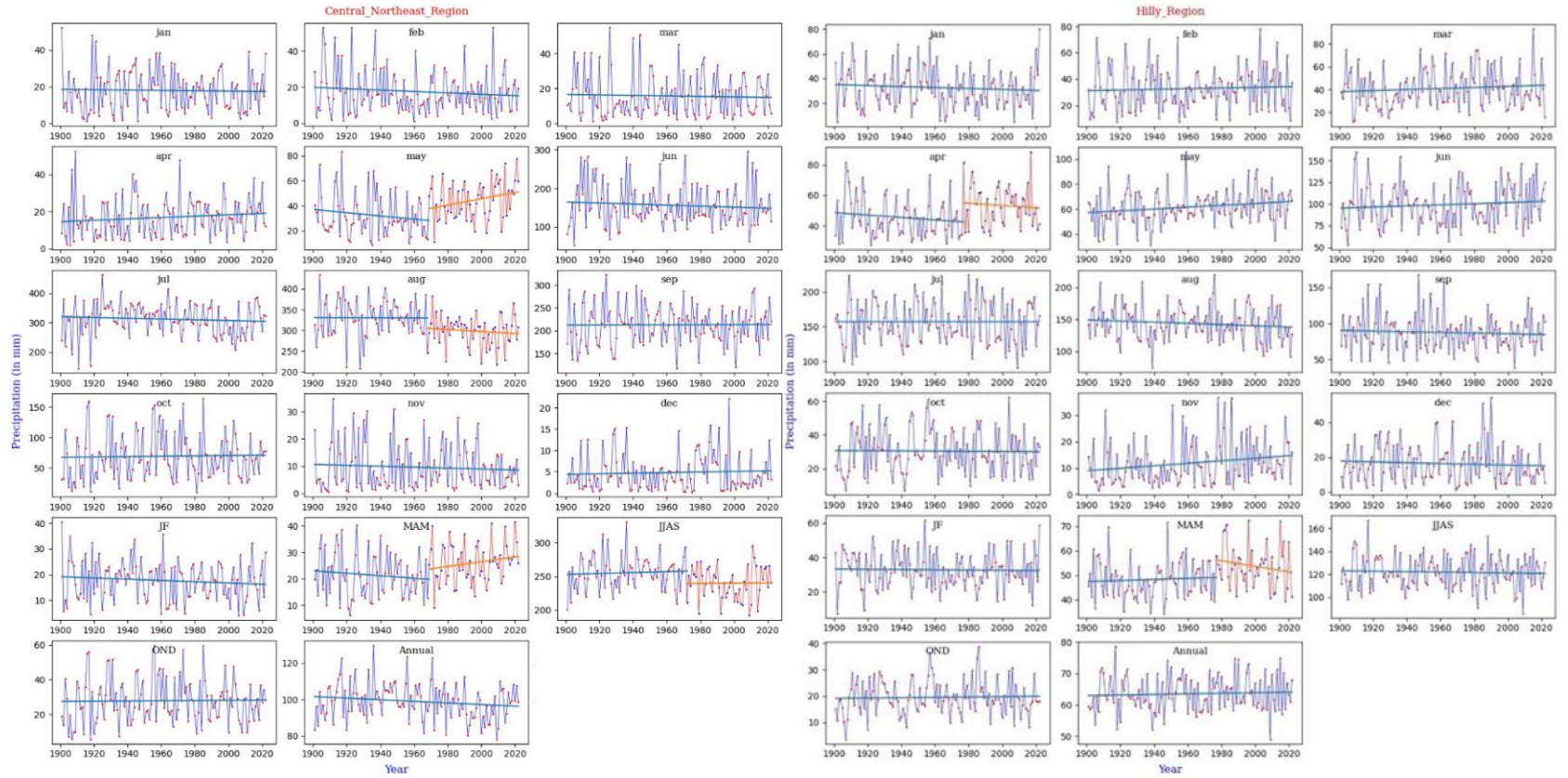


Fig. 9. Graphical representation of MK Test results of HRs along with break points

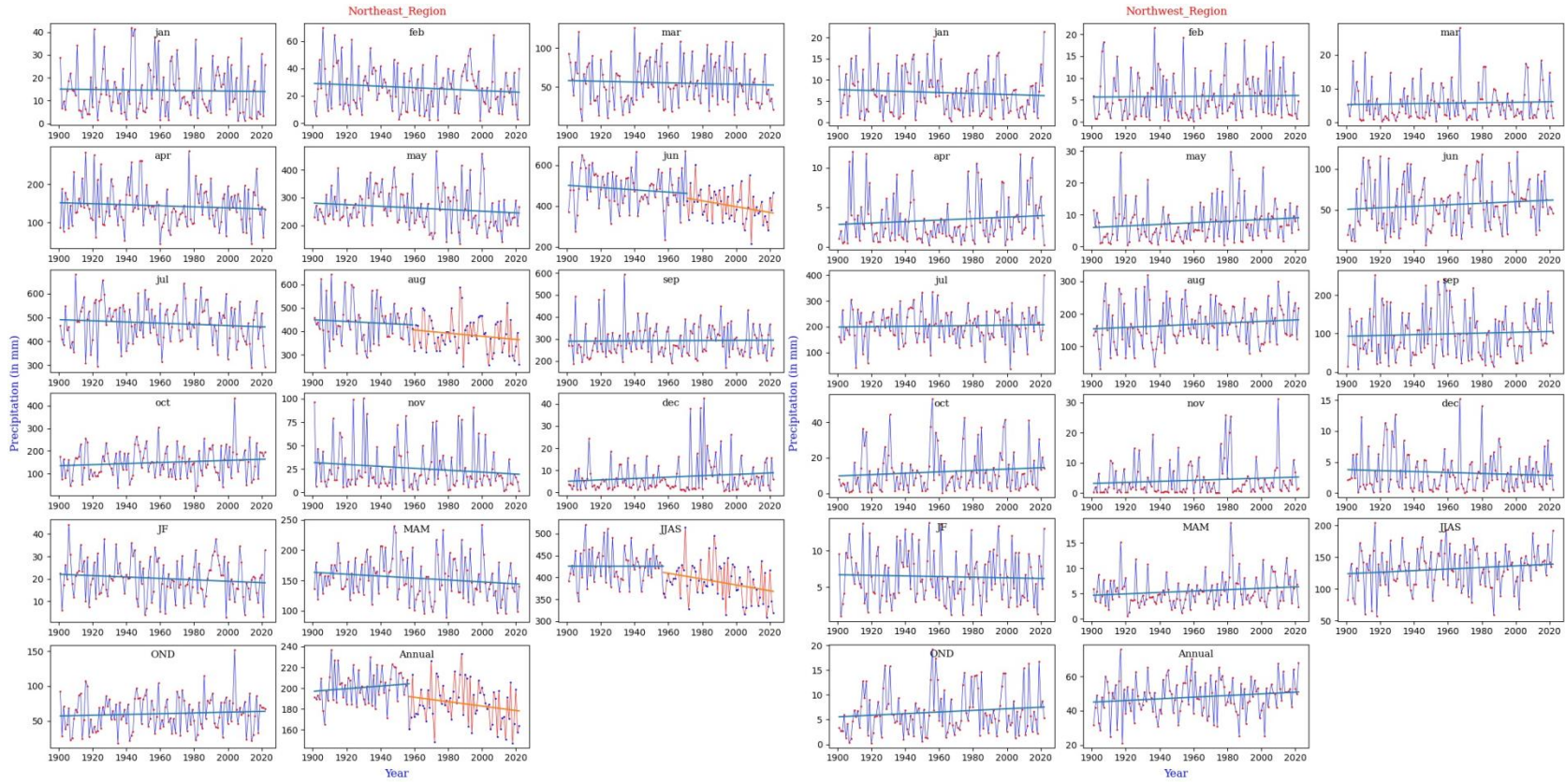


Fig. 9. Continued

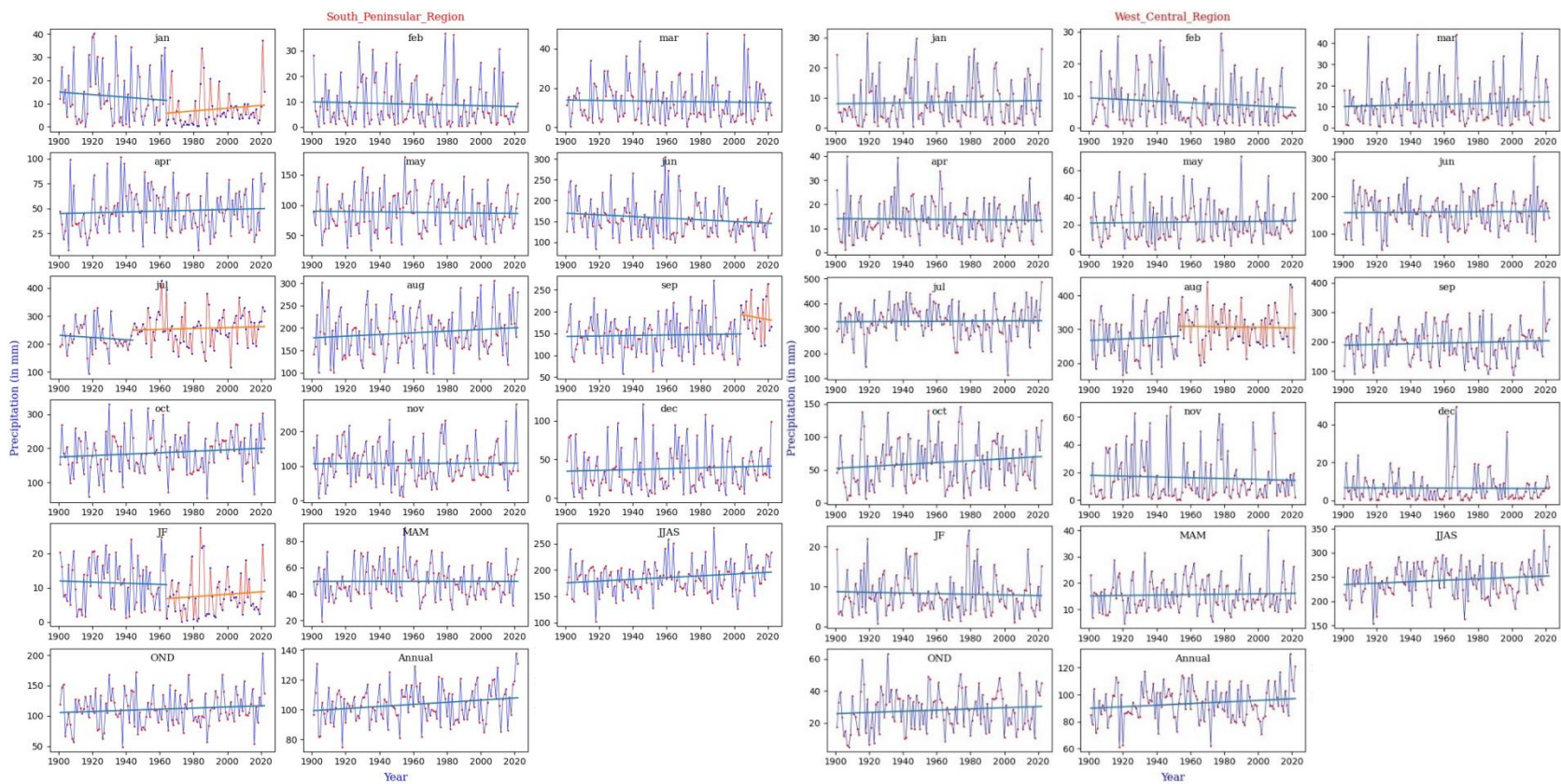


Fig. 9. Continued

Table 1: Post-changepoint MK Test (z-score values for annual, seasonal and monthly scale for the period of 1901-2022); bold values indicate the regions where there was a different value in pre-changepoint essentially those areas which have a break year

Regions	Index	January	February	March	April	May	June	July	August	September	October	November	December	Winter	Pre-Monsoon	Monsoon	Post Monsoon	Annual
Homogeneous Regions	Central Northeast region	-0.066	-0.637	0.345	2.138	1.895	-0.808	-1.492	-1.149	0.328	0.637	0.288	0.580	-1.044	1.327	-0.602	0.328	-1.509
	Hilly Region	-1.067	0.978	0.960	-0.284	2.390	1.067	-0.159	-1.345	-0.451	-0.257	2.576	-0.854	-0.451	-0.831	-0.142	0.124	0.536
	Northeast Region	-0.496	-1.031	-0.620	-0.518	-2.018	-1.852	-1.177	-1.186	0.947	1.266	-1.354	1.053	-1.270	-1.877	-2.270	0.748	-1.727
	Northwest Region	-0.797	0.474	0.823	1.708	2.248	1.562	0.336	1.496	0.850	1.775	2.054	-0.345	-0.434	1.859	1.363	1.399	1.691
	South Peninsular Region	1.744	-0.646	-0.836	1.177	-0.142	-1.739	0.984	1.323	-0.303	1.611	-0.119	1.257	0.604	-0.027	1.877	1.014	2.005
	West Central Region	0.476	-0.952	0.469	0.066	0.606	-0.159	0.199	-0.533	0.487	1.722	0.089	0.215	-0.531	0.412	1.337	1.146	1.430
Meteorological Subdivisions	Arunachal Pradesh	-1.359	-1.062	0.217	1.239	0.363	-0.425	-0.412	-2.124	-0.456	-0.111	-1.137	1.146	-1.633	0.628	-1.450	-0.283	-0.044
	Assam Meghalaya	-0.695	-0.912	-0.487	-0.575	-0.875	-0.824	-1.372	-1.186	0.509	1.137	-1.735	1.684	-1.301	-1.748	-2.338	0.544	-1.863
	Bihar	0.845	-0.389	0.819	2.505	0.330	-0.447	-0.713	0.254	-1.177	1.739	1.848	-0.636	-0.420	0.545	-0.696	1.381	-0.583
	Chhattisgarh	0.779	-1.498	-0.212	0.491	2.363	-0.836	-0.354	-0.133	0.589	0.567	-0.907	0.286	-1.173	0.823	-0.412	0.381	-0.252
	Coastal Andhra Pradesh	0.401	-0.080	0.378	0.761	1.337	1.053	1.730	-0.454	1.084	1.071	-0.350	1.022	-0.075	1.102	2.828	0.544	2.784
	Coastal Karnataka	-0.387	0.833	-0.013	0.257	1.619	-0.478	2.328	0.358	-1.030	0.664	-1.009	0.768	-1.086	1.784	0.536	-0.199	0.186
	Eastern Madhya Pradesh	0.350	-1.100	0.363	0.173	1.930	0.111	0.939	-0.633	-0.398	0.363	0.505	0.766	-0.536	0.668	-1.062	-0.841	-1.115
	Eastern Rajasthan	-0.872	0.367	1.301	1.832	1.823	1.469	0.230	1.846	0.168	1.700	1.420	0.133	-0.637	2.337	1.186	0.943	1.522
	Eastern Uttar Pradesh	0.197	-0.177	0.367	2.009	-0.069	0.589	0.081	-0.765	-0.713	0.434	0.830	0.874	-0.345	2.598	-1.205	0.292	0.667
	Gangetic West Bengal	0.133	-0.841	-0.027	1.748	1.540	-1.332	-0.058	-0.885	1.638	1.509	1.067	2.169	-0.226	1.040	-0.536	1.403	0.438
	Gujarat	0.855	-0.249	1.840	1.359	0.801	0.611	-0.181	2.062	1.160	1.797	2.299	2.710	-0.719	0.290	1.385	1.925	1.531
	Haryana	-0.969	0.345	0.416	1.492	1.020	-0.150	0.000	-0.549	0.447	1.286	3.480	-0.438	-0.841	-0.909	0.465	0.633	0.739
	Himachal	-1.160	0.266	0.237	1.757	-0.065	0.702	-0.084	-0.323	0.257	0.728	3.607	-1.405	-1.022	1.456	1.368	-0.243	1.261
	Jammu & Kashmir	-0.350	1.912	-1.185	2.111	1.447	0.232	2.284	1.208	0.288	1.036	0.866	-0.505	1.093	-0.909	0.319	-1.221	0.792
	Jharkhand	-0.024	-1.084	-0.212	2.062	2.266	-1.456	-1.186	-0.278	-0.027	1.708	1.301	-1.047	-1.354	1.368	-0.221	1.350	0.000
	Kerala	1.167	-0.254	-1.469	0.947	-1.027	-2.443	1.903	0.916	-0.303	0.000	-0.084	-0.195	-1.947	-0.381	0.819	-0.252	0.451
	Konkan Goa	-1.423	-2.113	0.864	-0.810	0.508	-0.137	0.863	2.133	-0.206	1.916	-0.697	0.988	-2.147	-0.218	2.213	1.646	2.266
	Madhya Maharashtra	0.186	-0.545	1.804	-0.854	-0.615	0.367	0.328	0.316	1.846	2.253	-0.122	0.669	-0.910	-1.199	-0.909	1.660	-0.455
	Marathwada	1.630	-0.412	1.952	-0.071	1.514	0.049	1.053	0.227	-0.035	3.072	1.151	0.829	-0.938	1.137	2.058	2.328	2.470
	NMMT	-0.283	-1.399	-0.735	-0.005	0.876	-1.478	-1.124	-1.069	0.991	0.969	-2.005	0.095	-1.341	-1.681	-2.290	0.270	-2.700
	North Interior Karnataka	0.466	0.512	0.520	1.669	-0.876	0.119	0.960	1.850	1.253	-0.094	-0.420	1.307	-0.929	-0.035	1.996	1.877	-0.247
	Orissa	0.487	-1.264	0.252	1.899	2.402	-0.938	0.235	0.836	-0.041	0.137	0.159	0.217	-0.664	2.164	1.483	-0.168	2.098
	Punjab	-0.903	0.593	0.451	1.199	0.078	0.907	0.748	0.518	0.947	1.337	0.394	-1.131	-0.447	1.629	2.147	0.456	2.346
	Rayalaseema	0.399	-0.007	0.797	2.470	2.182	1.660	2.589	2.204	0.606	2.275	0.009	1.615	-2.833	2.837	1.082	1.669	1.775
	Saurashtra Kutch	1.254	0.080	1.567	1.348	-0.432	0.952	0.438	1.770	1.456	1.547	3.795	1.684	-0.897	-0.732	1.797	1.967	1.969
	South interior Karnataka	0.162	-0.046	-0.544	1.584	-0.876	-1.381	2.894	1.040	2.155	0.850	-0.261	1.078	-2.317	-0.137	2.107	0.367	1.832
	Tamil Nadu	2.401	-0.443	-0.513	0.018	-0.717	-0.540	2.567	0.792	0.032	1.518	0.372	1.708	1.060	-0.474	2.009	1.412	1.314
	Telangana	1.538	-0.905	0.058	0.341	1.111	0.363	1.496	-0.078	0.531	2.430	0.035	0.901	-0.268	1.177	0.533	2.173	0.647
	Uttaranchal	-1.301	-0.119	-0.460	1.182	-0.418	1.089	-1.292	-1.360	-0.482	-0.496	1.766	-1.299	-1.390	1.306	0.021	-1.182	-1.682
	Vidarbha	1.178	-0.910	0.934	-0.089	1.735	-0.832	0.615	1.930	-0.097	1.058	0.662	-0.089	-0.407	0.947	0.779	0.115	0.597
	Western Madhya Pradesh	-0.347	-0.626	1.514	0.668	1.509	0.606	-0.420	-0.379	-0.372	0.766	0.250	-0.075	-0.540	1.779	0.819	-0.451	0.947

	Western Rajasthan	-0.836	0.438	1.137	0.968	2.116	2.049	0.053	0.465	0.544	1.695	1.598	-0.482	-0.106	1.930	0.717	1.168	1.222
	West Bengal & Sikkim	0.199	-0.872	-0.628	1.208	0.956	-1.036	-0.726	-0.610	-0.310	0.620	-2.647	-1.585	0.341	1.089	-1.417	0.394	-0.549
	Western Uttar Pradesh	-0.779	0.447	0.345	1.438	0.314	1.660	-1.027	1.637	-0.089	0.451	1.428	-0.367	-0.779	-0.734	-1.213	0.066	-0.850

4.4. Innovative Trend Analysis (ITA) and Comparative Assessment of the Rainfall Trend Detection Techniques

Various studies have pointed out limitations that accompany the MK Test and Sen's Slope, such as the presence of serial correlation, nonlinearity, and sample size constraints, which can influence the results. To address these drawbacks, Sen developed a method called the ITA. In this study, the ITA was computed for all six HRs and thirty-four MSDs at the annual, seasonal, and monthly scales. The slope of the ITA line indicates the significance and nature of trends. Graphically, a monotonic trend exists when data points are parallel to the 1:1 line in ITA plots (Sen, 2012). In this study, a strict predefined discretionary criterion was followed when analysing ITA results i.e., if data points coincide with the 1:1 line, the trend is insignificant. If points are scattered above and below the line, the trend is also insignificant. Only when all points distinctly lie on one side of the no trend line is the trend deemed significant.

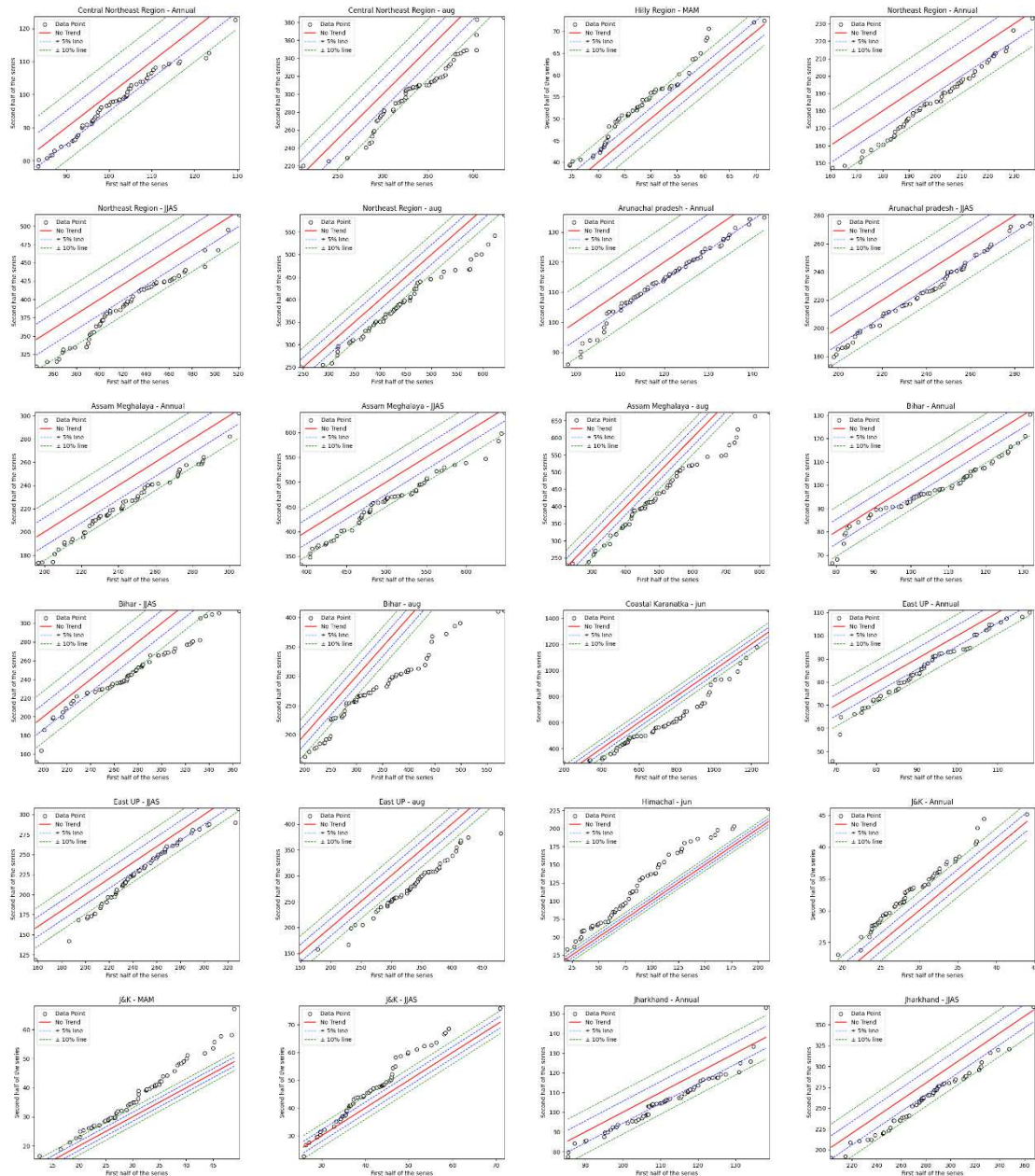


Fig. 10. Significant ITA graphs representing trends at 90% and 95% confidence level

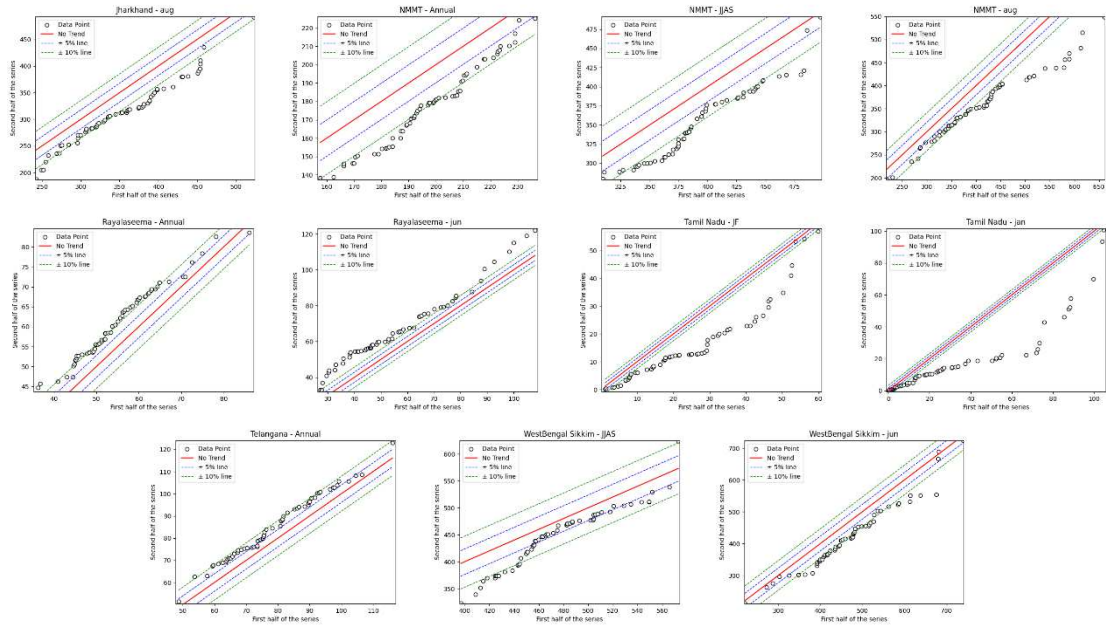


Fig. 10. Continued

The ITA results revealed that at the annual scale, NMMT MSD exhibited a significant negative trend (Fig. 10), consistent with the MK Test, validating the accuracy of previous findings. Telangana, along with Jammu & Kashmir and Rayalaseema MSDs, showed significant positive results in the ITA but insignificant trends in the MK Test, suggesting the ITA provides more precise trend detection. Central Northeast HR and Northeast HR along with the MSDs of Arunachal Pradesh, Assam Meghalaya and East UP also displayed significant negative ITA trends. For the monsoon season, Assam Meghalaya and Coastal Andhra Pradesh MSDs showed significant negative and positive trends respectively in both the MK Test and ITA, further validating the ITA findings. Additionally, several MSDs like Jharkhand, Arunachal Pradesh, Bihar, East UP, NMMT and West Bengal Sikkim and also the HRs of Central northeast and Northeast exhibited significant negative ITA trends, indicating monsoon rainfall has markedly decreased over India in the past 60 years, pointing to climatic variations. In the pre-monsoon season, Odisha MSD showed significant positive trends in the month of May in both ITA and MKT results. In June, Arunachal Pradesh, Assam Meghalaya, Himachal, Punjab, Rayalaseema and West Bengal Sikkim MSDs showed significant ITA results. August had the most significant ITA findings - Marathwada, Telangana and West MP MSDs exhibited positive trends, while Central Northeast HR and Northeast HR, along with the MSDs of Assam Meghalaya, Bihar, East UP, Jharkhand, NMMT and Uttarakhand were significantly negative, confirming the Gangetic West Bengal MSDs positive MK Test result. ITA graphs for all the regions are represented in Fig. S2-S40.

4.5. Causes of Rainfall Variation in India

India experiences extensive areas with moderate convective precipitation, through occurrences of moderate convective rainfall rates, which result from the landward influx of excessive moisture from the Indian Ocean. This moisture influx may hinder favourable conditions for rainfall formation (Fig. 11(a) – (f)). This resulted in a reduction in mean rainfall during the monsoon season, particularly impacting the extreme southern and mid-central regions of the country (Fig. 11). The intensification of the northeasterly wind across the entire country has resulted in a notable decrease in the intrusion of cooler air, leading to a decline in winter rainfall throughout India. By contrast, most of the parts of India had moderate convective precipitation rate (Fig. 11(a)), which increased rainfall up to some extent. Fig. 11(c) illustrates the widespread presence of low to moderate cloud cover across India. Increased cloud cover can amplify the atmospheric consolidation effect on solar radiation, potentially leading to a decline in rainfall trends. In addition, the mean total precipitation rate has had an impact throughout the country, except in the northeastern division where there is more convective precipitation, resulting in a higher mean total precipitation rate during the study period (1940-2022). Most of the regions in India exhibited a higher vertically integrated moisture divergence rate (Fig. 11(f)). This means that there is a large movement of moisture away from these areas, which can have ramifications for the nature of rainfall in

India. Regions with higher vertically integrated moisture divergence rates, notably in the western and central western regions, may have less moisture available for precipitation, potentially resulting to drier conditions. Conversely, locations with smaller divergence rates, particularly in the northeast, can store more moisture, resulting in more rainfall or more consistent precipitation patterns.

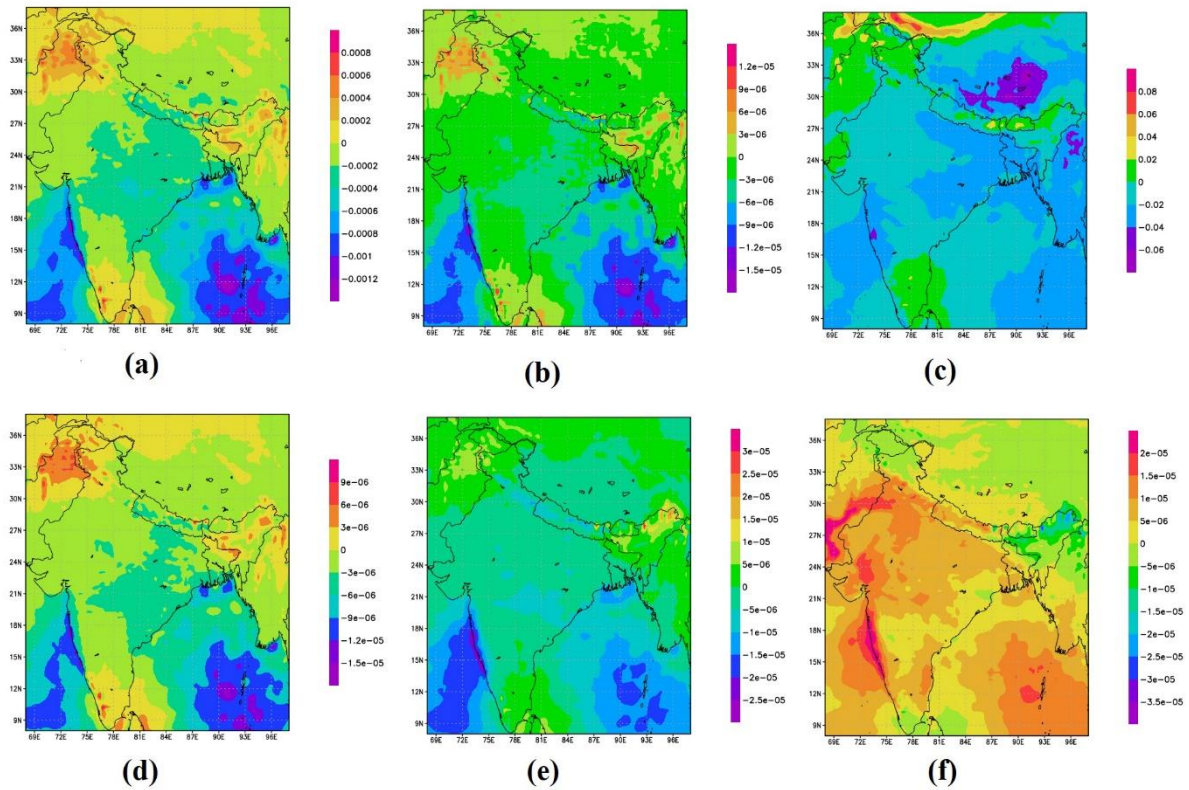


Fig. 11. (a) Convective Precipitation; (b) Convective Rainfall Rate; (c) Low Cloud Cover; (d) Mean Convective Precipitation Rate; (e) Mean Total Precipitation Rate; (f) Mean Vertically Integrated Moisture Divergence between the recent period of 2022–1957 and 1940–1956.

4.6. Rainfall Forecasting and Comparison with CMIP-6 SSP585 Projections

Analyses of meteorological data across India show concerning decrease in rainfall amounts in recent decades. This declining trend has intensified after the break years in the annual rainfall pattern. The current trajectory indicates rainfall could become even more scarce in the future if the existing patterns persist. These developments underscore the critical need for improved rainfall forecasting and forecasting to inform water resource management and planning.

The ANN-MLP model was employed in this study for forecasting annual rainfall on the basis of historical rainfall data. Numerous iterations of configuring the model parameters were conducted to achieve optimal forecasts as evaluated by root mean square error (RMSE) and mean absolute error (MAE). These errors expressed in mm were used to quantify the similarity between the forecasted and observed rainfall values. The optimized model was applied to forecast annual rainfall across six HRs and thirty-four MSDs in India for a future 28-year period through 2050. The number of iterations (h) for the ANN-MLP was set to 28 to align with the desired forecasting timeframe using the annual dataset. The resulting forecasted rainfall curves are given in **Table S5** and **Fig. 12 (a)** and **(b)** is the geographical depiction of 2050 rainfall as forecasted by the ANN-MLP model.

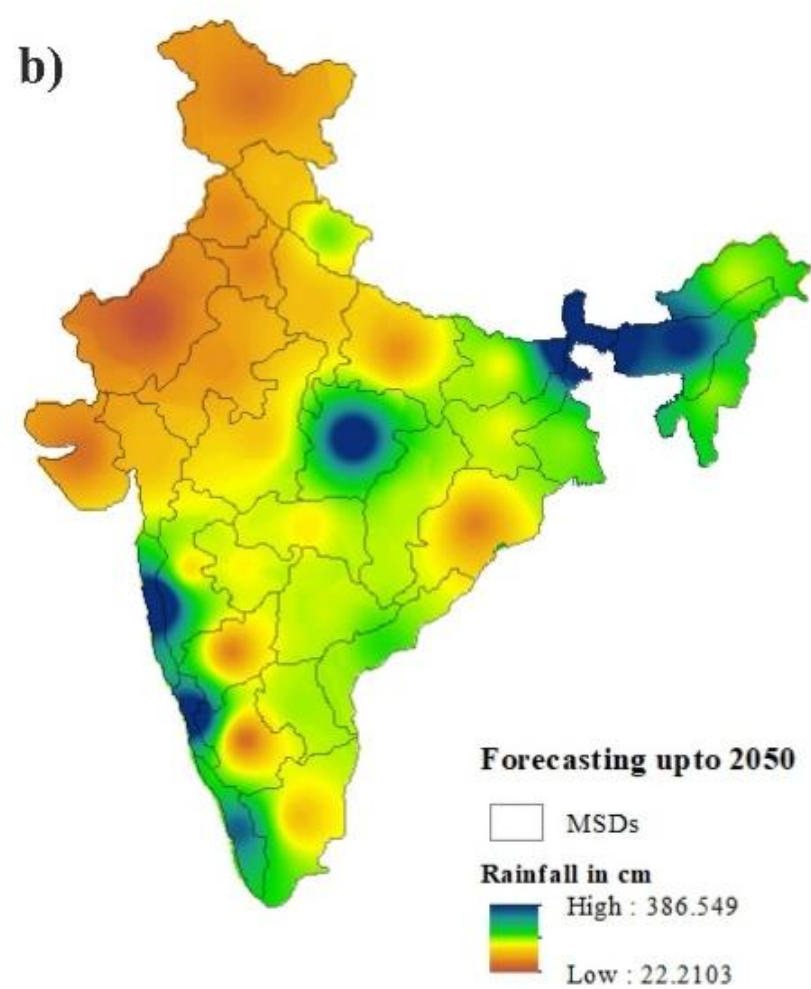
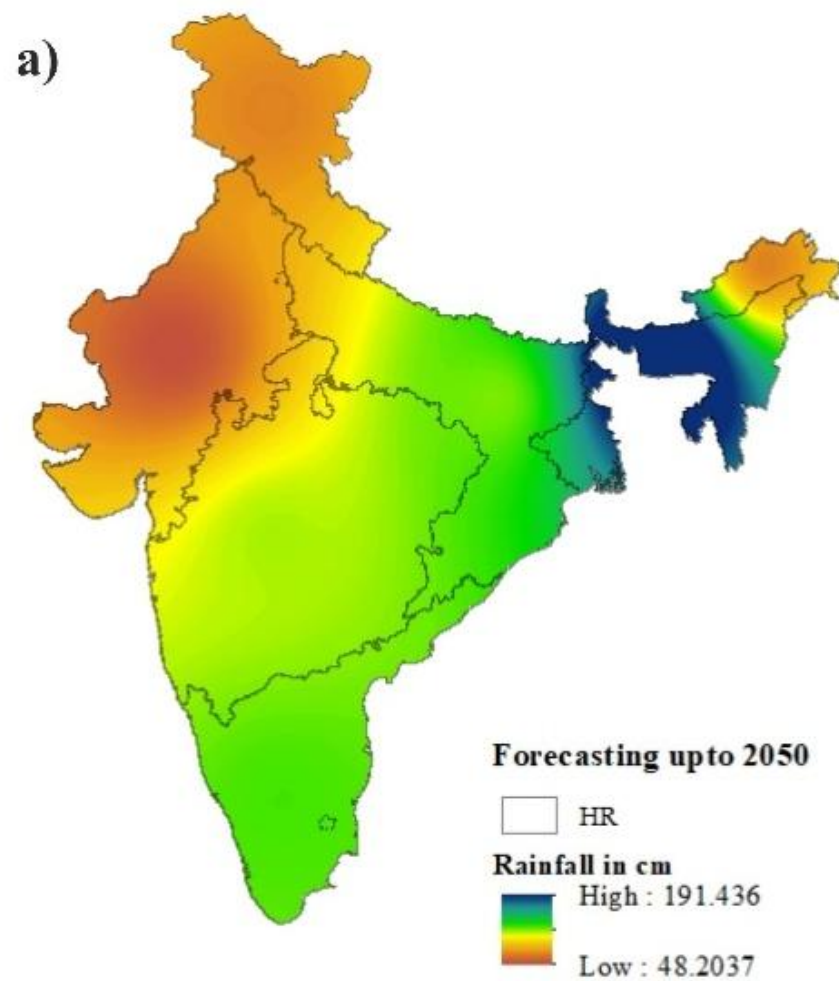


Fig. 12. ANN-MLP model derived annual rainfall forecast of India for the year 2050 at the level of HRs and MSDs

A recent 28-year (2023-2050) rainfall forecasting analysis for the MSDs of India reveals several key spatial and temporal trends. The findings indicate an overall decline in projected annual precipitation amounts throughout the country. However, the decline is not uniform, with the northeast HR expected to experience the least reduction in rainfall and maintain the highest annual average (approximately 1920 mm) by 2050. In contrast, the north-western HR is forecasted to undergo the largest decrease in rainfall over the projection period. While the northeast is projected to see a gradual, slow-moving reduction in annual precipitation, the northwest is likely to exhibit greater fluctuation interannually but demonstrate an overall consistent downward trend in rainfall. The MSDs of Coastal Karnataka, East Madhya Pradesh, Konkan Goa, Assam Meghalaya, and West Bengal Sikkim are found with relatively high annual rainfall totals through 2050. Conversely, projections suggest East Rajasthan, East Uttar Pradesh, Gujarat, Haryana, Jammu & Kashmir, North Interior Karnataka, Odisha, Rayalaseema, Saurashtra/Kutch, and West Rajasthan MSDs will likely emerge as the most rainfall-deficient meteorological subdivisions.

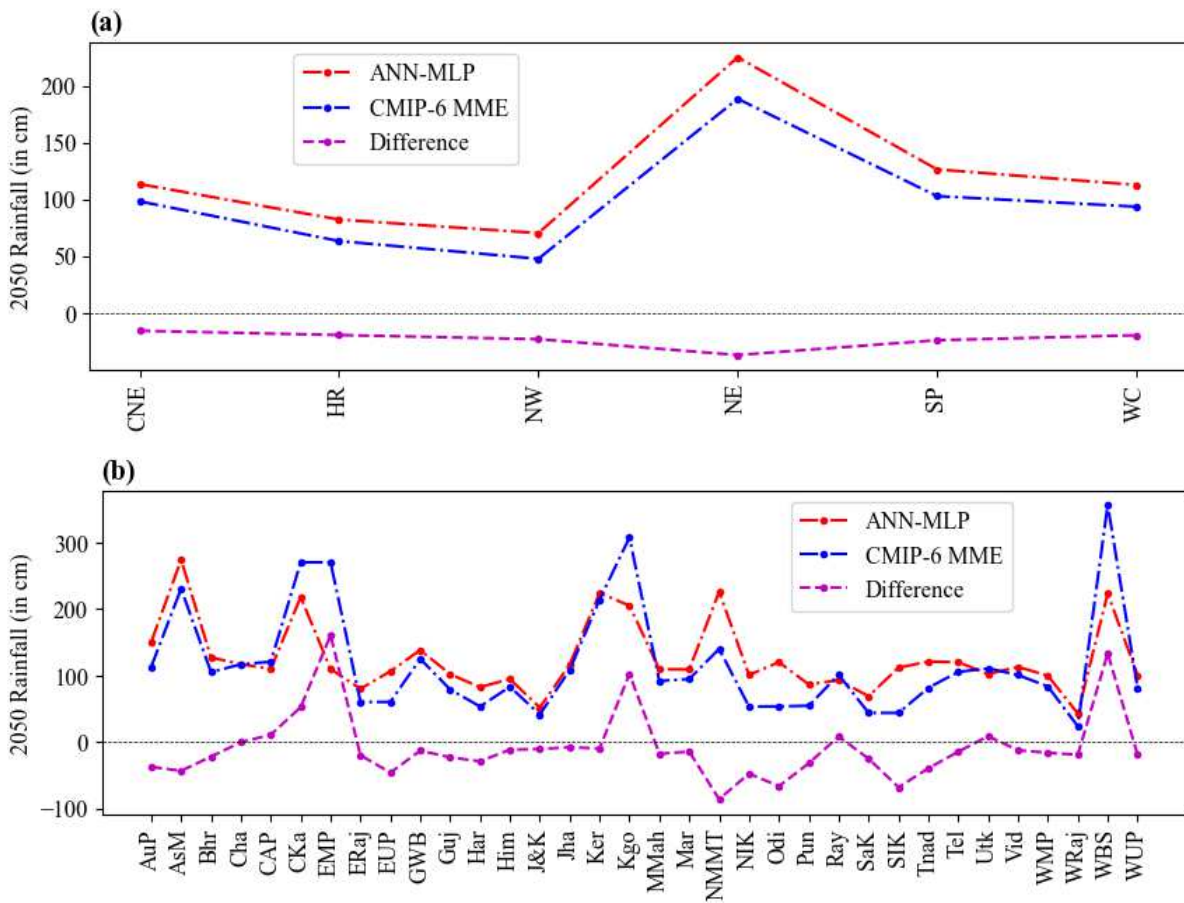


Fig. 13. ANN-MLP rainfall forecasts and CMIP-6 MME SSP585 scenario rainfall projections for (a) HRs and (b) MSDs of India

The ANN-MLP model-based forecasts of the annual rainfall for HRs and MSDs were compared with the CMIP-6 MME projections (SSP585 scenario, rli1p1fl realization) as shown in **Fig. 13 (a)** and **(b)**, respectively. The plots show that the forecasts made by the ANN-MLP model are in line with the CMIP-6 MME projections for all HRs and MSDs. This validates the quality of the forecasts made by the ANN-MLP model in this study. The forecasted trajectory of the mean rainfall indicates that India as a whole would breach the CMIP-6 MME based rainfall projection by 2050. This is indicated by the **Fig. 13 (a)** as the difference of ANN-MLP forecast and CMIP-6 MME rainfall projection turns out to be negative for all the HRs, indicating that India would receive lesser rainfall than the worst-case scenario represented by the business-as-usual (SSP585) scenario of CMIP-6 projections. Similar findings are revealed for 27 MSDs by the ANN-MLP forecasts as shown in **Fig. 13 (b)**. According to the ANN-MLP model, only 7 MSDs mostly including the coastal regions like Coastal Andhra

Pradesh, Coastal Karnataka, Konkan Goa, and West Bengal & Sikkim, along with some interior regions i.e., East Madhya Pradesh, Rayalaseema, and Uttarakhand MSDs will have rainfall greater than the projections of CMIP-6 MME SSP585 Scenario.

5. Discussions

The long-term trend analysis and forecasting of rainfall are crucial in light of possible water resource management strategies, sustainable irrigation practices, and soil management. In this context, the comprehensive examination of rainfall trends in India becomes crucial. Rainfall trends were thoroughly analysed for annual, seasonal and monthly scales for all HRs and MSDs as precisely defined by the IMD. Detailed spatial scales are available for both HRs and MSDs. Symmetry in rainfall at the homogeneous region scale is an intrinsic characteristic of annual rainfall patterns across India. Negative skewness in rainfall was found in the western part of the country, ideally in the MSDs of Marathwada and Gujarat regions, as well as in some parts of eastern India such as the MSDs of NMMT, West Bengal Sikkim and Arunachal Pradesh. Other regions of India displayed more positive kurtosis, with the west coast exhibiting asymmetry, where some of its subdivisions showed positive excess kurtosis while others exhibited the complete opposite. The same results of skewness and kurtosis were also revealed in the work of Saini & Sahu, 2021. The contribution of the Northeast Homogeneous Region was maximum in the total average rainfall of the country, while the northwest region's contribution was the least. The north interior Karnataka and the Northeast Madhya Pradesh subregions contributed the minimum and maximum rainfall, respectively.

The long-term data from 1901-2022 was available at the finest spatial scale across all regions, potentially offering a clearer depiction of rainfall trends. This study utilizes appropriate statistical techniques to reveal distinct rainfall patterns. Results after applying the MK Test and Sen's Slope estimator showed that the Northeast HR exhibited a significant downward monotonic trend out of the six HRs, while the other five regions saw insignificant minor fluctuations with a slight upward trend. Out of the thirty-four MSDs analysed, 7 MSDs displayed a significant negative rainfall trend, and 10 MSDs showed a significant positive trend according to the Mann Kendall test, although the intensity of increase was considerably less as compared to the intensity of decreasing rainfall as observed in other areas. This clearly demonstrates the phenomenon of climatic variability across India, with an overall reduction in total rainfall amounts. A similar study by Ahmed et al, 2022 also identified decreasing rainfall trends in Arunachal Pradesh and Eastern Madhya Pradesh. The south peninsular and central northeast HRs showed decreasing intensity of winter rainfall. On the other hand, the pre-monsoon and monsoon seasons showed varying intensity of rainfall trends. Subash & Sikka, 2014 also found similar results in their study, where the southern part of the country revealed a significant increasing trend in the post-monsoon season, while the Northwest HR showed increasing trends in the monsoon season. Pattanaik, 2007 carried out rainfall analysis for all six HRs of India where results revealed that north-western and central part of India showed significant increase during pre-monsoon but decrease during post monsoon and monsoon season. The similar results were observed in this study where central northeast HR showed increasing trend in the pre monsoon followed by significant decrease in the post monsoon season. In the monthly trends as well, Subash & Sikka, 2014 found a significant increasing trends in the for the Northwest HR for the months of May and October, which coincides with the MK Test results of this research. Ganguly et al., 2023 also obtained similar results while analysing trends for arid and semi-arid regions of India.

Most of the previous research only used fewer analytical tools to look at trend outcomes. Additionally, the discussion of results based on spatial scales is restricted to just one or two levels of spatial units or temporal scales (Almeida et al., 2017; Caloiero et al., 2018; Dash et al., 2007; V. Kumar & Jain, 2011; Mondal et al., 2015; Panda & Sahu, 2019; Praveen et al., 2020; Rana et al., 2012). Mondal et al. (2015) and Praveen et al., 2020 conducted changepoint analyses utilizing the Pettitt, SNHT, and Buishand Range Tests on both annual and seasonal rainfall data across all thirty-four MSDs. They noticed that 21 and 18 MSDs, respectively, had a changepoint using changepoint tests between 1950 and 1966, while 13 MSDs were also identified with a break year in this study. As a result, this study suggests that there was no repetitive tendency in the 122 years of annual, seasonal and monthly rainfall, and more investigation is required to precisely identify the trends and their sizes (Shen et al., 2018). Based on this, planners and scientists can propose management and developmental strategies. If the MK Test is applied initially without taking changepoints into account, it could potentially yield misleading or inaccurate results (N. Kumar et al., 2019). Praveen et al., 2020 thoroughly applied changepoint tests and their comprehensive analysis of post- changepoint results indicated that seventeen specific MSDs demonstrably showed strong negative trends during the monsoon season, sixteen MSDs in the

post-monsoon season, seventeen MSDs in summer, and twenty-one MSDs in the winter seasons while very similar findings were observed in this research as well with only a slight variation of twelve MSDs in pre-monsoon, eleven in monsoon, ten in post-monsoon, and twenty-eight in the winter season. Researchers have often made limited attempts to calculate break years at the monthly scale. Therefore, this research has advanced to a higher level of precision by conducting breakpoint analysis for all six HRs and thirty-four MSDs across all twelve months.

Statistical results of ITA indicate that at the annual time scale, the Northeast and Central Northeast HRs, as well as the MSDs of Arunachal Pradesh, Assam & Meghalaya, and Eastern Madhya Pradesh, exhibited highly significant negative trends. The winter season also conclusively exhibited the greatest number of important significant negative trends. Similar corroborating results can also be evidently seen in the work of R. Singh et al., 2021. To the best of authors' knowledge, there appears to be a shortage of studies examining intricate monthly

rainfall trends and patterns utilizing ITA analysis. The thorough application of ITA at such a micro-temporal scale is expected to enhance the precision and accuracy of climatic studies, particularly in understanding India's intricate weather patterns. Praveen et al., 2020 clearly showed that a strong negative trend was observed in the sub-divisions of North-eastern, Eastern, South Eastern and Southern sections in summer, North Eastern and some parts of Eastern India during the monsoon season, North Eastern and Eastern India in post-monsoon, and Western, Southwestern, Southern India in winter rainfall, which also fully validates our extensive results as well.

In this study, annual rainfall for six HRs and thirty-four MSDs was thoroughly forecasted up to the year 2050. The potential decline and increase in annual rainfall are forecasted for all six HRs and thirty-four MSDs. Highly detailed forecasting studies for the whole of India are carried out very rarely and infrequently. Som & Dey (2022) conducted a forecasting study for the Bundelkhand geographic region of Madhya Pradesh, predicting a decrease in rainfall intensity. This aligns with the findings for the Eastern Madhya Pradesh MSD in the present research, which also indicates a decline in rainfall intensity. The comparison of the model-based rainfall forecasts with the CMIP-6 MME projections (SSP585 scenario, r1i1p1f1 realization) is a unique aspect of this study. This approach introduces a distinct method for analysing the impacts of climate change at regional and local levels, offering a valuable framework for future studies to adopt. In the present study, it reveals that all the regions of India, except some of the coastal regions and the plateau interior regions, will receive rainfall lesser than the worst-case scenario of CMIP-6 MME projections.

The analysis of large-scale ocean-atmospheric changes using ECMWF ERA5 re-analysis data on GrAdS reveals significant findings regarding the rainfall trends in India. Comparing the periods from 1940–1956 to 1957–2022, notable variations are observed, including changes in convective precipitation and rainfall rates, changes in low cloud cover patterns, and shifts in moisture divergence pathways over the Indian Ocean, particularly towards the northwest direction. These findings are imperative in suggesting that the ocean-atmospheric dynamics might have exerted a considerable influence on the observed existing rainfall trends in India. From this point forward, the research has the potential to improve the understanding of climate science and has real-world applications for building resilience and adaptation in sensitive areas like Indian agriculture and water resource management in order to mitigate the adverse impact of the climate change. The findings of this study offer crucial insights for hydrologists and planners worldwide, facilitating the development and implementation of environmentally sustainable long-term management strategies for climate, hydrology, and agriculture. The results can greatly aid in proposing policies for the effective management of irrigation, climate, and atmospheric conditions over extended periods.

6. Conclusion

The quantity and availability of water resources are directly influenced by spatiotemporal variations in rainfall patterns within a specific area over time. Consequently, the analysis and forecasting of rainfall play a crucial role in policy-making and further exploration of issues such as droughts and floods. By understanding rainfall patterns, policymakers can better anticipate water resource challenges and implement effective strategies to manage them. Hence the present study analyzed the variability and trend analysis of annual rainfall for the entire study area which was further separated into six HRs and thirty-four MSDs. Various statistical techniques such as MK Test and Sen's Slope were used which revealed that eastern and northeastern parts of country is facing lesser amount of rainfall over the course of last 60 years. The findings of the MK Test on seasonal and monthly

scales also revealed that the central and eastern part of country experienced negative trend while regions such as Jammu and Kashmir, Marathwada, Konkan and Goa, Madhya Maharashtra and Rayalaseema experienced increasing trends of rainfall. Changepoint detection techniques were also carried out and results revealed that the period between 1950-1970 was those years in which most of the regions experienced a drastic change in their trends.

Following the identification of the changepoint year, the analysis of rainfall variability and trend was repeated for both the pre-changepoint and post-changepoint periods. The coastal Andhra Pradesh along with Konkan Goa, Marathwada and Punjab recorded an increase in yearly precipitation while in the seasonal scale areas like Rayalaseema, south interior Karnataka, NMMT and Assam Meghalaya experienced negative trends in rainfall. Although the MK Test identified certain subdivisions as having no trend, the ITA method revealed the presence of a trend in those subdivisions. Thus, the analysis indicates that a majority of the subdivisions exhibited a negative trend and high variability after 1970. Furthermore, the year-wise analysis revealed specific instances of departure in rainfall amounts, indicating the extent and timing of these deviations. These deviations in rainfall are caused by convective precipitation and rainfall rate fluctuations, increasing low cloud cover, and inadequate vertical moisture divergence, according to ERA5 atmospheric reanalysis data of ECMWF. Furthermore, to achieve sustainable development goals, it is crucial to understand and future trends in rainfall. Therefore, in the current study, rainfall forecasting for all MSDs were made utilizing the ANN-MLP model. The AI modelling also forecasted the depletion of annual rainfall over the upcoming 28 years in the majority of regions, which poses a threat to India's agriculturally sustained economy. The comparison of the forecasts with the CMIP-6 MME projections under the SSP585 scenario indicate that, with the exception of a few coastal and interior regions, all regions of the country will experience rainfall levels lower than the worst-case scenario projected by CMIP-6 MME.

India's economy is heavily reliant on rainfall, whether in the agricultural or industrial sectors. Consequently, water resources are indeed a vital component of India's modern economy. However, the global rainfall pattern has been disrupted due to climate change. The present study provides comprehensive information on various aspects, including rainfall variability, overall trends, and changepoints for annual, seasonal, monthly, and future rainfall. Studies of this nature have not been conducted across the entirety of India with such detailed monthly analysis before. Overall, the findings of the research are vital for policymakers and planners aiming to propose strategies for the sustainable and long-term management of water resources, irrigation, climate, and atmospheric conditions. Nonetheless, the study has one major limitation which need to be highlighted here in conclusion. Due to the wide coverage of the research area, encompassing 40 large regions, it is challenging to provide a comprehensive understanding of what occurred across the entire region. The lack of daily and current rainfall data for the studied time is one of the study's limitations and the research gap could be addressed by employing more advanced trend detection techniques at a micro scale, specifically at the district, block, and village levels. This approach will enable the development of highly precise micro-level management plans. Furthermore, carrying out rainfall studies on a grid-by-grid basis using advanced microwave remote sensing technology could prove advantageous for planners. Additionally, integrating ensemble machine learning techniques and deep learning methodologies such as the long short-term memory (LSTM) network can aid in producing high-quality forecasting data.

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