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Innovative trend analysis technique with fuzzy logic and K-means clustering approach for identification of homogenous rainfall region: A long-term rainfall data analysis over Bangladesh

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ABSTRACT

Understanding regional climatic trends is crucial for taking appropriate actions to mitigate the impacts of climate change and managing water resources effectively. This study aims to investigate the dissimilarities and similarities among various climate stations in Bangladesh from 1981 to 2021. Fuzzy C-means (FCM) and K-means clustering techniques were employed to identify regions with comparable rainfall patterns. Moreover, the innovative trend analysis (ITA) and the Mann-Kendall (MK) test family were utilized to analyze rainfall trends. The results indicate that both K-means and FCM methods successfully detected two rainfall regions in Bangladesh with distinct patterns. The ITA curve analysis revealed that out of the 29 stations, 13 had a non-monotonic increasing trend having no monotonic increasing trend, 8 had a non-monotonic decreasing trend, and 8 exhibited a monotonic decreasing trend. Additionally, the MK tests employed in the study showed predominantly negative trends across Bangladesh. The majority of stations (65.51%) fell into Cluster 1, while the remaining 34.48% were in Cluster 2. In terms of ITA analysis, 17.24% of stations exhibited a monotonic decrease, while there were no stations with a monotonic increase. However, 37.93% of stations showed a non-monotonic increase, and 44.83% displayed a non-monotonic decrease. These identified regions can provide valuable insights for water resource management, disaster risk reduction, and agricultural planning. Moreover, detailed rainfall analysis can help policymakers and scientists develop sustainable and effective regional-scale policies for managing the country's flood and drought situations, ultimately supporting agricultural development and environmental planning.

1. Introduction

The rapid process of urbanization in the past few decades has had a substantial influence on climatic patterns at both local and regional scales worldwide. Research has demonstrated that urban areas have an impact on precipitation, cloud cover, temperature at the surface, and the balance of energy at the surface. This results in modifications to the urban heat island effect and the radiance of the surface (Carbone et al., 2024; Chen et al., 2024). The climatic pattern and atmospheric circulation are both influenced by a variety of factors, including the atmosphere, biosphere, hydrosphere, land surface, and urbanization (Pielke et al., 2002). Over the past couple of decades, people have done a lot to change the way the world's climate functions. For example, the surge in energy consumption in industrial facilities and motor vehicles has undeniably led to a rise in the release of detrimental gases, specifically carbon dioxide (CO2), which plays a substantial role in intensifying the global greenhouse effect (Hu et al., 2021). Among various human behaviors, urbanization has had the most significant influence in modifying the global climatic pattern during the previous century, which has largely caused the harmful impact of climate change (Bazrkar

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et al., 2015; Chapman et al., 2017; Solecki et al., 2019). One of the most prominent effects of urbanization on climate patterns is an increase in temperature in major cities, known as the urban heat island (UHI) phenomenon (Murphy et al., 2011). Even though the effect of urban growth on temperature patterns is well known, less is known about how it affects rainfall patterns (Liu and Niyogi, 2019). Rainfall attributes such as distribution, amplitude, extremity, seasonality, and concentration pattern were affected by global climate change but varied with temporal and regional variability (Feng et al., 2013; Trenberth et al., 2015). Rainfall is not only the most important factor in hydrology and meteorology but also in the biotic environment. It has a major effect on the amount of food that can be grown than any other climate factor (Rahman et al., 2017). However, the way climate changes from a regional to a local scale affects the overall patterns of rainfall in the spatial-temporal dimension, and the effects are stronger in places that are different from each other geographically (Hamilton et al., 2001). Bangladesh is located in Southeast Asia (20°38′29″ to 26°38′4″ N latitude, and 88°0′38″ to 92°37′39″ E longitude) and experiences tropical monsoons; as a result, its economy is especially vulnerable to the effects of climate change (Kumar, 2007). This country's economy is heavily based on agriculture, and about 80% of its people depend directly or indirectly on primary economic activity (Kamruzzaman et al., 2018). Bangladesh gets the most rain during the monsoon and the least during the rest of the year. This means that there isn't enough water, which could lead to severe drought (Das et al., 2021a). However, the effects of urbanization and the corresponding LU/LC change also have a substantial impact on other aspects of the climate, including sunshine, cloud conditions, relative humidity, and precipitation (RAO et al., 2004).

Rainfall analysis influences water resource management, agricultural production, food security, and people's livelihoods. In hydrometeorological time series data, figuring out the trend is the most important thing. Several studies (Adarsh and Janga Reddy, 2015; Fathian et al., 2016; Kisi, 2015) have examined global rainfall trends. (Amiri et al., 2019) applied fuzzy regression method to estimate reference evapotranspiration under controlled environments, demonstrating the applicability of fuzzy logic techniques in hydrology. Some studies have also used parametric (i.e., linear regression) and non-parametric (i.e., Mann–Kendal (MK)/modified Mann–Kendal (mMK) tests to find trends in annual and seasonal rainfall in Bangladesh. For instance, Alam (2013) & Quadir (2015), explored the considerable rising trend in rainfall, whereas Basher et al., (2018) & Rahman et al., (2018) investigated the dropping trend in rainfall. On the alternative side, several studies found that the up or down trend in annual rainfall was not crucial (Das et al., 2021a; Rahman et al., 2015). Climate stations in Bangladesh may be divided into two major groups based on cluster analysis. In most situations, one cluster is situated in the northern part of the nation and includes drought-prone and susceptible regions, whilst the second cluster is typically found in the southern half and includes rain-prone and hilly regions (Mahmud et al., 2022). However, a developing country like Bangladesh doesn't have a good idea of how to evaluate important rainfall features like precipitation concentration, seasonality index, and trend. These features are very important for figuring out water resources, agriculture, and precipitation extreme events (Chatterjee et al., 2016; Huang et al., 2018a).

Even though the scientific community is interested in understanding how rainfall changes in different areas of the world, it is hard to do a quantitative analysis of rainfall patterns because the locations of weather stations (rain gauges) are not all the same (Qian et al., 2022; Rana et al., 2012). To deal with these problems, scientists all over the world have used different ways to study the trend and pattern of rainfall in localities. Chang et al., (2013) significantly used the clustering method, the Pettitt test, and the L-moment statistics to look at how changes in urbanization affect rain. In the same way, Mzava et al., (2020) looked at the trend and frequency of extreme rainfall events by using the MK test, Sen's slope, the generalized pareto model (GPM), and the regional climate model (RCM). The researchers also used advanced trend analysis methods like the innovative trend analysis (ITA), the mMK test, the MMK-Yue (MMKY) test, and the pre-whitening MK (PWMK) test to look at the trend of rainfall in different urban areas in the world (Mallick et al., 2021a; Oliveira-Júnior et al., 2022; Perera et al., 2020). A notable limitation of this study is that the dataset utilized for the study includes monthly rainfall data from 29 rain-gauge stations in Bangladesh among 35 stations from 1981 to 2021. While attempts were made to collect data from 35 meteorological stations, several stations were recently established, resulting in data gaps. Few missing data was present in the selected dataset besides, the study only focuses on rainfall data analysis and does not consider other climatic factors that could affect water resources and agricultural planning. However, the current study aims to investigate the trend and pattern of rainfall over Bangladesh by combining a rainfall regionalization technique with the ITA and a set of MK tests. As well as the rainfall station cluster will be defined using two different cluster methods. So, the novelty of this research lies in the fact that there has not been a significant previous study conducted in Bangladesh to investigate the regionalization of the rainfall pattern using the ITA and a series of MK tests using the most recent rainfall data. An analysis of rainfall patterns like this study in Bangladesh may help in the mitigation of water logging and hydrological and climatic dangers, such as flooding as well as drainage pattern designing and water resource planning over the country and mitigating the problem of drought.

2. Materials and method

Bangladesh Meteorological Department (BMD, www.bmd.gov.bd) provided the monthly rainfall data of 29 rain-gauge stations for the period 1981–2021, which was used in the study. Although there are 35 stations in Bangladesh, some of them were established within recent decades. As a result, the data series of some rain gauge stations contain a gap. Due to the station gap, 29 stations' data have been collected to prevent any errors that may have occurred. Fig. 1 illustrates the locations of Bangladesh meteorological stations that are utilized for this research.

2.1. Study area

Bangladesh is one of the most susceptible countries to climate change due to its geographical location and geomorphological conditions. Bangladesh is located in Southeast Asia, between the countries of India and Myanmar. Its geographical coordinates are 20°38′29″ to 26°38′4″ N latitude, and 88°0′38″ to 92°37′39″ E longitude. The total landmass of Bangladesh is calculated to be 147,630 km^2 (Bangladesh Bureau of Statistics, 2011). Bangladesh has an Asian tropical monsoon climate, which is characterized by heavy monsoon rain, high humidity, and mild temperatures. Bangladesh is made up of a long, flat deltaic plain that is often flooded and a small hilly area in the southeast. Bangladesh's climate is affected by its location, the difference in pressure between the north and south of the continent, changes in solar albedo caused by how the land is used, changes in land and sea surface temperatures, and other factors (Rahman et al., 2015). Bangladesh has four distinct seasons, including winter, pre-monsoon, monsoon, and post-monsoon, and experiences tropical and subtropical monsoonal climates in different regions. Hasan et al., (2019) identified seven climatic subzones for Bangladesh namely South-eastern (Chittagong and coastal strip from southwest Sundarbans to south of Comilla), south-western (Jessore, Khulna, and Satkhira), northern portion of the northern region (Rangpur), North-eastern (Greater Sylhet), north-western (Ishurdi, Dinajpur, and Bogra), western (Rajshahi and adjacent district), and south-central (Comilla, Chadpur, Mymensingh, Faridpur, and Dhaka). Climate-wise, the majority of the country is humid to sub-humid with irregular spatiotemporal variability. Due to its location in the tropical monsoon zone, Bangladesh's climate is characterized by relatively mild temperatures, considerable humidity, and distinct seasonal fluctuations in

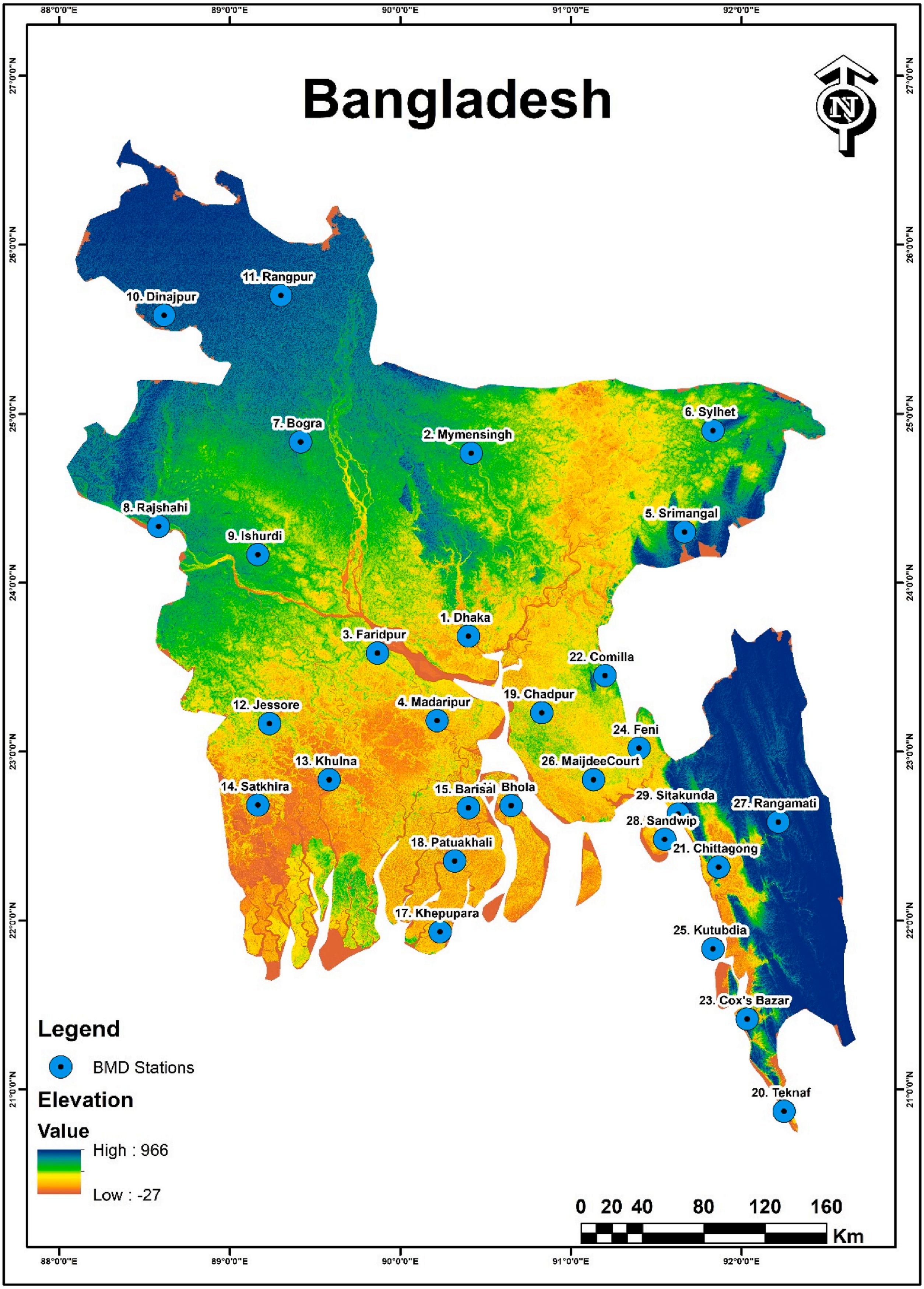

Fig. 1. Study Area Map (Location of BMD Station in Bangladesh).

rainfall. The monsoon season accounts for more than 80% of the normal annual rainfall in the country, and the overall annual average rainfall is approximately 2428 mm (Islam et al., 2018). During the monsoon season (July to September), Bangladesh was hit by a series of monsoon depressions that originated in the Bay of Bengal (BoB) and moved in a manner from south to north. According to the BMD, the average temperature for the year is 25.7 °C, with the greatest temperature being recorded in August at 31 °C and the lowest temperature being recorded in January at 5.2 °C. The effects of climate change and natural disasters are likely to be felt in Bangladesh. Already, the unfavorable effects of extreme weather have been felt in the nation with increasing severity as they continue to spread. It was noted that floods in 1988, 1998, 2004, and 2007 were particularly devastating, while cyclones in 1991, 1998, 2000, 2004, and 2007 caused a disproportionately high number of deaths and property losses (Mallick, 2008).

2.2. Data collection and processing

The dataset utilized in this study was sourced from the BMD and spans a four-decade period from 1981 to 2020. The comprehensive 40-year dataset was meticulously organized into the required format to facilitate systematic analysis. As a crucial step in ensuring data quality, outlier detection and correction were performed. Boxplot is employed for managing outliers and extreme values within the rainfall data. A specific R package, named "VIM," utilized the K-nearest neighbors (KNN) machine learning method to address missing data points. This approach leverages the proximity of data points to impute missing values and correct anomalies, enhancing the overall reliability and coherence of the dataset. The careful curation and preprocessing of the data using advanced techniques contribute to the robustness of the subsequent statistical analyses, providing a solid foundation for meaningful insights into the long-term rainfall patterns across the studied meteorological stations in Bangladesh.

2.3. Statistical data analysis

This research attempts a thorough statistical analysis of rainfall data obtained from 29 meteorological stations. The meteorological data collected and subsequently, various descriptive statistics were computed for each station, including the minimum and maximum rainfall values, offering insights into the extremities of observed precipitation. The range, depicting the spread between the minimum and maximum values, was also determined, indicating the overall variability. Moving beyond, central tendency measures, such as the mean, were calculated to identify the average rainfall at each station, while the standard deviation was employed to gauge the extent of data dispersion around the mean, offering insights into the consistency or volatility of precipitation patterns. Additionally, the coefficient of variation was computed, expressing relative variability as a percentage, facilitating meaningful inter-station comparisons. This multifaceted methodology ensures a comprehensive understanding of the diverse rainfall patterns across the 29 stations, crucial for informing decision-making in sectors dependent on precipitation data.

2.4. Methodology for identifying homogenous rainfall regions

2.4.1. Fuzzy C-means clustering approach

The Fuzzy C-means (FCM) clustering technique is an unsupervised learning approach. Fuzzy clustering is considered as a soft clustering, in which each element has a probability of belonging to each cluster. In other words, each element has a set of membership coefficients that represent the degree to which it belongs to a certain cluster. Points towards the center of a cluster are more likely to be in the cluster than points around the cluster's perimeter. The likelihood of one data point belonging to a cluster can be any number between 0 and 1, such as 75%, for which the cluster border can be represented as a fuzzy boundary. Dunn (1973) created the FCM clustering method to find similarities in the spatial pattern of hydro-meteorological data whereas Bezdek (Bezdek et al., 1984) made it even better. The fuzzy clustering technique identifies related datasets by utilizing the membership function of each dataset and establishing the association between datasets (Samaras et al., 2001). The fuzzy matrix represents the fuzzy relationship between datasets. Samaras et al., (2001) discusses the creation of the membership function and fuzzy matrix. For this study, the rainfall clustering done with FCM was performed using the Euclidian distance criterion (EDC), which does not involve any linear associations. The goal function was intended to be minimized by the EDC, as shown in Equation 1.

$$J\,(U,C) = \sum\nolimits_{J=1}^{M}\sum\nolimits_{i=1}^{c} u_{ik}^{a} \parallel Y_k - C_i \parallel^2 \tag{1}$$

where u_{ik} is the value of the kth data point's relationship to cluster i, $\parallel Y_k - C_i \parallel^2$ is the square of the Euclidean distance between the k data vector and the center of cluster i, C_i is the center of cluster i, and is the fuzzifier value that can be greater than 1.

With the FCM method, the homogeneity analysis is done in three steps. In the first step, the number of clusters and the number of data vectors at the center of each cluster are thought to be random. In the second step, Eq. (2) is used to build the membership matrix.

$$u_{i<k}^{t+1} = \left[\sum\nolimits_{j=1}^{c}\left[\frac{\parallel y_k - c_i \parallel}{\parallel y_k - c_i \parallel}\right]^{\frac{2}{a-1}}\right]^{-1} \tag{2}$$

Where $I = 1, 2, 3, \ldots$ c and $k = 1, 2, 3, \ldots\ldots$M. In the third step, the revised membership value and Eq. (1) are used to compute the cluster center using Eq. (3) as described by (Goyal and Gupta, 2014).

$$C_i = \frac{\sum_{k=1}^{M} u_{ik}^{a} y_k}{\sum_{k=1}^{M} u_{ik}^{a}} \tag{3}$$

Cluster count, fuzzifier value, c, and terminating criterion all influence the output of FCM. To accomplish reliable clustering, the parameters must be chosen with care.

2.4.2. K-means clustering approach

The number of clusters (k) in the K-means clustering approach is typically determined using methods such as the Elbow method, the Silhouette method, or the Gap statistic. In this study, the Elbow method was utilized, which involves plotting the within-cluster sum of squares (WCSS) against the number of clusters and identifying the point where the WCSS begins to level off, indicating the optimal number of clusters. This approach ensures that the chosen k value balances between minimizing the number of clusters and maximizing the cohesion within each cluster.In K-means clustering, the data is divided into distinct clusters, where each element is affected exactly by one cluster. This type of clustering is also known as hard clustering or non-fuzzy clustering. The unsupervised K-means clustering method is used to solve problems with many variables. In this method, the dataset is broken up into a group of k integers (Mallick et al., 2021b). Using Eq. (4), the k-means method is used to try to get the goal function to be smaller.

$$j = \sum\nolimits_{j=1}^{k}\sum\nolimits_{i=1}^{M} \parallel Y_i^{(j)} - C_j \parallel^2 \tag{4}$$

Here, $\parallel Y_i^{(j)} - C_j \parallel^2$ stands for the square of the Euclidean distance between point i and cluster j. In the K-means clustering technique, the data is put into *k clusters* with *k-arbitrary* centers. The separation of each centroid is followed by the calculation of the distance between the data point and the *k-center*. Finally, each point is assigned to the cluster that has the shortest distance between the data point and the *k-center*. In addition, a new cluster center is generated for each cluster using equation. (5).

$$Z_j = \frac{1}{n}\left(\sum\nolimits_{\forall Y_p \epsilon C_j} Y_p\right) \tag{5}$$

where n represents the total number of members in cluster j.

After that, the data points are distributed to the next centroid cluster in proximity, and the procedure is carried on until there is no discernible shift.

2.4.3. Validation of the clustering models

In this study, the silhouette width (SW) measure was used to figure out how many clusters were made and how good they were. The equation was used to figure it out. 6 put forward by Rousseeuw (1987).

$$S(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{6}$$

where $a(i)$ is the average difference between the data point i and the other data points in the cluster and $b(i)$ is the minimum difference between the data point i and all the other clusters where it doesn't belong. The cluster with the lowest average variation is the one closest to data point i.

2.5. Trend analysis

2.5.1. Innovative trend analysis

A lot of people have used ITA to find trends in hydro-meteorological data series (Ahmed et al., 2022; Wu and Qian, 2017). The ITA graph is used to identify monotonic and sub-trends in time series data. On the other hand, it is utilized to identify various combinations of trends across time. The meteorological data series (j) is divided into two sub-series in ITA, which are then reorganized in an ascending sequence and plotted against each other in a coordinate system based on Cartesian geometry, with the first half drawn on the x-axis and the second half drawn on the y-axis. A straight line is then drawn through the scatter plot to examine if there is a consistent pattern. If the scatter point concentration exceeds the 45° line (1:1), the length of the time series indicates that the trend is upward. If it is less than the line with a 1:1 ratio, the time series indicates that the trend is downward. Furthermore, the fact that the majority of the scattered points are clustered around the trend line indicates that the information set has no trend (Şen, 2012). The upper triangle represents an increasing trend, while the lower one indicates a decreasing trend. For the estimation of the trend, the S_{ITA} statistic is computed as follows

$$S_{ITA} = \frac{2(\overline{X_i} - \overline{X_j})}{n} \tag{7}$$

where S_{ITA} is the slope based on the ITA method, n is the sample size, X_i and X_j are the mean values of the first and second half of the series, respectively. The null hypothesis (H_0) of no significant trend cannot be rejected if the calculated slope value, s, remains below a critical value, S_{ITA}. While the alternative hypothesis (Ha) of the presence of a significant trend in time series is applicable if s > S_{ITA}. Additionally, the probability distribution function (PDF) is utilized to assess the significance of ITA. If the confidence interval of a standard PDF has a mean of zero and the standard deviation (σ_s) of the ITA slope is at α significance level, then Eq. (8) tells us what the confidence limit (CL) of the trend is.

$$CL_{(1-\alpha)} = 0 \pm S_{1TA}\delta_S \tag{8}$$

In this paper, the null hypothesis of no trend against the alternate hypothesis that there is a trend in the rainfall time series was tested at three different significance levels (α), i.e., α = 10%, α = 5% and α = 1%. The ITA was performed using the "trendchange" package in Rstudio with the help of MS Excel Software.

2.5.2. Mann–Kendall (MK) test

The MK test is a method that is widely utilized in the process of analyzing the trend of information about hydrology and meteorology (AlSubih et al., 2021; Towfiqul Islam et al., 2020). This test is a rank-based non-parametric test for determining whether or not a significant pattern exists in time series data (Bevan and Kendall, 1971; Mann, 1945). MK Test relies on several key assumptions: the data points are independent, the statistical properties of the data remain constant over time (stationarity), and the measurements accurately reflect the true conditions being studied without systematic biases. In this study, the MK test was used to the data to analyze the pattern of rainfall using equation (8).

$$S = \sum\nolimits_{i=1}^{n-1}\sum\nolimits_{j=i+1}^{n} sgn\left(y_j - y_i\right) \tag{9}$$

where n represents the total number of observations and Y_i and Y_j indicate the relative position of observations i and j in the list of observations. In the studies Praveen et al., (2020), the specifics of the MK test are broken down and discussed.

2.5.3. Modified Mann–Kendall-Yue (MMKY) test

To address Type II errors (i.e., rejection of a trend where one exists), Yue and Wang, (2004) suggested using the original data, not the rankings of sample data, to eliminate an existing trend before estimating the auto-correlation coefficients. Besides, came up with a new correction factor, which can be written as Eq. (10), to solve the problem of autocorrelation.

$$CF = 1 + 2\sum\nolimits_{n=k}^{n-1}\left(1 - \frac{k}{n}\right)r_k \tag{10}$$

where r_k is the *lag-k* coefficient of the data's serial correlation and n is the number of data points in the series. Yue and Wang (2004) came up with a better MK test, which can be shown in Eq. (11).

$$V^{*}S = V(S) \times \left\{1 + 2\sum\nolimits_{k=1}^{n-1}\left(1 - \frac{k}{n}\right)r_k\right\} \tag{11}$$

2.5.4. Modified Mann–Kendall (MMKH) test

A mMK test, also known as an MMKH test, was created by (Hamed and Ramachandra Rao, 1998) to solve the problem of serial autocorrelation in time series datasets. In this study, the MMKH test was used to look at the pattern of rainfall in Bangladesh. This was done to deal with the issue of autocorrelation by using the variance correction strategy, as shown in Eq. (12).

$$V^{*}(S) = V(S) \times \frac{n}{n^{*}} \tag{12}$$

where $\frac{n}{n^*}$ indicates the correction factor and $V(S)$ is determined by using the MK test's initial equation (Eq. (9)). Towfiqul Islam et al., (2020) study followed MMKH test for many aspects.

2.5.5. Pre-whitening Mann–Kendall (PWMK) test

Pre-whitening is applied in replacement of the correction factor to reduce serial correlation within a dataset. Pre-whitening is intended to reduce the possibility that the MK test will identify statistically significant trends (Yue et al., 2003). In this research, the autocorrelation across ranks of the observations ρk was looked at after Sen's median slope, and other estimates of non-parametric trends were taken out of the data. Because the variance of s is incorrectly estimated for directly auto-correlated datasets, Only significant ρk values were used in estimating the adjustment factor of variance n/n*s (Eq. (13)).

$$\frac{n}{n^{*}} = 1 + \frac{2}{n(n-1)(n-2)} \times \sum\nolimits_{k=1}^{n-1}(n-k)(n-k-1)(n-k-2)\rho k \tag{13}$$

where n is the total number of annotations, n^*s is the effective number of observations to account for auto-correlation in the dataset, and ρk is the auto-correlation function for the rankings of observations. Furthermore, the correction factor is determined according to Equation (14).

$$V^*(S) = V(S) \times \frac{n}{n_s^*} \tag{14}$$

where *V(S)* represents the results of the MK test that was computed in Equation (8).

2.5.6. Trend-free pre-whitening Mann–Kendall (TFPW-MK) test

The TFPW-MK test of a dataset is calculated as $X_{y_t} = y_1, y_2, y_3, \ldots. \ldots. \ldots. \ldots y_n$, followed by a series of stages. In the first phase, Sen's slope estimator is determined, and then the monotonic trend is eliminated for the development of a trend-free series z_t. The subsequent step involved calculating the *lag-1* serial correlation coefficient ($\rho 1$) of the z_t series, as described in (Anderson, 1942). If $\rho 1$ is not significant, the analysis of the trend is performed on the z_t series. If $\rho 1$ is significant, the pre-whitening is performed on the z_t series, and then the residual series (z_t') is determined using Equation (15).

$$z_t' = z_t - p_1 z_1 - 1 \tag{15}$$

In the end, the TFPW-MK test (Y_t^*) is determined by adding the monotonic trend component to the z_t' series and calculating the difference (Eq. (16)).

$$Y_t^* = z_t' + \beta_t \tag{16}$$

2.5.7. Sen's slope estimator

Sen's non-parametric estimator method has been used for predicting the magnitude (true slope) of hydro-metrological time series data (Shahid, 2010b). Sen's slope estimator method uses a linear model for the trend analysis. The slope Q can be obtained from N pairs of data as:

$$Q_i = \frac{x_k - x_j}{k - j}, i = 1, 2, 3, \ldots\ldots\ldots N, k \neq j\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \tag{17}$$

Where x_k *and* x_j represents values of data at k and j times, and Q_i is the median slope respectively. A positive value of Q_i indicate an increasing (upward) trend while the negative value represents the downward or decreasing trend of time series data. In this study, the Mann – Kendall test along with Sen's slope estimator is carried out using R programming.

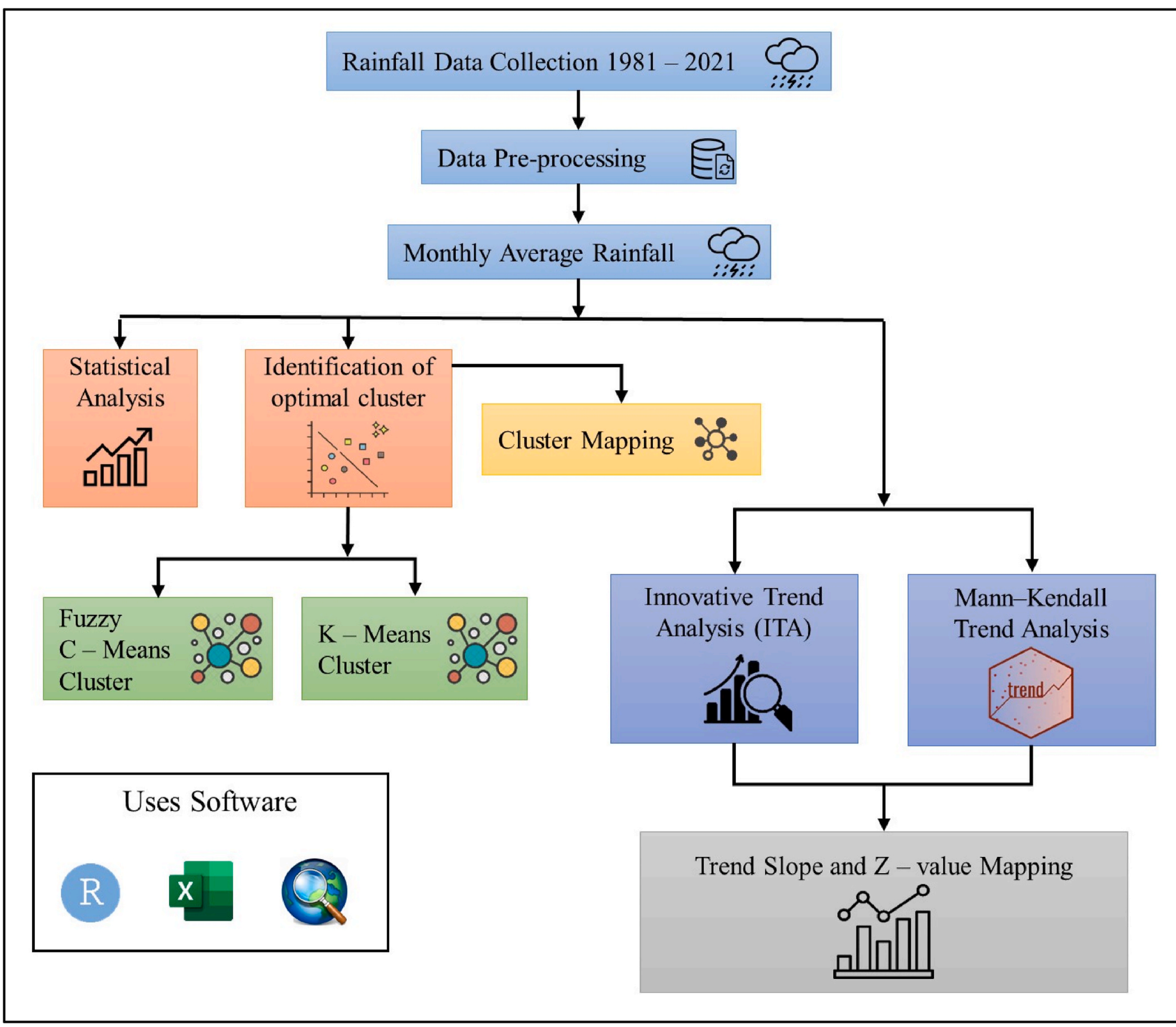

Fig. 2. Flowchart illustrating the step-by-step methodology used in this study.

2.5.8. Interpolation

The interpolation of rainfall data has been accomplished using a variety of techniques, including Kriging, Thiessen polygon, inverse distance weighting (IDW), and ANUDEM, amongst others (Mallick et al., 2022; Praveen et al., 2020). For this study, the IDW approach was utilized for the interpolation of rainfall data using version 10.8 of the ArcGIS software. The IDW is a simple and flexible interpolation technique that may be used for the study of the geographical pattern of hydrological and climatic information. Also, the IDW can be used for the analysis of the spatial pattern of other datasets, such as those dealing with weather (Rahman and Islam, 2019). The methodological outlined in Fig. 2 is employed to complete this study.

3. Results

3.1. Analysis of the descriptive statistics of rainfall

The rainfall statistics from 29 distinct meteorological stations in Bangladesh are displayed in Table 1. The minimum and maximum amounts of precipitation in millimeters (mm), the range (the difference between the minimum and maximum values), the median (the middle value among the sorted data), the mean (the average of all the data), the standard deviation (a measure of how dispersed the data is), and the coefficient of variation (a measure of how much variation there is in the data relative to the mean) are all included in the data.

The minimum rainfall recorded in all stations was 0 mm, indicating no rainfall in a certain period. The maximum rainfall recorded was 3001 mm in Sandwip station. The maximum range of rainfall varied from 664 mm in Ishurdi to 3001 mm in Sandwip, indicating a wide variation of rainfall among the stations. The median rainfall for all stations ranged from 75 mm in Rajshahi and Dinajpur to 248 mm in Sylhet. The median rainfall value for most stations is close to the 3rd quartile, meaning the rainfall data is not skewed.

The mean rainfall varied from 118.48 mm in Rajshahi to 345.78 mm in Teknaf. The standard deviation varied from 132.92 mm in Rajshahi to 448.52 mm in Teknaf. The coefficient of variation was generally around 1, indicating that the data has relatively low variability around the mean. However, there were a few stations that had higher variability, such as Teknaf, Kutubdia, and Sandwip, which had a coefficient of variations of 1.3, 1.27, and 1.23, respectively.

In summary, the rainfall data of the 29 meteorological stations in Bangladesh shows a wide range of rainfall, with some stations receiving much more rainfall than others. The majority of the stations have a relatively low variability around the mean, but some stations have higher variability. The data can be used to analyze rainfall patterns in different regions of Bangladesh and to inform decision-making for agriculture, water resource management, and disaster preparedness.

3.2. Analysis of homogenous rainfall regions

3.2.1. Identification of cluster number and validation of cluster

A method of data analysis known as cluster analysis looks at the naturally occurring groups within a data collection known as clusters. Cluster analysis is an unsupervised learning technique since it doesn't need to categorize data points into any predetermined categories. In Fig. 3 A set of five k-means clusters on a two-dimensional feature space. The clusters are labeled k = 2, k = 3, k = 4, k = 5, and in. The text in the figure indicates the percentage of variance explained by each dimension like 79% of the variance in dimension Dim1 and 4% of the variance in dimension Dim2. The different clusters in the figure represent different groups of data points, and the text in the figure indicates how much of the variance in each dimension is explained by each cluster. This information can be used to understand the different groups of data points and to make inferences about the data.

Example of a homogeneous region defined based on criteria such as similarity in annual and seasonal rainfall patterns, geographic proximity, and clustering results from the FCM and K-means algorithms, ensuring regions have statistically similar rainfall characteristics.

In Pattern Analysis, clustering is a key method for locating unique groups in data. In this work, two methods gap statistics and average SW

Table 1
Descriptive statistics of the rainfall variability in Bangladesh.

Meteorological stations	Rainfall (mm)						
	min	max	range	median	mean	std.dev	coef.var
Dhaka	0	839	839	136.5	169.64	173.09	1.02
Mymensingh	0	865	865	117	186.52	200.18	1.07
Faridpur	0	1005	1005	110.5	149.09	158.84	1.07
Madaripur	0	873	873	104	161.39	173.65	1.08
Srimangal	0	1116	1116	166.5	204.06	205.95	1.01
Sylhet	0	1394	1394	248	339.19	337.92	1
Bogra	0	756	756	84	141.19	161.69	1.15
Rajshahi	0	763	763	75	118.48	132.92	1.12
Ishurdi	0	664	664	79.5	124.39	135.42	1.09
Dinajpur	0	1196	1196	75.5	162.64	197.86	1.22
Rangpur	0	832	832	110	183.67	202.89	1.1
Jessore	0	917	917	93	138.84	151.44	1.09
Khulna	0	922	922	102	151.75	163.82	1.08
Satkhira	0	688	688	98	143.11	149.35	1.04
Barisal	0	1067	1067	107.5	171.12	183.76	1.07
Bhola	0	993	993	124	185.3	197.72	1.07
Khepupara	0	1092	1092	120.5	231.24	262.2	1.13
Patuakhali	0	1084	1084	132.5	214.96	244.61	1.14
Chadpur	0	1351	1351	124	180.51	200.74	1.11
Teknaf	0	2072	2072	105.5	345.78	448.52	1.3
Chittagong	0	1586	1586	124	256.55	319.52	1.25
Comilla	0	892	892	124.5	172.99	179.01	1.03
Cox'sbazar	0	1885	1885	137	307.19	375.19	1.22
Feni	0	1292	1292	152.5	243.71	268.95	1.1
Kutubdia	0	1805	1805	119	266.21	337.53	1.27
MaijdeeCourt	0	1512	1512	154	257.52	286.18	1.11
Rangamati	0	1189	1189	139	212.23	237.89	1.12
Sandwip	0	3001	3001	162	302.19	370.87	1.23
Sitakunda	0	1472	1472	168.5	271.77	313.15	1.15

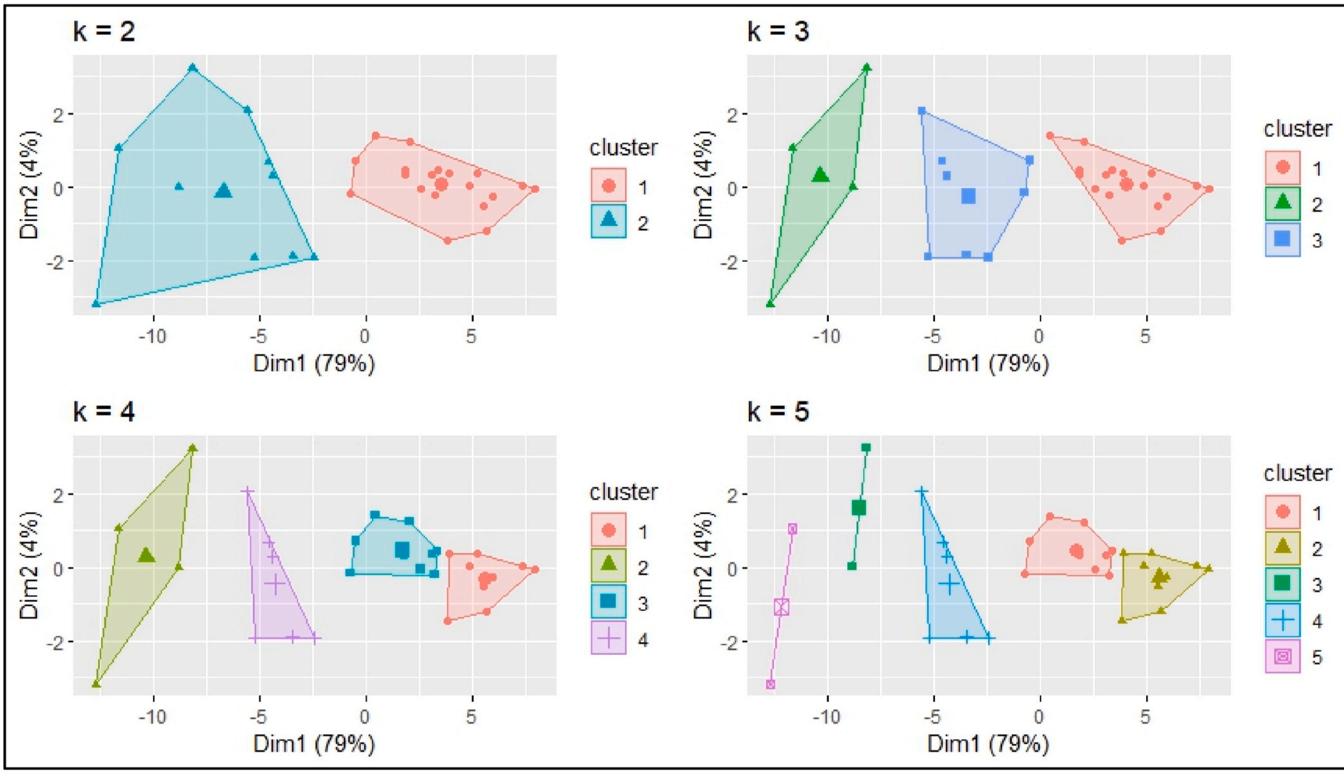

Fig. 3. Cluster scenario with labeled k = 2, k = 3, k = 4, and k = 5.

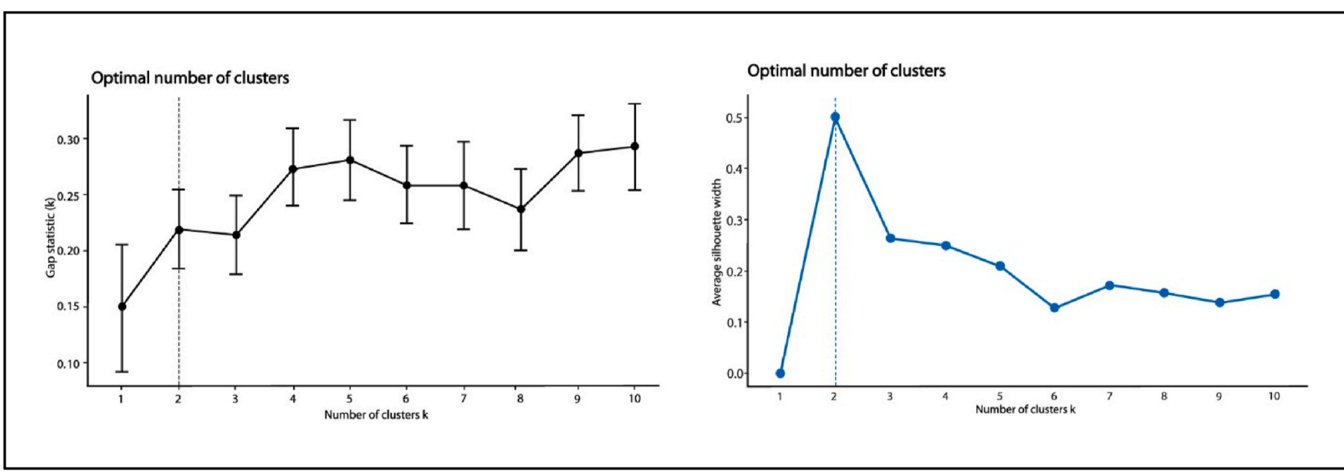

Fig. 4. Finding the optimal number of rainfall clusters in Bangladesh.

were devised, and both of them suggested two clusters for the dataset under review (see Fig. 4).

The average SW was calculated using several clusters ranging from 1 to 10 to select the right number of clusters using the k-means clustering technique represented in Fig. 5. The silhouette value spans from −1 to +1, with a high value signifying a strong match of the object to its cluster and a weaker match to neighboring clusters. A clustering is classified as "strong" if it maintains an average SW exceeding 0.7, deemed "reasonable" if surpassing 0.5, and categorized as "weak" if exceeding 0.25. Cluster 2 had the highest SW value in this experiment, which was 0.73, with a range from −0.25 to 0.73. Cluster 1, on the other hand, had a value that was virtually the absolute minimum. It is permissible to take into account any number of clusters when examining the homogeneity of rainfall in Bangladesh since all clusters aside from the cluster had an average SW that was larger than zero.

However, it is best to consider two clusters because they have the maximum average width, according to the investigation. The silhouette plot above and the average silhouette coefficient help to determine the clustering is good as a large majority of the silhouette coefficients are positive, which indicates that the observations are placed in the correct group. This suggests that the k-means and Fuzzy clustering approach can effectively cluster the rainfall data in Bangladesh, and by utilizing the optimum number of clusters, A better understanding of the region's rainfall homogeneity is possible.

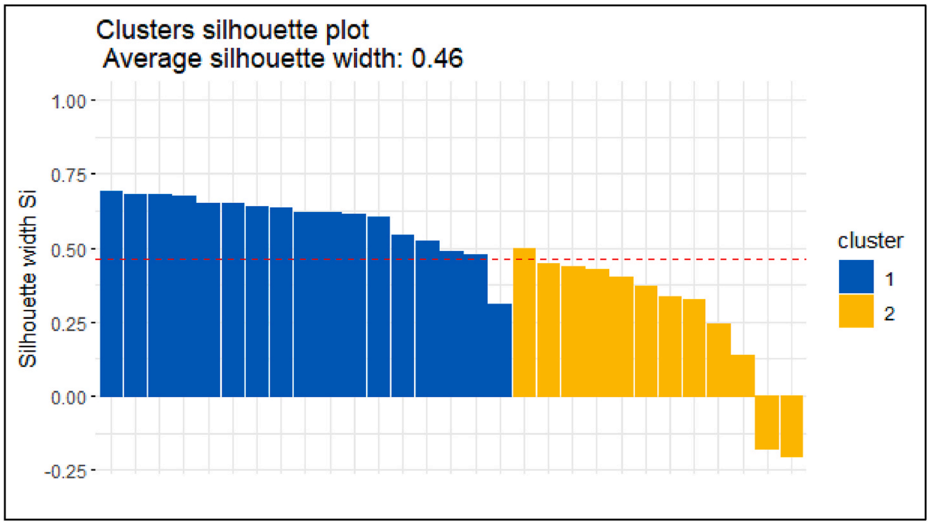

Fig. 5. Validation of homogeneous rainfall regions by using silhouette width (SW).

3.2.2. *Application of K-means clustering*

The k-means clustering technique was used to create two clusters based on the characteristics of rainfall patterns in the data series. Cluster 1 acquired nineteen meteorological stations, including Dhaka, Mymensingh, Faridpur, Madaripur, Srimangal, Bogra, Rajshahi, Ishurdi, Dinajpur, Rangpur, Jessore, Khulna, Satkhira, Barisal, Bhola, Patuakhali, Chadpur, Comilla, and Sitakunda. On the other hand, Cluster-2 acquired ten meteorological stations, such as Sylhet, Khepupara, Teknaf, Chittagong, Cox'sbazar, Feni, Kutubdia, MaijdeeCourt, Rangamati, and Sandwip (see in Fig. 6). The average SW for Cluster 1 and Cluster 2, is 0.46. This indicates that the nineteen meteorological stations in Cluster 1 have similar rainfall patterns, which differ from the ten meteorological stations in Cluster 2. The anomaly of the rainfall pattern was assessed across all meteorological stations using the k-means clustering approach to confirm the clustering. The results show two distinct clusters' formation, as confirmed by the anomaly finding (see Fig. 8), thus validating the k-means technique's clustering conclusion.

3.2.3. *Application of FCM clustering*

In the present study, the optimal clustering numbers were

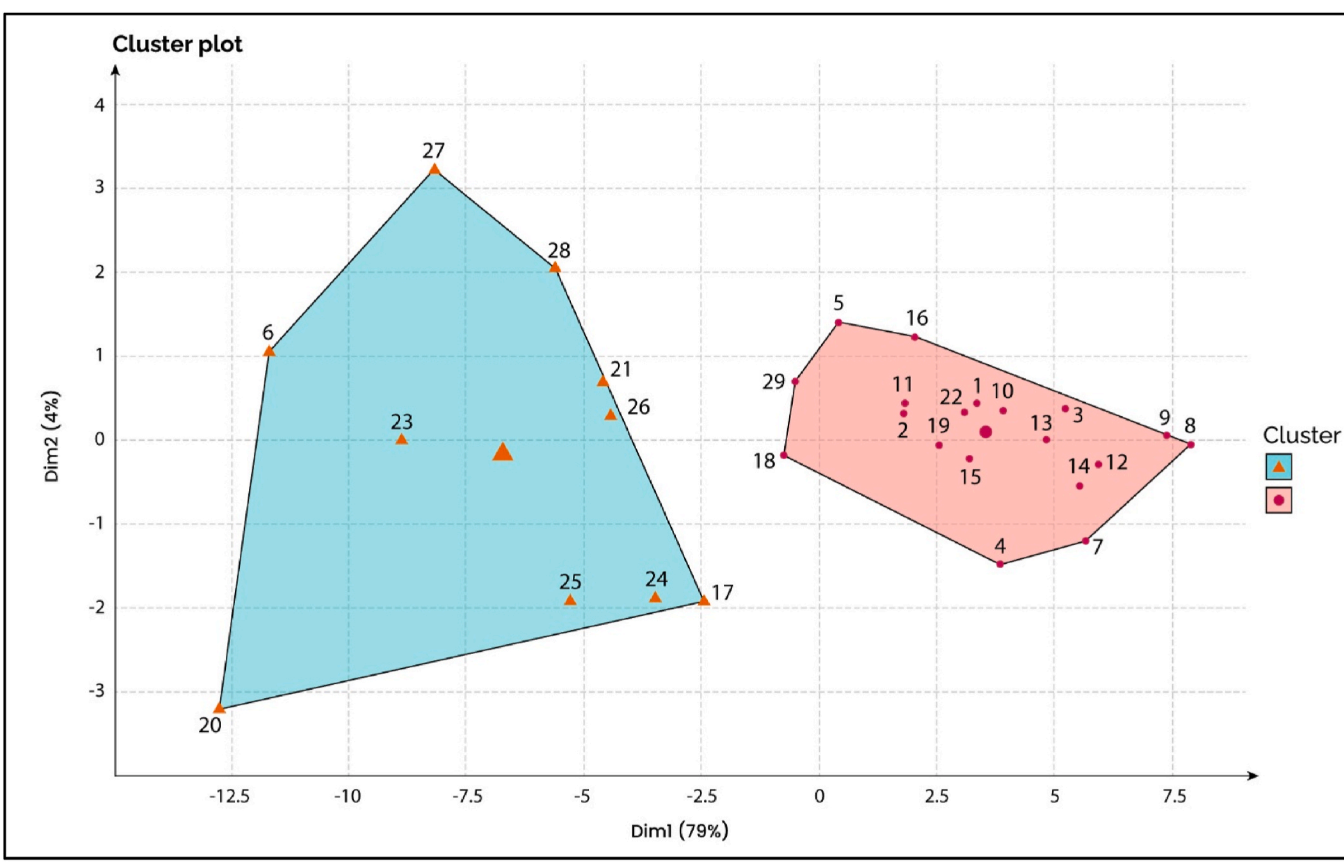

Fig. 6. Identification of homogenous rainfall region using K-means clustering.

determined based on SW value and anomaly analysis, which resulted in the identification of two clusters in the study area. The FCM approach was also used to assess if the same meteorological stations formed clusters and it revealed two homogeneous rainfall zones (see in Fig. 7). Cluster 1 comprised nineteen meteorological stations, including Dhaka, Mymensingh, Faridpur, Madaripur, Srimangal, Bogra, Rajshahi, Ishurdi, Dinajpur, Rangpur, Jessore, Khulna, Satkhira, Barisal, Bhola, Patuakhali, Chadpur, Comilla, and Sitakunda, with an average SW width

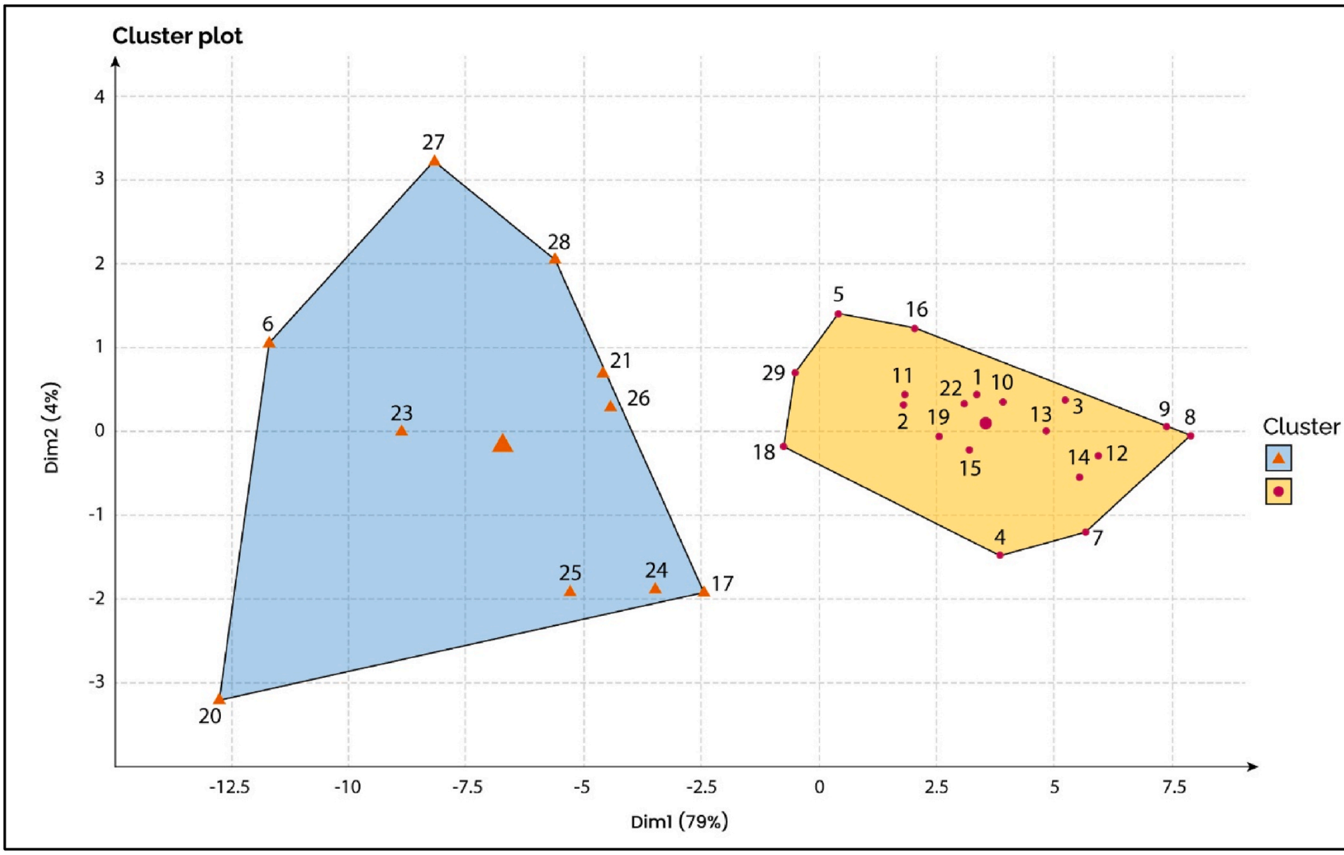

Fig. 7. Identification of homogenous rainfall region using FCM.

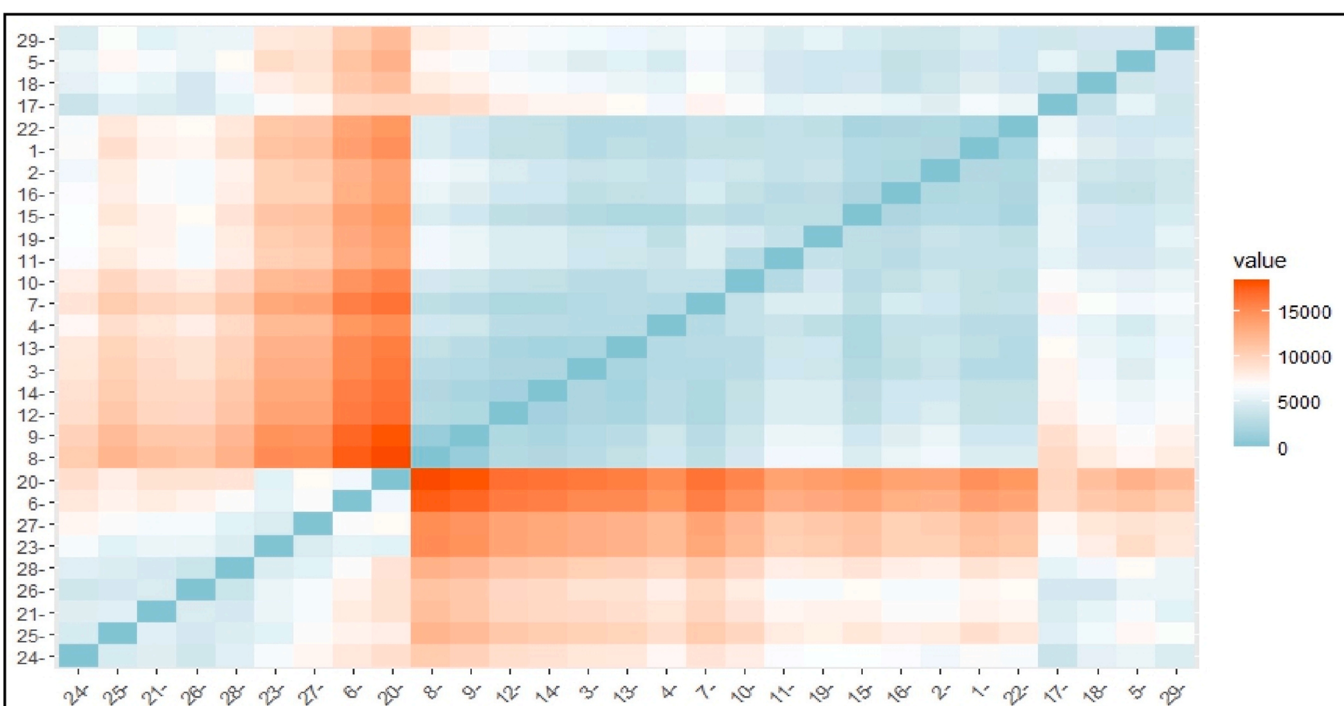

Fig. 8. Anomaly of rainfall among different meteorological stations.

value of 0.46. On the other hand, Cluster 2 comprised ten meteorological stations, including Sylhet, Khepupara, Teknaf, Chittagong, Cox'sbazar, Feni, Kutubdia, MaijdeeCourt, Rangamati, and Sandwip, with an above-average SW width value of 0.46. These findings are consistent with the results of k-means clustering and anomaly analysis, and the average SW plot validates the clustering results. Thus, it is evident that the study area was divided into two distinct regions based on rainfall pattern.

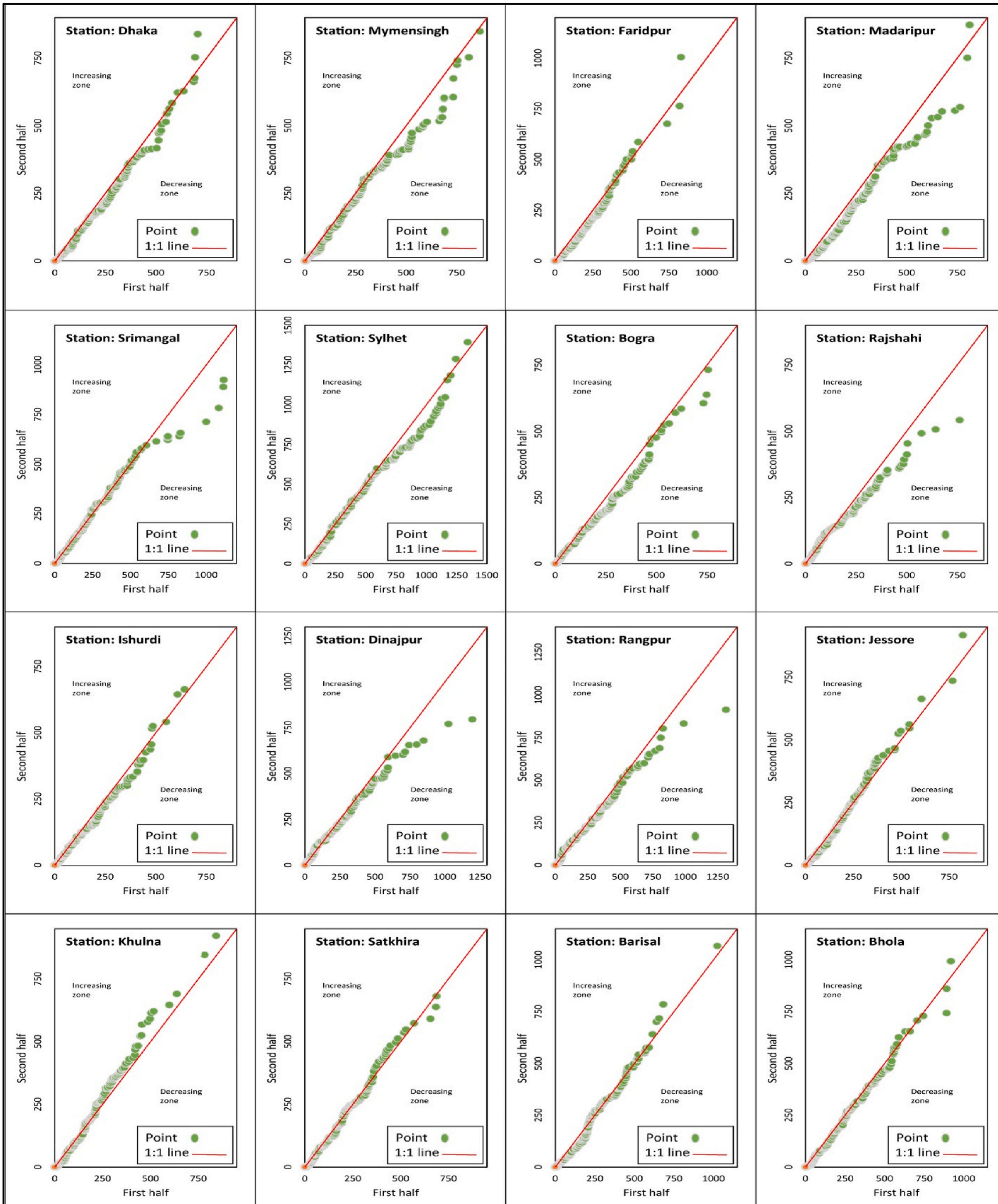

Fig 9. ITA analysis at the meteorological stations of Bangladesh.

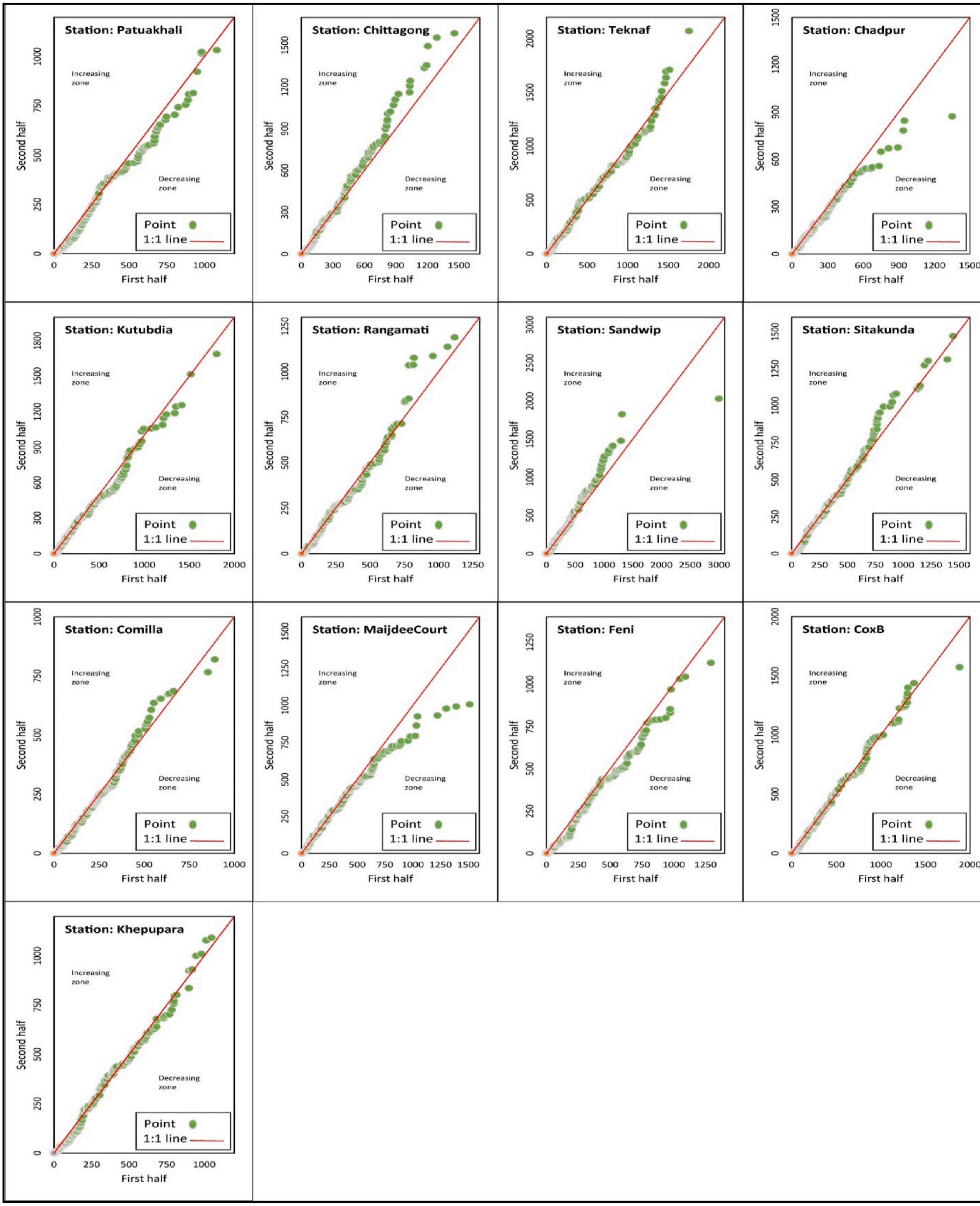

Fig 9. (*continued*).

3.3. Trend analysis

3.3.1. Trend analysis using ITA

The ITA has been calculated using R packages to identify the monthly precipitation trend for Bangladesh's 29 meteorological stations. All Bangladeshi meteorological stations' rainfall trends are represented graphically in Fig. 9. The graph demonstrates how data points from all Bangladeshi meteorological stations first sit below the 1:1 (45°) line in low clusters before rising over the line over time. This suggests that while a negative trend in rainfall was seen in the low clusters, a positive trend was seen in the intermediate and high clusters. This is because rainfall in the nation has risen significantly during the several decades before that, especially during the monsoon seasons (Rahman et al., 2015). All the rainfall stations of Bangladesh showed a non-monotonic rainfall trend, as the data point initially showed a negative rainfall trend but later a significant increasing trend.

The station-wise rainfall trend indicator, the slope of the trend indicator as well as confidence levels (at 0.1, 0.05, and 0.01 levels of significance) have been given in Table 2. The analysis of the table shows that all the meteorological stations of Bangladesh have observed a significant Negative trend in rainfall expecting Khulna, Chittagong, Sandwip, and Sitakunda. This implies that rainfall decreased in Bangladesh from 1981 to 2021 at 25 meteorological stations out of 29. Further, the trend of decrease in rainfall from 1981 to 2021 was highest for Madaripur, Feni, and MaijdeeCourt meteorological stations while lowest for the Jessore, Cox's Bazar, and Rangamati meteorological stations. The trend slope of rainfall in the city of Bangladesh from 1981 to 2021 reveals that there is a large variance in the rate of precipitation at various meteorological stations, which spans from 0.72 to −1.80 for the Trend Indicator. Additionally, the trend slope indication for the various meteorological stations ranges from 0 to 0.13.

3.3.2. Trend analysis using Mann-Kendall and MK family

The findings of different tests used to examine the rainfall trend for several stations in Bangladesh are displayed in Table 3. The MK test is a non-parametric test used to determine if there is a significant trend in data over time. The test calculates a Z-value that is compared to a standard normal distribution to obtain a p-value. A p-value less than 0.05 indicates a significant trend. Table 3 also illustrates the results of other tests, such as the mMK test, MMKY test, PWMK test, and TFPWMK test. These tests are variations of the MK test that address some of its limitations, such as the sensitivity to serial correlation and the presence of outliers. For the MK test, it can be observed that most of the meteorological stations have a negative Z-value, indicating that the rainfall data for these stations is below the mean. For example, Faridpur and Bogra have the largest negative Z-Values, indicating that their rainfall data is the most below the mean. Several meteorological stations in the given data table have a Sen's slope value of 0.00. These stations include Ishurdi, Dinajpur, Jessore, Khulna, Satkhira, Khepupara, Teknaf, Chittagong, Comilla, Cox'sbazar, Kutubdia, Rangamati, Sandwip, and Sitakunda. On the other hand, the lowest Sen's slope values are found in Faridpur, with values of −0.13. The p-values of Faridpur, Madaripur, and Bogra are less than 0.05, indicating a significant trend at a 95% confidence level. This means that there is strong evidence to reject the null hypothesis and conclude that there is a significant trend in the data for these meteorological stations. For the MMKH test, it can be observed that most of the meteorological stations have a negative corrected Z-Value, indicating that the rainfall data for these stations is below the mean. The three largest negative corrected Zc values belong to Rangpur (−5.65), Madaripur (−4.49), and Faridpur (−3.70), indicating a significant decreasing trend in these locations. On the other hand, the three smallest negative corrected Zc values belong to Khulna (−0.85), Srimangal (−1.10), and Satkhira (−1.24), indicating a less significant decreasing trend in these locations. The given data shows that there are 10 meteorological stations with a Sen's slope value of −0.01, indicating a decreasing trend in the data collected from this station. Furthermore, the data shows that the three meteorological stations with the smallest Sen's slope are Faridpur, Madaripur, and Srimangal, with Sen's slopes of −0.03 and −0.01, respectively. The rest of the stations display a 0.00 value. At a 95% confidence level, the new p-values for Mymensingh, Faridpur, Madaripur, Bogra, Rangpur, Sylhet, Barisal, Bhola, Khepupara, Chittagong, Comilla, and Dhaka are indicating a significant trend.

Table 2
Variation of station-wise ITA statistics for Bangladesh.

Metrological stations	Trend Slope	Trend Indicator	LCL at 90%	UCL at 90%	LCL at 95%	UCL at 95%	LCL at 99%	UCL at 99%
Dhaka	−0.07	−0.99	−0.01	0.01	−0.01	0.01	−0.01	0.01
Mymensingh	−0.09	−1.15	−0.01	0.01	−0.01	0.01	−0.01	0.01
Faridpur	−0.09	−1.37	−0.01	0.01	−0.01	0.01	−0.01	0.01
Madaripur	−0.13	−1.80	−0.01	0.01	−0.01	0.01	−0.01	0.01
Srimangal	−0.04	−0.49	−0.01	0.01	−0.01	0.01	−0.02	0.02
Sylhet	−0.12	−0.82	−0.01	0.01	−0.01	0.01	−0.01	0.01
Bogra	−0.09	−1.47	0.00	0.00	−0.01	0.01	−0.01	0.01
Rajshahi	−0.06	−1.25	0.00	0.00	−0.01	0.01	−0.01	0.01
Ishurdi	−0.05	−1.01	0.00	0.00	0.00	0.00	−0.01	0.01
Dinajpur	−0.06	−0.89	−0.01	0.01	−0.01	0.01	−0.01	0.01
Rangpur	−0.03	−0.39	0.00	0.00	0.00	0.00	−0.01	0.01
Jessore	−0.01	−0.15	0.00	0.00	0.00	0.00	−0.01	0.01
Khulna	0.03	0.48	0.00	0.00	0.00	0.00	−0.01	0.01
Satkhira	−0.02	−0.40	0.00	0.00	0.00	0.00	−0.01	0.01
Barisal	−0.05	−0.63	−0.01	0.01	−0.01	0.01	−0.01	0.01
Bhola	−0.06	−0.73	0.00	0.00	−0.01	0.01	−0.01	0.01
Khepupara	−0.04	−0.39	−0.01	0.01	−0.01	0.01	−0.01	0.01
Patuakhali	−0.09	−1.00	−0.01	0.01	−0.01	0.01	−0.01	0.01
Chadpur	−0.09	−1.12	−0.01	0.01	−0.01	0.01	−0.01	0.01
Teknaf	−0.03	−0.24	−0.01	0.01	−0.02	0.02	−0.02	0.02
Chittagong	0.06	0.60	−0.01	0.01	−0.01	0.01	−0.01	0.01
Comilla	−0.03	−0.35	−0.01	0.01	−0.01	0.01	−0.01	0.01
Cox'sbazar	−0.04	−0.30	−0.01	0.01	−0.01	0.01	−0.01	0.01
Feni	−0.13	−1.25	−0.01	0.01	−0.01	0.01	−0.01	0.01
Kutubdia	−0.09	−0.79	−0.01	0.01	−0.01	0.01	−0.01	0.01
MaijdeeCourt	−0.11	−0.97	−0.01	0.01	−0.01	0.01	−0.02	0.02
Rangamati	−0.03	−0.32	−0.01	0.01	−0.01	0.01	−0.02	0.02
Sandwip	0.08	0.72	−0.03	0.03	−0.03	0.03	−0.04	0.04
Sitakunda	0.00	0.04	−0.01	0.01	−0.01	0.01	−0.01	0.01

*LCL, lower confidence limit; UCL, upper confidence limit.

Table 3
Statistics of the family of MK tests for the meteorological stations of Bangladesh.

Meterological Stations	MK Test			MMKH Test			MMKY Test			PWMK Test			TFPWMK Test		
	Z-Value	Sen's slope	p-value	Corrected Zc	new p-value	Sen's slope	new p-value	Original Z	Sen's slope	Z-Value	Sen's slope	p-value	Z-Value	Sen's slope	p-value
Dhaka	−1.24	−0.02	0.21	−2.09	0.04	−0.02	0.01	−1.24	−0.02	−0.64	−0.02	0.52	−1.03	−0.03	0.30
Mymensingh	−1.29	−0.01	0.20	−2.97	0.00	−0.01	0.05	−1.29	−0.01	−0.37	−0.01	0.71	−0.71	−0.01	0.48
Faridpur	−2.06	−0.03	0.04	−3.70	0.00	−0.03	0.00	−2.06	−0.03	−1.48	−0.03	0.14	−2.22	−0.05	0.03
Madaripur	−2.20	−0.03	0.03	−4.49	0.00	−0.03	0.01	−2.20	−0.03	−1.13	−0.02	0.26	−2.17	−0.04	0.03
Srimangal	−0.86	−0.01	0.39	−1.10	0.27	−0.01	0.11	−0.86	−0.01	−0.30	−0.01	0.77	−0.48	−0.01	0.63
Sylhet	−1.33	−0.02	0.18	−2.40	0.02	−0.02	0.00	−1.33	−0.02	−0.17	0.00	0.86	−0.59	−0.02	0.55
Bogra	−2.19	−0.01	0.03	−3.97	0.00	−0.01	0.01	−2.19	−0.01	−0.95	−0.01	0.34	−1.62	−0.02	0.11
Rajshahi	−1.16	−0.01	0.24	−1.71	0.09	−0.01	0.04	−1.16	−0.01	−0.24	0.00	0.81	−0.56	−0.01	0.58
Ishurdi	−0.93	0.00	0.35	−1.51	0.13	0.00	0.03	−0.93	0.00	−0.63	−0.01	0.53	−0.84	−0.01	0.40
Dinajpur	−1.27	0.00	0.21	−1.49	0.14	0.00	0.04	−1.27	0.00	−0.18	0.00	0.86	−0.18	0.00	0.86
Rangpur	−1.46	−0.01	0.14	−5.65	0.00	−0.01	0.00	−1.46	−0.01	−0.66	−0.01	0.51	−1.02	−0.01	0.31
Jessore	−1.02	0.00	0.31	−2.00	0.05	0.00	0.01	−1.02	0.00	−0.23	0.00	0.82	−0.48	0.00	0.63
Khulna	−0.66	0.00	0.51	−0.85	0.40	0.00	0.00	−0.66	0.00	0.01	0.00	0.99	0.01	0.00	0.99
Satkhira	−1.06	0.00	0.29	−1.24	0.22	0.00	0.00	−1.06	0.00	−0.49	−0.01	0.62	−0.75	−0.01	0.45
Barisal	−1.38	−0.01	0.17	−3.43	0.00	−0.01	0.00	−1.38	−0.01	−0.28	0.00	0.78	−0.66	−0.01	0.51
Bhola	−1.05	−0.01	0.29	−2.31	0.02	−0.01	0.02	−1.05	−0.01	−0.31	0.00	0.76	−0.57	−0.01	0.57
Khepupara	−1.13	0.00	0.26	−2.36	0.02	0.00	0.00	−1.13	0.00	−0.48	−0.01	0.63	−0.75	−0.01	0.45
Patuakhali	−1.48	−0.01	0.14	−3.17	0.00	−0.01	0.01	−1.48	−0.01	−0.60	−0.01	0.55	−1.04	−0.02	0.30
Chadpur	−1.35	−0.01	0.18	−2.15	0.03	−0.01	0.11	−1.35	−0.01	−0.47	−0.01	0.64	−0.90	−0.02	0.37
Teknaf	−1.39	0.00	0.17	−1.64	0.10	0.00	0.00	−1.39	0.00	−0.49	0.00	0.63	−0.49	0.00	0.63
Chittagong	−1.01	0.00	0.31	−3.15	0.00	0.00	0.00	−1.01	0.00	−0.50	−0.01	0.62	−0.75	−0.01	0.45
Comilla	−0.83	0.00	0.41	−2.03	0.04	0.00	0.00	−0.83	0.00	−0.87	−0.02	0.38	−1.05	−0.02	0.29
Cox'sbazar	−1.26	0.00	0.21	−2.38	0.02	0.00	0.00	−1.26	0.00	−0.33	0.00	0.74	−0.61	−0.01	0.54
Feni	−1.62	−0.01	0.11	−3.25	0.00	−0.01	0.00	−1.62	−0.01	−0.60	−0.01	0.55	−1.04	−0.02	0.30
Kutubdia	−1.20	0.00	0.23	−1.93	0.05	0.00	0.00	−1.20	0.00	−0.30	0.00	0.77	−0.30	0.00	0.77
MaijdeeCourt	−1.02	−0.01	0.31	−1.92	0.05	−0.01	0.13	−1.02	−0.01	−0.38	−0.01	0.70	−0.64	−0.01	0.53
Rangamati	−0.70	0.00	0.48	−1.22	0.22	0.00	0.01	−0.70	0.00	−0.71	−0.01	0.48	−0.71	−0.01	0.48
Sandwip	−0.58	0.00	0.56	−1.20	0.23	0.00	0.23	−0.58	0.00	−0.34	0.00	0.74	−0.34	0.00	0.74
Sitakunda	−0.92	0.00	0.36	−1.52	0.13	0.00	0.00	−0.92	0.00	−0.75	−0.01	0.46	−0.75	−0.01	0.46

This means that there is sufficient evidence to reject the null hypothesis and conclude that the data from these meteorological stations exhibit a significant trend

For the MMKY test, the table provides new p-values for various meteorological stations, and only three stations, Srimangal, MaijdeeCourt, and Sandwip, have new p-values greater than 0.05, suggesting weak evidence against the null hypothesis with a 95% confidence level. All other stations have new p-values less than 0.05, indicating strong evidence against the null hypothesis and indicate a significant trend. In addition, the larger the absolute value of the Original Z, the further away the observed value is from the mean. Thus, Faridpur, Bogra, and Madaripur have the lowest Zc values among all meteorological stations, while Sandwip, MaijdeeCourt, and Srimangal have the highest values among all the meteorological stations and all the values are negative. The given data shows that there are 11 meteorological stations with a Sen's slope value of −0.01, indicating a decreasing trend in the data collected from this station. Furthermore, the data shows that the three meteorological stations with the smallest Sen slope are Faridpur, and Madaripur, with Sen's slopes of −0.03 and the second smallest Sen's slope is Sylhet, Dhaka, with Sen's slopes of –0.02. The rest of the stations display a 0.00 value. For the PWMK test, the given data shows the Z-values for various meteorological stations. The three stations with the largest negative Z-values are Faridpur with a Z-value of −1.48, Madaripur with a Z-value of −1.13, and Bogra with a Z-value of −0.95. On the other hand, the three stations with the smallest negative Z-values are Khulna with a Z-value of 0.01, Sylhet with a Z-value of −0.17, and Dinajpur with a Z-value of −0.18. It's important to note that negative Z-values indicate that the observed value is below the mean value, and larger negative values indicate more extreme deviations from the mean.

There are no meteorological stations with p-values less than 0.05 that indicate that there is strong evidence against the null hypothesis and that the alternative hypothesis is likely true and indicates no significant trend. The given data shows that there are 15 meteorological stations with a Sen's slope value of −0.01, indicating a decreasing trend in the data collected from this station. Furthermore, the data shows that the meteorological station Faridpur with the smallest Sen's slope value of −0.03. The rest of the stations display a 0.00 value. For the TFPWMK test, the table given shows the Z-values of three meteorological stations. The largest negative Z-value is recorded for Faridpur with a value of −2.22. The second and third largest negative Z-values are recorded for Madaripur and Bogra with values of −2.17 and −1.62, respectively. Among the meteorological stations, Khulna has a positive Z-value of 0.01. Dinajpur and Kutubdia follow with a Z-value of −0.18 and −0.30 respectively. There are only two meteorological stations Madaripur and Faridpur with p-values less than 0.05 which indicates that there is strong evidence against the null hypothesis and that the alternative hypothesis is likely true and indicates a significant trend. The given data shows a wide range of Sen's Slope values from 0.00 to −0.05. In addition, 14 meteorological stations with a Sen's slope value of −0.01, indicate a decreasing trend in the data collected from this station. Furthermore, the data shows that the meteorological station Faridpur with the smallest Sen's slope value of −0.05. Whereas, six of the stations display a 0.00 value.

3.3.3. Comparison and representation of ITA tests

The family of the MK tests and ITA were used to determine the variance in rainfall trend for each meteorological station in Bangladesh's areas with uniform rainfall. The trend analysis reveals that there are four different patterns of change in rainfall in the meteorological stations (Fig. 9). 13 stations have a non-monotonic increasing trend,

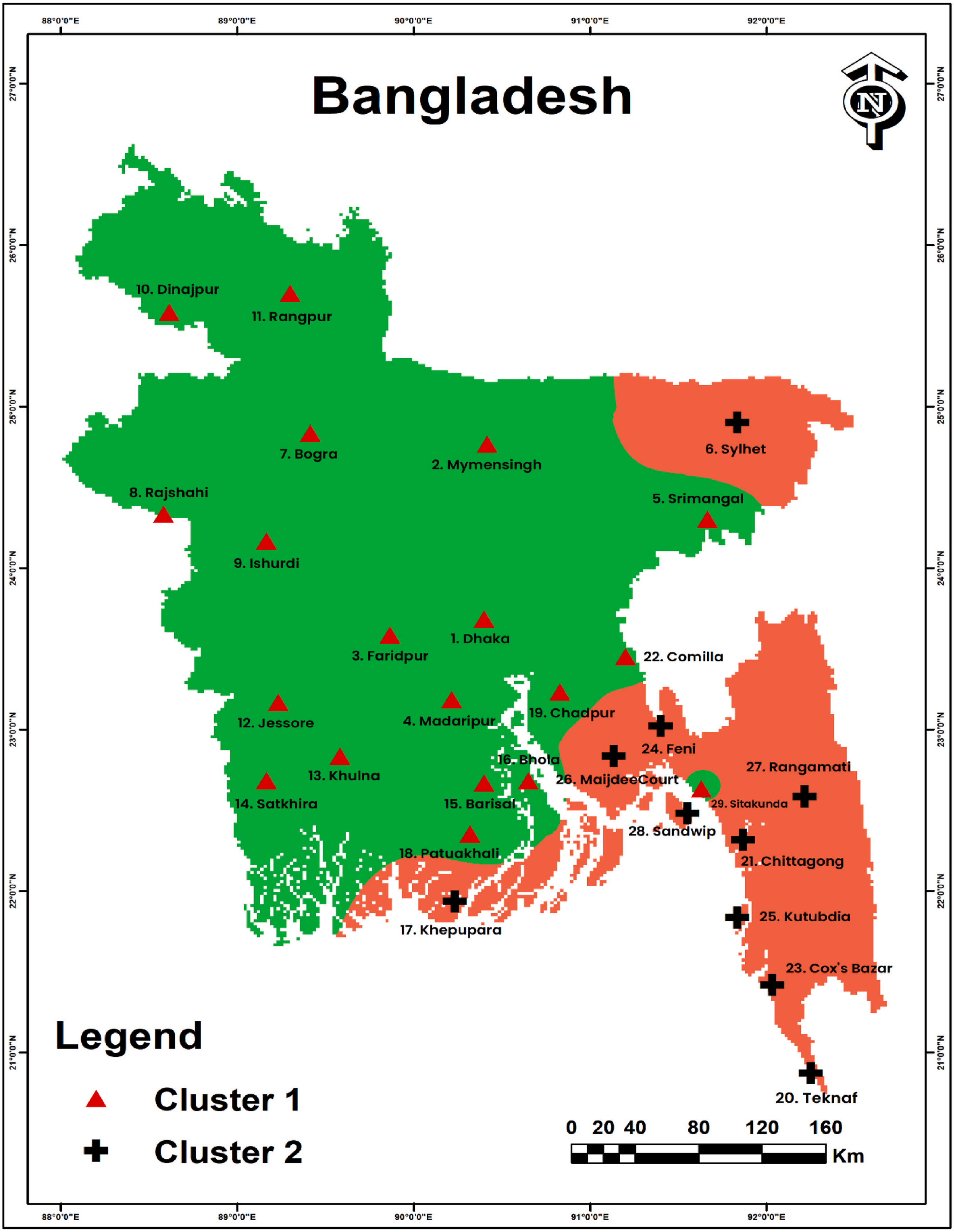

Fig. 10. Clustering map of Bangladesh meteorological station.

which means that they experience fluctuations in their rainfall values over time. These stations include Dhaka, Madaripur, Ishrudi, Khepupara, Rangamati, Sylhet, Teknaf, Sitakunda, Barisal, Bhola and Jessore. Where no stations showed a monotonic increasing trend. On the other hand, 8 stations have a monotonic decreasing trend, which means that their rainfall values are consistently decreasing over time. These stations include Mymensingh, Bogra, Rajshahi, Dinajpur, Rangpur, Chandpur, MaijdeeCourt, and Feni. Additionally, 8 stations have a non-monotonic decreasing trend, which means that their values fluctuate and decrease over time.

These stations include Faridpur, Srimangal, Satkhira, Patuakhali, Kutubdiya, Swandip, Comilla, and Cox's Bazar. Furthermore, there is one station, Swandip, which has the maximum increasing trend, indicating that its rainfall values have consistently increased over time. Lastly, there is one station, Madaripur, that has the maximum decreasing trend, indicating that its rainfall values have decreased consistently over time.

3.3.4. Comparison of trend analysis and homogenous rainfall regions

Bangladesh was divided into two regions with the same amount of rain based on both K-means clustering and FCM clustering. Fig. 10 demonstrates that, out of the 29 meteorological stations, 19 stations were classified as being homogeneous in the first cluster (Cluster 1), while the second cluster only had 10 stations designated as being homogeneous (Cluster 2). Meteorological stations in the northwest, southwest, north-central, part of northeast and part of south-central of Bangladesh, such as Rangpur, Dinajpur, Srimangal, Bogra, Mymensing, Rajshahi, Ishurdi, Dhaka, Faridpur, Comilla, Madaripur, Jessore, Chadpur, Khulna, Satkhira, Barishal, Patuakhali, Sandwip and Bhola had the same pattern of rainfall from 1981 to 2021, so these areas were

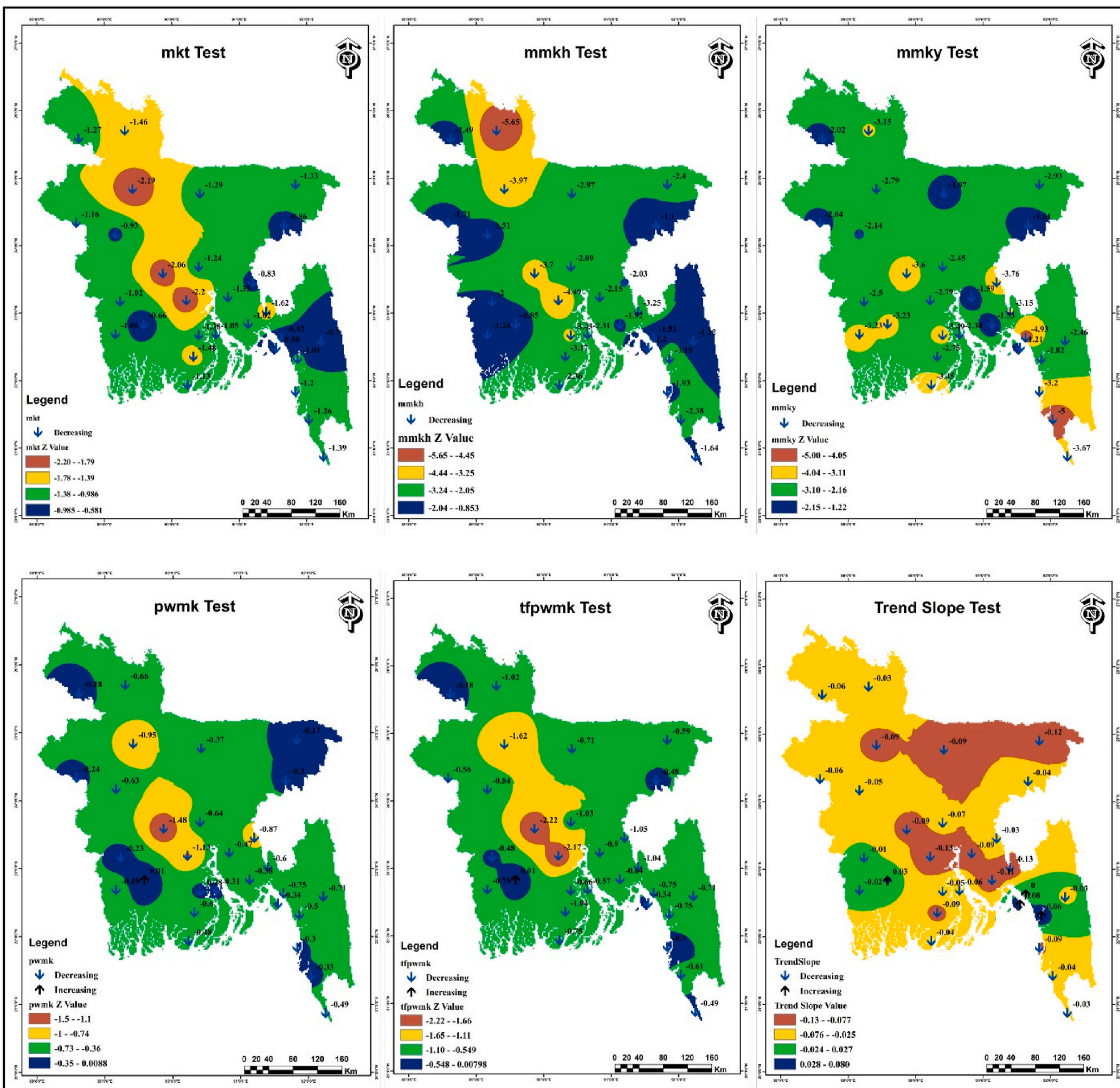

Fig. 11. Rainfall trends distribution over the selected stations in Bangladesh.

taken Cluster 1 as homogeneous rainfall regions. During the same period, the meteorological stations located in the part of the northeast, southeast, south-central and eastern hill sections of Bangladesh, such as Sylhet, Khepupara, Feni, MaijdeeCourt, Sitakunda, Rangamati, Chittagong, Kutubdia, Cox's Bazar and Taknaf all displayed an identical pattern of rainfall and were determined to be homogenous rainfall zones within Cluster 2. The sensitivity of the results may reflect the condition of the rainfall trends in Bangladesh for a long period. It can introduce how the pattern changes over time and affect environmental behavior. Analyzing the result has great significance on the hydrological condition in Bangladesh and has great reliability according to the findings.

Fig. 11 depicts the variation of rainfall trend for each meteorological station in Bangladesh's homogeneous rainfall zones using ITA and the MK family of tests. Both K-means and FCM clustering were used to divide the weather stations in Bangladesh into two groups, with 19 stations in the first group and 10 stations in the second. The trend of rainfall was observed to be greatest at the meteorological stations of Cluster 1, whereas the trend of rainfall was decreasing at the meteorological stations of Cluster 1. Meanwhile, the pattern of rainfall in the second cluster, which is located in the hilly eastern section of Bangladesh, followed the same pattern as the first cluster. The ITA and homogeneous rainfall regions research showed that all of the rain-gauge stations in Cluster 2 had a low (−0.13 to −0.04) or moderate (>-0.04) slope in rainfall trend, except for Feni, which had a low slope in rainfall trend (−0.13248). On the other hand, the rain-gauge stations that were part of Cluster 1 indicated that the slope of the trend in rainfall was decreasing. When analyzing rainfall trends using the MK test family and homogenous rainfall areas, the amplitude of rainfall trend (z value) ranges from low to moderate for all rain-gauge stations in Cluster 1, which is decreasing for the majority of stations in the MK test family but increasing for only the Khulna station in PWMK and TFPWMK. Similarly, MK family analysis showed a decreasing amount of rainfall at all Cluster 2 stations. In addition, the amount of rainfall trend was decreasing at every rain gauge station in Clusters 1 and 2 but just a few stations in Cluster 1 were increasing (see Fig. 12).

3.3.5. *Trend and homogenous rainfall station*

In this study, on rainfall trend analysis across various stations in Bangladesh, distinct patterns were observed, categorized into different clusters. Cluster 1, comprising 65.51% of the stations, showed diverse trends. Among these, a notable trend was the Non-Monotonic Decrease (NMD), evident in Dhaka, Madaripur, Srimangal, Rajshahi, Dinajpur, Rangpur, Satkhira, Bhola, Patuakhali and Comilla. Monotonic Decrease (MD) was observed in Mymensingh, Bogra, and Chadpur, reflecting a consistent downward trajectory in rainfall. Additionally, Non-Monotonic Increase (NMI) trends were prominent in Faridpur, Ishurdi, Jessore, Khulna and Barisal, indicating fluctuations in rainfall over time (see Fig. 12). Meanwhile, Cluster 2, representing 34.48% of stations, showed different trends. Notably, NMD was predominant in this cluster, seen in Cox's Bazar, Kutubdia and Sandwip. NMI was observed in Sylhet, Teknaf, Khepupara and Chittagong suggesting varying rainfall patterns across different regions. MD was noticeable in Feni and MaijdeeCourt. Regarding the ITA, 17.24% of the 29 stations examined displayed a monotonic decreasing trend over time. In contrast, none of the stations (0%) showed a monotonic increasing trend. However, a sizable proportion of the stations, 37.93%, exhibited a non-monotonic increasing trend. An even larger percentage, 44.83%, demonstrated a non-monotonic decreasing trend. These findings provide valuable insights into the complex dynamics of rainfall trends across Bangladesh, essential for understanding and managing climate variability in the region. No monotonic increase trend was observed in any station across the clusters.

4. Discussion

Overall, the findings of this study provide significant insights into the

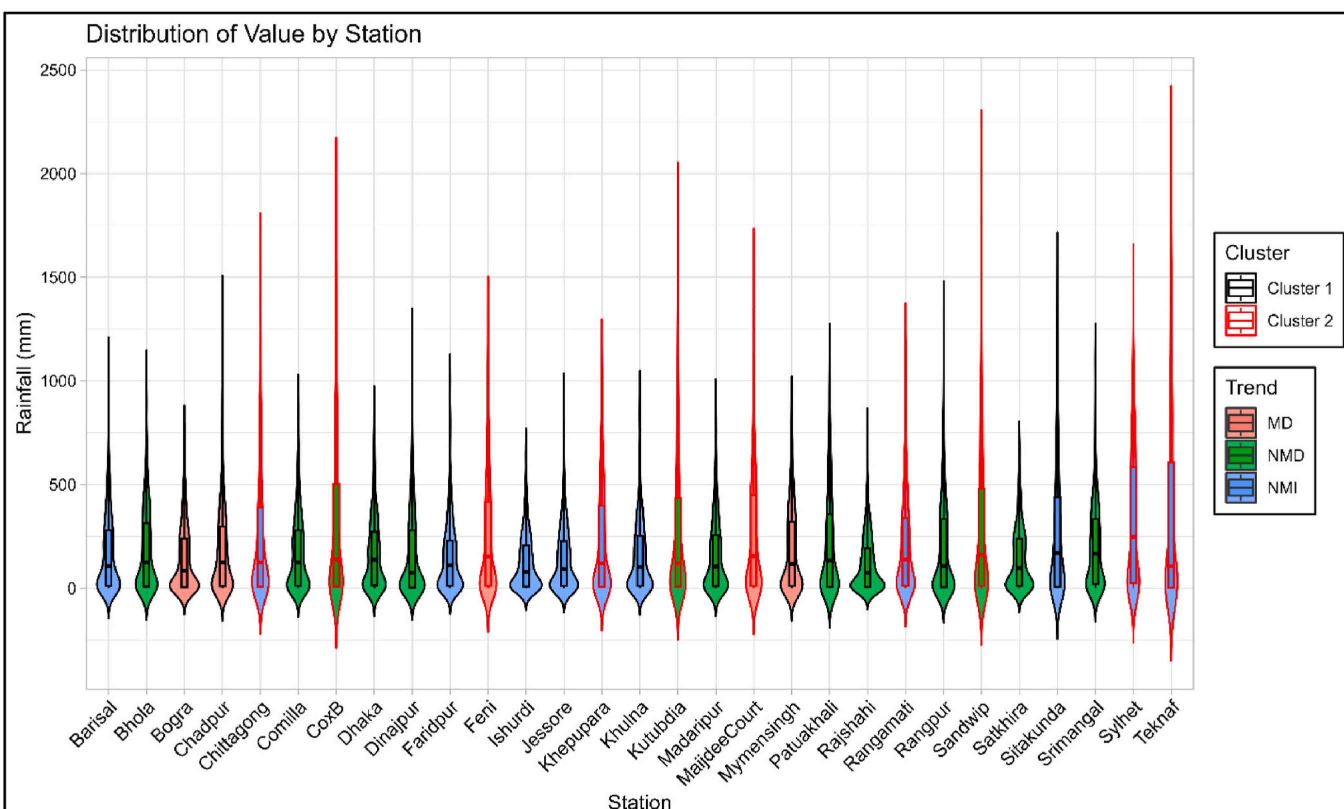

Fig. 12. Stations wise rainfall distribution with trend and cluster in Bangladesh.

rainfall patterns across Bangladesh over a span of 40 years. A rainfall regionalization approach based on FCM and K-means clustering, in conjunction with the ITA and the MK tests family, to assess the trend and pattern of rainfall in Bangladesh. Few studies in Bangladesh have explored the trend and pattern of rainfall (Das et al., 2021b; Shahid, 2010c). L-moment method statistics were employed to assess the homogeneity of identified clusters in Bangladesh can be categorized into two main clusters. The identification of two distinct clusters, each exhibiting unique rainfall trends, underscores the spatial heterogeneity of rainfall distribution in the country.

The cluster analysis revealed a clear spatial pattern, with the majority of stations (65.51%) grouped into Cluster 1, while the remaining 34.48% fell into Cluster 2. This suggests the presence of distinct rainfall regimes across the study area. The trend analysis using ITA further elucidated the temporal dynamics. A notable 17.24% of stations exhibited a monotonic decreasing trend, observed in Mymensingh, Bogra, Chadpur, Feni and MaijdeeCourt are a cause for concern as it reflects a consistent downward trajectory in rainfall. This could potentially impact agricultural productivity and water availability in these regions. While no stations showed a monotonic increase among the selected stations. However, a significant proportion of stations, 37.93%, displayed a non-monotonic increasing trend including Faridpur, Ishurdi, Jessore, Khulna, Barisal, Sylhet, Teknaf, Khepupara, and Chittagong suggest an increase in rainfall over time, albeit with fluctuations. This could lead to increased instances of flooding and other water-related disasters in these regions. Menwhile, 44.83% had a non-monotonic decreasing trend, particularly in coastal regions such as Cox's Bazar, Kutubdia, and Sandwip for Cluster 2. This could be linked to changes in sea surface temperatures and atmospheric dynamics. Then Dhaka, Madaripur, and Srimangal for Cluster 1. This could be attributed to various factors such as changing land use patterns, urbanization, and climate variability. These findings highlight the substantial spatial and temporal variability in rainfall characteristics within the region, underscoring the need for nuanced, location-specific approaches to water resource management and climate adaptation strategies.

The study conducted by Shahfahad et al., (2023) in Delhi metropolitan city from 1991 to 2018 with 22 stations, identified two almost homogeneous clusters. The rainfall pattern in these clusters was distinct, with none of the rain-gauge stations showing a monotonic trend. This is similar to the findings of this study where none of the stations across the clusters showed a monotonic increase trend. In addition, study of Das et al., (2021b) which analyzed rainfall in Bangladesh from 1966 to 2019 across 23 stations, found that the increasing and decreasing trends were equally dominating all over the study area. This contrasts with this study where the NMD was evident in several stations in both clusters. Furthermore, (Siraj-Ud-Doulah and Islam, 2019) conducted a study in Bangladesh from 1991 to 2013 across 34 stations, identified seven clusters. This is a higher number of clusters compared to this study which identified two clusters. Additionally, Naikoo et al., (2022) studied rainfall in Mumbai city from 1991 to 2018 across 13 stations, also identified two clusters. The city witnessed a significant rise in rainfall in the past few decades, particularly during the monsoon seasons. This is similar to this study where several stations in both clusters showed a NMI trend. Some significant seasonal trend analysis was done across Bangladesh where the results also indicate that the rainfall trends in Bangladesh vary across different regions, with some areas experiencing an increasing trend in rainfall, particularly in the zones adjacent to the Bay of Bengal as well as seasonal trend variability is present (Das et al., 2021b; Huang et al., 2018b; Shahfahad et al., 2023). The study found that Bangladesh can be divided into two prime clusters based on climate stations, with one cluster located in the northern part of the country and the other in the southern hilly part. The clusters exhibit regional disparities and similarities in terms of rainfall. This new insight provides valuable information for water resource planning, management, and addressing the impact of climate change in Bangladesh.

5. Conclusion

The techniques utilized in this research provided useful insights into rainfall variability. Results from the current trend analysis and MK tests revealed mostly identical decreasing precipitation trends across stations and timescales, indicating reliable analysis. The study found significant changes in rainfall patterns at most stations from 1981 to 2021. The current trend analysis revealed decreasing trends at 25 out of 29 meteorological stations, with negative trend slopes. Eleven stations exhibited non-monotonic trends, while eight had non-monotonic decreasing trends and eight displayed monotonic decreasing patterns. Only four stations (Khulna, Chittagong, Sandwip, and Sitakunda) showed increasing precipitation. The steepest declines in rainfall occurred at Madaripur, Feni, and MaijdeeCourt stations, while the smallest decreases were observed at Jessore, Cox's Bazar, and Rangamati. The MK tests showed that approximately half the stations had no rainfall trend, while the rest exhibited negative trends ranging from -0.03 to -0.01, translating to medium-high vulnerability. These rainfall changes could have an impact on crop cycles, rotation, and Bangladesh's entire agricultural system. Further study is necessary to link climate issues to agriculture and precise rainfall variation. This analysis did not examine other environmental factors such as temperature, pressure, evapotranspiration, sunlight, moisture, and winds. As well as the method can also be applied to seasonal studies for more accurate policy and decision-making for water management, flood control, and water budgeting. The detected negative precipitation patterns highlight the need for improved water resource management, disaster planning, and agricultural strategies. Identified rainfall zones can aid policymakers in crafting regional climate adaptation approaches. This methodology can be replicated elsewhere to discover rainfall patterns and promote sustainable water use. Overall, combining current techniques such as fuzzy logic and clustering enables insightful large dataset analysis for informed decision-making across sectors.

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CRediT authorship contribution statement

Sujit Kumar Roy: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Abrar Morshed:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Pratik Mojumder:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation. **Md. Mahmudul Hasan:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Formal analysis, Data curation. **A.K.M. Saiful Islam:** Writing – review & editing, Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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