



Long-term trends and spatial variability in rainfall in the southeast region of Bangladesh: implication for sustainable water resources management

Hrithik Nath^{1,2} · Sajal Kumar Adhikary¹ · Srijan Nath³ · Abdulla - Al Kafy⁴ · Abu Reza Md. Towfiqul Islam^{5,6} · Saleh Alsulamy⁷ · Khaled Mohamed Khedher⁸ · Ahmed Ali A. Shohan⁷

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Abstract

Accurate and in-depth rainfall studies are crucial for understanding and assessing precipitation events' patterns, intensities, and impacts, enabling effective planning and management of water resources, agriculture, and disaster preparedness. Despite many rainfall studies in Bangladesh at the national and regional scales, study on the spatiotemporal rainfall variability is still rare at the local scale. The current study aims to apply Mann–Kendall (MK), Modified Mann–Kendall (MMK), and Innovative Trend Analysis (ITA) techniques to assess the long-term annual and seasonal rainfall trends and variability over the southeast region of Bangladesh. Monthly rainfall data from ten Bangladesh Meteorological Department climate stations between 1981 and 2022 was used for the analysis on annual and four seasonal scales. The precipitation concentration index results showed significant variations in annual rainfall across the study area, whereas seasonal PCIs were consistent with moderate rainfall. According to standardized rainfall anomaly findings, each station experienced at least one severe to extremely severe drought episode during the 42-year study period. Homogeneity tests revealed significant breakpoints in some rainfall datasets, while 78% were declared homogeneous. MK, MMK, and ITA techniques revealed similar increasing and decreasing trend patterns throughout the study area. Annual rainfall showed an upward trend in the coastal part and a downward trend in the northern part of the study area, with monsoon rainfall exhibiting a similar trend pattern. The ITA technique outperformed the MK and MMK techniques in detecting trends, identifying significant increasing and decreasing trends in 76% (38 out of 50) of the observations, while the MK and MMK techniques detected trends in only 8% and 44% of the total observations, respectively. The outcome of the current study is expected to be helpful for the sustainable planning and management of water resources in the southeast region of Bangladesh.

Keywords Mann–Kendall Test · Innovative Trend Analysis · Rainfall · Trend analysis · Sustainable water resources management

1 Introduction

Academics and climate experts worldwide have expressed their increased concerns over the impact of climate change brought on by global warming (Mekonen & Berlie 2020; Shahid 2009; Zhang et al. 2009). The implications of increasing global surface temperature on the hydrological cycle at various scales are expected to manifest in substantial transformations, ultimately affecting rainfall distribution, intensity, and frequency, thereby inducing alterations in regional rainfall patterns, evaporation rates, and overall

water availability (Harvey et al. 2020; Mohammed & Scholz 2019). Understanding the patterns of rainfall variability is essential for comprehending and analyzing climatological, hydrological, meteorological, and agricultural phenomena on both global and local scales (Almazroui et al. 2012; Chatterjee et al. 2016; Marengo & Espinoza 2016; Sanchez et al. 2017; Singh et al. 2021; Wang et al. 2016; Xia et al. 2015; Yu et al. 2014). Like many other developing countries, rainfall patterns are pivotal to the economy of Bangladesh, as these countries rely heavily on rainfall patterns to sustain rain-fed agricultural productivity and ensure a stable food supply (Degefu 1987; Mekonen & Berlie 2020). Variations in rainfall patterns can significantly impact crop sowing and harvesting (Khan et al. 2009). The analysis of rainfall

Extended author information available on the last page of the article

is an essential step in determining the extent of climatic change and implementing the necessary adaptation measures (Asfaw et al. 2018). Accurate knowledge and understanding of long-term patterns (e.g., trend) of rainfall are crucial for the sustainable management and optimal utilization of water resources (Fatichi et al. 2013; Praveen et al. 2020; Shawul & Chakma 2020; Singh et al. 2021; Sun et al. 2018; Zolina et al. 2010).

Numerous techniques, including linear regression analysis, Spearman's rho (SR) test, Theil-Sen approach (TSA), Sen's slope indicator (SS), family of Mann–Kendall (MK) tests, innovative trend analysis (ITA), and innovative polygonal trend analysis (IPTA), have been developed during the past several years for detecting trends in rainfall data series (Caloiero et al. 2011; Das et al. 2021; Nisan-sala et al. 2020; Shahid 2010a; Sonali & Kumar 2013; Song et al. 2015). The Mann–Kendall trend test is the most widely used of these techniques and has been used in many world regions. Zang & Liu (2013) used the MK test for investigating how rainfall, runoff, and evapotranspiration varied in the Heihe River Basin, China. Adarsh and Janga Reddy (2015) utilized the MK test to examine annual rainfall data in four subdivisions of southern India, revealing a decline in rainfall in the Kerala subdivision but an upsurge in the other regions. Westra et al. (2013) assessed monotonic trends in the annual maximum daily rainfall globally between 1900 and 2009 using the MK test. However, numerous issues affect the acceptability and dependability of the trend result in the MK test. Serial correlation in time series data and a greater reliance on sample size, distribution, and degree are a few examples of these (Sen 2012). Additionally, the MK method is purely statistical; it is not possible to detect low, middle, and high trend values throughout a single calculation phase (Mekonen & Berlie 2020). These variables significantly influence the robustness and reliability of the trend detection test (Wang et al. 2020). Thus, a flexible graphical method is required to study time series patterns and prevent mistakes when significant hidden trends are found.

Sen (2012, 2017) introduced a new visual trend detection approach known as innovative trend analysis (ITA), which has gained popularity for detecting trends in various environmental, hydrological, and meteorological parameters such as rainfall, streamflow, pan evaporation, and water quality across different regions worldwide. Over the past several years, multiple research studies have employed ITA to compare its performance against classical methods, highlighting the distinct advantages it offers over traditional approaches (Das et al. 2021; Gedefaw et al. 2018; Girma et al. 2020; Machiwal et al. 2019; Mallick et al. 2021; Sanikhani et al. 2018). Dabanlı et al. (2016) believed the ITA approach to be more beneficial than the MK test for identifying trends in hydro-meteorological data. Caloiero et al. (2018) used MK

and ITA trend tests using a high-quality monthly dataset to examine the temporal variation in rainfall across a significant area of southern Italy in search of potential trends in seasonal and annual rainfall levels. They verified that the "high" and "low" data values for the trend analysis of seasonal and annual precipitation levels may be evaluated successfully using the ITA approach. Wu & Qian (2017) claimed that compared to linear regression and the MK test, the ITA approach had numerous advantages in detecting trends.

The duration and amount of rainfall received throughout four distinct rainfall seasons—pre-monsoon, monsoon, post-monsoon, and winter—control the overall agricultural operations in Bangladesh (Ahammed et al. 2018; Das & Islam 2023; Hossain et al. 2014; Shahid 2010b). The pre-monsoon season spans from March to May and is characterized by comparatively lower levels of rainfall. On the other hand, the monsoon season, which lasts from June to September, receives the highest amount of rainfall. The post-monsoon season falls between October and November, commonly known as the harvesting season. Finally, the winter season, which spans from December to February, is called the dry season due to the minimal or no rainfall during this period. The rainfall levels exhibit significant regional differences within the country, ranging from approximately 1400 mm in the western regions to 4400 mm in the eastern parts (Rahman & Islam 2019). This spatial variation indicates a pronounced gradient of nearly 7 mm per kilometer from west to east. The enhanced rainfall in the northeastern section can be attributed to the supplementary uplifting impact facilitated by the presence of the Meghalaya Plateau (Shahid 2010b). The southeast region of Bangladesh is known for its heavy rainfall due to its proximity to the Bay of Bengal and the Chattogram Hill Tracts. The area experiences a significant amount of rainfall throughout the year, with the monsoon season bringing the heaviest rainfall, which often leads to widespread flooding, waterlogging, and landslides (Azad et al. 2022; Islam & Raja 2021; Pavel et al. 2021; Shahid 2010b). Over the years (e.g., 1988, 1998, 2004, 2007, 2017, and so on), these events have caused significant damage to the existing infrastructures, agricultural systems, and the livelihoods of the people. Thus, a thorough understanding of long-term rainfall patterns is crucial for fostering resilience and promoting the population's well-being in the southeastern parts of the country.

This study aims to explore the spatial and temporal variability and long-term trends in the annual and seasonal rainfall of the Bangladesh's southeast region using 42-years of rainfall data (1981–2022). In order to assess the variability of rainfall, metrics such as the coefficient of variation (CV), precipitation concentration index (PCI), and standardized rainfall anomaly (SRA) were employed at both the annual and seasonal scales. Multiple homogeneity tests — Standard

Normal Homogeneity test (SNHT), Buishand Ranking test (BRT), and Pettitt test (PT) — were conducted on the annual and seasonal rainfall time series datasets to quantify potential change points and to determine homogeneity of the data sets. Eventually, long-term trends in annual and seasonal rainfalls were estimated using classical Mann–Kendall (MK), Modified Mann–Kendall (MMK) and newly developed Innovative Trend Analysis (ITA) techniques. The incorporation of the ITA technique with ten hydrological stations from the southeast region of Bangladesh represents a significant novelty in the field of trend analysis. This approach offers a more comprehensive, accurate, and spatially explicit assessment of trends in hydrological variables, overcoming the limitations of the traditional techniques of MK family. The findings of this study can contribute to the scientific understanding of hydrological processes in the region and support evidence-based decision-making for sustainable water resource management.

2 Materials and methods

2.1 The Study Area

The southeast region of Bangladesh, which is unique and diverse with its rich natural resources, unique geography, and varied climate patterns, was selected as the study area to carry out this study. The location of the study area, along with the rainfall stations, is shown in Fig. 1. This sub-tropical, low-lying, humid region shares borders with Myanmar and the Bay of Bengal. It spans across an area of around 34,529.97 sq. km ranging from 24°16'04" N to 20°35'27" N latitude and 90°32'19" E to 92°40'50" E longitude. The topography of this region is defined by its undulating landscape, vast expanses of woodland, and wide-ranging plant and animal life. This region is home to the Karnaphuli River, the largest and most significant river in the region, and other notable rivers such as Sangu, Halda, Feni, Gomti, and Ichamoti. This region has a tropical monsoon climate, characterized by significant rainfall between June and September, contributing to its reputation as one of the country's most humid and wettest areas. Unfortunately, the heavy rainfall during this period often results in natural calamities such as landslides and floods. Several factors, including its geographical location, fluctuations in sea surface and terrestrial temperature, and the north–south continental atmospheric pressure gradient, all influence this region's climate (Das et al. 2021; Islam & Neelim 2010).

2.2 Data Sourcing and Description

It is recommended to analyze climate variables using historical data that spans at least 30 years (WMO 2021),

which can provide a comprehensive understanding of long-term trends and patterns in climatic conditions, which aids in identifying and evaluating significant changes over time, understanding the impacts of natural and human-induced factors, identifying climate cycles and patterns, and developing effective strategies to mitigate the effects of climate change (WMO 2017). The Bangladesh Meteorological Department (BMD) operates 12 weather stations in the southeastern region. However, not all stations have continuous rainfall data due to technical issues or being newly established. For this study, ten stations (e.g., Chandpur, Chattogram, Cox's Bazar, Cumilla, Feni, Majidee Court, Rangamati, Sandwip, Sitakunda and, Teknaf) were chosen for rainfall trend analysis with 42 years (1981–2022) of monthly records (Fig. 1). These stations are evenly spread throughout the study area and considered representative of the southeast region of Bangladesh. The Sandwip station had missing data for the year 2003, which was obtained from NASA's TRMM database. All data were initially stored and processed using MS Excel Spreadsheet for further analysis.

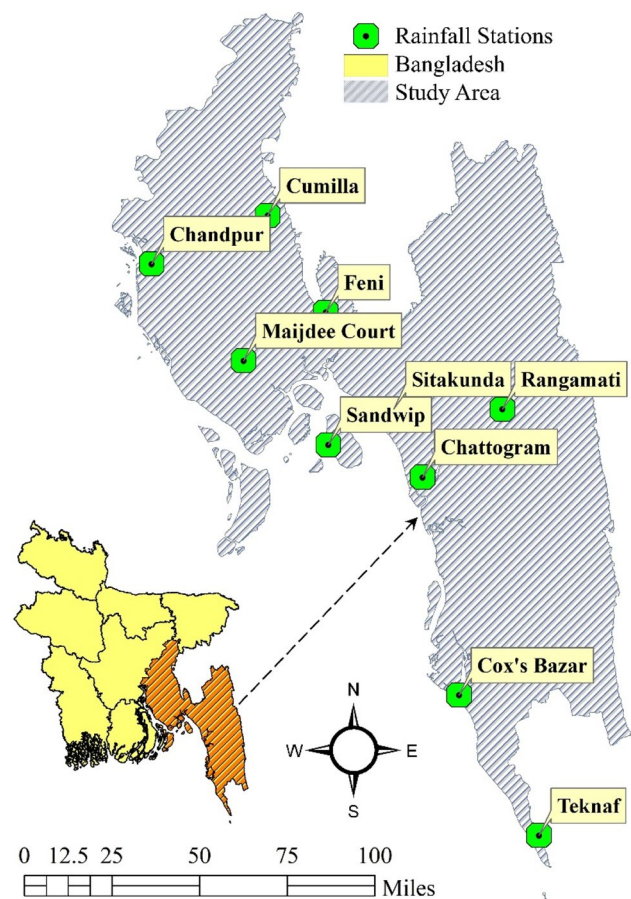


Fig. 1 Map addressing the study area and the rainfall stations

2.3 Data Analysis and Statistical Techniques

This study employed several statistical measures including the Coefficient of Variation (CV), Precipitation Concentration Index (PCI), and Standardized Rainfall Anomaly (SRA) to evaluate rainfall variability at all the BMD stations in both annual and seasonal scales. To identify the break points and determine the homogeneity of the rainfall datasets, three separate homogeneity tests were conducted (e.g., Standard Normal Homogeneity test, the Buishand Ranking test, and Pettitt test). Moreover, three non-parametric trend tests – the Mann-Kendal (MK) Trend Test, the Modified Mann-Kendal (MMK) Trend Test, and the Innovative Trend Analysis (ITA) – were utilized to identify any trends in the historical rainfall data. All the statistical analyses and modelling was carried out in R programming language (version 4.3.2) by using different packages (Table 1). Coefficient of Variation (CV) is utilized to assess the variability of rainfall which is expressed by Eq. 1.

$$CV(\%) = \frac{\sigma}{\mu} \times 100\% \tag{1}$$

where, σ is the standard deviation of long-term annual rainfall and μ is the long-term mean rainfall at each station. A higher CV value indicates increased variability, and vice versa. Using CV, rainfall event variability is categorized rainfall event variability as low ($CV < 20\%$), moderate ($20\% \leq CV \leq 30\%$), high ($CV > 30\%$), very high variability ($CV > 40\%$), and extremely high variability ($CV > 70\%$) (Abraham & Kundapura 2022; Asfaw et al. 2018; Hare 2003; Panda & Sahu 2019). The Precipitation Concentration Index (PCI) (Michiels et al. 1992; Oliver 1980) is a widely used method in hydro-environmental studies (Asfaw et al. 2018; Das et al. 2021) to evaluate the temporal distribution of precipitation in a specific area. The PCI varies due to multiple factors and is closely related to global climatic features. A wide range of factors impacts changes in the PCI and exhibits a strong connection with larger-scale patterns

and phenomena in the Earth's climate system (Nandargi & Aman 2018). PCIs in annual (Eq. 2) and seasonal (Eq. 3) scales can be calculated as follows:

$$PCI_{Annual} = \frac{\sum_{i=1}^{i=12} P_i^2}{\left[\sum_{i=1}^{i=12} P_i\right]^2} * 100\% \tag{2}$$

$$PCI_{Seasonal} = \frac{\sum_{i=1}^{i=n} P_i^2}{\left[\sum_{i=1}^{i=n} P_i\right]^2} * \frac{n}{12} * 100 \tag{3}$$

where, P_i is the rainfall in a specific ‘i’ month. A high PCI value suggests that precipitation is concentrated over a small number of months, whereas a low value suggests that precipitation is more evenly distributed over the course of the year. A PCI value below 10% signifies uniform rainfall distribution and low rainfall concentration. In contrast, PCI values ranging from 11 to 15% correspond to a moderate level of concentration, 16% and 20% suggest irregular rainfall concentration, and $PCI > 20\%$ means high irregularity (substantial monthly variability) in rainfall. Standardized Rainfall Anomalies (SRA) are employed to identify the dry and wet years in the data series and help in evaluating the frequency and intensity of droughts (Agnew & Chappell 1999; Viste et al. 2013). SRA for a specific year ‘i’ in the data series can be calculated using Eq. 4.

$$SRA_i = \frac{P_i - \bar{P}}{\sigma} \tag{4}$$

where, P_i is the annual rainfall for a specific year, \bar{P} is the long-term mean annual rainfall over a period of observation, and σ is the annual rainfall standard deviation over the observation period. Z is the standardized rainfall anomaly. According to SRA, drought severities are categorized as extreme drought ($SRA < -1.65$), severe drought ($-1.28 > SRA > -1.65$), moderate drought

Table 1 RStudio Packages used for statistical analysis and modelling in this study

Methods	RStudio Package	References
Descriptive statistics	hydroTSM	Zambrano-Bigiarini (2017)
Co-efficient of Variability	hydroTSM	Zambrano-Bigiarini (2017)
Precipitation Concentration Index	precintcon	Povoa & Nery (2016)
Standard Rainfall Anomaly	precintcon	Povoa & Nery (2016)
Standard Normal Homogeneity Test	trend	Pohlert (2015)
Buishand Range Test	trend	Pohlert (2015)
Pettitt Test	trend	Pohlert (2015)
Classical Mann Kendall Test (MK)	modifiedmk	Patakamuri & O’Brien (2021)
Modified Mann Kendall Test (MMK)	modifiedmk	Patakamuri & O’Brien (2021)
Innovative Trend Analysis (ITA)	trendchange	Patakamuri & Das (2022)

($-1.65 > SRA > -0.84$), and no drought ($SRA > -0.84$) (Agnew & Chappell 1999; Asfaw et al. 2018).

A multi-test approach comprising of the Standard Normal Homogeneity test (SNHT), the Buishand Ranking test (BRT), and the Pettitt test (PT) were employed to analyze the homogeneity of the rainfall at all temporal scales (annual and seasonal) in this study. Previous studies stated that different homogeneity tests may have different sensitivities to specific types of breakpoints, providing a more comprehensive understanding of the temporal dynamics and enhancing the overall confidence in identifying homogeneity or inhomogeneity in the data. The SNHT test can identify abrupt shifts at the start or end of a time series, while the BRT and PT tests specialize in identifying mid-series breakpoints, complementarily enhancing the comprehensiveness of the analysis (Arikan & Kahya 2019; Kabbilawsh et al. 2023). All these three homogeneity tests were conducted at 5% confidence level.

The SNHT (Alexandersson 1986; Patakamuri et al. 2020), a likelihood ratio test to ascertain the inhomogeneity in time series dataset, checks if a series of rainfall measurements has a sudden change, like a jump or break, instead of being smooth and consistent. It assumes the data normally follows a bell curve and any changes happen all at once at a specific time. While, for a time series X_i (i is the year from 1 to n) having X_m average and ' D_s ' standard deviation, the test statistic (T_k) involves comparing the average of the initial n data points to the average of the subsequent ($n - k$) data points. The test statistic (T_k) is calculated using the following Eq. 5, 6, and 7.

$$T_k = \overline{z_1}^{-2} + (n - k)\overline{z_2}^{-2}k, \text{fork} = 1, 2, 3, 4, \dots, n \tag{5}$$

$$\overline{z_1} = \frac{1}{k} \sum_{i=1}^k (X_i - X_m) / D_s \tag{6}$$

$$\overline{z_2} = \frac{1}{n - k} \sum_{i=1+k}^n X_i - X_m / D_s \tag{7}$$

Using Eq. 8, the maximum T_k value is examined against the critical value (T_0), and the associated p-value is recorded. If the p-value for the time-series data is below 0.05, the null hypothesis is rejected in favor of the alternative hypothesis (Praveenkumar & Jothiprakash 2020).

$$T_0 = \max_{0 \leq k \leq 1} (T_k) \tag{8}$$

The Buishand Range test (BRT) is a distribution-free statistical test which relies on the assumptions of data independence, no trend or seasonality, and constant variance (Buishand 1982; Wijngaard et al. 2003). The null hypothesis is "the rainfall time-series is independent and identically normally distributed," while the alternative hypothesis

suggests a breakpoint, such as a shift or jump, in the rainfall dataset (Kabbilawsh et al. 2023). For a time series X_i (i is the year from 1 to n) having X_m average, ' D_s ' standard deviation, and the time stamp of the breakpoint as ' k ', the mathematical representation of the test statistic is given in adjusted partial sums (Eq. 9, 10, and 11).

$$S_0^* = 0 \tag{9}$$

$$S_k^* = \sum_{i=1}^k (X_i - X_m), \text{fork} = 1, 2, 3, 4, \dots, n \tag{10}$$

$$S_k^{**} = \frac{S_k^*}{D_s}, \text{fork} = 1, 2, 3, 4, \dots, n \tag{11}$$

In a homogeneous series, the S_k^* value stays around zero, indicating no systematic deviations from the mean of X_i values. However, when a breakpoint occurs at year $k = K$, the S_k^* value peaks (for a negative shift) or troughs (for a positive shift) (Patakamuri et al. 2020). According to Buishand (1982), If the Q/\sqrt{n} less than the predefined critical values, the null hypothesis is accepted (Eq. 12).

$$Q = \max_{1 \leq k \leq n} |S_k^{**}| \tag{12}$$

The Pettitt test (PT), a nonparametric rank test, is employed to identify change points in time series data without presuming any specific data distribution (Pettitt 1979). However, it does rely on the assumption that observations are independent and identically distributed across time (Yozgatligil & Yazici 2016; Zhou et al. 2019). In PT, the null hypothesis assumes an independent and random series distribution, whereas the alternative hypothesis suggests the presence of a sudden change (Kabbilawsh et al. 2023). The test statistic (Y_k) is calculated using Eq. 13.

$$Y_k = 2 \sum_{i=1}^k [r_i - k(n + 1)] \text{fork} = 1, 2, 3, 4, \dots, n \tag{13}$$

where, r_i is the rank of time-series X_n . If a breakpoint occurs at year K , the statistic reaches its maximum or minimum at the specific year $k = K$. Using Eq. 14, The statistical significance of Y_K is assessed by comparing its value with the predefined critical values (Pettitt 1979).

$$Y_K = \max_{1 \leq k \leq n} |Y_k| \tag{14}$$

The Mann–Kendall (MK) test (Kendall 1975; Mann 1945) is the mostly used technique for identifying trends in hydro-climatic time series data, such as rainfall, due to its reliability, adaptability, and ability to provide statistical significance (Das & Bhattacharya 2018; Hajani et al. 2017). This nonparametric test is suitable for evaluating trends as it is reasonably robust to outliers and skewed

data. The methodology does not make any assumptions about the distribution of the data. Instead, it assesses the strength of the correlation between the data and time based on their ranking. When the total number of observations in the time series data is more than ten ($n > 10$), the trend is measured using a standardized trend measurement ‘ Z_{MK} ’ (Eq. 15). The time series test statistic ‘ S ’ is calculated using the following Eq. 16 and 17.

$$Z_{MK} = \begin{cases} \frac{S+1}{\sqrt{\text{var}(S)}}, \text{ when } S < 0 \\ 0, \text{ when } S = 0 \\ \frac{S-1}{\sqrt{\text{var}(S)}}, \text{ when } S > 0 \end{cases} \tag{15}$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_i - x_j) \tag{16}$$

$$\text{sgn}(x_i - x_j) = \begin{cases} +1, \text{ when } (x_i - x_j) > 0 \\ 0, \text{ when } (x_i - x_j) = 0 \\ -1, \text{ when } (x_i - x_j) < 0 \end{cases} \tag{17}$$

Here, n is the total observation count in the selected period, and x_i and x_f are data points of i and f time events. The variance of S statistic ‘ $\text{var}(S)$ ’ is calculated using (Eq. 18).

$$\text{var}(S) = \frac{1}{18} \left[\{n(n-1)(2n+5)\} - \left\{ \sum_{i=1}^{n-1} t_i(t_i-1)(2t_i+5) \right\} \right] \tag{18}$$

Positive Z_{MK} indicates an increasing trend, and negative Z_{MK} means a decreasing trend. During detecting trends, the null hypothesis was considered "there is no significant trend in the time series," while the alternative hypothesis was "there is a significant trend (either positive or negative) in the data series." A p -value of 0.05 indicates statistical significance, which is equivalent to a Z_{CR} (Critical Z_{MK} value) of ± 1.96 . The trend in a particular region/station is considered significantly increasing (decreasing), if the test Z_{MK} is greater (less) than $+1.96$ (-1.96).

The Modified Mann–Kendall (MMK) test offers enhanced accuracy for trend detection in time series data by correcting the variance of the test statistic using Effective Sample Size, leading to more reliable results compared to the standard Mann–Kendall test (Hamed 2008; Hamed & Rao 1998; Hu et al. 2020). The variance ‘ $\text{var}(S)$ ’ in the MMK method is calculated using Eq. 19.

$$\text{var}(S) = \left(\frac{n(n-1)(2n+5)}{18} \right) \left(\frac{n}{n_e^*} \right) \tag{19}$$

In this context, the adjustment of the correction factor n/n_e^* for autocorrelated data is expressed using Eq. 20.

$$\frac{n}{n_e^*} = 1 + \left(\frac{2}{n^3 - 3n^2 + 2n} \right) \sum_{f=1}^{n-1} (n-f)(n-f-1)(n-f-2)\rho_e(f) \tag{20}$$

where, $\rho_e(f)$ denotes the autocorrelation function among the ranks of observations and can be approximated using Eq. 21.

$$\rho(f) = 2\sin\left(\frac{\pi}{6}\rho_e(f)\right) \tag{21}$$

The Innovative Trend Analysis (ITA) technique is a newly developed non-parametric method that can detect monotonic and sub-trends in time series data and identify combinations of trends in different periods through graphical presentation (Sen 2012). This method is rapidly gaining popularity due to having an advantage over other methods because it does not require assumptions such as serial correlation, non-normality, or sample number (Caloiero et al. 2018; Das et al. 2021; Kisi 2015). Initially, if the number of observations in the time series is odd, the very first observation in the time series data is removed so that the latest data is not lost (Dong et al. 2020). The time series is then split into two equal halves and sorted separately in ascending order. Both series are then plotted against one another in a Cartesian coordinate system, where the first half is plotted on the X-axis and the second half is on the Y-axis. Patterns accumulating in the upper (lower) triangular area of the 1:1 line indicate the existence of a monotonic rising (decreasing) deterministic trend, while mixed patterns—in which some points are above and some below the 1:1 line—can be connected to non-monotonic trends (Sen 2012, 2014). The S_{ITA} statistic is the numerical estimation of the trend in this method (Sen 2017), which is calculated using Eq. 22.

$$S_{ITA} = \frac{2}{n}(\bar{x}_2 - \bar{x}_1) \tag{22}$$

Here, n is the total size of data event, \bar{x}_1 and \bar{x}_2 are the means of the 1st and 2nd sub-series. The trend is statistically significant if the series' slope is greater (less) than the upper (lower) confidence limits (CLs). The slope (which has a Gaussian probability density function with a mean and standard deviation of zero) has the following confidence limits, expressed in Eq. 23.

$$CL_{1-\alpha} = 0 \pm (S_{cri})(\sigma_S) \tag{23}$$

Here, S_{cri} is the confidence limit of a standard normal probability distribution function (with zero means). At 95% significance level, used in this study, s_{cri} is equivalent to 1.96. The standard deviation (σ_S) of the sampling slope value is calculated using Eq. 24.

$$\sigma_S = \frac{2\sqrt{2}}{n\sqrt{n}}\sigma\sqrt{1 - \rho_{\bar{x}_2\bar{x}_1}} \tag{24}$$

where, $\rho_{\bar{x}_2\bar{x}_1}$ is the correlation coefficient between the two mean values of the two equally split data series and is calculated in the stochastic process using Eq. 25.

$$\rho_{\bar{x}_2\bar{x}_1} = \frac{E(\bar{x}_2\bar{x}_1) - E(\bar{x}_2)E(\bar{x}_1)}{\sigma_{\bar{x}_2}\sigma_{\bar{x}_1}} \tag{25}$$

2.4 Spatial Interpolation Technique

All the spatial maps in the current study (e.g., annual averaged rainfall, mean annual rainfalls, mean seasonal rainfalls, PCI, CV, Z_{MK} , Z_{MMK} , S_{ITA} , etc.) were prepared using the widely used Inverse Distance Weighting (IDW) technique in the ArcGIS v10.5 software. IDW is a widely used interpolation technique in preparing rainfall interpolation maps and can be implemented easily using GIS (Das et al. 2021; Nath & Rafizul 2022; Río et al. 2011; Yang et al. 2015). The IDW interpolation method uses a weighted average of sample points to calculate cell values, with the weight being determined by the inverse distance (Eckstein 1989). This approach works best when extrapolating a location-dependent variable (Cressie 1993), where nearby data points have a greater impact and produce a surface that is less smooth and more detailed. The IDW function in the geostatistical analysis toolbox of the ArcGIS software was used to carry out IDW interpolation with a moderate power ‘2’ that regulates the significance of known points based on their separation from the output point. Since the IDW is a weighted average technique based on distance, the resulting average value cannot exceed the highest input or fall below the lowest input (Abraham & Kundapura 2022).

3 Results

Analysis of rainfall variability is crucial for policymakers in water resource management as it is a significant factor that affects the water availability of a region (Panda & Sahu 2019). The collected data provided valuable insights into the rainfall patterns of the Chattogram division. The descriptive of the annual and seasonal rainfalls are summarized in Table 2. In the study area, the mean annual rainfall and standard deviation (SD) range from 2062.4 mm (in Cumilla) to 4154.76 mm (in Teknaf) and 405.44 mm (in Cumilla) to 697.38 mm (in Sandwip), respectively. The highest rainfall recorded during these 42 years was 6095 mm at Sandwip station in 2001 and the lowest was 1240 mm at Cumilla station in 1992. The mean pre-monsoon rainfall ranged from

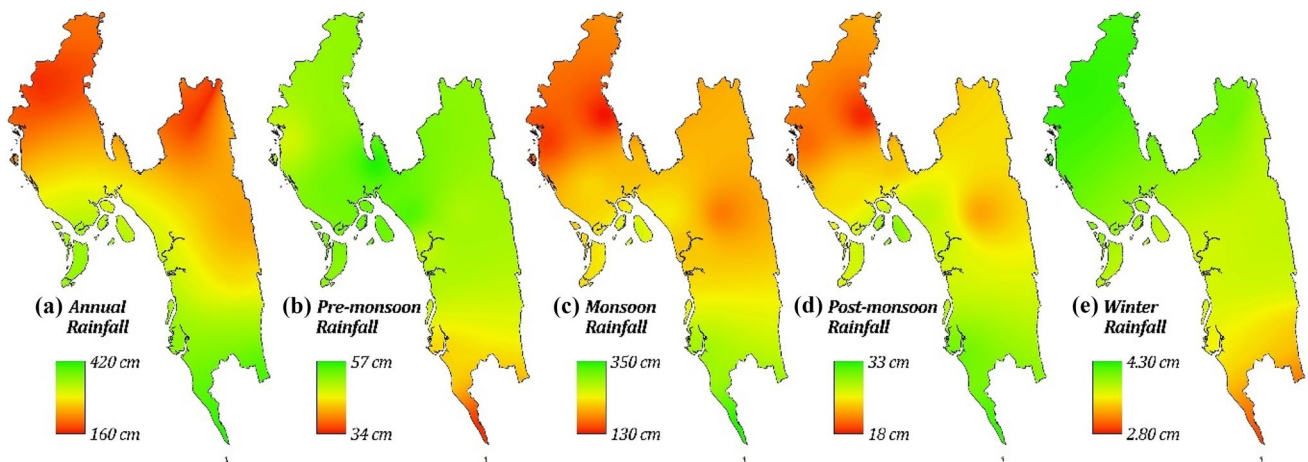
351 mm in Teknaf to 566 mm in Feni. During the monsoon season, the mean rainfall was highest in Teknaf at 3454 mm, while Cumilla had the lowest mean rainfall at 1322 mm. In the post-monsoon season, the mean rainfall was lowest in Cumilla at 185 mm and highest in Cox's Bazar at 306 mm. The mean winter rainfall was the lowest across all seasons, ranging from 29 mm in Teknaf to 42 mm in Chandpur and Cumilla. The spatial distribution of the annual and seasonal mean rainfalls during the study period is visualized in Fig. 2. The spatial map of annual rainfall (Fig. 2a) showed that the annual rainfall was the lowest in north-western and eastern parts of the Chattogram division and moderate to highest along the coastal regions. Spatial maps of monsoon and post-monsoon rainfalls showed similar distributions to that of annual rainfall (Fig. 2c and 2d). The southern parts of the division faced the lowest amount of pre-monsoon and winter rainfall during this time, whereas the division’s central and northern parts faced the maximum amount of pre-monsoon and winter rainfall, respectively (Fig. 2b and 2e).

The asymmetry of the rainfall data distribution was evaluated in this study using the coefficient of skewness, with positive skewness suggesting a longer right tail and negative skewness indicating a longer left tail. Among the stations, Chandpur (1.18) and Sandwip (1.14) relatively higher exhibit positive skewness, indicating that their annual rainfall distributions have longer right tails, suggesting occasional extreme annual rainfall events. Chattogram, Cox's Bazar, Cumilla, Feni, Majjdee Court, Rangamati, Sitakunda, and Teknaf show relatively lower skewness values, indicating more symmetric distributions. The shape and distribution of rainfall datasets was evaluated using coefficient of kurtosis, where a positive kurtosis value indicates a relatively peaked and heavy-tailed distribution, suggesting the presence of outliers or extreme rainfall events in the dataset. Stations such as Chandpur, Majjdee Court, and Sandwip exhibit positive kurtosis values (1.42, 1.02, and 3.50, respectively), indicating a higher probability of extreme annual rainfall events. The rest of the stations exhibited relatively lower positive or negative kurtosis values, implying a flatter and more spread-out distribution of annual rainfall data.

Between 1981 and 2022, the CV of annual rainfall in the Chattogram division was between less (14.02%) and moderate (25.38%) variable (Fig. 3a). Chandpur, Rangamati, and Sitakunda stations had moderate rainfall variability while the rest of the station faced less variability. Rainfall was less variable in the stations where mean annual rainfalls were higher (e.g., Teknaf had the highest mean annual rainfall of 4154.46 mm and the least rainfall variability of 14.02%). The CV of annual rainfall variability became higher towards the north-western (rolling terrain proximity) and eastern parts (mountainous terrain), compared to the coastal parts of the division. This phenomenon could be attributed to the orographic effect, whereby the hills act as

Table 2 Information of stations and descriptives of annual and seasonal rainfalls across the study area

Seasons	Variables	Chandpur	Chattogram	Cox's Bazar	Cumilla	Feni	Maijdee Court	Rangamati	Sandwip	Sitakunda	Teknaf
Longitude (E)		90.70	91.82	91.97	91.18	91.42	91.08	92.15	91.43	91.70	92.30
Latitude (N)		23.23	22.35	21.45	23.43	23.03	22.83	22.63	22.48	22.63	20.87
Altitude (m)		4.88	33.20	2.10	7.50	6.40	4.87	68.89	2.10	7.30	5.00
Annual	Mean	2163.4	2947.0	3671.9	2062.6	2947.6	3054.0	2525.1	3511.4	3206.1	4154.8
	SD	549.1	520.7	581.3	405.4	585.7	531.7	568.0	697.4	648.6	582.5
	Min	1332.0	1930.0	2064.0	1240.0	1740.0	1903.0	1452.0	2234.0	2031.0	2628.0
	Max	3772.0	4108.0	4716.0	3179.0	4476.0	4571.0	3878.0	6095.0	4868.0	5447.0
	CV (%)	14.21	16.44	18.04	14.04	15.54	15.82	15.11	16.49	15.88	19.49
	PCI (%)	25.38	17.67	15.83	19.66	19.87	17.41	22.50	19.86	20.23	14.02
	Skewness	1.18	0.34	-0.48	0.42	0.28	0.50	0.25	1.14	0.54	-0.15
	Kurtosis	1.42	-0.60	0.18	0.59	0.42	1.02	-0.25	3.50	0.09	0.87
Pre-monsoon	Mean	478	486	437	514	566	534	501	537	549	351
	SD	286	197	203	205	229	185	214	257	222	189
	CV (%)	60.44	41.08	46.89	40.31	40.82	35.14	43.13	48.36	40.78	54.38
	PCI (%)	11.25	12.42	13.81	11.50	11.84	11.62	11.83	12.02	11.48	15.93
Monsoon	Mean	1442	2153	2892	1322	2103	2232	1761	2638	2343	3454
	SD	453	513	541	296	439	478	462	585	579	570
	CV (%)	31.05	23.55	18.50	22.11	20.65	21.16	25.91	21.90	24.41	16.30
	PCI (%)	8.52	9.05	9.03	8.61	8.72	8.69	8.71	8.76	8.73	8.99
Post-monsoon	Mean	204	271	306	185	239	247	226	300	277	321
	SD	113	147	156	101	135	147	119	178	154	180
	CV (%)	55.99	55.03	51.59	55.52	57.24	60.15	53.41	59.87	56.02	56.61
	PCI (%)	12.01	11.77	10.74	11.54	11.88	12.04	11.10	12.36	12.07	11.23
Winter	Mean	42	37	36	42	40	41	38	37	37	29
	SD	39	41	34	47	36	39	37	35	50	41
	CV (%)	92.80	110.41	94.33	112.04	90.11	94.11	99.32	94.18	136.85	142.07
	PCI (%)	10.63	9.53	9.56	9.48	10.71	9.72	9.99	9.45	11.12	9.18

**Fig. 2** Spatial pattern of (a) mean annual, (b) mean pre-monsoon, (c) mean monsoon, (d) mean post-monsoon, and (e) mean winter rainfall across the study area

barriers to moisture-laden winds, causing them to rise and cool, resulting in condensation and rainfall on the windward side (coastal areas). The pre-monsoon rainfall variabilities were significantly high in the other stations, except for Maijdee Court (high). The monsoon rainfalls were moderately variable in all the stations, except for Chandpur (high), Cox's Bazar (low), and Teknaf (low). Conversely, post-monsoon and winter rainfall variabilities were very high and extremely high, respectively, in all stations.

The rainfall concentrations in annual and seasonal scales were estimated using PCI for every station and are summarized in Table 2. The majority (80%) of the stations were dominated by irregular distribution of rainfall, while only two stations showed moderate distribution: Chandpur (PCI = 14.81%) and Cumilla (PCI = 14.04%). Teknaf exhibited the highest annual PCI of 19.49% suggesting a substantial monthly variability in the rainfall. The spatial distribution of annual PCI across the study area is illustrated in Fig. 3b. Like annual CV, annual PCI was also lower in the north-western and eastern parts of the Chattogram division while being higher close to the coastal and southernmost regions. Moderate rainfall distribution was dominant in most stations, except for Teknaf being irregular with 15.93% seasonal PCI. Monsoon rainfall was uniform (PCI ranged between 8.52% to 9.05%) in all the stations, while post-monsoon rainfall was slightly irregular (moderate distribution) in all stations with seasonal PCI ranging from 10.74% to 12.36%. Distributions of winter rainfalls were uniform in 70% of stations, while Chandpur (10.63% PCI), Feni (10.71% PCI), and Sitakunda (11.12% PCI) indexed moderate distribution.

The results of the Standardized Rainfall Anomaly tests (Fig. 4) indicate the severity of drought events in ten rainfall

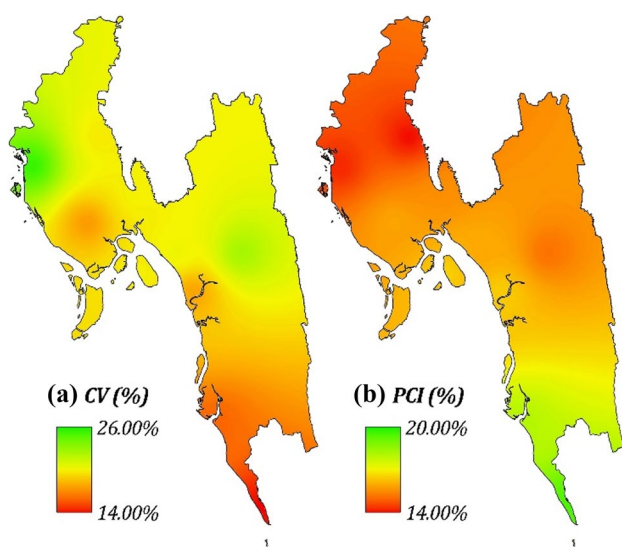


Fig. 3 Annual averaged (a) CV, and (b) PCI across the study area

stations during the study period. The severity of drought varied spatially and temporally, highlighting the localized nature of these events. Throughout the 42-year research period, each station encountered severe to extreme drought events at least once, with the number of occurrences ranging from one to five times. Chandpur experienced no to moderate droughts 41 times, Sandwip 40 times, and Maijdee Court and Teknaf 39 times each. The occurrence of extreme drought has been observed across multiple stations, with the highest frequency recorded in 2022 (5 stations). In addition, same occurrences were recorded in 1992 (3 stations), 1983 (2 stations), and 2021, 2014, 2006, 1995, 1994, and 1982 (1 station each). Teknaf station experienced extreme drought three times (1983, 2021, and 2022), while Chandpur station encountered none. Chattogram, Rangamati, and Sitakunda experienced the frequency of severe drought events (4 times each), followed by Cox's Bazar (3 times). The year 1992 had the highest number of stations (8) experiencing severe or extreme drought conditions, followed by years 2022 (7), and 1994 (4). During the 42 years study period, all the stations faced severe to extreme drought events at least once (ranging between 1 to 5 times), while Chandpur (41 times), Sandwip (40 times), Maijdee Court (39 times), and Teknaf (39 times) are some notable ones to least face no to moderate droughts.

The study analyzed the homogeneity of rainfall data from 50-time series observations, utilizing five datasets per station. Three statistical tests – the Standard Normal Homogeneity test (SNHT), Buishand Ranking test (BRT), and Pettitt test (PT) – were employed at a 5% significance level to assess the homogeneity of each time series. For the time series data to be genuinely homogeneous, it must pass all three tests. Notably, 22% (11 of 50) of the time series were identified as inhomogeneous since either one or more tests rejected the respective null hypotheses ($p < 0.05$). Among the analyzed time series data, 14% (7 observations) exhibited significant breakpoints as identified by the SNHT, a powerful tool for detecting such shifts at the start or end of a series (Arikan & Kahya 2019). The SNHT test identified the most statistically significant ($p < 0.05$) break points in the time series observations until 1991. Interestingly, most of these breakpoints (6) occurred before 1988, with only one detected in 2020. Six (three in the middle) out of 50 time series were identified as inhomogeneous by the BRT test, while the PT test revealed only one inhomogeneous time series, confirming both tests' ability to detect mid-series break points (Arikan & Kahya 2019). Moreover, no single time series was flagged as inhomogeneous by all three tests, whereas two-time series showed inhomogeneity for both SNHT and BRT tests, and 1 showed homogeneity for both BRT and PT tests. Table S1 summarizes all these tests' results with corresponding p-values. Figure 5 visualizes the mapped inhomogeneity distribution across stations for annual and temporal time scales, as revealed by different test methods.

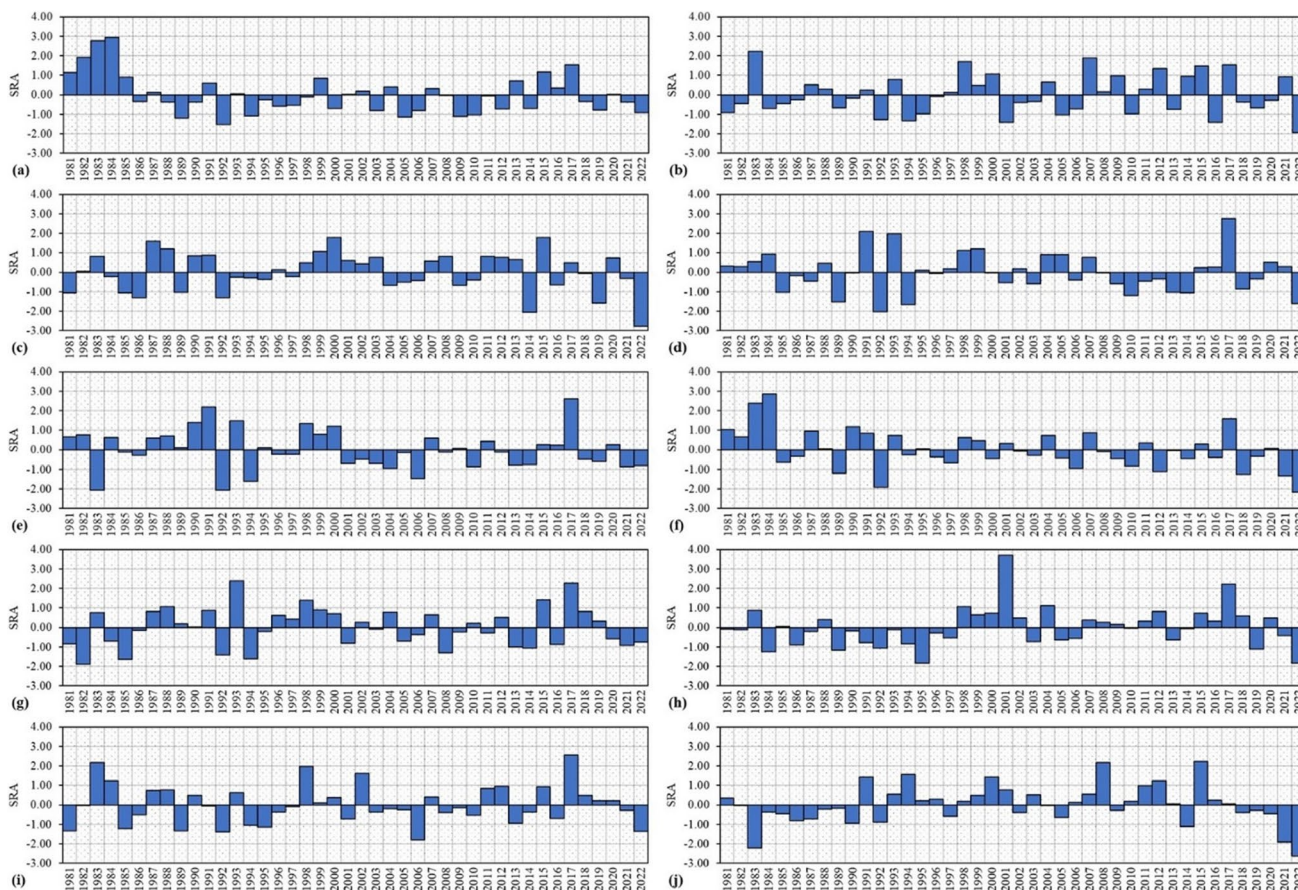


Fig. 4 Rainfall Anomalies at (a) Chandpur, (b) Chattogram, (c) Cox’s Bazar, (d) Cumilla, (e) Feni, (f) Maijdee Court, (g) Rangamati, (h) Sandwip, (i) Sitakunda and (j) Teknaf BMD stations during 1981–2022

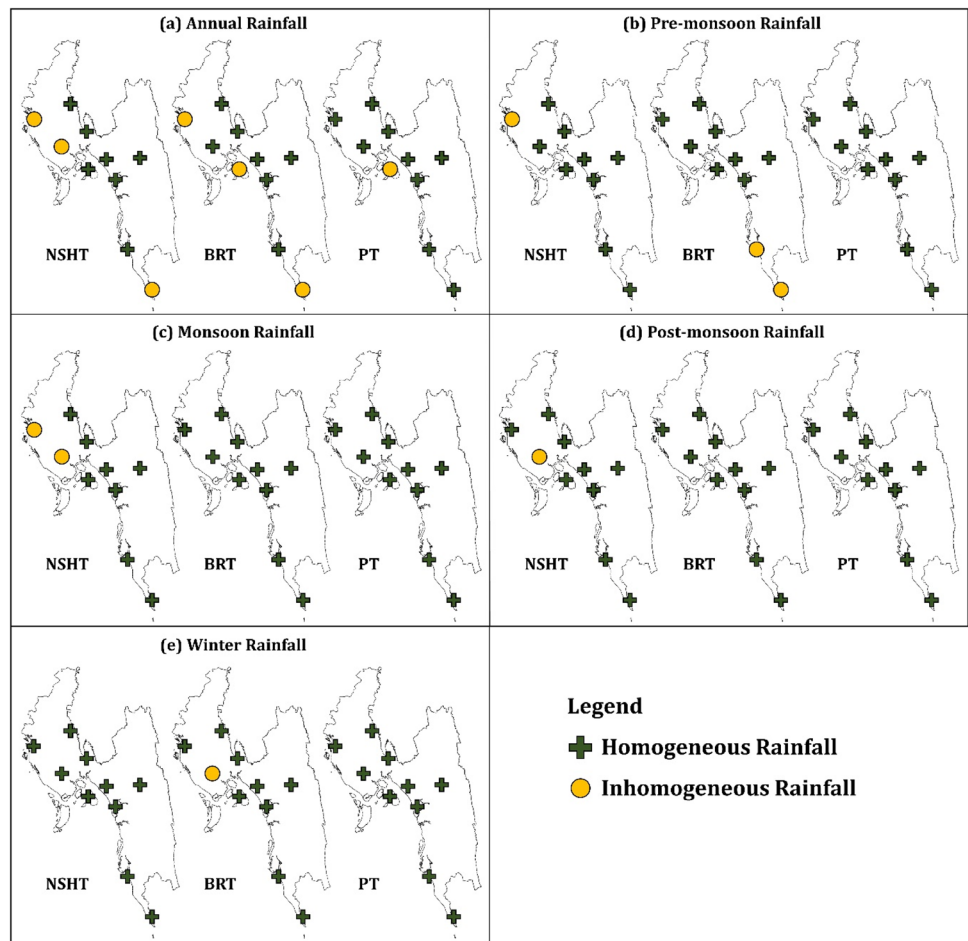
The Chandpur station showed significant breakpoints ($p < 0.05$) in annual rainfall in 1985, verified by SNHT and BRT tests. SNHT indicated significant pre-monsoon and monsoon rainfall break points in 1985 and 1984, respectively. Similarly, Cox's Bazar's pre-monsoon rainfall saw a significant breakpoint in 2013, as revealed by the BRT test. Moving inland, Maijdee Court witnessed break points in annual and monsoon rainfall in 1984 (SNHT), followed by a post-monsoon break point in 1987 (SNHT) and a winter one in 1993 (BRT). Further south, Sandwip's annual rainfall displayed significant breakpoints in 1997, captured by BRT and PT. Finally, at Teknaf, the annual rainfall time series revealed significant breakpoints in 2020 (SNHT) and 2017 (BRT), while the pre-monsoon data showed a shift in 1992, identified by the BRT test.

Table 3 summarizes the station-wise variation in the test statistics (Z_{MK} , Z_{MMK} , S_{ITA}) with respective test significance (at 5% significance level). The spatial distributions of test statistics indicating rainfall trends in annual and seasonal scales by MK and MMK tests are illustrated in Figs. 6 and 7, respectively. The results from the ITA test are illustrated in Figs. 8 and 9. The spatial maps of test statistics from the ITA

tests are shown in Fig. 10. The contrast between the conventional MK method, modified MK method and ITA method in identifying trends at various BMD stations at annual and four seasonal scales is illustrated in Fig. 11.

The trend indicator of MK test (Z_{MK}) on long term annual rainfall varied between -2.74 and 1.24 for annual rainfall across the stations, whereas MMK ranged between -7.22 and 2.59. Six of the ten stations, (e.g., Chandpur, Cox’s Bazar, Cumilla, Feni, Maijdee Court, and Rangamati stations) exhibited decreasing annual rainfall trends, and the rest had non-significant increasing trends ($p > 0.05$). Only Maijdee Court station with Z_{MK} of -2.74 detected a significant decreasing trend ($p < 0.05$) in annual rainfall. Compared to the MK test’s significant decreasing trend detection ($p < 0.05$) in just one station (10%), MMK detected statistically significant declining trends at three stations (30%), while the ITA test detected significant negative trends at seven stations (70%) for annual rainfall. The MMK method detected significant decreases in annual rainfall at the Cumilla, Feni and Maijdee Court, and significant increase at the Sandwip station. According to ITA, Chandpur ($S_{ITA} = -10.59$, $CL = \pm 1.71$), Cox’s

Fig. 5 Spatial distributions of homogenous and inhomogeneous time series at annual and local scales according to different homogeneity tests



Bazar ($S_{ITA} = -5.89$, $CL = \pm 3.22$), Cumilla ($S_{ITA} = -3.08$, $CL = \pm 2.06$), Feni ($S_{ITA} = -12.26$, $CL = \pm 4.76$), and Majj-dee Court ($S_{ITA} = -15.18$, $CL = \pm 1.64$) stations faced significant decreasing trend ($p < 0.05$) in annual rainfall during the time period, whereas Chattogram ($S_{ITA} = 3.12$, $CL = \pm 2.10$) and Sandwip ($S_{ITA} = 6.19$, $CL = \pm 3.14$) faced significant increasing trend. Figure 8 demonstrates the evident decline in annual rainfall in the ITA test, as indicated by the positioning of scatter points (highlighted in red). Most stations' scatter points are below the 1:1 trend line within the Cartesian coordinate system. The distribution of trend indicators for annual rainfall Z_{MK} , Z_{MMK} , and S_{ITA} are illustrated in Fig. 6a, 7a, and 10a, respectively. Both figures made it clear that the yearly rainfall pattern was declining over much of the study region. During the study period, the northernmost parts of the study region experienced the sharpest decreasing trend, followed by certain southern areas close to the Cox's Bazar district. An increasing trend in annual rainfall was observed in the coastal parts of the mid-study region.

Almost all stations (9/10; 90%) faced a decline in pre-monsoon rainfall according to MK, MMK, and ITA test techniques. The ITA test detected a significant increasing trend ($p < 0.05$) at the Teknaf station ($S_{ITA} = 1.34$,

$CL = \pm 0.75$), while MK and MMK detected decline in rainfall but couldn't prove the significance ($Z_{MK} = 0.29$, $Z_{MMK} = 0.42$, $p > 0.05$). MK test detected significant a decreasing trend (1/9; 11.11%) only at Feni station ($Z_{MK} = -2.11$), the MMK indicated significant decrease in six stations (6/9; 66.66%), including Chattogram, Cumilla, Feni, Majjdee Court, Rangamati, and Sitakunda. In contrast, ITA detected significant decreasing trend (8/9; 88.89%) at Chandpur ($S_{ITA} = -7.71$, $CL = \pm 1.61$), Chattogram ($S_{ITA} = -3.69$, $CL = \pm 0.59$), Cumilla ($S_{ITA} = -5.00$, $CL = \pm 0.66$), Feni ($S_{ITA} = -8.48$, $CL = \pm 1.22$), Majjdee Court ($S_{ITA} = -5.13$, $CL = \pm 0.39$), Rangamati ($S_{ITA} = -6.13$, $CL = \pm 0.59$), Sandwip ($S_{ITA} = -2.00$, $CL = \pm 1.20$), and Sitakunda ($S_{ITA} = -6.73$, $CL = \pm 1.12$). Cox's Bazar station was the only station that had a statistically non-significant decrease ($p > 0.05$) in pre-monsoon rainfall with the S_{ITA} of -7.71 ($CL = \pm 1.61$). Spatial distribution maps of trend indicators revealed a decline in pre-monsoon rainfall across almost the entire Chattogram Division during the study period, except for the northern areas adjacent to Teknaf (Figs. 6b, 7b, and 10b). The southern districts and particular parts of the Chattogram district both experienced the steepest decrease.

Table 3 Variation in test statistics (Z_{MK} , Z_{MMK} , S_{ITA}) among the rainfall stations across the study area at various time scales

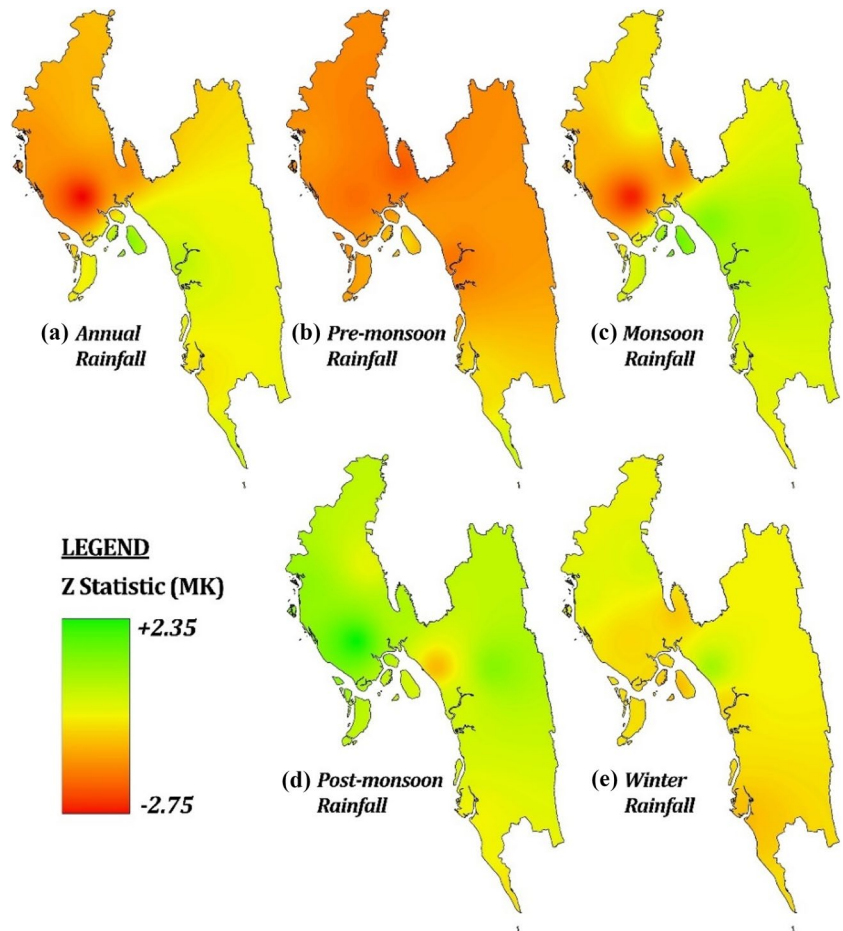
Station Names	Annual Rainfall			Pre-monsoon Rainfall		
	Z_{MK}	Z_{MMK}	S_{ITA}	Z_{MK}	Z_{MMK}	S_{ITA}
Chandpur	(∇) -1.41	(∇) -1.81	(▼) -10.59	(∇) -1.35	(∇) -1.79	(▼) -7.71
Chattogram	(Δ) 0.54	(Δ) 1.72	(▲) 3.12	(∇) -1.78	(▼) -3.89	(▼) -3.69
Cox's Bazar	(∇) -0.40	(∇) -0.85	(▼) -5.89	(∇) -0.46	(∇) -0.69	(∇) -0.30
Cumilla	(∇) -0.92	(▼) -2.69	(▼) -3.08	(∇) -1.68	(▼) -6.12	(▼) -5.00
Feni	(∇) -1.46	(▼) -4.40	(▼) -12.26	(▼) -2.11	(▼) -5.60	(▼) -8.48
Maijdee Court	(▼) -2.74	(▼) -7.22	(▼) -15.18	(∇) -1.86	(▼) -7.81	(▼) -5.13
Rangamati	(∇) -0.11	(∇) -0.25	(∇) -2.37	(∇) -1.35	(▼) -3.39	(▼) -6.13
Sandwip	(Δ) 1.24	(▲) 2.59	(▲) 6.19	(∇) -0.52	(∇) -1.28	(▼) -2.00
Sitakunda	(Δ) 0.11	(Δ) 0.39	(Δ) 2.55	(∇) -1.37	(▼) -3.93	(▼) -6.73
Teknaf	(Δ) 0.24	(Δ) 0.33	(Δ) 0.53	(Δ) 0.29	(Δ) 0.42	(▲) 1.34
Station Names	Monsoon Rainfall			Post-monsoon Rainfall		
	Z_{MK}	Z_{MMK}	S_{ITA}	Z_{MK}	Z_{MMK}	S_{ITA}
Chandpur	(∇) -0.99	(∇) -1.83	(▼) -4.00	(Δ) 1.13	(▲) 3.71	(▲) 1.18
Chattogram	(Δ) 0.72	(▲) 2.49	(▲) 7.00	(Δ) 0.31	(Δ) 0.93	(Δ) 0.76
Cox's Bazar	(Δ) 0.02	(Δ) 0.07	(▼) -3.28	(∇) -0.17	(∇) -0.55	(▼) -1.33
Cumilla	(∇) -0.05	(∇) -0.17	(▲) 2.15	(-) 0.00	(-) 0.00	(∇) -0.04
Feni	(∇) -1.44	(▼) -2.86	(▼) -4.24	(Δ) 0.76	(▲) 2.08	(▲) 1.10
Maijdee Court	(▼) -2.62	(▼) -4.56	(▼) -12.59	(▲) 2.34	(▲) 4.71	(▲) 3.27
Rangamati	(Δ) 0.78	(▲) 2.37	(▲) 4.33	(Δ) 1.25	(▲) 3.45	(Δ) 0.26
Sandwip	(Δ) 1.56	(▲) 4.19	(▲) 9.07	(Δ) 0.35	(Δ) 0.96	(Δ) 0.14
Sitakunda	(Δ) 1.26	(▲) 3.68	(▲) 11.64	(∇) -0.92	(▼) -2.85	(▼) -2.22
Teknaf	(∇) -0.20	(∇) -0.40	(∇) -0.50	(∇) -0.41	(∇) -0.99	(∇) -0.11
Station Names	Winter Rainfall					
	Z_{MK}	Z_{MMK}	S_{ITA}			
Chandpur	(Δ) 0.11	(Δ) 0.18	(∇) -0.06			
Chattogram	(∇) -0.53	(∇) -0.91	(▼) -0.95			
Cox's Bazar	(∇) -0.88	(∇) -1.67	(▼) -0.98			
Cumilla	(Δ) 0.25	(Δ) 0.50	(▼) -0.18			
Feni	(∇) -0.73	(∇) -1.40	(▼) -0.64			
Maijdee Court	(∇) -0.57	(∇) -0.94	(▼) -0.73			
Rangamati	(∇) -0.20	(∇) -0.35	(▼) -0.83			
Sandwip	(∇) -0.89	(∇) -1.67	(▼) -1.02			
Sitakunda	(Δ) 0.87	(Δ) 1.74	(∇) -0.14			
Teknaf	(∇) -0.50	(▼) -1.98	(∇) -0.20			

(▲) = Significant Increasing Trend ($p < 0.05$), (Δ) = Increasing Trend, (-) = No Trend, (∇) = Decreasing Trend, (▼) = Significantly Decreasing Trend ($p < 0.05$)

All three tests showed 5 stations with increasing monsoon rainfall and 5 with decreasing trends. The magnitude of the trend indicator in the MK test (Z_{MK}) varied between -2.42 to 1.56, and in the ITA test (S_{ITA}) between -12.59 to 11.64. ITA test technique detected significant decreasing trends ($p < 0.05$) at four stations (4/5; 80%), namely, Chandpur ($S_{ITA} = -4.00$, $CL = \pm 1.67$), Cox's Bazar ($S_{ITA} = -3.28$, $CL = \pm 1.56$), Feni ($S_{ITA} = -4.24$, $CL = \pm 3.70$), Maijdee Court ($S_{ITA} = -12.59$, $CL = \pm 2.63$). In contrast, the MMK test detected significant decreasing trends in Feni ($Z_{MMK} = -2.86$) and Maijdee Court ($Z_{MMK} = -4.56$) stations, while MK in just Maijdee Court

station ($Z_{MK} = -2.62$). The ITA test detected significant increasing trends ($p < 0.05$) at Chattogram ($S_{ITA} = 7.00$, $CL = \pm 1.86$), Cumilla ($S_{ITA} = 2.15$, $CL = \pm 1.13$), Rangamati ($S_{ITA} = 4.33$, $CL = \pm 1.71$), Sandwip ($S_{ITA} = 9.07$, $CL = \pm 3.04$), and Sitakunda ($S_{ITA} = 11.64$, $CL = \pm 2.78$). Z_{MMK} results also showed at the Chattogram (2.49), Rangamati (2.37), Sandwip (4.19) and Sitakunda (3.68) stations. While, respectively, the ITA and MMK test techniques detected significantly increasing trends in 100% and 80% monsoon rain-rich stations, the MK test failed to detect any. The northern districts of the research area clearly had the highest declining trends of annual rainfall,

Fig. 6 Spatial patterns of Z_{MK} for (a) annual, (b) pre-monsoon, (c) monsoon, (d) post-monsoon, and (e) winter rainfall trends across the study area with detected trends in stations



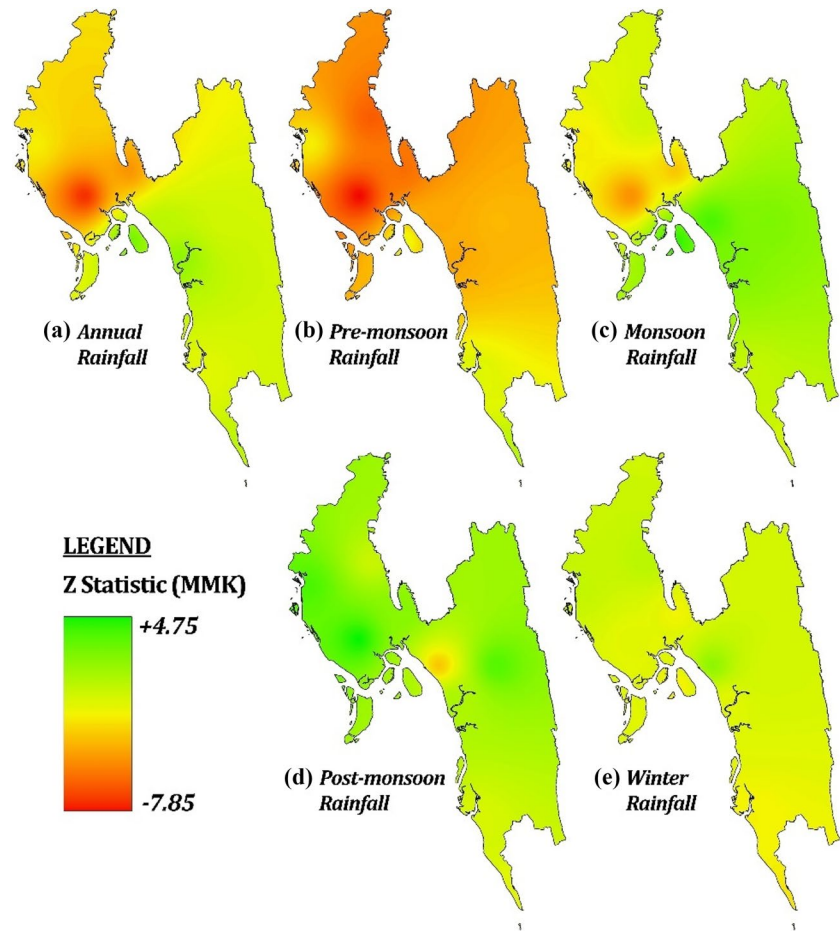
as seen by the trend distribution maps (Figs. 6c, 7c, and 10c). In contrast, the northern regions of the study area had a rise in annual rainfall over the study period.

MK, MMK and ITA techniques commonly detected decreasing post-monsoon rainfall at three stations (Cox's Bazar, Sitakunda, and Teknaf) and increasing rainfall at 6 stations (e.g., Chandpur, Chattogram, Feni, Maijdee Court, Rangamati and Sandwip). At the Cumilla station, both MK and MMK tests couldn't detect any trend ($Z_{MK} = Z_{MMK} = 0$), while ITA detected a slightly negative trend ($S_{ITA} = -0.04$, $CL = \pm 0.35$). MK test detected significant trend ($p < 0.05$) in one station in case of post-monsoon rainfall, while the MMK and ITA test both found significant trends at 5 stations (50%). It was interesting to see that ITA couldn't detect significant trend ($S_{ITA} = 0.26$, $CL = \pm 0.35$, $p > 0.05$) at the Rangamati station while MMK ($Z_{MMK} = 3.45$, $p < 0.05$) detected it. Significantly increasing trends for ITA were observed at Chandpur ($S_{ITA} = 1.18$, $CL = \pm 0.37$), Feni ($S_{ITA} = 1.10$, $CL = \pm 0.50$), and Maijdee Court ($S_{ITA} = 3.27$, $CL = \pm 0.39$) stations, and a significantly decreasing trend at Cox's Bazar ($S_{ITA} = -1.33$, $CL = \pm 0.36$) and Sitakunda ($S_{ITA} = -2.22$, $CL = \pm 0.51$) stations. The northern and north-western districts experienced a significant rise in post-monsoon rainfall,

whereas a decline in rainfall was observed in the southern regions (Fig. 6d, 7d, and 10d). This differed from the annual, pre-monsoon, and monsoon rainfall patterns.

MK and MMK methods showed winter rainfall trends were dominated by decreasing trends across the stations (7/10; 70%), while ITA method indicated decline at all the stations. The magnitude of MK trend detector Z_{MK} varied from -0.89 to 0.87 and there was no significant positive or negative trend detected by the MK method in any of the stations. The MMK detected a significant decline ($p < 0.05$) at the Teknaf station ($Z_{MMK} = -1.98$) with Z_{MMK} ranging from -1.98 to 1.74. In contrast, the ITA method showed decreasing trends in all the stations with S_{ITA} values ranging between -0.98 and -0.06. ITA method detected significant decreasing trends ($p < 0.05$) at all the stations, which were Chattogram ($S_{ITA} = -0.95$, $CL = \pm 0.10$), Cox's Bazar ($S_{ITA} = -0.98$, $CL = \pm 0.11$), Cumilla ($S_{ITA} = -0.18$, $CL = \pm 0.14$), Feni ($S_{ITA} = -0.64$, $CL = \pm 0.18$), Maijdee Court ($S_{ITA} = -0.73$, $CL = \pm 0.10$), Rangamati ($S_{ITA} = -0.83$, $CL = \pm 0.10$), and Sandwip ($S_{ITA} = -1.02$, $CL = \pm 0.10$). It's worth mentioning that the MK and MMK tests detected increasing winter rainfall trends at the stations of Chandpur, Cumilla, and Sitakunda, but ITA detected decreasing rainfall at all three

Fig. 7 Spatial patterns of Z_{MMK} for (a) annual, (b) pre-monsoon, (c) monsoon, (d) post-monsoon, and (e) winter rainfall trends across the study area with detected trends in stations



stations, with Cumilla Station's decline being significant ($p < 0.05$). The trend distribution maps indicated a greater decline in winter rainfall in the southern regions compared to the northern regions (Figs. 6e, 7e, and 10e).

4 Discussion

This study intends to extensively examine the annual and seasonal rainfall patterns by analyzing 42-years of historical data from 10 Bangladesh Meteorological Department (BMD) stations in the Southeast regions of Bangladesh. From 1981 to 2020, the overall average annual rainfall across the study area was 302.44 cm, a notably higher figure than the national average reported in previous studies. The World Bank (2023) recorded an average of 220 cm over the last 30 years, whereas Yousuf & Ahmed (2015) observed an annual average rainfall of 245.6 cm in Bangladesh from 1948 to 2011. Figure 2a illustrates a clear spatial trend, indicating a decline in the mean annual rainfall as one moves away from the coastal region. Teknaf stations exhibited the

highest average annual average rainfall at 415.48 cm, establishing it as the most rainfall-prone locale.

In contrast, Cumilla station, located in the southernmost part of the study area, recorded the lowest annual averaged precipitation at 206.26 cm, underscoring the decreasing trend in mean rainfall towards the south. These observations, consistent with earlier research, align with the overall pattern wherein coastal areas experience higher annual rainfall than inner regions, signifying a notable geographical influence on precipitation levels. Islam et al. (2020) noted a concentration of annual rainfall in the southern and eastern parts of Bangladesh, a trend supported by Shahid (2009), who anticipated continued normal rainfall conditions in the southern region. The post-monsoon season accounted for 8.52% of the total, and the winter season registered a minimal 1.25% of the overall rainfall. Notably, average rainfall in both monsoon and post-monsoon seasons exhibited a noticeable uprise from the northern to southern parts of the study area. Teknaf, the southernmost station, recorded the maximum averaged monsoon (345.4 cm) and post-monsoon (32.1 cm) rainfall while experiencing the lowest averaged amount of pre-monsoon rainfall at 35.1 cm, accentuating the seasonal variations within the region.

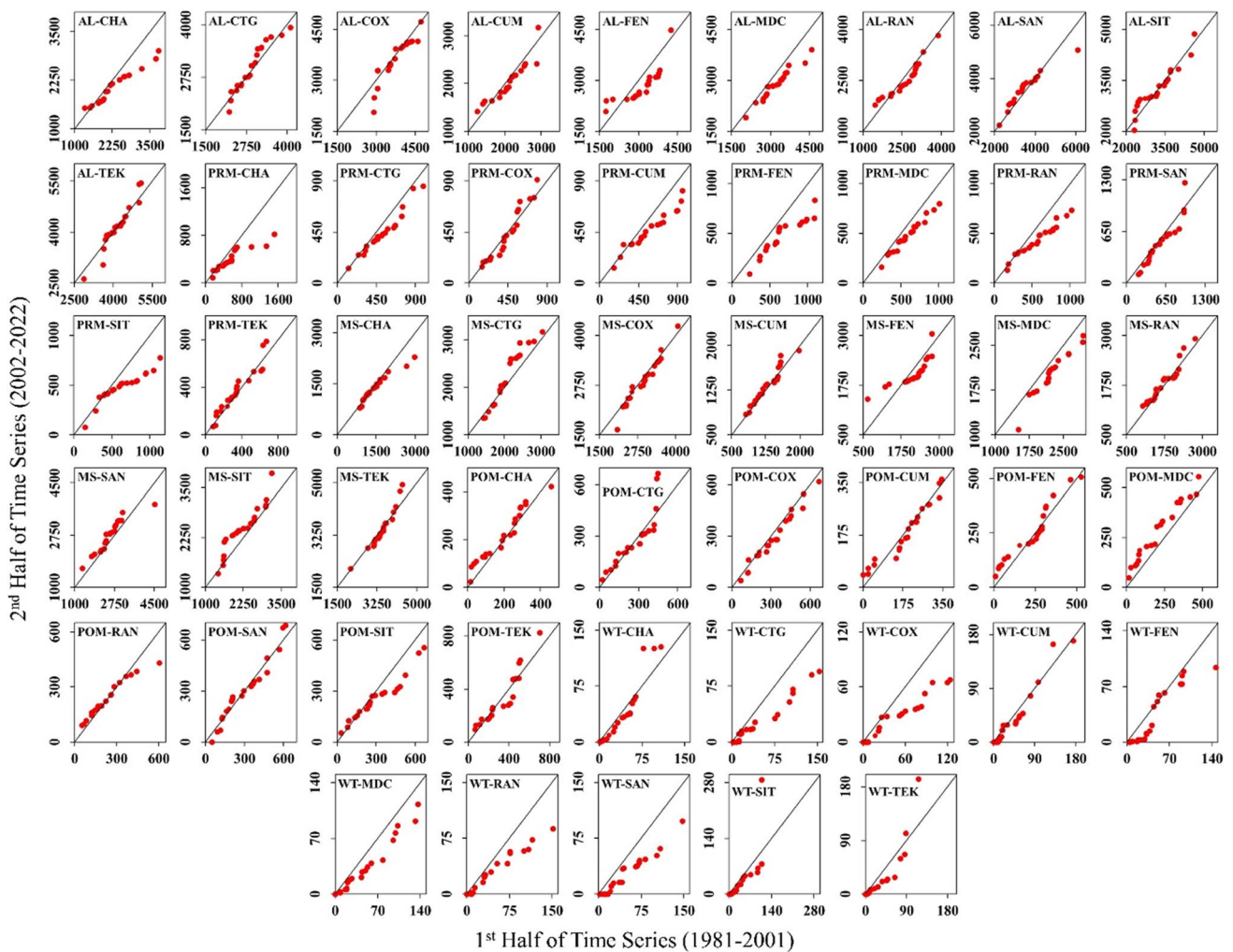


Fig. 8 Plots of ITA for seasonal and annual rainfall (Abbreviations used at the top of each plots — AL: Annual, PRM: Pre-monsoon, MS: Monsoon, POM: Post-monsoon, WT: Winter, CHA: Chand-

pur, CTG: Chattogram, COX: Cox's Bazar, CUM: Cumilla, FEN: Feni, MDC: Majidee Court, RAN: Rangamati, SAN: Sandwip, SIT: Sitakunda, TEK: Teknaf)

Bangladesh receives moderate to heavy convective rains in numerous areas, meaning rain from heat buildup. When the rain is light, less water vapor from the Bay of Bengal (BoB) reaches the land, hindering raindrop formation. The country has a small area with changes in geopotential height (related to atmospheric pressure). It does not bring as much moisture from the BoB to the nearby land, affecting the amount of rainfall (Rahman & Islam 2019). This is why annual rainfall increases during the summer monsoons in the southeast parts of the country (Azad et al. 2022). The strong southeast breeze plays a role in lessening the influence of colder air, leading to reduced rainfall during the post-monsoon season. Creating an anti-clockwise circulating weather system weakens the power of the southeast wind, reinforcing the summer monsoon and bringing warmer air into the country, resulting in increased rainfall (Zhu et al. 2023). Again, there has been an increase in low cloud coverings

across the country and neighboring regions, which enhances the atmosphere's ability to turn sunlight into rain, potentially reducing the overall trend in rainfall (Shahid 2009).

The trend analysis results revealed that 40% of the meteorological stations, primarily in the southern coastal regions, observed an upward trend in annual rainfall, while the remaining areas experienced a substantial decrease in annual precipitation. Monsoon rainfall exhibited a reduction in the central-western parts. Still, it increased in the remaining area, with a significant upturn in the southeastern coastal and mountainous regions. In an earlier study, Islam et al. (2020) found a notable rise in rainfall exceeding 15 mm in the southeast region of the country that included Chattogram, Cox's Bazar, Hatiya, Rangamati, and adjacent districts. Pre-monsoon and winter rainfall demonstrated a consistent decrease across all stations throughout the study region, contradicting the findings of Hasan et al. (2014),

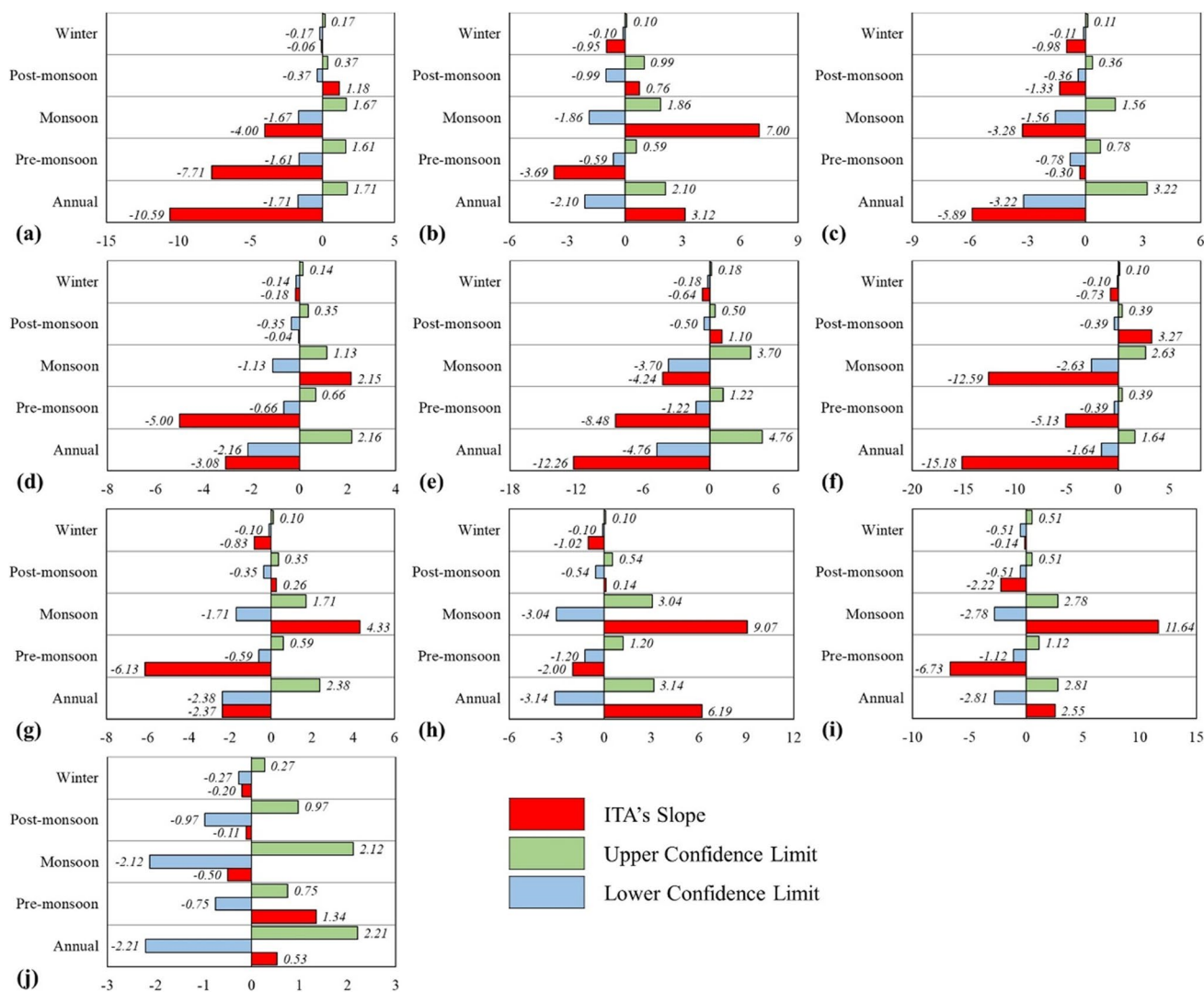


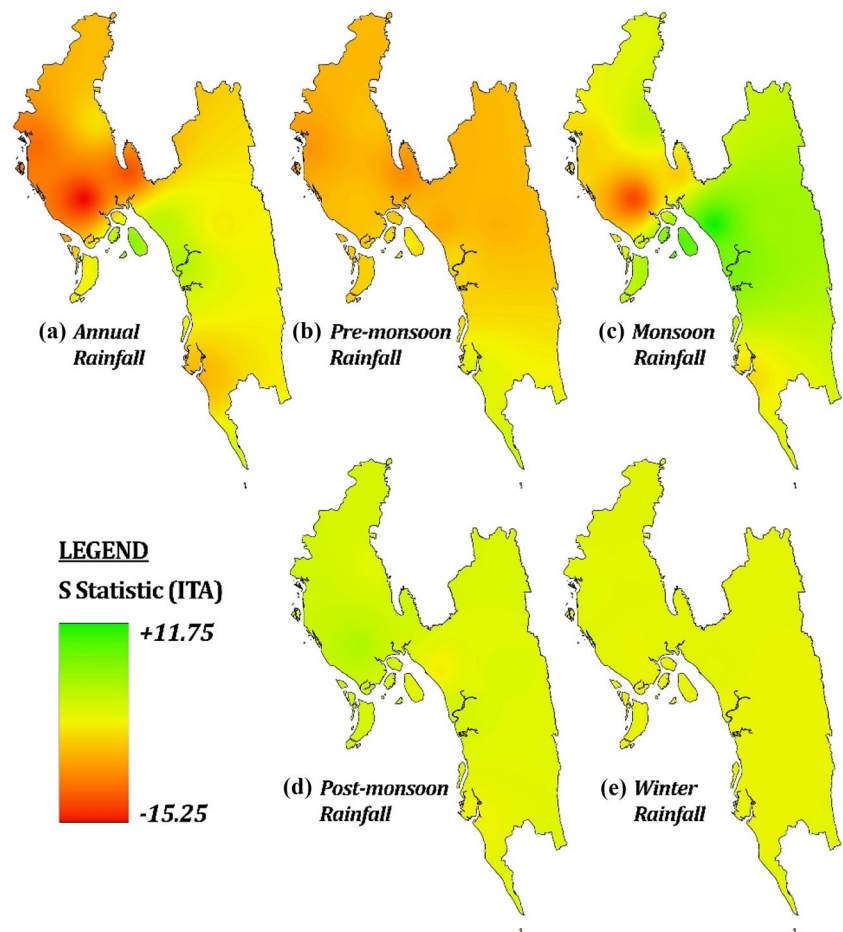
Fig. 9 Results of ITA compared to upper and lower confidence limits at (a) Chandpur, (b) Chattogram, (c) Cox's Bazar, (d) Cumilla, (e) Feni, (f) Majjdee Court, (g) Rangamati, (h) Sandwip, (i) Sitakunda and (j) Teknaf BMD stations

who reported significant increases in precipitation trends along the southeast coast of Bangladesh from 1949 to 2011. Post-monsoon rainfall increased almost throughout the study area, except for certain southern coastal regions. Monir et al. (2023) also showed a declining trend in the dry season rainfall and predicted that there would be little to no winter rainfall in the country by 2030. Islam & Uyeda (2008), Shahid (2010a, b) suggested a decline in dry season rainfall and an increase in monsoon rainfall from the 1950s to the 2010s. These diverse trends highlight the complexity of rainfall variations in the region over time. The findings of this study were also comparable to those of some earlier studies on trends in annual and seasonal rainfall for the region under consideration (Ahmed et al. 2017; Akter et al. 2023; J. Das et al. 2021; Mullick et al. 2019; Pervin & Khan 2023; Rahman et al. 2017).

High spatial and temporal variability of rainfall has significant implications on sustainable water resources management (Cristiano et al. 2017; Ogunbode & Ifabiye 2019). Changes in rainfall directly impact water availability, affecting urban water supply and agricultural, residential, and industrial uses (McDonald et al. 2011; Miller et al. 2021). This study reveals significant decreasing trends in annual rainfall across most stations, except for southern coastal zones. A continued decline in rainfall suggests an increased severity and frequency of droughts compared to the past, leading to reduced streamflow and reservoir inflow (Barua et al. 2013). The observed rainfall trends underscore the need for a drought response plan to manage future water resource changes (Wilhite & Easterling 2019).

Both decreasing and increasing trends in rainfall can have detrimental effects on the country's economy, food security,

Fig. 10 Spatial patterns of S_{ITA} for (a) annual, (b) pre-monsoon, (c) monsoon, (d) post-monsoon, and (e) winter rainfall trends across the study area



and overall resilience (Chen et al. 2021; Etzold et al. 2014). In the context of the southeast region, changing rainfall patterns might hold direct implications for two major sectors: urban water resources and agriculture (Yu et al. 2010). Insufficient rainfall could lead to drought conditions, affecting crop growth, reducing yields, and threatening food security (Kogo et al. 2021). Since the overall economy of Bangladesh is sensitive to fluctuations in agricultural productivity (Emran & Shilpi 2018; Rahman & Amit 2022; Senan et al. 2022), variations in rainfall can have cascading effects on employment, income, and food security. Groundwater, used for essential purposes such as drinking water, industry, and municipal services, is a vital resource that contributes to the sustainable resilience and functionality of densely populated urbanized areas in the southeast region (Datta et al. 2022; Debnath et al. 2022; Khan et al. 2022). A significant decrease in rainfall within the study area could potentially harm the replenishment of groundwater reserves (Havril et al. 2018; Ostad-Ali-Askari et al. 2019), leading to water scarcity and disrupting supply to urban areas. Conversely, heavy rainfall leading to floods can contaminate both surface and ground water sources (Andrade et al. 2018; Hartmann et al. 2021; Vryzas 2018), putting critical infrastructure like power grids

and transportation systems at risk and severely disrupting essential services and livelihoods in densely populated areas (Isiaka et al. 2023; Sakuma et al. 2017). Particularly in hilly areas, increased rainfall may trigger landslides, posing risks to lives and property (Khatun et al. 2023; Sultana 2020). This aligns with recent patterns in the study region, as periods of intense rainfall during the monsoon season in the past have caused landslides and flash floods that have resulted in severe damage and relocation (Alam 2020; Sarker & Rashid 2013; Sultana & Tan 2021). Coastal areas, experiencing rising sea levels alongside heavy rainfall, could face saltwater intrusion into freshwater sources, impacting agriculture and drinking water supplies (Rajendiran et al. 2019; J. Yang & Zhang 2024). Additionally, increased rainfall in the hills may contribute to soil erosion, affecting land fertility and agricultural productivity (Piacentini et al. 2018). Therefore, effective measures are crucial to mitigate the risks associated with fluctuating rainfall patterns. Developing an effective water supply and demand strategy to adapt to these changes is now more critical than ever.

The higher frequency of inhomogeneity in rainfall datasets of stations closer to the sea, such as Chandpur, Majdee Court, Sandwip, and Teknaf, raises questions

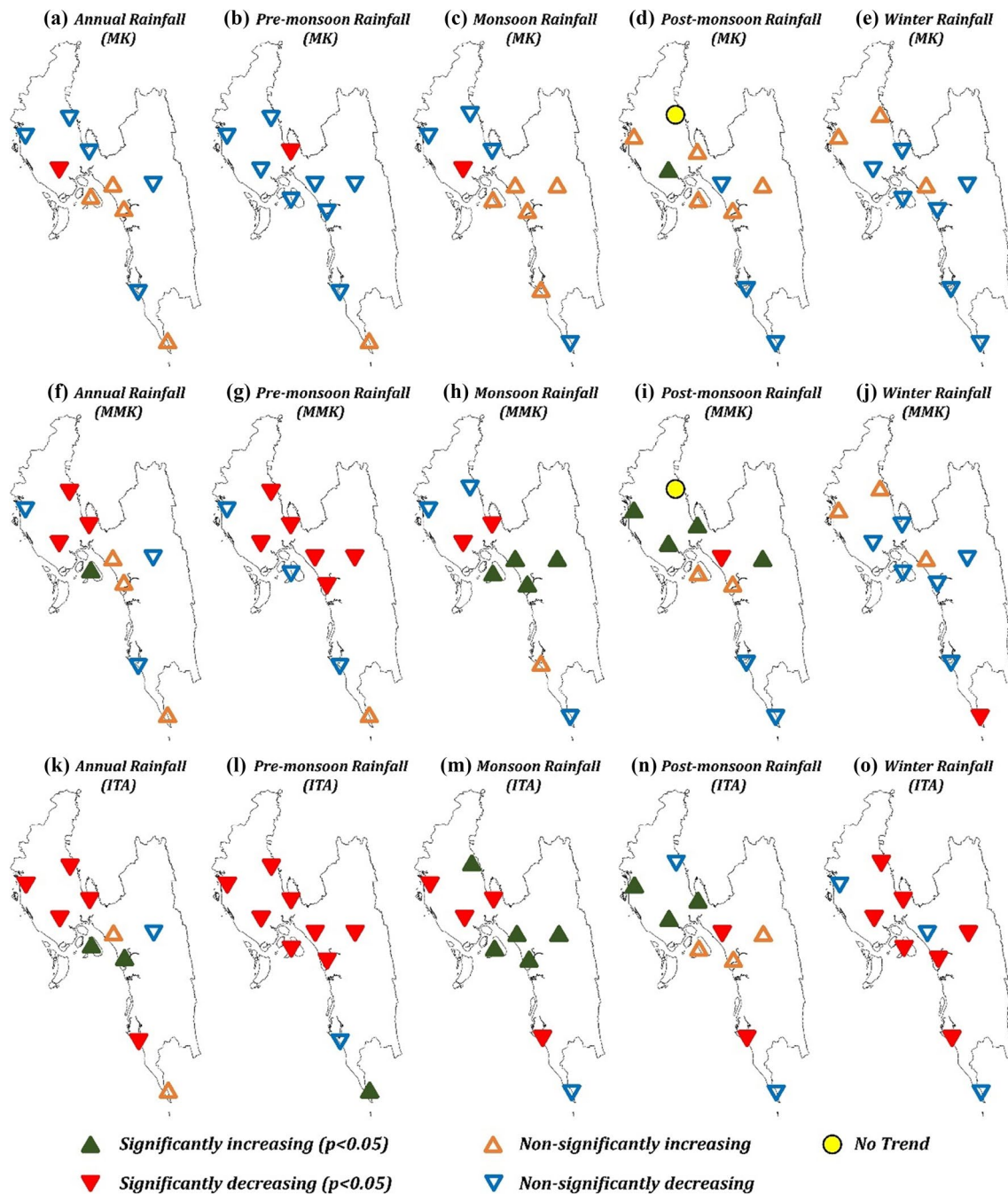


Fig. 11 Comparative distributions of rainfall trends determined by MK (a–e), MMK (f–j), and ITA (k–o) tests in the rainfall stations

about the potential influence of coastal dynamics on rainfall variability. These coastal stations may be more susceptible to climate-driven changes, such as land-sea contrasts, topographical influences, ocean circulation patterns, marine aerosol effects rise, or alterations in regional weather patterns, contributing to the observed breakpoints (Bari et al. 2016; Hoque et al. 2019). On the contrary, the homogeneous rainfall patterns in stations from the inner part of the study area indicate a relatively stable climate in

these regions during the analyzed period. Human activities, such as widespread agricultural practices and deforestation, could potentially influence changes in regional rainfall trends. The findings of the present study indicate a more pronounced decrease in the trend of annual rainfall at rainfall stations located in the northern parts of the study area compared to those in the southern parts. This variation could be attributed to differing patterns of urbanization and industrialization across the districts of

Chattogram Division (Mandal et al. 2021; Shahid et al. 2016). As exemplified by Singh et al. (2020), a substantial correlation exists between the trajectory of urbanization and the escalation of rainfall intensity in the USA. Additionally, Liu et al. (2021) observed a comparable trend, affirming that urban expansion contributes to heightened extreme rainfall events within Beijing city.

Compared to MK and MMK techniques, ITA technique is a relatively recent addition to the field of trend analysis. Previously, the ITA technique has consistently been considered a superior trend detector compared to the MK and MMK techniques in numerous environmental, hydrological, and hydrometeorological studies. This is primarily due to its extensive applicability, as it can be effectively employed regardless of the dataset's distribution assumptions, size, and serial correlation (Das et al. 2021; Güçlü et al. 2020; Seenu & Jayakumar 2021). This study corroborates similar findings, further supporting the notion that ITA is a robust and versatile trend detection method. The result suggests that the ITA technique could identify a larger number of significant trends that were missed by the MK and MMK techniques. This outcome aligns with the findings of Mallick et al. (2021) and Nisansala et al. (2020), both of whom observed a superior performance of ITA compared to the MK tests. Additionally, Caloiero et al. (2019) utilized ITA to reveal a consistent increase in rainfall trends in Calabria, Southern Italy, while Gedefaw et al. (2018) noted a rise in annual rainfall trends in Ethiopia's Amhara region, an outcome almost similar to current one. According to Malik et al. (2019), the MK test is unable to identify some hidden trends in the time series data that ITA can identify. Conforming to the above discussion, it can be concluded that the ITA is a superior method than the MK family in detecting accurate time-series trends.

The detection of rainfall trends in the study carries significant implications, both in theory and in practice, for our understanding of hydrological processes and the management of water resources. From a theoretical standpoint, the study contributed to the existing knowledge by applying the MK, MMK and ITA methods to detect and analyze trends in rainfall data. The novel approach of ITA expanded the methodology for trend analysis and provided valuable insights into the spatial and temporal variations of rainfall patterns in the southeast region of Bangladesh. The results of the study have significant practical implications specifically related to sustainable water resource management in the study region. The identified trends can inform the development of adaptive strategies for flood control, water allocation, and drought management. By utilizing the ITA method and considering the identified trends, policymakers, water managers, and other stakeholders can make informed decisions to ensure sustainable water resource management, mitigate the

impacts of hydrological extremes, and promote resilience in the face of climate change.

5 Conclusions

The study aims to analysis the long-term annual and seasonal rainfall trends spanning 42 years (1980 to 2022) across the southeast region of Bangladesh using MK, MMK, and ITA techniques on data collected from ten BMD stations. The results show that the ITA test emerged as the most appropriate and dependable trend test method, demonstrating more pronounced outcomes than the other two techniques. Among the 50 observations of annual and seasonal rainfall, the MK, MMK, and ITA tests detected alterations in 4, 22, and 38 instances, respectively, exhibiting a significant trend ($p < 0.05$) of either increase or decrease. On the other hand, a contrasting pattern in annual rainfall, with marked increases with reduced variability in the southern coastal regions and decreases in the remaining area. While moderately variable, monsoon rainfall increased in the southeastern coastal and mountainous regions but declined significantly in the central-western parts. Furthermore, pre-monsoon rainfall notably decreased within the entire study region, with a moderate decline in dry season rainfall, while post-monsoon rainfall significantly increased throughout the study period.

The outcome of this research can offer valuable insights for future development projects and aid engineers and practitioners in implementing structures designed to cope with climatic events such as floods and droughts. The heightened monsoon rainfall in the southeastern hill tract region may exacerbate the severity of monsoon floods in the southern areas of Bangladesh. Additionally, a decrease in annual rainfall in the northern regions could have significant future implications for Bangladesh, an agriculture-dependent developing nation, directly impacting agriculture, water resources, and local communities. Particular attention should be paid to regions exhibiting decreasing rainfall trends, notably the southern areas during the winter and post-monsoon seasons and the northern regions during the monsoon and pre-monsoon periods. This could include implementing water conservation measures and supporting climate-resilient alternative farming practices. To address the increasing monsoon rainfall trend in the Chattogram Division and its associated risks, comprehensive measures such as improved drainage systems, thoughtful land-use planning, and resilient infrastructure development are recommended to enhance flood resilience and minimize inundation impact.

However, this study has certain limitations. Firstly, the analysis relied heavily on the precision and reliability of the rainfall data collected from the selected weather stations

which were not homogeneously distributed across the study area. Any errors or inconsistencies in the data could have influenced the results. Secondly, this study focused solely on rainfall trends during the predefined time period and did not consider other climatic factors that could influence precipitation patterns, such as temperature, humidity, or atmospheric circulation. Future research should incorporate these variables to gain a more comprehensive understanding of the complex dynamics driving rainfall changes. Furthermore, the study did not account for localized variations in rainfall patterns, which could have occurred due to topography or other regional factors. This study focused on rainfall trends, it did not explore the underlying causes or mechanisms driving these changes, deserve further examination. Investigating the drivers of rainfall variability, such as climate change, land-use changes, or natural climate cycles, would provide a more nuanced understanding of the observed trends. Although extending the data period (1981–2022) would have enhanced the robustness of the outcomes, acquiring dependable rainfall data for Bangladesh before 1981 posed difficulties due to substantial missing values at different stations preceding 1980. Consequently, it is suggested that future studies consider incorporating satellite data in positions where real-time data is missing. This approach would provide more comprehensive insights into the historical trends and variability within the study region.

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Author Contribution **Hrithik Nath:** Conceptualization, Methodology, Investigation, Project administration, Supervision, Resources, Data preparation, Validation, Data analysis, Writing—original draft, Writing—review & editing, Visualization. **Sajal Kumar Adhikary:** Conceptualization, Supervision, Resources, Validation, Writing—original draft, Writing—review & editing, Visualization. **Srijan Nath:** Data collection, Data preparation, Validation, Writing—original draft. **Abdulla – Al Kafy:** Project administration, Data collection, Data preparation, Validation, Writing—original draft. **Abu Reza Md. Towfiqul Islam:** Supervision, Validation, Data analysis, Writing—original draft, Writing—review & editing. **Saleh Alsulamy:** Data preparation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing—review & editing, Investigation. **Khaled Mohamed Khedher:** Data preparation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing—review & editing. **Ahmed Ali A. Shohan:** Data preparation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing—review & editing. All authors have read and agreed to the published version of the manuscript.

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Data availability The data that support the findings of this study are available from the corresponding author [Hrithik Nath, hrithiknath.ce@gmail.com] upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

Competing interest The authors declare no conflict of interest.

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Authors and Affiliations

Hrithik Nath^{1,2} · Sajal Kumar Adhikary¹ · Srijan Nath³ · Abdulla - Al Kafy⁴ · Abu Reza Md. Towfiqul Islam^{5,6} · Saleh Alsulamy⁷ · Khaled Mohamed Khedher⁸ · Ahmed Ali A. Shohan⁷

✉ Hrithik Nath
hrithiknath.ce@gmail.com

Sajal Kumar Adhikary
sajal@ce.kuet.ac.bd

Srijan Nath
srijan1626@gmail.com

Abdulla - Al Kafy
abdulla-al.kafy@localpathways.org

Abu Reza Md. Towfiqul Islam
towfiq_dm@brur.ac.bd

Saleh Alsulamy
s.alsulamy@kku.edu.sa

Khaled Mohamed Khedher
kkhedher@kku.edu.sa

Ahmed Ali A. Shohan
ashohan@kku.edu.sa

¹ Department of Civil Engineering, Khulna University of Engineering & Technology (KUET), Khulna 9203, Bangladesh

² Department of Civil Engineering, University of Creative Technology Chittagong (UCTC), Chattogram 4212, Bangladesh

³ Department of Geography, Planning and Environment, Concordia University, 1455 Boul. de Maisonneuve Ouest, Montréal, QC H3G 1M8, Canada

⁴ Department of Urban & Regional Planning, Rajshahi University of Engineering & Technology (RUET), Rajshahi 6204, Bangladesh

⁵ Department of Disaster Management, Begum Rokeya University, Rangpur, Bangladesh

⁶ Department of Development Studies, Daffodil International University, Dhaka 1216, Bangladesh

⁷ Department of Architecture & Planning, College of Engineering, King Khalid University, 61421 Abha, Saudi Arabia

⁸ Department of Civil Engineering, College of Engineering, King Khalid University, 61421 Abha, Saudi Arabia