Journal of Environmental Informatics Letters 10(2) 74-88 (2023)

Journal of Environmental Informatics Letters

www.iseis.org/jeil

Analysis of Rainfall Trends in India, Incorporating Non-Parametric Tests and Wavelet Synopsis over the Last 117 Years

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Received 09 August 2023; revised 30 August 2023; accepted 11 September 2023; published online 10 December 2023

ABSTRACT. Rainfall trend analysis is very important in the economic and sociocultural context of the country, like the development of irrigation and water resource management practices. In this paper, Mann-Kendall (M-K), Sen's slope estimator, and wavelet analysis were used to analyze long-term (1901 ~ 2017) annual and seasonal rainfall trends in India. The sequential Mann-Kendall (SQMK) test is used to estimate the temporal variation of rainfall. The analysis shows monsoon precipitation in "Jammu and Kashmir, Himachal Pradesh, Uttarakhand, Uttar Pradesh, Chhattisgarh, Sikkim, Arunachal Pradesh, Mizoram, Assam, Karnataka, Nagaland, Kerala, Meghalaya, and Goa" have significant trends. The above-mentioned states were subjected to a discrete wavelet transform (DWT) analysis using Daubechies (db5-db10) and Symlet (sym5-sym10) mother wavelet families. The analysis revealed that the trends of subdivisions had a short-term periodicity of less than a decade. Therefore, the present study indicates significant changes over time. By utilizing wavelet techniques, it is possible to gain insight into both short- and long-term tendencies, making it simpler to spot patterns and sudden changes. Therefore, the present study by combining non-parametric tests with wavelet synopsis, offers a thorough comprehension of rainfall trends in India. The collaborative use of these techniques improves the precision of trend identification, offering valuable insights to make well-informed decisions for water resource management and climate adaptation strategies.

Keywords: rainfall trend, Mann-Kendall, SQMK, discrete wavelet transforms, daubechies, symlet, changepoint, India, 117 years

1. Introduction

Trend analysis is a quantitative analysis of the variation in data collected over time (Esterby, 1996). The main objective of this analysis is to extract information about trends over time and express this information quantitatively. Climate change is a long-term, continuous change that either increases or decreases with a specific range of average weather conditions (Sahu et al., 2021a, 2022a; Dhiwar et al., 2022; Mehta et al., 2023). It is generally said that climate change has changed on a global scale, but its effects are felt even on a regional scale. Although climate change is a major concern, it also includes variations in rainfall, temperature, humidity, and other factors. The hydrological cycle includes the key element of precipitation, and variations in its pattern can directly affect the region's water resources, soil moisture, groundwater reserves, and streams (Jain et al., 2013; Verma et al., 2021, 2023a, b, c; Sahu et al., 2023b; Tandel et al., 2023). The rainfall analysis focuses on the impact of rainfall on food production, water availability, floods, and drought (Dore, 2005), the productivity of wheat and rice can suffer from a 1 or 2 °C moderate temperature increase, respectively (Aggarwal et al., 2006). Kalra et al. (2008) found that the production of mustard, barley, wheat, and chickpea showed signs of a steady decline in production as a result of temperature rises in four northern Indian states. Global precipitation is expected to rise, but its effects may vary on a continental and regional scale (Sahu et al., 2021c, 2022b). Also, changes in rainfall amount and intensity (more or less) may affect the spatial and temporal distribution of groundwater level, soil moisture, and runoff, affecting frequency of flooding and droughts (Azharuddin et al., 2022; Sahu et al., 2022c; Shaikh et al., 2022). Similarly, if precipitation changes unexpectedly, the cropping pattern and productivity will be significantly impacted. The study of rainfall and temperature is of great importance for understanding the evolving trends in climate variables, which would directly affect the streamlined flow, leading to a change in surface and groundwater availability (Sahu et al., 2021d; Verma et al., 2022a, b, d, 2023d, e). As per the "Inter-governmental Panel on Climate Change (IPCC, 2007)", future climate change will probably affect agriculture production, water scarcity, and freshwater availability in many water basins in India and increase the risk of hunger due to climate change.

According to the IPCC report for 2018, if it continues to increase at the same pace, global warming is likely to reach 1.5 °C between 2030 and 2052. Whereas, due to the melting of glaciers, the seawater level is continuously increasing, also referring to Kishtawal et al. (2010) for other urbanization impacts of rainfall. Due to global warming, the soil and ocean ecosystems and some of the facilities they provide have already

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ISSN: 2663-6859 print/2663-6867 online
 doi:10.3808/jeil.202300117

been altered (IPCC, 2018). Many studies concerning rainfall trends in Indian regions have been carried out using conventional methods, including linear regression, the Mann-Kendall (M-K) test, and Sen's slope estimator, etc. (Verma et al., 2022c, e, f; Sahu et al., 2023a). Wavelet analysis has also been used in recent research, but only in specific areas (Adarsh and Janga Reddy, 2015) or specific regions of the country (Pandey et al., 2017). Some of these studies were performed in various parts of India to detect trends in hydro-climatic variables (Sahu et al., 2023c). Guhathakurta and Rajeevan (2008) used a linear regression technique to analyze 36 meteorological subdivisions in India. Similarly, Kumar et al. (2010) have used M-K and Sen's slope method to analyze 30 such meteorological subdivisions in India. Soman et al. (1988) studied Kerala state to analyze its seasonal and annual trends with the help of the M-K test. Raj and Azeez (2012) used the M-K test and wavelet analysis to find a trend and its periodicity. "The M-K test is best viewed as an exploratory analysis and is most appropriately used to identify stations with significant changes or large-scale improvements as well as to quantify these findings" (Hirsch et al., 1982). The magnitude of the recent trend is usually determined using a non-parametric method known as Sen's slope estimator (Sen, 1968), and the time series' statistical significance was assessed using the M-K test (Mann, 1945; Kendall, 1975; Sonali and Kumar, 2013). Besides analyzing fundamental trends, it is essential to identify sequential trend changes and periodicity assessments in hydro-climatic variables, which is efficiently achieved using the SQMK method. The combination of DWT and SQMK techniques has recently proven successful in identifying trends and periodicity in hydrological datasets. For instance, Partal and Kucuk (2006) studied Turkey and used the above sort of strategy for rainfall data series, whereas Li et al. (2013) used it for the analysis of historical rainfall over long durations. Ontario and southern Quebec in Canada were studied for testing the discrete wavelet transform (DWT) to identify trends for rainfall (monthly, seasonally, and annually) and streamflow information (Nalley et al., 2012; Mehta et al., 2022; Kumar et al., 2023). Their study observed that the identified trends in the regions were more effectively affected by intra- and inter-annual events. A similar combination was used in another study to analyze temperature datasets to detect trends (Nalley et al., 2013).

In the recent past, literature discovered the use of a limited or standard approach for trend estimation, but advanced techniques for detecting sequential changes in trend and periodicity assessment were lacking. The analyzed research gap was accomplished in this study, which focused on using advanced trend detection techniques to examine patterns, pattern shifts, and the periodicity of precipitation time series. The study uses discrete wavelet transform analysis for subdivisions having significant monsoon rainfall trends and shows a monotonic trend in the 6^{th} approximation level. In this study, the DWT and SQMK methods were analyzed for periodicity in the trends.

The main objectives of this study are to (1) find seasoal and annual rainfall trends for entire subdivisions using the M-K test, Sen's slope estimator, and Pettitt's change point method; (2) to use the SQMK test to identify temporal variation in the trend; (3) to use the DWT to analyze the trend's periodicity. The methodology adopted for this study is summarized in this paper in section 2. A summary of the research topics and the data used is provided in section 4. The outcomes of the use of various methodologies are described in section 5 and the conclusion is summarized in section of this article.

2. Study Area and Data Used

The monthly and seasonal rainfall patterns of all states of India (Telangana and Ladakh are studied together with Andhra Pradesh and Jammu & Kashmir (J&K) subdivisions, respectively) are analyzed. The research area's map is depicted in Figure 1.

The data is obtained from the India Meteorological Department (IMD), Pune, and is of resolution 0.25° × 0.25° and has a record length of 117 years (1901 ~ 2017). The data is believed to be error-free since it was published by IMD, Pune. The geographical region of the subdivisions under consideration in this research is 3.28×10^6 km^2 (3.29×10^6 km^2 in India as a whole). One mean rainfall representative is prepared from available grid data for a specific region using the Thiessen polygon in ArcGIS based on homogeneous climatic characteristics. As the first step in data processing, a monthly dataset is prepared from daily available gridded data for each grid in India. The statewise monthly rainfall is calculated using a weighted average of all the grid rainfall data available in states or subdivisions.

3. Methodology

In the present study, the approach used to analyze rainfall trends in India combines non-parametric tests with wavelet synopsis for a comprehensive evaluation of temporal patterns. Initially, historical rainfall data from meteorological stations throughout India was gathered. To detect trends, methods such as the M-K test, which evaluates monotonic trends without requiring assumptions about a particular distribution, are employed. In addition, wavelet analysis is utilized to examine specific localized changes within the time series data. This involves breaking down the data into different time-frequency domains using wavelet transforms. This process allows for the detection of various periodic patterns and trends across different scales. By utilizing wavelet transform, it becomes possible to pinpoint important periods where shifts in rainfall patterns take place. Hence, the integration of non-parametric tests and wavelet analysis offers a comprehensive insight into both enduring patterns and momentary variations in rainfall patterns. Nonparametric tests excel at capturing overarching trends, while wavelet analysis excels at detecting fleeting changes. This all-encompassing method significantly improves the precision of recognizing and describing rainfall trends in India. Such insights are crucial for making well-informed decisions regarding agriculture and water resource management.

3.1. Importance of Trend Analysis in Water Resources

Examining patterns in rainfall is of utmost significance in the realm of water resource engineering. Effective water resource management is a pivotal element of sustainable progress,

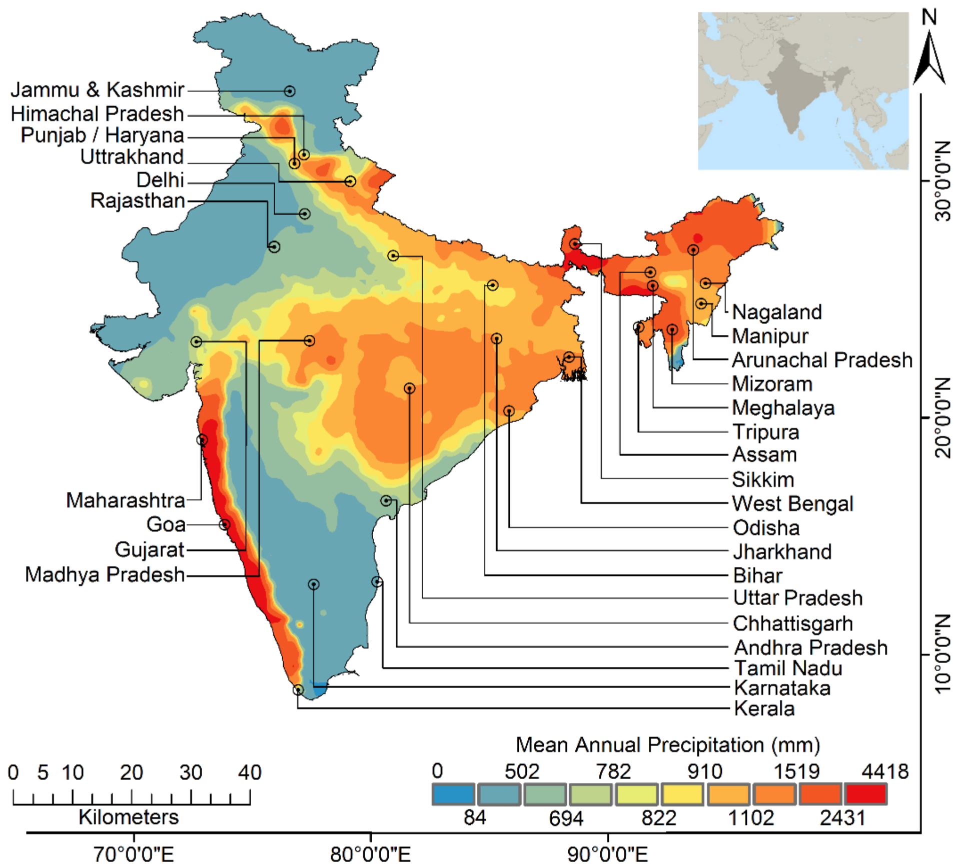

Figure 1. Study area showing the mean annual rainfall (note: Bullets on the map are the administrative centers of the states).

and gaining insights into rainfall trends is essential for optimizing strategies in water resource planning. A precise examination of rainfall patterns offers a valuable understanding of shifting precipitation trends, with direct consequences for factors like surface water availability, groundwater replenishment, and reservoir capacities. This data holds significant importance in the planning and management of water related structures like dams, reservoirs, and irrigation networks. Through the identification of extended trends, water resource planners and policymakers can predict changes in water supply and requirements, enabling proactive strategies to address possible water scarcity or occurrences of flooding. Integrating rainfall data into hydrological models improves their precision and predictive capacities, enabling more effective management of watersheds and more accurate flood prediction. Furthermore, analyzing patterns in rainfall assists in fine-tuning the allocation of water for diverse purposes, such as agriculture, industry, and household use. This optimization guarantees a fair dispersion of water resources and reduces disputes related to water availability. Additionally, in the face of ongoing shifts in rainfall due to climate change, the importance of conducting a thorough analysis of rainfall trends cannot be overstated. This analysis plays a pivotal role as it enables engineers to adjust infrastructure designs and operational approaches, thus lessening the potential consequences of evolving rainfall patterns. This proactive approach ultimately safeguards both communities and ecosystems by ensuring a stable water supply. Essentially, the examination of rainfall trends provides water resource engineers with the knowledge needed to make well-informed choices. These decisions contribute to optimizing water usage, enhancing the ability to withstand fluctuations in climate, and upholding the enduring viability of water systems.

3.2. Estimating Trends by the Mann-Kendall Test

Numerous scholars have examined the existence of statistically significant patterns in hydroclimatic variables including precipitation, streamflow, temperature, etc. in the past using nonparametric M-K tests (Hirsch et al., 1982; Esterby, 1996; Guhathakurta and Rajeevan, 2008; Kumar et al., 2010; Nalley et al., 2012; Nikhil Raj and Azeez, 2012; Li et al., 2013; Jain et al., 2013; Nalley et al., 2013; Adarsh and Janga Reddy, 2015; Pandey et al., 2017; Sahu et al., 2021b). The M-K test possesses a benefit in its suitability for data containing outliers. This advantage stems from its statistics relying on the sign of differences rather than directly on the variable values. The benefit of a nonparametric trend test used for the statistical analysis of hydro-climatic time series is that (i) normally distributed time series data is not required and (ii) not affected by the duration of the time series. The states of India are examined to assess annual and seasonal rainfall trends through Equations (1) to (4):

$$\left(y_j - y_i\right) = \alpha \tag{1}$$

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} sgn(\alpha) \tag{2}$$

$$sgn(\phi) = \begin{cases} 1 & if\ (\alpha) > 0 \\ 0 & if\ (\alpha) = 0 \\ -1 & if\ (\alpha) < 0 \end{cases} \tag{3}$$

The test is applied for a length of data series N. Let y_i and y_j be the subset of the time series, where i = 1, 2, 3, …, $N - 1$ and $j = i$ +1, i + 2, i + 3, …, N. The variation of "S", Var(S) is calculated as:

$$Var(S) = \frac{1}{18}\left[N(N-1)(2N+5) - \sum_{j=1}^{q} t_j(t_j - 1)(2t_j + 5)\right] \tag{4}$$

where q and t_j are the number of tied groups of time series and the number of data in the j^{th} tied groups.

The standard test statistics Z_c are calculated by using Equation (5):

$$Z_c = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & if\ S < 0 \end{cases} \tag{5}$$

A positive, negative, or zero value of Z_c signifies an increasing, decreasing, or no trend, respectively. The two-tailed test (α = 0.025) is performed at a 5% significance level to check the monotonic nature of the trend. If the computed probability p-value is less than the value of $2\alpha = 0.05$, then the trend is statistically significant at a 95% confidence interval, otherwise considered to be insignificant.

3.3. Sen's Slope Estimator Test

A frequently employed method in analyzing time-series data is to measure the extent of the trend (Sen, 1968). This involves computing the inclines of each set of data points and calculating by the following [refer to Equations (6) and (7)]:

$$m_i = \left[\frac{(x_j - x_k)}{j-k}\right] \quad where\ i\ =\ 1,\ 2,\ 3,\ \ldots,\ N \tag{6}$$

Sen's slope estimator (β) is determined by taking the median of N data points in a time series, where N is the total number of data points. The data values at time j and k, where $j > k$, are represented by x_j and x_k, respectively. The median of N values denoted as m_i, is used as Sen's slope estimator:

$$\beta = \begin{cases} m_{(N+1)/2} & if\ N\ is\ odd \\ \dfrac{m_{N/2} + m_{(N+2)/2}}{2} & if\ N\ is\ even \end{cases} \tag{7}$$

When Sen's slope estimator (β) has a positive value, it indicates an increasing pattern, whereas a negative value indicates a decreasing pattern. To test for statistical significance, a two-tailed test with a significance threshold of 5% ($\alpha = 0.025$) is used. If the calculated p-value is found to be lower than 2α = 0.05, then the slopes are deemed to be statistically significant; otherwise, they are considered insignificant.

3.4. Pettitt's T-Test

It is a rank-based correlation test that is employed to look for a sudden change in the time series dataset's mean. (Pettitt, 1969). The test is analyzed by splitting the first time series of sample size (T) into two continuous parts X_i and X_j, where i = 1, 2, 3, … X_t and j = t + 1, t + 2, t + 3, …, X_t. For the index $U_{t,T}$, it is considered that $(X_j - X_i) = \alpha$:

$$U_{t,T} = \sum_{t=1}^{t} \sum_{j=i+1}^{T} \mathrm{sgn}(\alpha) \tag{8}$$

where:

$$sgn(\phi) = \begin{cases} 1 & if\ (\alpha) > 0 \\ 0 & if\ (\alpha) = 0 \\ -1 & if\ (\alpha) < 0 \end{cases} \tag{9}$$

Now another index K_T is defined as:

$$K_T = max\ \left|U_{t,T}\right| \tag{10}$$

From the Equations (8) to (10), the change point is located at point K_T. The position of K_T is nothing but the position of time in the time series. A two-tailed test with a 5% significance level (α = 0.025) is used to further examine the significance of the change point. If the calculated p-value is less than 2α, then the change point is termed significant.

3.5. Sequential Mann-Kendall Test

The test is carried out to calculate the temporal variation in the time series trend. The duration in which the progressive series $u(t)$ lies beyond the threshold line (M-K Z value, ± 1.96), is said to have statistically significant trends. Increasing and decreasing trend properties are the same as in the M-K test. There are two modes in the SQMK test (Sen, 1968), the progressive mode ($u(t)$) and the retrograde mode ($u'(t)$). The intersection point of the two modes is considered to be the beginning point of a trend, and the intersecting points that lie beyond the threshold line (M-K Z value = ± 1.96) are considered to be the beginning points of statistically significant trends. The progressive series is considered to have a zero mean and a unit standard deviation for the M-K analysis. There are two subsets of time series x_i and x_j that are considered where i = 1, 2, 3, …, n and j = 1, 2, 3, …, i − 1.

The comparison between x_i *and* x_j is made and records the number of counts (denoted as n_i) when $x_i > x_j$. The test statistics (t_i), mean $E(t)$ and variance $Var(t)$ of (t_i) are calculated as:

$$t_i = \sum_{j=1}^{i} n_j \tag{11}$$

$$E(t) = \frac{n(n-1)}{4} \tag{12}$$

$$Var(t_i) = \frac{i(i-1)(2i+5)}{72} \tag{13}$$

The sequential M-K test's progressive value is given as:

$$U(t) = \frac{t_i - E(t)}{\sqrt{Var(t_i)}} \tag{14}$$

Similarly, retrograde series values ($u'(t)$) are calculated, by treating the time series beginning as the end, repeating the above steps from Equations (11) to (14).

3.6. Discrete Wavelet Transform

A wavelet is a finite-duration waveform having a mathematical function (Altunkaynak and Ozger, 2016), with zero mean value that can be used to localize a function on temporal and spatial scales (Labat et al., 2005). It is an improvement over Fourier analysis, which decomposes a signal into an infinite number of soft sinusoids, as wavelet analysis disintegrates a signal into different scaled frequencies of the mother wavelet and shifts throughout the signal (Daubechies, 1990). The primary strength of employing the wavelet method lies in its robustness, as it avoids incorporating any potentially flawed assumptions or parametric testing procedures (Kisi, 2009). Another benefit of this method is that it enables the examination of distinct investing behaviors in various time scales in an independent manner through wavelet variance decomposition (Ma, 2006). When it comes to non-stationary time series, wavelet transform analysis is regarded as a more effective method than Fourier transform (Li et al., 2013). During the transformation, a wavelet coefficient is produced at each stage, reflecting how the wavelet's resemblance to the original signal has changed over time and

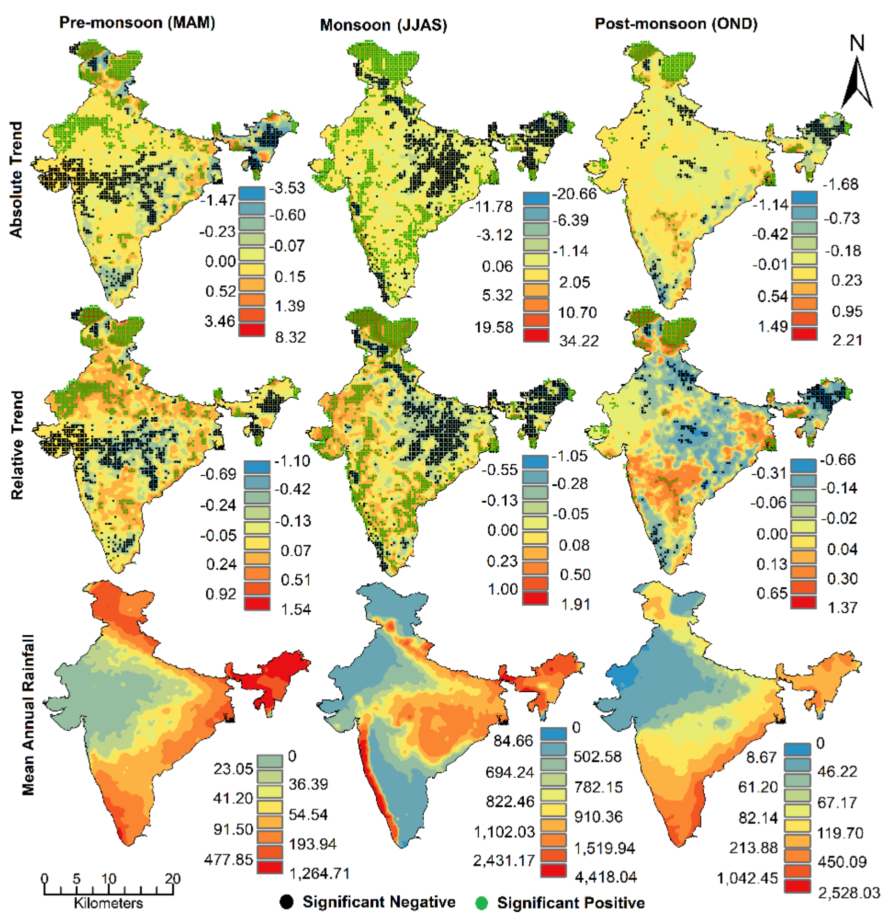

Figure 2. Spatial distribution of precipitation characteristics (note: row 1: absolute trend; row 2: relative trend; row 3: mean annual rainfall (mm) for different seasons in sequence: pre-monsoon, monsoon, and post-monsoon).

Table 1. State-Wise Mann-Kendall, Sen's Slopes (SS), and Pettitt's Change Point for Monsoon Rainfall

No.	States	M-K (*Z*)	*p*-value	SS (mm/year)	Pettit's "*t*"	*p*-value
1	Arunachal Pradesh	−3.022	0.003	−3.380	1949	0.000
2	Assam	−3.852	0.000	−1.495	1966	0.001
3	Chhattisgarh	−2.820	0.005	−1.241	1961	0.000
4	Himachal Pradesh	−2.641	0.008	−1.359	1964	0.001
5	Jammu & Kashmir	5.147	0.000	1.099	1946	0.000
6	Karnataka	2.485	0.013	0.781	1945	0.013
7	Kerala	−3.404	0.001	−3.394	1961	0.001
8	Meghalaya	3.484	0.000	6.378	1969	0.000
9	Mizoram	4.374	0.000	2.671	1975	0.000
10	Nagaland	−4.125	0.000	−1.998	1966	0.000
11	Sikkim	−4.756	0.000	−4.737	1985	0.000
12	Uttar Pradesh	−2.382	0.017	−1.079	1985	0.012
13	Uttrakhand	−2.254	0.024	−1.476	1964	0.014
14	Goa	7.376	0.000	9.491	1944	0.000

Note: The bold letter indicates the significant Z value and the year of the significant change point.

at different frequencies (Nalley et al., 2012). In DWT, the transformation process is made simpler and the number of computation rounds is decreased, resulting in a very accurate and effective analysis (Partal and Kucuk, 2006). By using DWT, time-series data is decomposed into a dyadic scale and location (Mallat, 1989), resulting in an accurate and effective analysis. The DWT is expressed in Equation (15) (Pandey et al., 2017):

$$\psi_{(m,n)}\left(\frac{t-\tau}{s}\right) = s_o^{-\frac{m}{2}}\psi\left(\frac{t-n\tau_o s_o}{s_o^m}\right) \tag{15}$$

where "m" and "n" are integers. s_0 and τ_0 are dilation (scale) and location (translation) parameters respectively, where ($s_0 > 1$) and ($\tau_0 > 0$). The reference values of the s_0 and τ_0 parameters are 2 of two logarithmic translations and dilation scaling is referred to as a dyadic grid structure, which is considered the most convenient scenario. To calculate the DWT coefficients for a discrete-time series, represented by x_i where "i" is a discrete-time index, one can use the following Equation (16):

$$W_{m,n} = 2^{-\frac{m}{2}}\sum_{i=0}^{N-1} x_i \varphi(2^{-m}i - n) \tag{16}$$

where $W_{m,n}$ is the discrete wavelet coefficient of the scale 2^m and location $\tau = 2^n$. Thus, DWT offers information at various scales and locations about time series data.

The steps involved in finding periodicity in rainfall trends using DWT are:

(1) Determine the level of decomposition and select the relevant wavelet families displaying various approximation series for particular wavelet groups. A family with a monotonic trend in the approximation series should be chosen (Mallat, 1989).

(2) The decomposition of the original time series into various detailed components at a different level from the selected mother wavelet.

(3) Reconstruction of the signal with different combinations of detailed components and approximation series at that level.

(4) Find the M-K value of different combinations and the original rainfall series; select the combinations having an M-K value nearer to the original rainfall time series.

(5) Calculate the SQMK value of the original rainfall as well as different series combinations. Find the "root mean square error (*RMSE*)" and the "correlation coefficient (*R*)" between the SQMK value of the original rainfall and the decomposition series. Plot the curve between the original rainfall's SQMK value and other combination series.

(6) Check the harmony in the plot. The most harmonies in the plot show the best correlation with the original data.

(7) Selection of components by identifying the combinations having a high "correlation coefficient (*R*)" and a low "root mean square error (*RMSE*)".

4. Results and Discussion

4.1. Rainfall Trend Analysis Using Mann-Kendall and Sen's Slope Estimator

The daily rainfall datasets were arranged into four climatic seasons "(a) winter (JF); (b) pre-monsoon (MAM); (c) monsoon (JJAS); (d) post-monsoon (OND)" and annual scale. Non-parametric M-K test, Sen's slope, and Pettitt's tests were applied to all subdivisions at seasonal and annual scales at a 95% confidence level. The results of "M-K, Sen's slopes, and Pettitt's change point test" for monsoon rainfall are shown in Figure 2 and Table 1 for all subdivisions having a significant trend. Observation analysis of the M-K and Sen's slope test:

a. Both the "M-K test" and the "Sen's slope test" give similar kinds of results.

b. The winter rainfall was observed to have a significant increasing trend in J&K and Sikkim and a significant decreasing trend in Tamil Nadu, Kerala, Nagaland, Maharashtra, As-

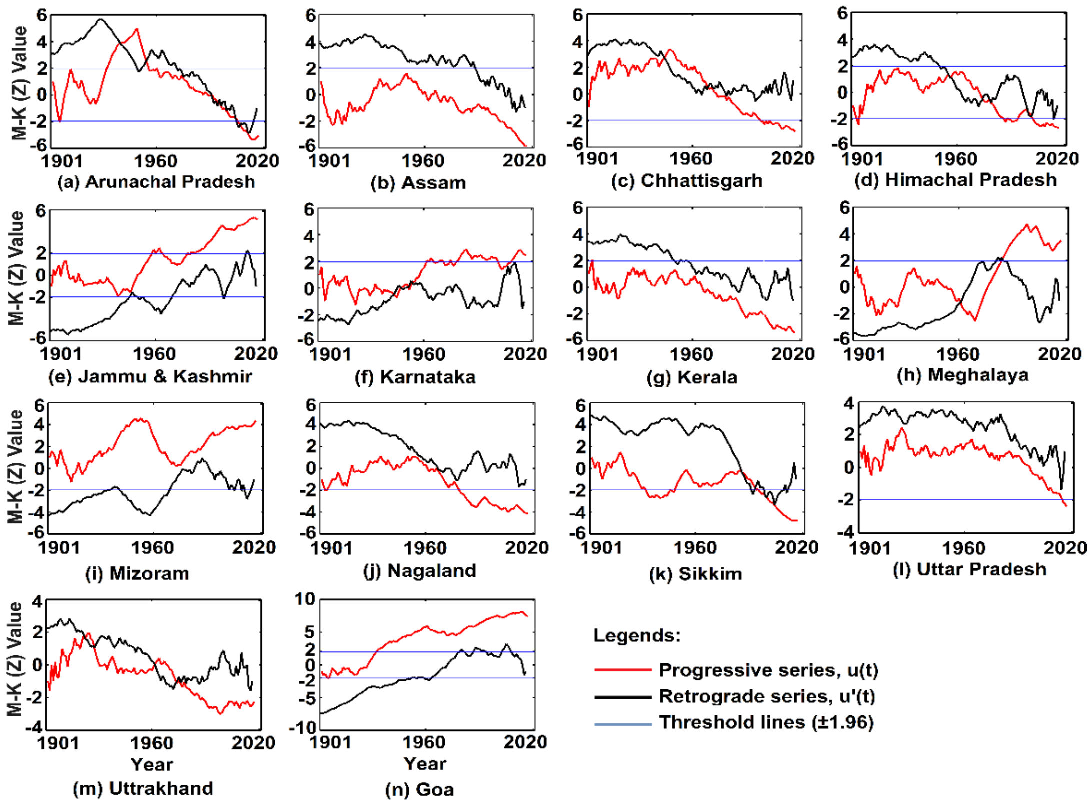

Figure 3. Graphical representation of SQMK results for subdivisions having significant monsoon rainfall trends.

sam, Madhya Pradesh, Bihar, Gujarat, Chhattisgarh, and Jharkhand in this subdivision.

c. In J&K, Meghalaya, Sikkim, and Delhi, a notable rise was observed in pre-monsoon rainfall, while in Chhattisgarh, Gujarat, Madhya Pradesh, and Nagaland, a substantial decrease was observed in pre-monsoon rainfall.

d. Monsoon rainfall showed a significant increasing trend in J&K, Karnataka, Meghalaya, Mizoram, and Goa while a significant decreasing trend in Sikkim, Assam, Arunachal Pradesh, Nagaland, Uttar Pradesh, Himachal Pradesh, Kerala, Chhattisgarh, and Uttarakhand.

e. There was a considerable increase in post-monsoon rainfall in J&K, Meghalaya, Mizoram, and Sikkim, whereas a significant decrease in post-monsoon rainfall was observed in Kerala and Uttarakhand.

f. There was a significant rise in annual rainfall trend in J&K, Karnataka, Meghalaya, Mizoram, and Goa, while there was a notable decline trend in Assam, Chhattisgarh, Jharkhand, Kerala, Nagaland, Uttar Pradesh, and Uttarakhand.

In the next section, the application of the SQMK method for a detailed investigation of significant rainfall trends in various subdivisions.

4.2. Rainfall Trend Analysis Using Mann-Kendall and Sen's Slope Estimator

The SQMK test is a robust technique employed to analyze temporal trends in rainfall patterns. This method effectively combines the seasonal Kendall test with a modification that amplifies its ability to detect subtle fluctuations in precipitation data. SQMK stands out in its capacity to capture both straightforwardly increasing or decreasing trends and more intricate, nonlinear patterns commonly encountered in climate investigations. By working with ranked data, SQMK minimizes the influence of anomalies and accommodates the influence of seasonal variations. Researchers benefit from this approach as it helps identify statistically significant trends, a crucial aspect for comprehending enduring shifts in rainfall patterns and their implications in hydrology, agriculture, and climate science.

In the present study, the SQMK test was carried out to study the fluctuation in trends for annual and seasonal rainfall (pre-monsoon, monsoon, post-monsoon, and annual) series having a significant trend. The intersection points signify turning points in the data series.

4.2.1. Sequential Mann-Kendall Results for Pre-Monsoon Rainfall

J&K had a significant turning point in pre-monsoon rainfall in 1986. Chhattisgarh's rainfall showed decreasing trends for seven decades after 1953 but became significant after 1986. Gujarat's rainfall had a decreasing trend after 1949 and significant after 1988. J&K had a long-term increasing trend for nine decades after 1922, with significant trends in 1979. Madhya Pradesh had a long spell of decreasing trends for eight decades after 1941, with significant trends during 1996 ~ 2005 and 2010 ~ 2014. Meghalaya had an increasing trend for six decades (1904 ~ 1967) and after 1973, with significant trends from 1990 onwards. Nagaland had a decreasing trend for ten decades, with significant trends after 1972. Sikkim had a decreasing trend from 1923 ~ 1988 and an increasing trend from 1989 onwards, with significant trends during 1965 ~ 1976 and from 2001 onwards. Delhi had increasing rainfall trends for the last 56 years (1962 ~ 2017), with significant trends beyond 2016. The details can be seen in Figure S1 in Supplementary Information (SI).

4.2.2. Sequential Mann-Kendall Results for Monsoon Rainfall

Statistically significant turning points in trends were observed in the following subdivisions during monsoon rainfall: Arunachal Pradesh (1940, 2007), Chhattisgarh (1944), Meghalaya (1985), and Sikkim (1999, 2000).

Rainfall trends were observed in multiple regions of India (Figure 3). In Arunachal Pradesh, rainfall increased from 1929 to 1988, decreased after 1989, and considerably decreased by 2005. In Assam, rainfall showed a decreasing trend for about 50 years during 1967 ~ 2017, followed by a significant trend from 2002 onwards. Chhattisgarh had a continuous long-term increasing trend for about 7 decades (1903 ~ 1973) and later observed a decreasing trend, with significant decreasing trends after 1998. Himachal Pradesh had an increasing trend for 63 years (1910 ~ 1972) and a declining tendency for 45 years (1973 ~ 2017), with significant rainfall trends since 2003. In J&K, rainfall showed a drastic increasing tendency for around 68 years (1950 ~ 2017) after a decreasing trend for over 38 long years (1912 ~ 1949). Karnataka showed a long-term increasing trend of around 70 years (1948 ~ 2017) with significant increasing trends during 1979 ~ 2001 and 2009 ~ 2017. Kerala's rainfall trend increased from 1922 to 1965 and decreased from 1966 onward, with significant decreasing trends reported by 2000. In Meghalaya, rainfall decreased for two decades (1954 ~ 1975), increased after 1977, and significantly increased after 1984. Mizoram observed an increasing rainfall trend in the past 95 years after 1923, with significant increasing trends during 1938 ~ 1962 and after 1988. Nagaland had an increasing trend during 1928 ~ 1961 and a decreasing trend after 1962, but a significant decreasing trend in the past three decades after 1979. Sikkim had a decreasing trend for about ten decades (1922 ~ 2017), while a significantly decreasing trend occurred from 1933 to 1948 and in the recent past after 1996. Uttar Pradesh experienced long-term increasing trends from 1902 to 1996 and decreasing trends in the last two decades, with significant increasing trends from 1924 to 1927 and significant decreasing trends since 2015. In Uttarakhand, a decreasing trend in rainfall was observed from 1969 to 2017, with a significant decrease in the last three decades (1987 ~ 2017). Goa showed increasing trends for nine decades (1928 ~ 2017), with the past 85 years being significant (1933 ~ 2017).

4.2.3. Sequential Mann-Kendall Results for Post-Monsoon Rainfall

Post-monsoon rainfall observed a statistically significant turning point in the trend of the below subdivisions. J&K (1979) and Meghalaya (1979, 1980, and 1988) identified the maximum number of turning points. In J&K, the rainfall series showed increasing trends except during 1907 ~ 1909 and a significant trend after 1956. In Kerala, rainfall showed decreasing trends after 1953 and after 1985, the trend turned to a significant decrease, except for some years. Meghalaya observed increasing rainfall trends in the past 70 years and a significantly increasing trend during 1984 ~ 2017, i.e., the last 35 years, except 1985, which does not fall on threshold lines (± 1.96). In Mizoram, a long-term rainfall increasing trend of nine decades (1928 ~ 2017), excluding a few years and the significant increasing trend observed for short spells during 1991 ~ 1993, 2002 ~ 2005, and 2008 ~ 2010, was observed. In Sikkim, a decreasing trend for about four decades (1940 ~ 1978), and after 1979, an upward trend was observed except for some years. In Uttarakhand, rainfall observed an increasing trend for about forty years (1955 ~ 1994) and a decreasing trend in the recent past after 1995. The details can be seen in Figure S2 in SI.

4.2.4. Sequential Mann-Kendall Results for Annual Rainfall

Assam (1959, 2011, and 2012), Chhattisgarh (1946), Karnataka (2010), and Meghalaya (1985) had statistically significant annual rainfall turning points. Assam experienced an increasing trend from 1928 to 1977 and a decreasing trend since 1978, with a significant decrease after 2002. Chhattisgarh had an upward trend from 1903 to 1971 and a downward trend since 1972, with a significant increase from 1937 ~ 1953 and a significant decrease after 1987. J&K had a continuously increasing trend for 12 decades except for a few years and a significant increase since 1950. Jharkhand had an increasing trend from 1904 to 1964 except for 1915, and a decreasing trend since 1965. Karnataka had an increasing trend since 1932, except for a few years. Kerala had a decreasing trend from 1903 to 1922 and after 1970, and an increasing trend from 1923 to 1969 with a significant decrease after 1970.

In Meghalaya, there was an increasing trend from 1927 ~ 1961 and after 1974, and a decreasing trend during 1962 ~ 1973, with a significant increase after 1982. Mizoram had an increasing trend from 1916 to 1969 except for 1920 and 1922 and since 1976, with a significant increase after 1989. Nagaland had a decreasing trend from 1905 ~ 1928 and 1960 ~ 2017, and a significant decrease in the past 46 years. Uttar Pradesh had an increasing trend from 1908 ~ 1991 and a decreasing trend since 1992, with a significant decrease after 2009. Uttarakhand had a declining trend in the previous 44 years, with a significant decrease from 1997 ~ 2001 and in the recent past from 2015 ~ 2017. Goa initially had a decreasing trend for about 25 years (1902 ~ 1927) and a long-term increasing trend for about nine decades after 1928, with a significant increase after 1933. The details can be seen in Figure S3 in SI.

4.2.5. Analysis of Rainfall Trends in the Monsoon Season Using DWT

The M-K and Sen's slope estimator analysis shows that Arunachal Pradesh, Goa, J&K, Karnataka, Meghalaya, Kerala, Mizoram, Chhattisgarh, Nagaland, Sikkim, Himachal Pradesh,

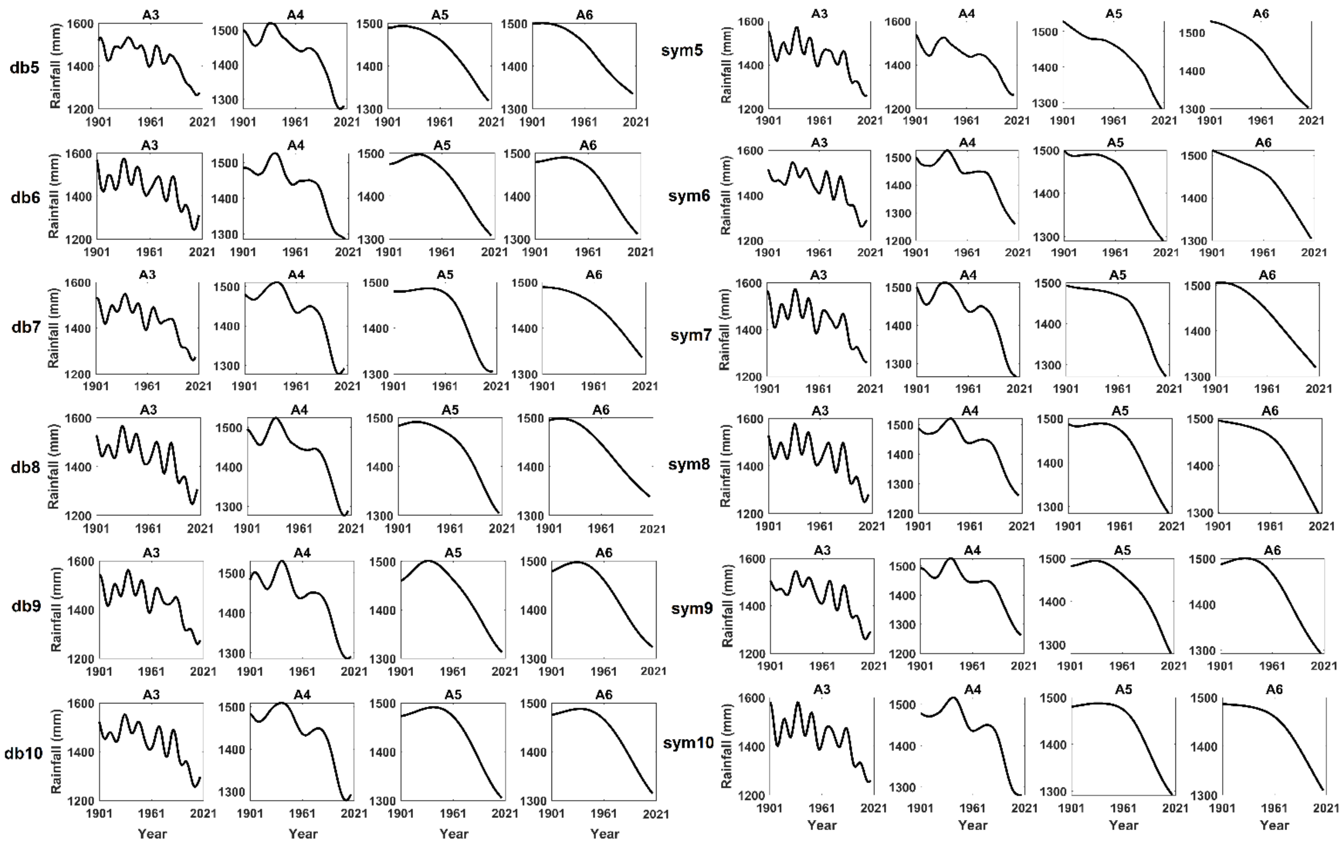

Figure 4. Approximation curves of Assam subdivision using mother wavelet of Daubechies (db5-db10) and symlet (sym5-sym10) families.

Uttar Pradesh, and Uttarakhand have a significant trend. The detailed analysis performed using DWT indicates a significant trend as observed in the preliminary analysis. It is a very important step to select the proper wavelet for the DWT analysis of rainfall series for individual subdivisions. The selection criteria of wavelet for analyzing data or time-series characteristics include compactness, smoothness, and self-similarity (Daubechies, 1990). Most of the literature widely adopted "wavelet", which is a part of the Daubechies family (De Artigas et al., 2006; Nalley et al., 2012). The wavelet symlet group (symN, where "*N*" signifies the number of vanishing moments) is almost symmetrical as well as similar to the well-known family of Daubechies.

The method involves three steps: considering their inherent trend, length of data, and mother wavelet characteristics for choosing the proper wavelet and optimum level of decomposition. The procedure is as below.

a) To obtain the optimum level of decomposition (L), the Equation (17) followed by Kaiser (1994) is used:

$$L = \frac{\log(\frac{x}{2m-1})}{\log 2} \tag{17}$$

where "*m*" represents the "number of vanishing moments" and "*x*" signifies the "number of data points" in the next higher dyadic scale to the number of current time-series data points. In this study, the number of data points is 117. The value of "*x*" is considered 128 ($2^7 = 128$). Daubechies and Symlet families of wavelets were used for the analysis of data. The optimum number of decomposition levels for each dbN (where $N \in 2 \sim 10$) and symN (where $N \in 2 \sim 10$) are 6, 5, 5, 4, 4, 4, 4, 3, and 3.

According to a recent study, the wavelet family that has the greatest vanishing moments, or "*N*" (smoother wavelet), is better able to identify long-term time-varying data points' properties, and it also exhibits better frequency localization behavior (Adamowski et al., 2009).

b) A variety of distinctive "smoother" wavelet families were employed to produce the approximation component for the highest level.

c) For obtaining the maximum decomposition level, a meticulous trial and error method was applied at different levels 3 ~ 6 for each dbN (where N $\in$ 2 ~ 10) and symN (where N $\in$ 2 ~ 10) wavelet family. To detect the optimization level, the plots of the approximation component were checked throughout for cyclicity. The next higher decomposition level was checked in the case of cyclicity and minimum level selection, as the optimum stage of decomposition at which the monotonic trend information was observed.

Table 2. List of Mother Wavelets That Showed a Monotonic Rainfall Trend for Different States at the 6th Approximation Level and Selected Wavelet Component

Sr. No.	States	The monotonic trend at the 6th approximation level	Selected mother wavelet component
1	Assam	db5, db7, sym5, sym6, sym7, sym8, and sym10	sym8
2	Jammu & Kashmir	db6, sym5, sym6, and sym8-sym10	sym8
3	Karnataka	sym5, sym6, sym8, sym9, and sym10	sym8
4	Kerala	sym6, sym8, and sym10	sym8
5	Meghalaya	db6, db7, db10, sym6, and sym8	sym8
6	Mizoram	db8, db9, sym6, sym7, sym8, and sym10	sym8
7	Nagaland	db6, db7, db10, sym5, sym6, and sym8-sym10	sym8
8	Sikkim	db5-db10, sym5, sym6,and sym8-sym10	sym8
9	Goa	sym5	sym5

Table 3. *RMSE* and Correlation Coefficient (*R*) between the SQMK Value of the Observed and Transformed Rainfall Dataset of Assam

Models	*RMSE*	*R*	M-K	Models	*RMSE*	*R*	M-K
Observed rainfall			−3.85	Ø1 + Ø2 + Ø4 + A6	0.71	0.85	−4.00
Ø1 + A6	1.22	0.71	−5.27	Ø1 + Ø4 + Ø5 + A6	0.68	0.91	−4.81
Ø2 + A6	1.94	0.66	−6.90	Ø2 + Ø4 + Ø5 + A6	0.97	0.91	−5.74
Ø3 + A6	3.84	0.78	−10.09	Ø1 + Ø4 + Ø5 + Ø6 + A6	0.61	0.94	−4.91
Ø4 + A6	2.65	0.80	−8.78	Ø1 + Ø3 + Ø4 + Ø5 + A6	0.68	0.93	−4.76
Ø5 + A6	3.92	0.87	−10.45	Ø2 + Ø4 + Ø5 + Ø6 + A6	0.80	0.94	−5.74
Ø6 + A6	4.60	0.86	−11.42	Ø1 + Ø2 + Ø3 + Ø4 + Ø6 + A6	0.47	0.94	−4.11
Ø1 + Ø4 + A6	0.86	0.85	−4.88	Ø1 + Ø2 + Ø3 + Ø4 + Ø5 + A6	0.37	0.99	−3.73
Ø2 + Ø4 + A6	1.30	0.83	−6.09	Ø1 + Ø2 + Ø3 + Ø5 + Ø6 + A6	0.53	0.91	−4.16

The observed monsoon rainfall dataset with significant trends was decomposed into various approximation components using mother wavelets "db5-db10" and "sym5-sym10". No monotonic trends were found up to the 6th approximation wavelet analysis for those subdivisions was omitted. A detailed DWT analysis of several other subdivisions was conducted, resulting in 57 transformed series. The periodicity of the trend was selected based on the transformed series with the lowest *RMSE*, highest correlation coefficient, and M-K values that were closest to the original rainfall series.

Figure 4 presents the approximation components of Daubechies (db5-db10) and Symlet (sym5-sym10) mother wavelets for the Assam subdivision. Most cases show some seasonality or cyclic patterns at levels three (A3), four (A4), and five (A5). By the sixth approximation level (A6), all wavelet families demonstrate a monotonous decreasing trend, and thus "A6" is marked as an optimum stage of decomposition. The Assam subdivision's time series is broken down into different components of 2, 4, 8, 16, 32, and 64-year mode (Ø1 ~ Ø6) and (A6), and Figures 4 and 5 show the plot of the original rainfall, various decomposition (Ø1 ~ Ø6), and approximation modes (A6) of rainfall for the Assam subdivision. To evaluate the superiority of a particular wavelet component, all combinations of different wavelet components are assessed, and the SQMK values are computed for six basic DW components (Ø1 ~ Ø6) and monsoon rainfall in Assam. The analysis of different combinations of components reveals that Ø1, Ø2, and Ø4 have higher correlation, indicating the presence of short-term (2 ~ 4 years) and long-term (16-year periodicity) in the trend. Some plots of combinations are presented in Figure 6. The mother wavelet(s) that exhibited a monotonic trend up to the 6th approximation level were identified and listed in Table 2. From Table 2, it is observed that "sym5" is the most suitable mother wavelet for the Goa subdivision and "sym5" for other subdivisions. Table 3 shows the *RMSE* and correlation (*R*) of some different combinations of components for Assam. Other subdivisions were also analyzed similarly. Generally, the mother wavelet with a higher vanishing moment "*N*" is preferred for DWT analysis, and one of the listed wavelets is chosen accordingly. The combined analysis of short-term components (D1 ~ D3) in the time series reveals their significant impact on the precipitation characteristics within different regions. In Assam (Table 3), the time series formed by combining components D1, D2, D3, D4, D5, and A6 closely approximates the original series, with an M-K value of −3.73 compared to the original's −3.85. This combination also exhibits the lowest *RMSE* (0.37) and the highest *R* value among all variations. Similarly, for rainfall in Goa (Table 4), the combination of D1, D2, D3, D5, D6, and A6 produces an M-K value of −7.80, closely resembling the original's 7.38 M-K value, along with the lowest *RMSE* (0.34) and the highest *R* value compared to other combinations. This trend continues across various regions, such as Karnataka (Table S2), Jammu and Kashmir (Table S3), Kerala (Table S4), Meghalaya (Table S5), Mizoram (Table S6), Nagaland (Table S7), and Sikkim (Table S8), where the consistent pattern emerges. The time series formed by combining D1, D2, D3, D5, D6, and A6 demonstrate

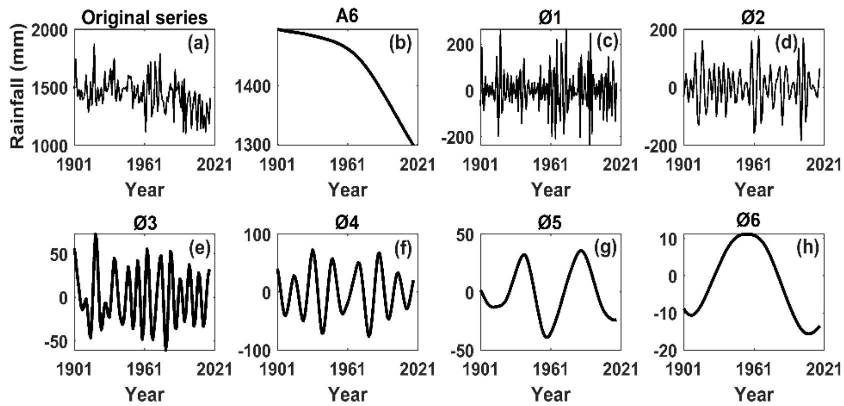

Figure 5. Original rainfall series, approximation (A6), and details component at Nth level (ØN) for monsoon rainfall of Assam subdivision.

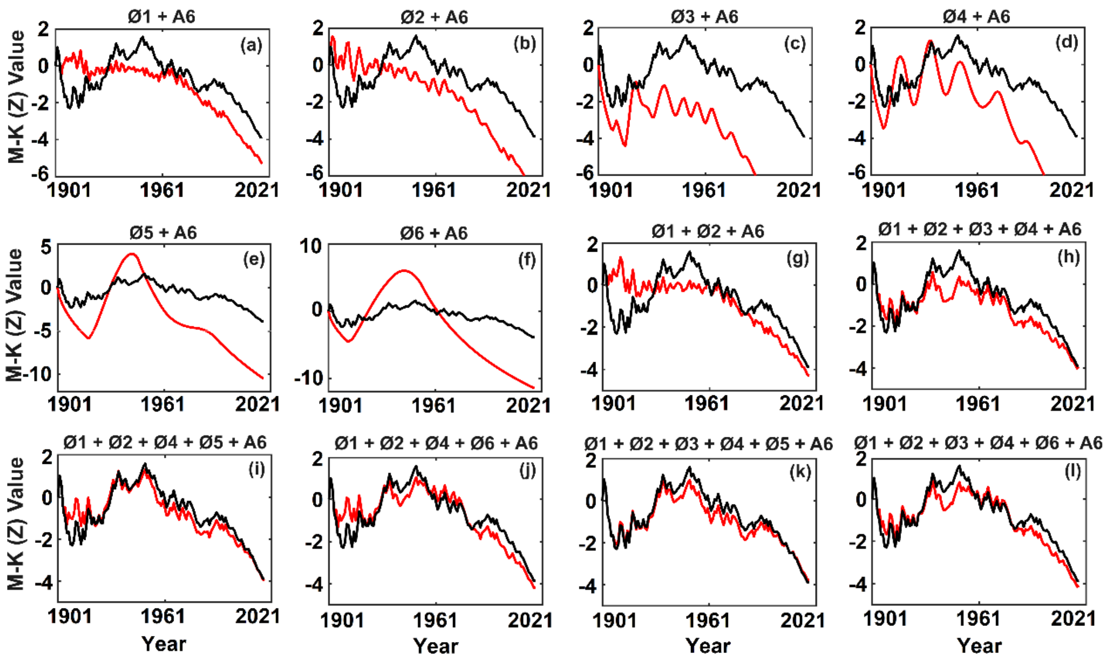

Figure 6. A plot of SQMK values for monsoon rainfall of Assam subdivision (black line) and combinations of basic details "Ø1 ~ Ø6" and approximation component "A6" (red line).

remarkable proximity to the M-K values of the original series in each case, with associated lowest *RMSE* values and highest *R* values compared to alternative combinations.

The mother wavelet selected for Goa is "sym5" and can be seen in Figure S4 in SI. The various details and approximation components are displayed in Figure S5 in SI. Based on the analysis of different combinations of details and approximations, there is a short-term periodicity of 2, 4, and 8 years, and a long-term periodicity of 32 years present in the trend. This conclusion is drawn from the lowest *RMSE*, high correlation coefficient "*R*", and M-K values closest to those of the observed series (see Table S1 in SI). Some plots of combinations are shown in Figure S6. Figures S7, S10, and S16 show approximation curves using different wavelets for J&K, Karnataka, and Meghalaya subdivisions respectively. The exercise shows that in J&K, "db6, sym5, sym6, sym8-sym10", for Karnataka "sym5, sym6, sym8-sym10" and for Meghalaya "db6, db7, db10, sym6, sym8" show a monotonic trend. Hence the most used mother wavelet "sym8" was used for trend analysis of these subdivisions. The details and approximation components are shown in Figures S8, S11, and S17 for J&K, Karnataka, and Meghalaya, respectively. The trend has a short term of 2 and 4 years and a long term of 32 years based on the analysis of various combinations of details and approximation. (see Tables S2, S3, and S5 in SI) show the *RMSE*, *R*, and M-K values of some combinations for Karnataka, J&K, and Meghalaya, respectively, and the plots of these combinations are shown in Figures S9, S12, and S18. Figure S13, S22, and S25 show approximation curves using different wavelets for the Kerala, Nagaland, and Sikkim subdivisions respectively. The exercise shows that in Kerala, "sym6, sym8, sym10", in

Nagaland, “db6, db7, db10, sym5, sym6, sym8-sym10”, and in Sikkim, “db5-db10, sym5, sym6, sym8-sym10” show a monotonic trend, hence mostly used “sym8” was taken for trend analysis of these subdivisions. The details and approximation components are shown in Figures S14, S23, and S26 for the Kerala, Nagaland, and Sikkim subdivisions, respectively. According to the analysis of various combinations of details and approximation, the trend has a short-term of 2, 4, 8-year, and a long-term 32-year periodicity. (see Tables S4, S7, and S8 in SI) show the *RMSE*, *R*, and M-K values of some combinations for Kerala, Nagaland, and Sikkim, respectively, and some plots of combinations are shown in Figures S15, S24, and S27.

Figure S19 displays different wavelets used for approximating curves in Mizoram. “sym8” mother wavelet is predominantly used for trend analysis, showing a monotonic trend among the families of wavelets “db8, db9, sym6-sym8, and sym10”. Figure S20 displays the details and approximation components. The analysis identified short-term (2, 4, and 8 years) and long-term (32 and 64 years) periodicity in trend from various combinations of details and approximation (see Table S6 in SI) shows the *RMSE*, *R*, and M-K values of some combinations, and some plots of combinations are presented in Figure S21.

5. Summary and Conclusions

The research presents a trend analysis of various Indian states applying methods such as “Mann-Kendall, sequential Mann-Kendall test, Sen’s slope estimator, and discrete wavelet transforms”. A downtrend in winter rainfall was observed throughout the region of the country except for “J&K, Arunachal Pradesh, Himachal Pradesh, and Sikkim”. The significant decreasing trend in “Tamil Nadu, Kerala, Karnataka, Maharashtra, Madhya Pradesh, Gujarat, Chhattisgarh, Jharkhand, Assam, Nagaland, and Bihar”. J&K and Sikkim experience a significant increasing trend. For pre-monsoon rainfall, Chhattisgarh, Gujarat, Madhya Pradesh, and Nagaland Chhattisgarh observed significant decreasing trends while significantly increasing trends were observed in J&K, Meghalaya, Sikkim, and Delhi. Most of the states lying in the central part and northeast regions of India observed a decrease in rainfall trends. Significant decreasing trends were observed in the states of “Arunachal Pradesh, Assam, Chhattisgarh, Himachal Pradesh, Kerala, Nagaland, Sikkim, Uttar Pradesh, and Uttarakhand”. Significant increasing trends were observed in Karnataka, J&K, Meghalaya, Mizoram, and Goa. For post-monsoon rainfall, decreasing rainfall patterns were observed in most northeast and northcentral parts of the region. Significant increasing trends were observed in J&K, Sikkim, Mizoram, and Meghalaya only, and significantly decreasing trends were observed in Uttrakhand, Kerala, and Nagaland only. While increasing rainfall pattern is observed in West Bengal, Jharkhand, Bihar, Andhra Pradesh, Tamil Nadu, Gujarat, Tripura, and Manipur. The annual rainfall pattern in India shows that significant decreasing trends were observed in only seven states viz. Uttrakhand, Uttar Pradesh, Jharkhand, Chhattisgarh, Kerala, Assam, and Nagaland. Significantly increasing trends were observed only in four states, J&K, Karnataka, Meghalaya, and Mizoram, while the majority of the states in the northeast and center have declining trends.

The periodicity in the trend has been analyzed using a discrete wavelet transform (DWT). Mother wavelet of Daubechies (db5-db10) and Symlet (sym5-sym10) families are used for decomposing the time series into various details (Ø) and approximation. At the 6th approximation level, only Assam, Goa, J&K, Karnataka, Kerala, Meghalaya, Mizoram, Nagaland, and Sikkim show monotonic trends hence these subdivisions were analyzed. Rainfall patterns in various regions of India exhibit different periodicities. Assam experiences periodic rainfall trends at intervals of 2, 4, and 16 years. In Goa, short-term cycles of 2, 4, and 8 years are observed, along with a long-term cycle of 32 years. Jammu and Kashmir (J&K) shows rainfall patterns repeating at 2-year and 4-year intervals and a longer term cycle of 32 years. Karnataka and Meghalaya both exhibit a long-term rainfall periodicity of 32 years. Kerala, Sikkim, and Nagaland share short-term rainfall cycles occurring every 2, 4, and 8 years, along with a long-term cycle lasting 64 years. Mizoram showcases short-term rainfall periodicities spanning 2, 4, and 8 years, as well as a long-term cycle ranging from 32 to 64 years.

The results also suggest that there can be the possibility of the effect of natural phenomena such as the quasi-bienni-aloscillation (QBO), Indian Ocean dipole (IOD) movement, and ENSO in the Indian region, which causes shifting of monsoon in some subdivisions as well as decreasing the amount of rainfall in some areas. This study will be helpful and very useful in the areas of water resource management, crop pattern analysis, and effective utilization of water in irrigation.

Limitations of the present study: The present study gives useful insights but also has certain limitations due to its use of non-parametric testing and wavelet summaries to analyze changes in India’s rainfall over the past 117 years. The use of non-parametric tests and wavelet analysis, which can look at data that does not follow a normal distribution and find patterns in time, respectively, improves the reliability of the study. Nonetheless, a few caveats should be mentioned. To begin, the research is highly dependent on the accuracy and consistency of historical rainfall data, which may include flaws and data gaps, potentially reducing the credibility of the trends identified. It is also worth noting that while wavelet analysis is great at spotting frequency-based patterns, it may not be able to properly capture complicated interactions among the many meteorological conditions that influence rainfall tendencies.

Future scope of the present study: In the present analysis, incorporating non-parametric testing and a wavelet symposium for the analysis of rainfall patterns in India over the past 117 years holds great potential and a wide range of applications. As climate change continues to have a profound impact on weather patterns, this investigation may eventually yield crucial insights into the changing character of rainfall throughout the Indian subcontinent. In addition, to the continuous advancement of climate science and statistical approaches, the study’s future phases could involve the integration of machine learning methods to enhance predictive modeling. This integration would facilitate more precise forecasts of forthcoming rainfall trends and their potential repercussions on water resources, agriculture, and ecosystems. Therefore, the present analysis's ultimate potential lies in its ability to adjust to changing climatic conditions and evolving analytical approaches. It can form the basis for shaping policies, managing resources, and preparing for disasters. By doing so, it can play a pivotal role in fostering a stronger, more sustainable future for India, effectively addressing the challenges posed by shifting rainfall patterns.

Acknowledgements. The authors would like to thank the National Institute of Technology, Raipur for their kind support and for providing the opportunity for conducting the present study.

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