



Trends of seasonal and annual rainfall of semi-arid districts of Karnataka, India: application of innovative trend analysis approach

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Abstract

Trend analysis of rainfall is often carried out in water resources management to understand its distribution over a given region. The cumulative seasonal and annual rainfall derived from monthly datasets spanning 102 years (1901–2002) for 11 districts of the semi-arid Karnataka, India, was used for the trend analysis. The two-step homogeneous test approach was carried out on all the time series. Then, lag-1 autocorrelation was conducted only on homogeneous time series. Only 78.18 % of the total time series data were detected as homogeneous, and 95.35% of time series data were found to have insignificant autocorrelation. Then, the Innovative Trend Analysis (ITA) method was applied to 43 homogeneous rainfall time series, as well as to 41 time series using the MK and SR tests, and to two time series using the mMK test. The MK and SR tests detected a significant trend in 14.63% of the time series, while the ITA method was able to detect a trend in 93.02% of the total time series data. The MK and SR tests revealed significant trends in winter and post-monsoon season precipitation for two districts, but only for one district in the case of summer and annual rainfall. No trend was identified for monsoon season precipitation. The mMK test showed a positive trend for the post-monsoon season in a district, while the ITA method revealed significant trends for all seasons in most districts. The sub-trend analysis revealed trends that traditional methods were unable to detect.

1 Introduction

The demand for fresh water is ever increasing because of the myriad of needs that are encountered daily in different sectors. Its availability and occurrences result from the quantum of precipitation received during a given period. Even groundwater, which forms a significant source of fresh water in many parts of the world, is recharged by rainfall. Therefore, precipitation is the major component of the hydrologic cycle. One peculiar characteristic of precipitation is that its occurrence is uneven over space and time (Sansom

et al. 2017). The precipitation occurrence can lead to flood (drought) when it is excess (scanty). For example, the recent occurrences of devastating floods of 2018 in Kerala (Mishra and Nagaraju 2019) and 2021 in Germany (Fekete and Sandholz 2021) remind how costly precipitation can be when it occurs in excess. On the other extreme, some parts of the United States of America (USA) experienced significant drought during 2020 (Yaddanapudi and Mishra 2022), and 2021 also shows the continuation of the drought in other parts of the USA. It is also known that scanty rainfall leads to meteorological drought (Sajeev et al. 2021; Muthuvel and

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Mahesha 2021). This drought is often the precursor to agricultural drought (Behrang Manesh et al. 2019) and hydrological drought (Hao et al. 2016). This erratic behaviour of rainfall calls for a proper understanding of rainfall distribution in space and time. Moreover, it is imperative to understand the precipitation trend due to anthropogenic activities and climate alteration in the hydrologic cycle (Zhang et al. 2007; Wu et al. 2013; Yi et al. 2016).

One of the ways to understand the distribution of rainfall patterns over an area of interest is the trend analysis that helps us ascertain how much rainfall amount increases or decreases on a particular time scale. The most widely used nonparametric methods to capture monotonic trends are the Mann-Kendall (MK) and Spearman's rho (SR) methods (Kendall 1938; Mann 1945; Daniel 1990). Some of the recent studies on the use of MK and SR tests for rainfall trend analysis have been reported in the literature (Kalra and Ahmad 2011; Abghari et al. 2013; Gocic and Trajkovic 2013; Formetta et al. 2016; Güner Bacanlı 2017; Hajani et al. 2017; Pandey and Khare 2018; Nikzad Tehrani et al. 2019; Raja and Aydin 2019; Gado et al. 2019). However, the MK and SR approaches are limited to the assumptions of the absence of serial correlation (autocorrelation) of a given time series of a variable, normal distribution of the time series, and the sample size of the data. In order to circumvent the requirement of the limiting assumptions, Şen (2012) proposed the innovative trend analysis (ITA) method for carrying out trend investigation of hydrometeorological variables. The ITA method also does not require the pre-whitening of time series data prior to applying it. Since then, several studies on the ITA method have been conducted for trend analysis of hydrometeorological variables in different regions. For example, Güçlü (2018a) extended the ITA method to half time series method (HTSM) that could aid the ITA method to detect trend analysis better. Similarly, the same author proposed double-ITA (D-ITA) and triple-ITA (T-ITA) approaches to use in tandem with ITA to improve trend detection with stability identification (Güçlü 2018b).

In yet another study, innovative triangular trend analysis (ITTA) that aids in detecting partial trends within a given time series was applied using the triangular array after splitting a given time series to a pair of equal length sub-series to make a comparison of trends (Güçlü et al. 2020). The extended version of ITA – the Innovative Polygonal Trend Analysis (IPTA) cannot only detect trends captured by the traditional methods but also trend transitions of a time scale (weekly, monthly, etc.) of two equal sub-series derived from the original data (Şen et al. 2019). In extending the IPTA, Ceribasi et al. (2021) proposed the Innovative Trend Pivot Analysis Method (ITPAM) to determine the five risk classes using the inherent relationship in data.

Despite the extended versions of the ITA method in literature, the original ITA method (Şen 2012, 2017a) is still

widely used for trend analysis of hydrometeorological variables, as evident from recent literature. For instance, Harka et al. (2021) carried out a comparative study of MK, and ITA approaches to detect rainfall trends in Ethiopia's Upper Wabe Shebelle River Basin (UWSRB). The ITA test detected both monotonic and non-monotonic trends that could not have been possible with the MK test. In a similar study of the Bumbu watershed, Papua New Guinea, Doaemo et al. (2022) did a comparative study of rainfall trend analysis using linear regression, Mann-Kendall rank statistics, Sen's Slope, and ITA. In addition, spectral analysis was carried out to remove cyclic components from the rainfall time series. Their findings, however, indicate that all the four methods consistently indicated a decreasing trend of annual rainfall. Several other studies on ITA application are reported in the literature (Danandeh Mehr et al. 2021; Şişman and Kizilöz 2021; Mallick et al. 2021; Phuong et al. 2022; Ay 2022). The extended version of ITA - IPTA is the most widely used method to detect trends and trend transitions of different hydrometeorological variables (Şan et al. 2021; Ceribasi and Ceyhunlu 2021; Ahmed et al. 2021; Akçay et al. 2021; Hırca et al. 2022).

Recent studies on precipitation trend analysis in India witnessed the ITA method being increasingly applied. Often the ITA method has been compared with MK, SR, and linear regression methods (Sanikhani et al. 2018; Machiwal et al. 2019; Meena et al. 2019; Praveen et al. 2020; Singh et al. 2021a; Saini and Sahu 2021; Aher and Yadav 2021). A few studies are worth mentioning using the ITA and classical trend analysis methods at the national level. The study by Praveen et al. (2020) presented the rainfall trend analysis of all the meteorological sub-divisions of India from 1901 to 2015 at the seasonal and annual scales. It was noticed that the change detection point conducted using the Pettitt test was mostly found to be after 1960 for the meteorological divisions. The application of the MK test revealed the trend to be positive during 1901-1950; however, the trend reduced after 1951. The ITA method detected mostly negative trends even when the MK test detected no trend. Singh et al. (2021) presented a similar study of the same region using gridded rainfall data (1901 to 2019), both seasonal and annual. The ITA method was compared with MK, modified Mann-Kendall (mMK), and the linear regression analysis (LRA) tests. Interestingly, the ITA method could detect trends beyond traditional approaches. An increasing trend was observed for the monsoon and annual rainfall in the northwest and peninsular India; however, the northeast central portion of the nation experienced a negative trend. Most of the zones, however, experienced decreasing winter rainfall. Extracting the rainfall events from anomalous rainfall time series (1871–2016), Saini and Sahu (2021) carried out a unique (not raw rainfall

time series) study for the same meteorological zones of India using the MK, ITA, and LRA methods. Although the study is unique in terms of data input and detailed, refined trend analysis, the ITA test captured other trends like the above-mentioned studies.

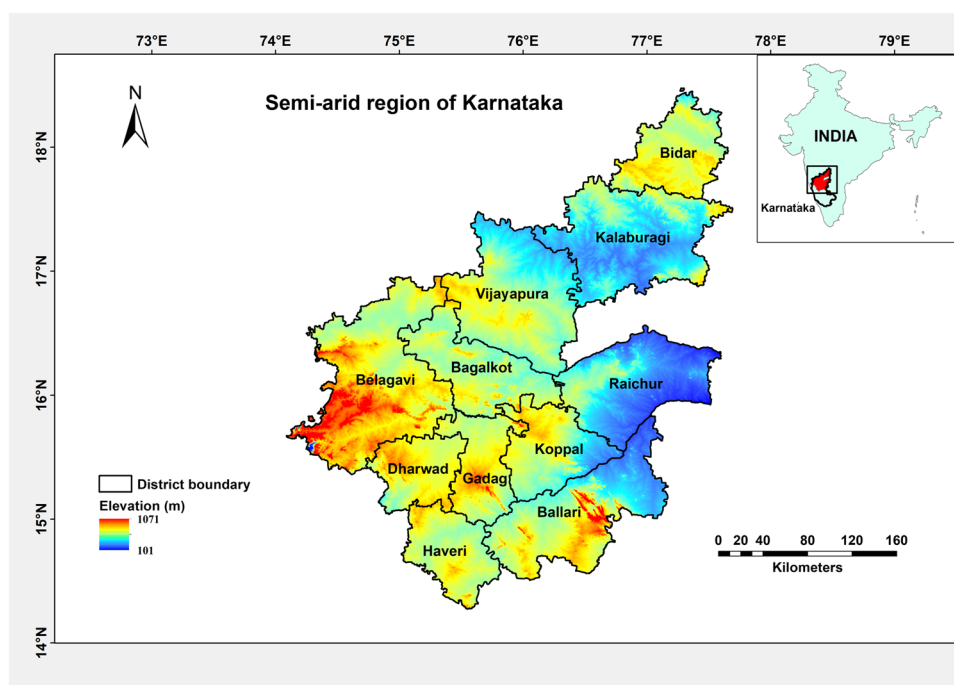
The ITA method can be used to analyze hydrometeorological time series data, but it is important to ensure that the time series data is homogeneous to avoid false trends. Karnataka stands only next to Rajasthan state in India to be the most drought prone area (Jayasree and Venkatesh 2015), receiving a little over 700 mm of mean annual rainfall. The northern region of the state, Rajasthan and northern-central Maharashtra constitute 72% of India's total pearl millet production (Singh et al. 2017) and is home to several large crop-producing districts. These districts are located on the leeward side of the Western Ghats and are therefore drought prone. Nearly 90% of the population in the semi-arid region of Karnataka depend on agriculture for their livelihood (Jayasree and Venkatesh 2015). From the literature, it is evident that no such study on the ITA method for precipitation trend analysis has been reported for this region. Hence, the present investigation is focused on (a) to carry out homogeneity tests of seasonal and annual rainfall time series of each district within the region, (b) to determine the serial correlation of each time series, and (c) to compare the trend of seasonal and annual rainfall using the MK, mMK, SR, and ITA approaches.

2 Study area description and data sets

2.1 Study area description

The semi-arid region, also known as North Interior Karnataka, lies between 14.26°N to 18.49°N latitude and 74.07°E to 77.71°E longitude, with an elevation of about 100 to 1100 m above msl (Fig. 1). It has 11 districts, namely Bagalkot, Belagavi (Belgaum), Ballari (Bellary), Bidar, Vijayapura (Bijapur), Dharwad, Gadag, Kalaburagi (Gulbarga), Haveri, Koppal, and Raichur. The region makes up 84,560 km², which is about 44% of the area of the state. The population is over 23 million (about 40%) (<https://www.census2011.co.in/district.php>). There are four seasons in the state of Karnataka in a year: January and February- winter, March to May-summer, June to September-monsoon, and October to December-post-monsoon. The temperature ranges between 5–25 °C during the winter and 20–40 °C during the summer. Although the temperature drops during the monsoon, the rise in humidity level could cause the weather to be unpleasant. The post-monsoon and winter seasons are generally pleasant. The district of Raichur experienced the lowest mean of total annual rainfall at 564 mm, while the district of Dharwad experienced the highest mean of total annual rainfall at 2233 mm (1901–2002). The region receives about 80% of the total annual rainfall during the southwest monsoon (June–September). The most commonly grown crops in the region are paddy, jowar, sugarcane, cotton, and finger millet (ragi).

Fig. 1 Study area map of 11 semi-arid districts in northern Karnataka



2.2 Data sets

The monthly rainfall data of 11 districts (Fig. 1) of semi-arid Karnataka were retrieved from the India water portal (<http://www.indiawaterportal.org/metdata>) spanning 102 years (1901–2002). The monthly rainfall data at the district level have been applied for trend analysis for different regions across India (Chatterjee et al. 2016; Meshram et al. 2017; Pandey and Khare 2018; Sharma and Goyal 2020; Mahato et al. 2021). Each monthly time series dataset was further summed up to obtain seasonal and annual rainfall time series.

The representative rainfall time series of the largest district of Bagalkot is shown in Fig. 2. The linear trend of winter rainfall is decreasing, while for rest of the seasons and annual rainfall the trends are increasing. For non-linear variables like precipitation and climate index (ENSO), non-parametric rank-based correlation is preferred over the Pearson's correlation coefficient (Uttarwar et al. 2020). In this study, Niño 3.4 of the El Niño Southern Oscillation Index (ENSO) was used to determine the Spearman's correlation with precipitation of each district. The annual average precipitation and annual average Niño 3.4 are shown in Figs. 3 and 4. The values of correlation of the two variables are -0.07 , 0.05 , 0.04 , -0.08 , -0.10 , 0.02 , 0.01 , -0.09 , 0.02 ,

-0.01 , and -0.02 corresponding to Bagalkot, Belagavi, Ballari, Bidar, Vijayapura, Dharwad, Gadag, Kalaburagi, Haveri, Koppal, and Raichur, respectively. It is evident from the correlation values that the large atmospheric circulation did not have significant relationship with precipitation of all the 11 districts. The correlations between elevation and average seasonal and annual rainfall of the 11 districts are 0.05 (winter), 0.46 (summer), 0.71 (monsoon), 0.31 (post monsoon), and 0.70 (annual). It is evident from the value of monsoon precipitation that it is highly correlated to elevation, whereas winter precipitation has weak correlation with elevation.

3 Methods

3.1 Rainfall data tests

Homogeneity tests check for similarity in samples, while serial correlation tests assess the relationship between values in a time series data set. Both are useful in water planning and management for identifying trends, patterns, and potential issues that aid decision making. These tests are particularly useful in agriculture for determining irrigation strategies and identifying issues that may impact

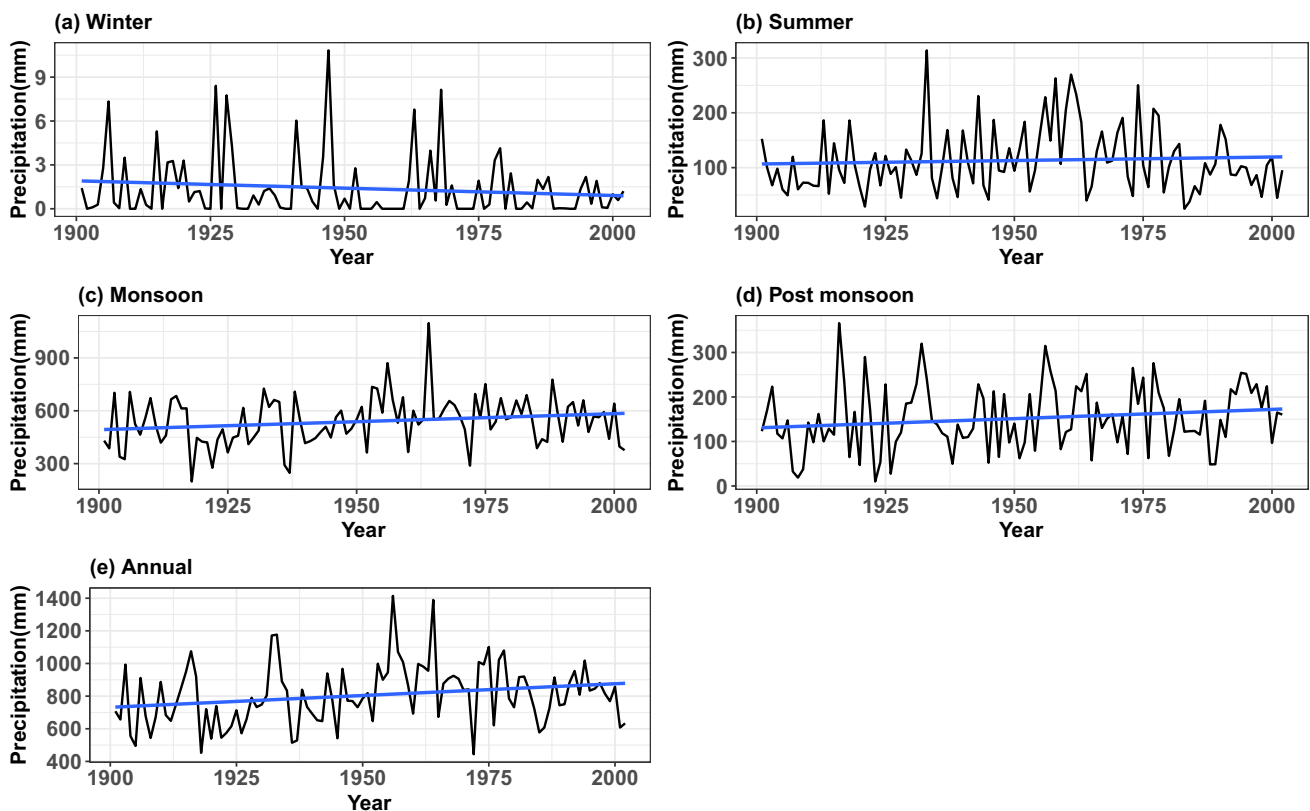


Fig. 2 Representative seasonal and annual rainfall time series of Bagalkot district

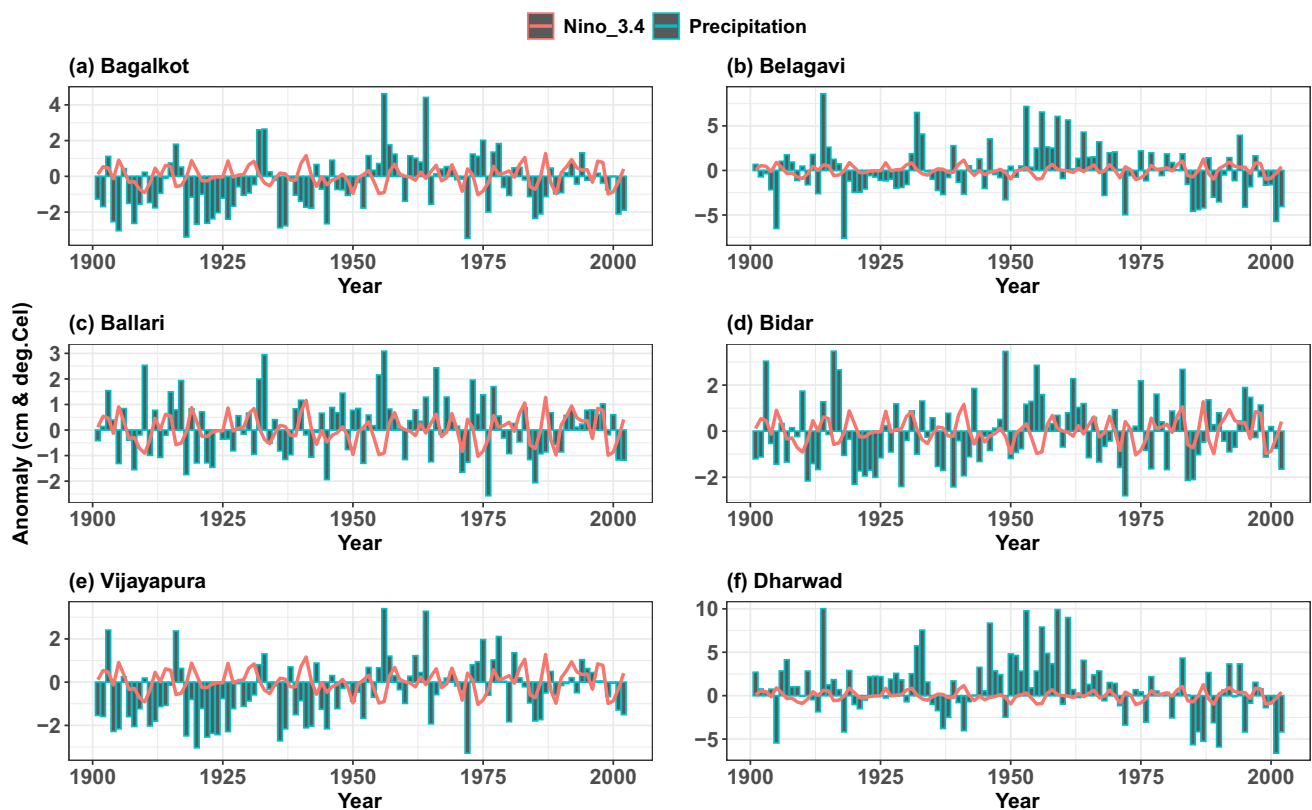


Fig. 3 Annual anomalies of rainfall and ENSO Niño 3.4 of first six districts of the study region

crop productivity. They also aid in understanding causes of droughts and floods and developing more effective drought and flood management strategies. For example, if a homogeneity test shows change in rainfall over time, it may indicate underlying issues that need addressing to prevent future droughts. Similarly, if a serial correlation test shows a strong relationship between low/high precipitation levels, it may indicate a need for drought/flood control measures to protect against future droughts/floods.

Trend tests determine if there is a significant trend in data over time, often used to identify long-term trends like changes in temperature or precipitation levels over several years or decades. Homogeneity tests check if two or more samples come from the same population. Both tests can identify patterns and trends at annual and seasonal scales that aid decision making, for example, a significant trend of increasing temperature at annual scale could indicate climate change and action needs to be taken. A homogeneity test revealing change in water quality of a river over time at seasonal scale could indicate underlying issues that need addressing. Trend and homogeneity tests are useful tools for understanding patterns and trends in data, and identifying potential problems or issues that may need to be addressed to improve decision making. They are commonly used in

various fields such as water planning and management, agriculture, and climate science.

Trend tests detect long-term trends or patterns in time series data, while serial correlation refers to the degree of correlation between values in a time series. Serial correlation must be considered when analyzing time series data at annual and seasonal scales, as it may require specific statistical techniques like autoregressive or moving average models. Trend tests can identify trends at annual and seasonal scales, but serial correlation must be considered when interpreting the results, as it can affect test reliability. These tests provide valuable information for policymakers and resource managers working to prevent or mitigate the impacts of droughts and floods.

Trend and homogeneity tests examine different characteristics in time series data. Trend tests detect long-term patterns, homogeneity tests identify sudden changes. Both are important for water planning and management, long-term trend in water demand may indicate need for additional infrastructure, sudden changes in demand or supply may require immediate action. Trend and serial correlation tests also assess different aspects of time series data. Trend tests detect long-term trends, while serial correlation tests measure correlation between values in the data.

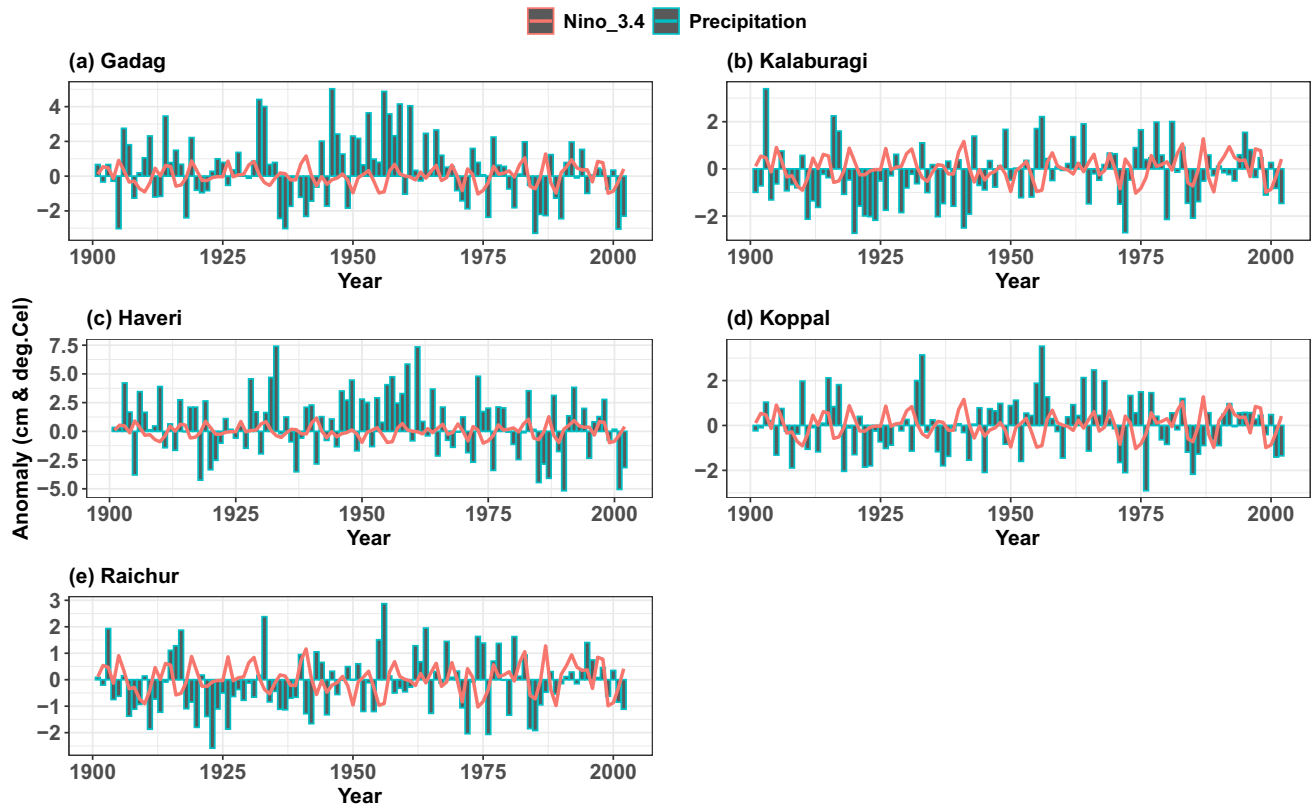


Fig. 4 Annual anomalies of rainfall and ENSO Niño 3.4 of the remaining five districts of the study region

In water planning and management, it is important to consider both trend and serial correlation when analysing time series data on water resources. For example, a long-term trend of increasing water demand could indicate the need for additional water infrastructure or management measures to ensure a sufficient supply. On the other hand, high levels of serial correlation in the data could indicate the need to use statistical techniques that take this into account, such as autoregressive or moving average models, when analysing the data.

3.1.1 Homogeneity tests

A homogeneity test is conducted to check whether inhomogeneity in a time series is present due to human intervention. In the current study, the two-step approach proposed by Wijngaard et al. (2003) is applied to ascertain the deviation from absolute homogeneity of the time series. In the first step, the seasonal and annual rainfall data subjected to four standard statistical tests are (a) the Von Neumann ratio test (VNRT) (von Neumann 1941), (b) the Pettitt test (PT) (Pettitt 1979), (c) the Buishand range test (BRT) (Buishand 1982), and (d) the standard normal homogeneity test (SNHT) (Alexandersson 1986). The standard equations of the four tests are:

(a) The Von Neumann ratio test (VNRT) compares the ratio of the sum of the squares of the differences between successive observations (i.e., the variance of the differences) to the variance of the original series. The test statistic is given by:

$$VNRT = \frac{\sum_{i=1}^{n-1} (X_{i+1} - X_i)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (1)$$

where n is the number of observations in the series, X_i is the i th observation, and \bar{X} is the mean of the series. If the VNRT is less than a critical value (which depends on the sample size and the level of significance), then the null hypothesis of no change in variance over time is accepted. Otherwise, the null hypothesis is rejected and there is evidence of a change in variance over time.

(b) Pettitt test (PT): The Pettitt test (PT) is a non-parametric test for detecting change in a continuous time series values of a variable of interest. It tests the null hypothesis (H_0) to be true when there is no change and otherwise for alternative hypothesis (H_a). The test may be carried out as mentioned below (Pohlert 2020) :

$$K_P = \max |U_{i,P}| \quad (2)$$

where

$$U_{t,p} = \sum_{i=1}^t \sum_{j=i+1}^P \text{sgn}(Y_i - Y_j) \quad (3)$$

If the test is significant at 5%, then K_p is the location of the change-point of the time series. The significant test is valid when $p < 0.05$, which is determined as:

$$p \cong 2 \exp\left(\frac{-6 K_p^2}{P^3 + P^2}\right) \quad (4)$$

(c) Buishand range test (BRT):

If Y is the normal random variate, then the single change-point is given by (Pohlert 2020):

$$y_i = \begin{cases} \mu + \epsilon_i, & i = 1, \dots, m \\ \mu + \Delta + \epsilon_i, & i = m + 1, \dots, n \end{cases} \quad (5)$$

where $\epsilon_i \approx N(0, \sigma)$. The null hypothesis is true when there is no change ($\Delta = 0$) and for alternative hypothesis it is otherwise. The normalized adjusted partial sums are determined as:

$$S_k = \sum_{i=1}^k (y_i - \hat{y}), \quad (1 \leq i \leq n) \quad (6)$$

Then the test statistic can be determined as:

$$R_b = \frac{\max(S_k) - \min(S_k)}{\sigma} \quad (7)$$

Monte Carlo simulation using m replicates is carried out to determine p -value.

(d) Standard normal homogeneity test (SNHT):

The test statistic of SNHT is determined as (Pohlert 2020):

$$P_k = kz_1^2 + (n-k)z_2^2, \quad (1 \leq k \leq n) \quad (8)$$

where

$$z_1 = \frac{1}{k} \sum_{i=1}^k \frac{y_i - \hat{y}}{\sigma}, \quad z_2 = \frac{1}{n-k} \sum_{i=1}^k \frac{y_i - \hat{y}}{\sigma} \quad (9)$$

Then the critical value is given as:

$$P = \max(P_k) \quad (10)$$

Monte Carlo simulation using m replicates is used to estimate p -value.

In the second step, the following three classes are obtained based on the outcome of the four tests rejecting the null hypothesis when there is inhomogeneity:

(1) Category A: “useful”— when three or all tests fail to accept the alternative hypothesis.

(2) Category B: “doubtful”— when two tests accept the alternative hypothesis.

(3) Category C: “suspect”— when one or none tests fail to accept the alternative hypothesis.

In this study, only the time series of category A were considered for further analysis at a 5% level of significance.

3.1.2 Serial correlation test

One of the assumptions of the classical trend analysis methods like the MK and SR tests is that the time series should have no significant serial correlation (lag-1) that influences the strength of trend analysis. The autocorrelation function (ACF) in the R programming language (R Core Team 2022) was used to determine a significant lag-1 correlation at a 95% confidence level. If the data sample points are y_1, y_2, \dots, y_n , then lag-1 autocorrelation is simply the Pearson's correlation expressed as:

$$r = \text{correlation}(y_i; y_{i-1}) = (y_2, y_3, \dots, y_n ; y_1, y_2, \dots, y_{n-1}) \quad (11)$$

If $r > \alpha = \frac{1.96}{\sqrt{(n-1)}}$, then there is a lag-1 autocorrelation significance at 5% level, else it is insignificant.

3.2 Trend analysis

3.2.1 Mann-Kendall

The Mann-Kendall (MK) and Spearman's rho (SR) tests (Kendall 1938; Mann 1945; Daniel 1990) and Sen's slope estimator (SSE) (Sen 1968) were applied to the time series of rainfall to identify monotonic trends (Gocic and Trajkovic 2013; Formetta et al. 2016; Gado et al. 2019). The modified MK method (Yue and Wang 2004) was applied to reduce autocorrelation influence. The MK and SR tests show the direction of the trend, while the SSE shows the magnitude of the trend. The modifiedmk R package (Patakamuri and O'Brien 2020) was used to perform the tests at 5 and 10% significance levels.

The Mann-Kendall test statistic is determined as:

$$S = \sum_{k=1}^{n-1} \sum_{i=k+1}^n \text{sgn}(Y_i - Y_k) \quad (12)$$

where

$$\text{sgn}(y) = \begin{cases} 1 & \text{if } y > 0 \\ 0 & \text{if } y = 0 \\ -1 & \text{if } y < 0 \end{cases} \quad (13)$$

The mean of the test statistic (S) is expressed as $E(s) = 0$ and the variance is expressed as:

$$Var(S) = \left[n(n-1)(2n+5) - \sum_{i=1}^p t_i(t_i-1)(2t_i+5) \right] / 18 \tag{14}$$

where the number of tied groups in the data set is represented by p , and the number of data points in the i th tied group is represented by t_i . The statistic S follows an approximately normal distribution if it is transformed using the Z-transformation method.

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{2Var(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{2Var(S)}} & \text{if } S < 0 \end{cases} \tag{15}$$

When there is a significant lag-1 correlation, then modified Mann-Kendall (mMK) test is carried out to inhibit the effect of serial correlation on variance of the MK statistic. The modified variance $Var^*(S)$ is obtained by using effective sample size (ESS) (Yue and Wang 2004) as:

$$Var^*(S) = Var(S) \frac{n}{n^*} \tag{16}$$

where n is the actual sample size (ASS) of a given sample data, n^* is the ESS.

For lag-1 correlation (ρ_1), a formula was formulated to compute n^* (Matalas and Langbein 1962) as follows:

$$n^* = \frac{n}{1 + 2 \left\{ \frac{\rho_1^{n+1} - n\rho_1^2 + (n-1)\rho_1}{n(\rho_1-1)^2} \right\}} \tag{17}$$

The thresholds used in this study to evaluate whether the trend is significant or not are 90% and 95% confidence levels corresponding to $Z_{1-\frac{\alpha}{2}} = \pm 1.65$ and $Z_{1-\frac{\alpha}{2}} = \pm 1.96$, respectively for two tailed tests. For example, if we want to determine whether the trend is statistically significant or not at 5% level of significance ($1 - \alpha = 1 - 0.05 = 0.95 = 95\%$ confidence level). If the Z statistic from MK/mMK test is less than -1.96 or greater than 1.96 , then the trend is significant.

The MK/mMK test helps to identify the direction of monotonic trend (either increasing or decreasing). The magnitude, which is known as Sen's slope, of such trend was calculated as (Sen 1968):

$$\beta = \text{median} \left[\frac{y_j - y_k}{j - k} \right] \text{ for all } k < j \tag{18}$$

where y_j and y_k are the data samples corresponding to j and k time steps. The Sen's slope (β) indicates the median of the slopes between consecutive data points. The

negative (positive) slope indicates decreasing (increasing) trend.

3.2.2 Spearman's rho tests

The Spearman's rho (SR) is a non-parametric rank-based correlation test that measures the strength between two variables. For trend analysis, one of the variables is the time of observation and the other variable is the variable of interest, which is precipitation in our case. The test statistic is given by (Yue et al. 2002):

$$D = 1 - \frac{6 \sum_{i=1}^n |R(Y_i) - i|^2}{n(n^2 - 1)} \tag{19}$$

where $R(Y_i)$ denotes the rank of the i th observation Y_i in each sample of n . When there is no significant trend, the marginal distribution of D follows normal with the mean and variance as:

$$Mean = E(D) = 0 \tag{20}$$

$$Variance = Var(D) = \frac{1}{(n-1)} \tag{21}$$

The p -value of the SR statistic (D) of the observed data is determined using the standardized normal distribution (with zero mean and 1 standard deviation) as:

$$Z_{SR} = \frac{D}{\sqrt{V(D)}} \tag{22}$$

The p -value of SR test statistic (D) of the sample data can be determined using the normal cumulative distribution function (CDF) as:

$$p = 0.5 - \Phi(|Z|) \tag{23}$$

where Z = test statistics of MK (S) and SR (D) = Z_{MK} , Z_{SR} and

$$\Phi(|Z|) = \frac{1}{\sqrt{2\pi}} \int_0^{|Z|} e^{-t^2/2} dt \tag{24}$$

In this study, if $p \leq 0.05$ (5% level of significance) or $p \leq 0.1$ (10% level of significance), the trend is significant.

3.2.3 Innovative trend analysis

The innovative trend analysis (ITA) (Şen 2012a, 2017b) was conducted on the homogeneous rainfall time series, irrespective of the significance of the autocorrelation of the time series. The ITA test is independent of autocorrelation, normality, and

data length. Two equal sub-series are obtained from the original rainfall time series to conduct ITA. Next, the two segregated datasets are arranged in increasing order. Then, the first sub-series data are placed on the x-axis and the second on the y-axis of the Cartesian coordinate system. The coordinates lying on the 45° line indicate the absence of a trend, below indicate a negative trend, and above indicate an increasing trend. The ITA test can also identify obscure trends, which is impossible with traditional methods because such methods can detect only monotonic trends (Şen 2012). In this study, the sub-trends were obtained based on certain thresholds. Accordingly, three clusters were created based on those thresholds (Wang et al. 2020). The high cluster is set for all values greater than 90 percentiles of the first (second) half of the original time series on x-axis (y-axis). The medium cluster lies between values greater than equal to 10 percentile and less than equal to 90 percentiles of the first (second) half of the original data. Similarly, the low cluster is for those values less than 10 percentile of the first (second) half of the time series. It is to be noted here that the trend in high cluster reflects on the occurrence of flood and trend in low cluster denotes occurrence of drought (Öztopal and Şen 2017).

The monthly ITA slope (s) can be calculated as (Şen 2017b):

$$s = \frac{2(\bar{y}_2 - \bar{y}_1)}{n} \quad (25)$$

where \bar{y}_2 is the mean of the second half time series in ascending order, \bar{y}_1 is the mean of first half time series in ascending order, and n is the data length of the original time series. The slope (s) is significant at 5% level of significance if $s < \text{Confidence limit } (CL_{(1-\alpha)} = 0 - 1.96 * \sigma_s)$ or $s > \text{Confidence limit } (CL_{(1-\alpha)} = 0 + 1.96 * \sigma_s)$. For 10% level of significance 1.96 is replaced by 1.65. The standard deviation of the slope (σ_s) can be expressed as (Şen 2017b):

$$\sigma_s = \frac{2\sqrt{2}}{n\sqrt{n}} \sigma \sqrt{1 - r_{y_1 y_2}} \quad (26)$$

where σ is the standard deviation of the original sample and $r_{y_1 y_2}$ is the correlation coefficient between the first and second half of the data.

The trendchange R package was applied to detect trends using the ITA method (Patakamuri and Das 2019) at 5 and 10% significance levels. In addition to the package, modified R code created for this study using ggplot2 library was used for sub-trend plots.

4 Results and discussion

4.1 Homogeneity tests of seasonal and annual rainfall

Four homogeneity tests were applied to 55 time series of 11 districts, as shown in Table 1. The rainfall data of the Ballari and Haveri districts in the winter season were doubtful. All the data for the summer season were useful. The data for the monsoon season in the Bagalkot, Vijayapura, and Dharwad districts were doubtful. The rainfall data for the post-monsoon season in the Bidar and Vijayapura districts were suspect. The annual rainfall data for the Bagalkot, Vijayapura, and Dharwad districts were also suspect. The rainfall data for the Bagalkot, Gadag, and Kalaburagi districts were doubtful. The doubtful or suspect data were discarded, resulting in 78.18% (43/55) of the data being used for further analysis.

4.2 Lag-1 correlation tests of seasonal and annual rainfall

Out of the 43 time series data carried out for lag-1 correlation, 95.35% (41/43) time series data were found to have insignificant autocorrelation (Table 2). The datasets of the post-monsoon and annual rainfall of the Belagavi district were found to have a significant ($p < 0.05$) lag-1 correlation. Therefore, the modified Mann Kendall (mMK) was applied to these two time series rainfall data.

Table 1 Homogeneity test of the seasonal and annual rainfall of semi-arid region of Karnataka

District	Winter	Summer	Monsoon	Post monsoon	Annual
Bagalkot	Useful	Useful	Doubtful	Useful	Suspect
Belagavi	Useful	Useful	Useful	Useful	Useful
Ballari	Doubtful	Useful	Useful	Useful	Useful
Bidar	Useful	Useful	Useful	Suspect	Useful
Vijayapura	Useful	Useful	Doubtful	Suspect	Suspect
Dharwad	Useful	Useful	Doubtful	Useful	Suspect
Gadag	Useful	Useful	Useful	Useful	Doubtful
Kalaburagi	Useful	Useful	Useful	Useful	Doubtful
Haveri	Doubtful	Useful	Useful	Useful	Useful
Koppal	Useful	Useful	Useful	Useful	Useful
Raichur	Useful	Useful	Useful	Useful	Useful

“Doubtful” and “Suspect” categories were discarded for further analysis

Table 2 Lag-1 correlation test of seasonal and annual rainfall of semi-arid region of Karnataka

District	Winter	Summer	Monsoon	Post monsoon	Annual
Bagalkot	No	No	-	No	-
Belagavi	No	No	No	Yes	Yes
Ballari	-	No	No	No	No
Bidar	No	No	No	-	No
Vijayapura	No	No	-	-	-
Dharwad	No	No	-	No	-
Gadag	No	No	No	No	-
Kalaburagi	No	No	No	No	-
Haveri	-	No	No	No	No
Koppal	No	No	No	No	No
Raichur	No	No	No	No	No

“No” means significant lag-1 correlation does not exist, “Yes” means lag-1 correlation exists

4.3 Trend analysis of seasonal and annual rainfall

4.3.1 Trend analysis of winter rainfall

For the winter season, the MK and SR tests detected an insignificantly decreasing (negative) trend in seven of the nine districts with homogeneous rainfall time series (Table 3 and Table S1). On the other hand, the rainfall of the Koppal and Raichur districts shows a significantly decreasing trend at a 10 % significance level. The ITA method, however, detected decreasing trend in all the nine districts at a 5% level of significance. The magnitudes of Sen’s slope for Koppal and Raichur districts are significantly decreasing at 0.0002 and 0.0003 mm/year (Table 4, Fig. 5), respectively. The slopes of the ITA method indicate that the Vijayapura

district experienced the least decreasing trend, whereas Dharwad experienced the highest decreasing trend among all the districts. The ITA slope ranges -0.008 to -0.07 mm/year (Fig. 6).

From the Figs. 7, 8, 9, 10, 11, and 12, the clusters are represented by the colours: blue (high), green (medium), and red (low). The brick red colour represents the trend of the original time series, while the remaining colours represent sub-trends. In the high cluster, the district of Dharwad (Fig. 9c) experienced the highest decreasing trend (4.47 mm/year). On the other hand, the district of Vijayapura (Fig. 9a) experienced the least decreasing trend (0.09 mm/year). In the medium cluster, the Bidar district (Fig. 8e) experienced the highest decreasing trend (0.07 mm/year), the least by the Belagavi district (0.007 mm/year) as shown in Fig. 8 d. All the districts experienced an undefined trend due to many zeros or no rain occurring during this season in the low cluster. Only the Bidar district experienced an increasing trend (0.10 mm/year) in the high cluster (Fig. 8e).

4.4 Trend analysis of summer rainfall

The MK and SR tests for the districts (5/11; 45.45%) of Bagalkot, Belagavi, Bidar, Vijayapura, and Raichur show an insignificant increasing (positive) trend of rainfall, whereas the districts (5/11; 45.45%) of Ballari, Dharwad, Gadag, Haveri, and Koppal show insignificant decreasing trend at 95% confidence interval (Table 5). The district (9.1%) of Kalaburagi is the only one to experience a significantly increasing trend at a 90% confidence interval as per the MK and SR tests (Fig. 5). Out of the 11 districts with homogeneous rainfall, except the district of Gadag, the remaining districts (90.91%) show a significantly increasing trend at a 5% significance level as per the ITA method (Table 3). Gadag is

Table 3 Trend indication of seasonal and annual rainfall of the semi-arid districts of Karnataka

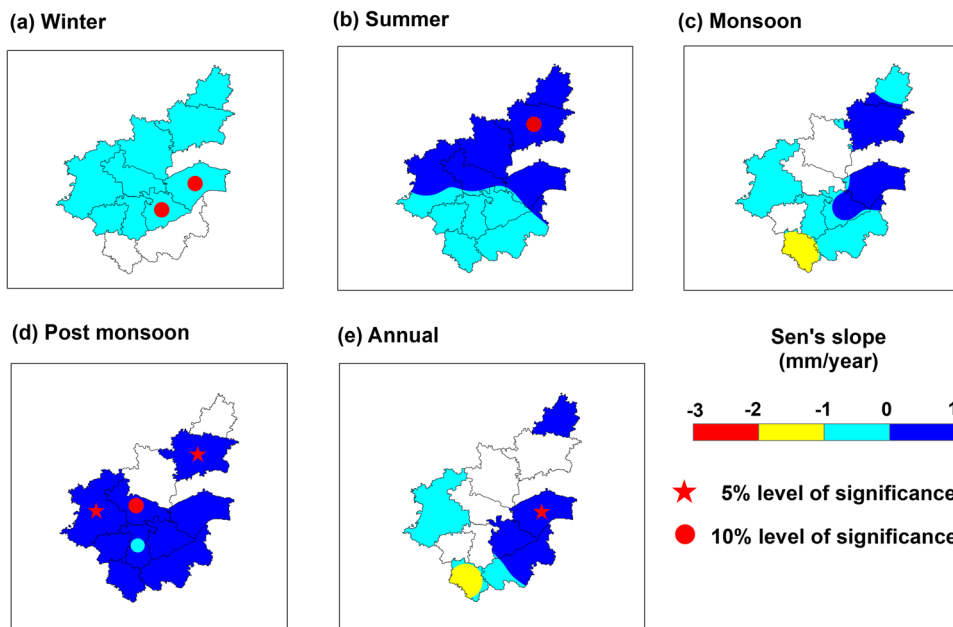
District	Winter			Summer			Monsoon			Post monsoon			Annual		
	MK	Spearman	ITA	MK	Spearman	ITA	MK	Spearman	ITA	MK	Spearman	ITA	MK	Spearman	ITA
Bagalkot	-	-	-*	+	+	+	NA	NA	NA	+	+	+	NA	NA	NA
Belagavi	-	-	-*	+	+	+	-	-	+	+/+*	+	+	-/-	-	+
Ballari	NA	NA	NA	-	-	+	-	-	-	+	+	+	+	+	+
Bidar	-	-	-*	+	+	+	-	-	+	NA	NA	NA	+	+	+
Vijayapura	-	-	-*	+	+	+	NA	NA	NA	NA	NA	NA	NA	NA	NA
Dharwad	-	-	-*	-	-	+	NA	NA	NA	+	+	-*	NA	NA	NA
Gadag	-	-	-*	-	-	-	-	-	+	-	-	-*	NA	NA	NA
Kalaburagi	-	-	-*	+	+	+	+	+	+	+	+	+	NA	NA	NA
Haveri	NA	NA	NA	-	-	+	-	-	-*	+	+	+	-	-	-*
Koppal	-**	-**	-*	-	-	+	+	+	+	+	+	+	+	+	+
Raichur	-**	-**	-*	+	+	+	+	+	+	+	+	+	+	+	+

A minus sign indicates negative trend; a plus sign indicates positive trend; a single asterisks indicates 5% significance level; a double asterisk indicates 10% significance level; NA indicates no analysis was carried out

Table 4 Magnitude of trends of the winter rainfall

District	Sen's slope	ITA slope	Slope of SD (SSD)	Correlation (r_{y_1, y_2})	Lower CL	Upper CL
Bagalkot	0	-0.01*	0.0009	0.98	-0.002	0.002
Belagavi	-0.00004	-0.01*	0.001	0.93	-0.002	0.002
Ballari	NA	NA	NA	NA	NA	NA
Bidar	0	-0.06*	0.009	0.91	-0.02	0.02
Vijayapura	0	-0.008*	0.001	0.96	-0.003	0.003
Dharwad	0	-0.07*	0.003	0.98	-0.005	0.005
Gadag	0	-0.03*	0.001	0.99	-0.002	0.002
Kalaburagi	-0.0004	-0.03*	0.002	0.97	-0.005	0.005
Haveri	NA	NA	NA	NA	NA	NA
Koppal	-0.0002**	-0.03*	0.002	0.95	-0.003	0.003
Raichur	-0.0003**	-0.02*	0.001	0.98	-0.002	0.002

A single asterisk indicates 5% significance level; a double asterisk indicates 10% significance level; NA indicates no analysis was carried out

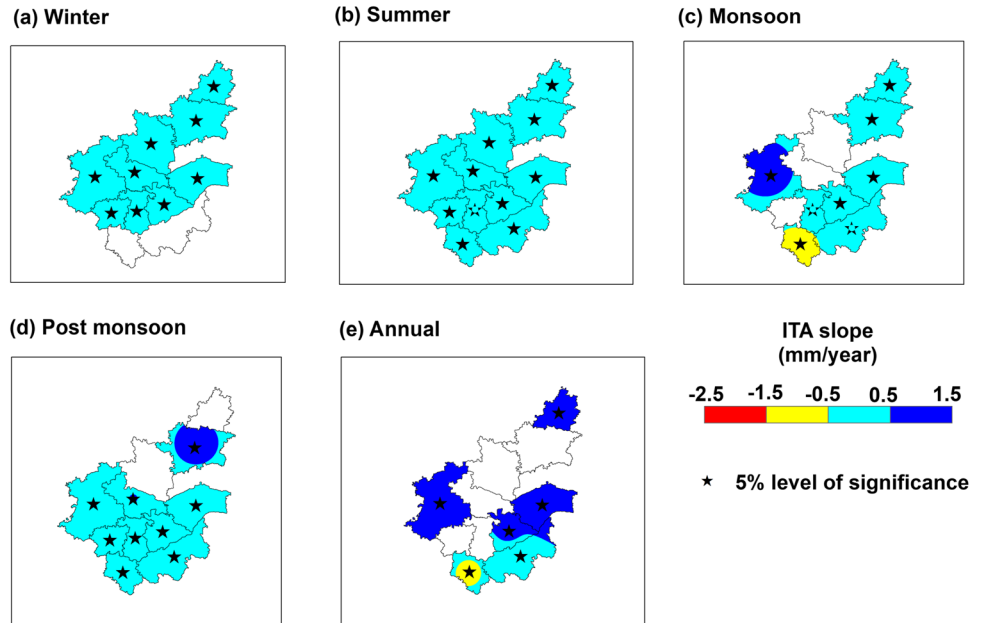
Fig. 5 Sen's slope map of seasonal and annual rainfall

the only district to show an insignificantly decreasing trend using the ITA method. The Sen's slope of Kalaburagi is 0.18 mm/year. The ITA slope lies in the range 0.13–0.38 mm/year, in which the district of Koppal shows the least positively significant trend of 0.13 mm/year (Fig. 6). Moreover, Belagavi and Vijayapura districts show the highest positively significant trend of 0.38 mm/year.

In the high cluster category, the district of Haveri experienced the highest increasing trend of 12.16 mm/year of precipitation (Fig. 10f), while the least magnitude of trend was experienced by the district of Vijayapura (3.70 mm/year) as depicted in Fig. 9 b. Interestingly, the latter district

experienced the highest increasing trend (0.54 mm/year) in the medium cluster category, while the least increasing trend was experienced by the Dharwad district (0.08 mm/year) as shown in Fig. 9d. In the Fig. 10 f, for the low cluster category, the district of Haveri shows the highest increasing trend at 2.87 mm/year, while the district of Kalaburagi shows the least increasing trend (0.053 mm/year) (Fig. 10c). Only the district of Gadag in Fig. 9 g shows a decreasing trend (0.14 mm/year) in the medium category. The highest and least decreasing trends are respectively shown in Figs. 9 b and 7 e for the Vijayapura district (0.64 mm/year) and the Belagavi district (0.019 mm/year).

Fig. 6 ITA slope map of seasonal and annual rainfall



4.5 Trend analysis of monsoon rainfall

Out of the eight districts with homogeneous time series for monsoon rainfall, none showed a significant trend using the MK and SR tests at 5% and 10% significance levels (Table 3). However, the ITA method captured significant positive and negative trends for five (62.5%) and one (12.5%) of the eight districts, respectively, at a 5% significance level. Only Ballari and Gadag districts experienced insignificantly decreasing and increasing trends using the ITA method, respectively. Belagavi, Ballari, Bidar, Gadag, and Haveri districts show a negatively insignificant trend, whereas Kalaburagi, Koppal, and Raichur indicate a positively insignificant trend. Using the ITA method, the Haveri district experienced the most decreasing trend at 1.07 mm/year, whereas Belagavi at 0.86 mm/year shows the most increasing trend (Table 6). Bidar district had the least increasing trend at 0.2 mm/year.

With a magnitude of about 16.3 mm/year, Belagavi and Haveri districts in Figs. 7 f and 10 g show the highest increasing trend in the high cluster category, whereas the least positive trend as shown in Fig. 11 d was experienced by Koppal district. In the medium category, Belagavi district (Fig. 7f) depict the highest positive trend (1 mm/year), while Bidar (Fig. 8g) shows the least increasing trend (0.37 mm/year). In Figs. 9 h and 10 d, for the low cluster category the highest increasing trend was experienced by Gadag district (9.80 mm/year) and the least increasing trend by Kalaburagi district (0.77 mm/year). A highest decreasing trend of 1.47 mm/year was experienced by Ballari in the high cluster (Fig. 8b), whereas a magnitude of 1.24 mm/year decreasing trend was revealed by Bidar in the same cluster (Fig. 8). In

the medium cluster (Fig. 10g), Haveri experienced the highest decreasing trend (1.81 mm/year), whereas the district of Ballari in Fig. 8 b shows the least negative trend (0.006 mm/year). The low cluster category (Fig. 10g) has again Haveri district showing the highest decreasing trend (6.51 mm/year) and the least decreasing by Bidar district (Fig. 8g) (2.84 mm/year).

4.6 Trend analysis of post-monsoon rainfall

Out of nine districts with homogeneous post-monsoon rainfall, the MK and SR tests detected an increasing trend for two districts (Bagalkot at 90% and Kalaburagi at 95% confidence intervals) (Table 3). The mMK test was applied to the post-monsoon rainfall for the Belagavi district because it had a significant lag-1 correlation ($p < 0.05$). Therefore, the rainfall for the Belagavi district turned out to have an increasing trend ($p < 0.05$). The Belagavi, Ballari, Bidar, Vijayapura, Dharwad, Haveri, Koppal, and Raichur districts show an insignificantly increasing trend ($p < 0.1$). In contrast, the district of Gadag shows an insignificantly decreasing trend using the MK and SR tests. The ITA method detected a significant ($p < 0.05$) trend in all the nine districts. The Bagalkot, Belagavi, Ballari, Kalaburagi, Haveri, Koppal, and Raichur districts experienced increasing trends, while Dharwad and Gadag showed decreasing trends using the ITA method. The Sen's slopes of Bagalkot, Belagavi, and Kalaburagi are 0.47, 0.25, and 0.63 mm/year, respectively (Table 7, Fig. 2). The Ballari district shows the least increasing ITA slope (0.06 mm/year), and the highest increasing ITA slope (0.62 mm/year) is shown by the Kalaburagi

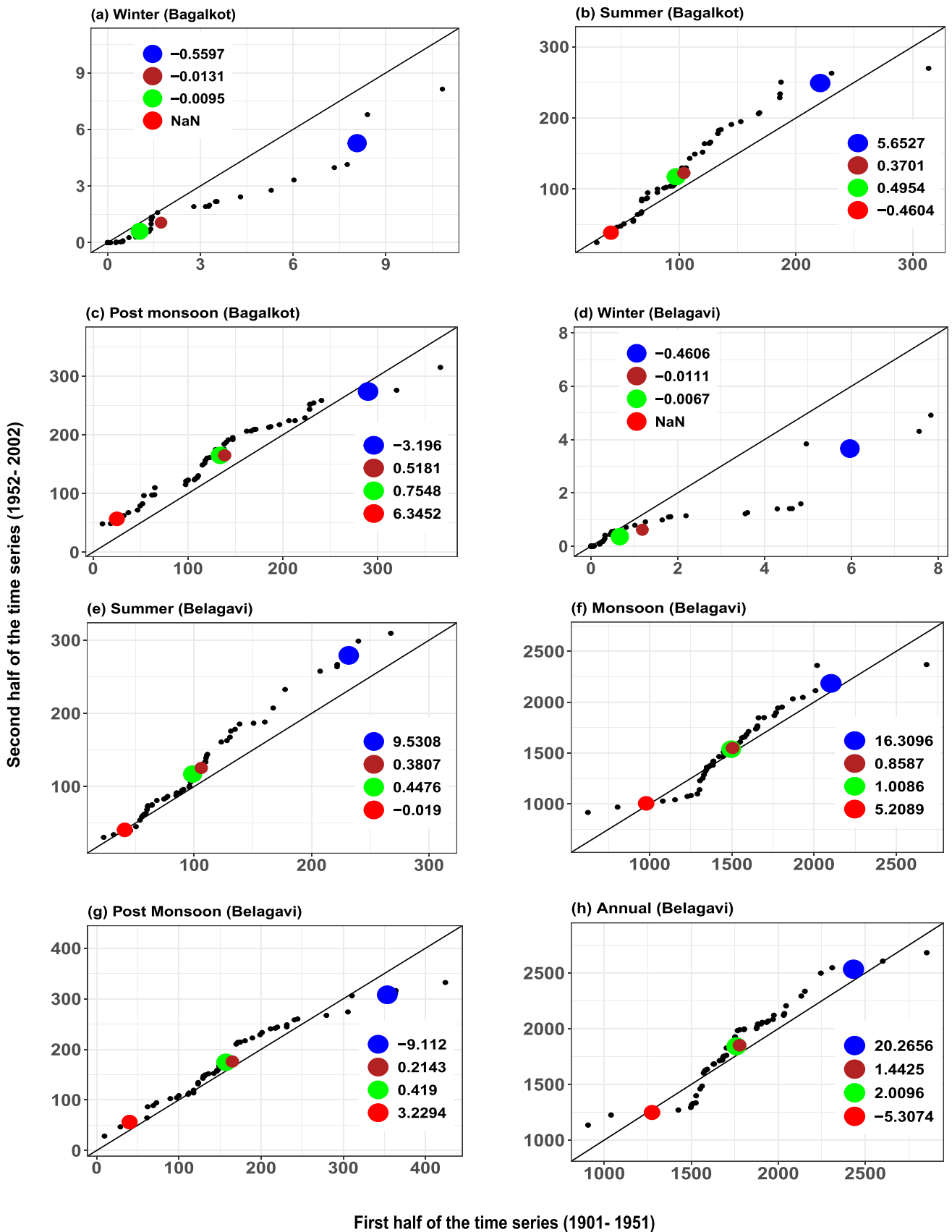


Fig. 7 Innovative trend analysis of Bagalkot and Belagavi districts

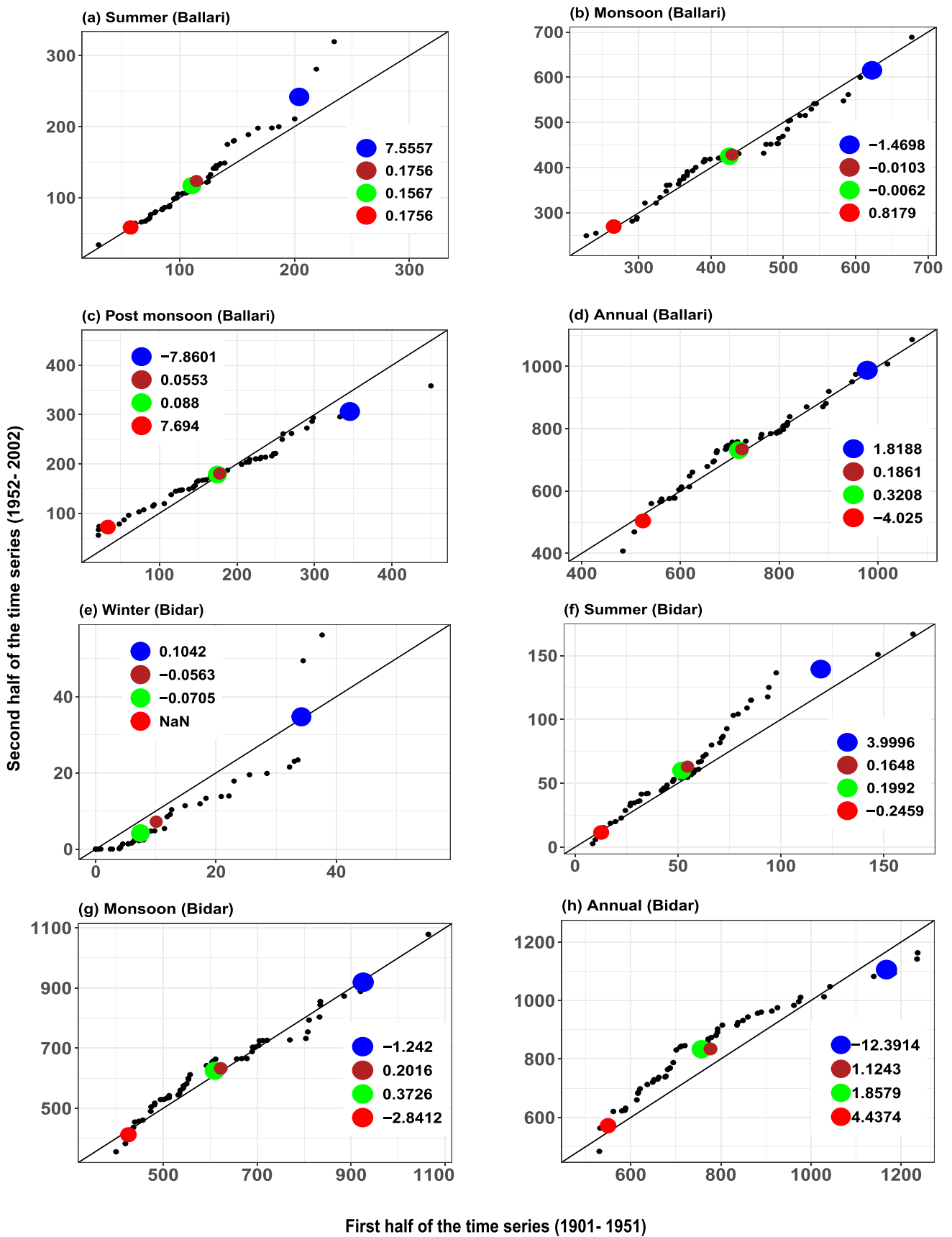


Fig. 8 Innovative trend analysis of Ballari and Bidar districts

district. Dharwad and Gadag districts show decreasing ITA slope at 0.05 mm/year (Table 7, Fig. 3).

In Fig. 10 e, Kalaburagi district depicts the highest increasing trend (5.59 mm/year) in the high cluster category, whereas the district of Haveri (Fig. 10h) shows the least increasing trend (2.01 mm/year). In the medium cluster (same figures), the districts of Kalaburagi and Haveri again show the highest increasing trend (0.81 mm/year) and the least increasing trend (0.05 mm/year), respectively. In the low cluster category (Figs. 8c, 7e), Ballari district experienced the highest increasing trend (7.70 mm/year) and least positive trend by Belagavi district (3.23 mm/year). In the high cluster (Figs. 11e, 7g), the highest decreasing trend was experienced by Koppal district (10.33 mm/year) and the least by Bagalkot district (3.2 mm/year). In the medium category (Figs. 9e, 10a), Dharwad experienced a decreasing trend of 0.08 mm/year, while Gadag experienced a decreasing trend of 0.07 mm/year.

4.7 Trend analysis of annual rainfall

Out of the six districts with homogeneous annual rainfall, only Raichur experienced an increasing trend ($p < 0.05$) using the MK and SR tests (Table 3). Even after the annual rainfall of the district of Belagavi (significant lag-1 correlation at $p < 0.05$) was subjected to the mMK test apart from the two tests, the district experienced an insignificant trend. Belagavi and Haveri districts experienced an insignificant decreasing trend. In contrast, Ballari, Bidar, and Koppal districts show an insignificant increasing trend using the MK, SR, and mMK tests. The ITA method detected significant increasing/decreasing trends in all six districts. The Belagavi, Ballari, Bidar, Koppal, and Raichur districts were found to have a significantly increasing trend, whereas Haveri had a significant decreasing trend using the ITA method ($p < 0.05$). The Sen's slope of the Raichur district indicates an increasing trend (0.88 mm/year) (Table 8, Fig. 2). The ITA slope of the Ballari district shows the least increasing trend (0.19 mm/year), whereas the Belagavi district shows the most increasing trend (1.44 mm/year) (Table 8, Fig. 3). The magnitude of the slope of the Haveri district shows decreasing trend (0.68 mm/year).

In Figs. 7 h and 8 d, the highest increasing trend was shown by Belagavi district (20.27 mm/year) in the high category, whereas the least one was shown by Ballari district (1.82 mm/year). Similarly, in the medium category, the same districts show the highest (2.01 mm/year) and least increasing (0.32 mm/year) trends. In the low category (Figs. 8h, 12c), Bidar shows the highest increasing trend (4.44 mm/year) and Raichur shows the least increasing trend (2.76 mm/year). In the high category (Fig. 12c), only the district of Bidar shows a decreasing trend of 12.40 mm/year. Similarly, in the medium category (Fig. 10h) only the district of Haveri

experienced a decreasing trend of 0.85 mm/year. The low category (Figs. 10h, 11f) shows interesting figures for the decreasing trend, the highest being Haveri district at 21.28 mm/year and least being Koppal at 3.59 mm/year.

5 Comparative analysis of the ITA with MK, mMK and SR tests

Out of the 43 homogeneous rainfall time series, only six showed significant trends using the MK and SR methods. Since two time series showed significant lag-1 correlation ($p < 0.05$), only 14.63% of the time series ($6/(43-2) = 0.1463$) reveal significant trend using the two tests. Only a district out of the two shows a significant trend. However, the ITA method could detect 93.02% of the total time series ($40/43=0.9302$). This outcome could be because the classical trend test methods like the MK and SR detect only monotonic (decreasing/ increasing) trend in time series. In contrast, the ITA method can capture obscure trends that are not easily captured by the traditional methods (Şen 2012). The trends of the MK, SR, and ITA tests match for the Bagalkot district irrespective of whether the trend is significant or not.

For the Belagavi district, except monsoon and annual rainfall trends, the direction of trends in winter, summer, and post-monsoon match each other using the MK, SR, and ITA tests irrespective of whether the trend is significant or insignificant. In Fig. 7 f–h, the ITA method detected a monotonic insignificant decreasing trend, whereas the MK and SR tests detected otherwise for the corresponding time scales. For the summer in the Ballari district, the MK and SR detected an insignificantly decreasing trend. All the methods detected insignificantly decreasing trends for the monsoon season as reflected by scatter points lying slightly downward to the 1:1 line (Fig. 8b). For post-monsoon and annual rainfall of the district, all the trend methods have the same direction of trend (increasing) though only the ITA method has a significant trend (Fig. 8c, d).

There is an opposing direction of the trend for the Bidar district between traditional and innovative methods in the monsoon season. In contrast, the trend direction matches winter, summer, and annual scales. However, only the ITA method indicates significance in all the tested seasonal and annual rainfall (Fig. 8e–h). Though the trend directions for the winter and summer seasons of Vijayapura and Dharwad districts are the same using the MK, SR, and ITA tests, only the ITA method captured the trend (Fig. 9a–d). For the post-monsoon season of Dharwad, the trend direction is insignificantly increasing using the MK and SR tests but significantly decreasing using the ITA (Fig. 9e). The Gadag district experienced decreasing trend for winter and post-monsoon seasons using all three methods, but only the ITA test captured a significant trend (Figs. 9f, 10a). The trend

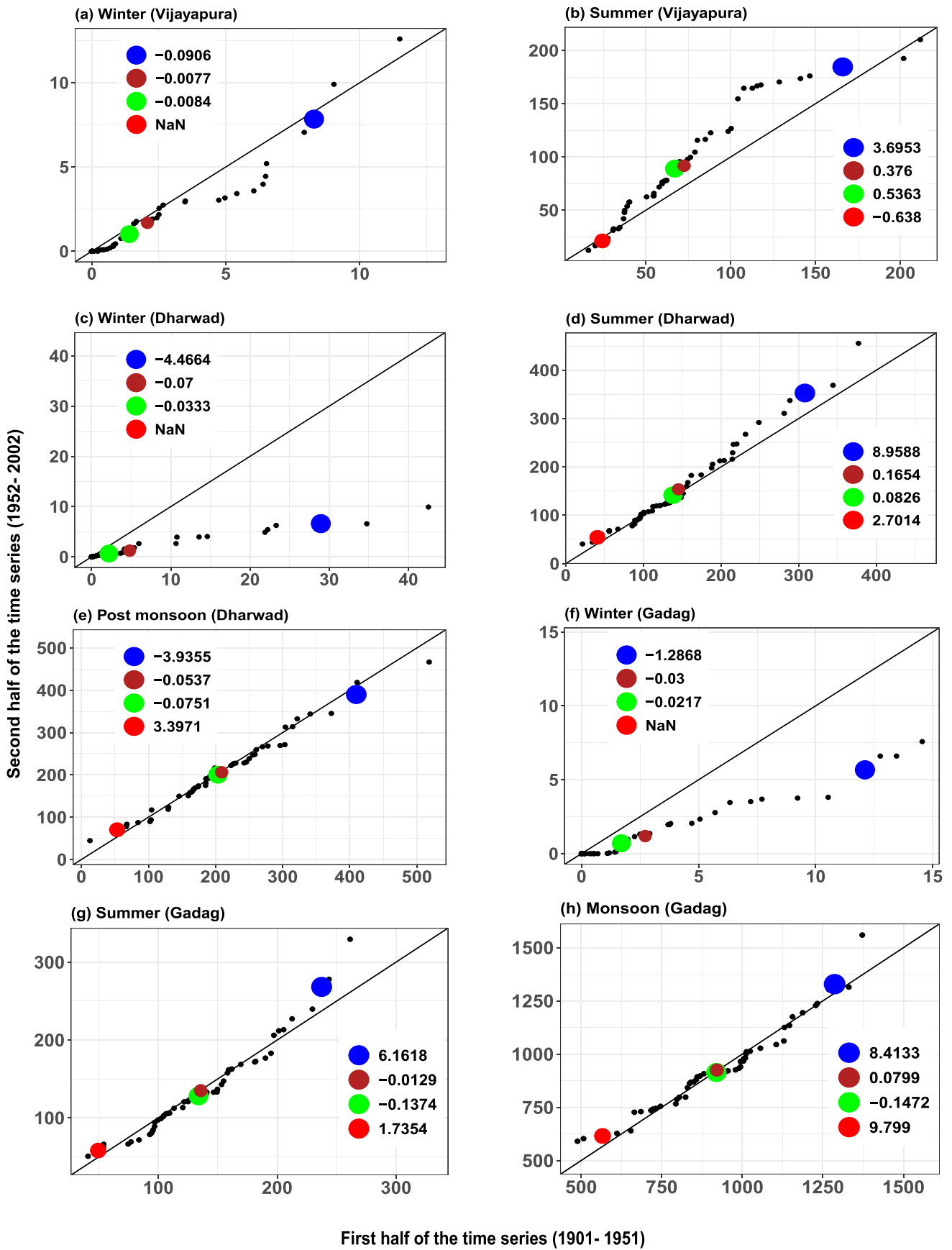


Fig. 9 Innovative trend analysis of Vijayapura, Dharwad and Gadag districts

direction in all the seasons of the Kalaburagi district matches for all three methods; however, the classical methods could capture a significant trend (10% significance level) only for the summer season (Table 3). On the other hand, ITA could detect a significant trend in all the seasons (Fig. 10b–e).

Except for the summer season in the Haveri district, the trend direction of monsoon, post-monsoon, and annual rainfall is the same. As with other districts, ITA captured a significant trend for all the mentioned seasons and annually (Figs. 10f–h, 11a). For the Koppal district, except for the summer season trend, all other seasons and annual rainfall showed the same trend direction using all three methods. The two traditional methods could capture a significant trend in the winter season, whereas the ITA captured a significant trend in all the seasons (Fig. 11b–f). For the Raichur district, the trend direction matches for all the seasons and annual scale. The trend is significant for winter and annual rainfall using the MK and SR tests, but the ITA could detect a significant trend for all seasonal and annual scales (Figs. 11g, 12c). The comparisons carried out for all seasonal and annual rainfall of the 11 districts using the ITA and traditional methods reveal that the ITA approach was indeed able to capture the monotonic trends detected by the traditional methods and the obscure trends. The outcome of the current study corroborates with the findings reported in recent literature (Marak et al. 2020; Singh et al. 2021b, a).

6 Conclusions

In this study, trend analysis was investigated using the MK, mMK, SR, and the ITA methods for the seasonal and annual rainfall of 11 semi-arid districts in Karnataka for 102 years (1901–2002) of data. Only 78.18 % (43/55) of the total time series data were homogeneous based on a two-step approach that involved four statistical methods and classification of

the methods into three categories. For instance, if a homogeneity test reveals that the rainfall of a particular place has changed over time, it could be an indication that there are underlying issues that need to be addressed to prevent future droughts. Similarly, if a serial correlation test reveals that there is a strong relationship between low (high) precipitation levels, it could be an indication that there is a need to implement drought (flood) control measures to protect against future drought (floods).

Out of the 43 homogeneous time series data, 95.35% (41/43) time series data were found to have insignificant autocorrelation. The post-monsoon and annual rainfall of the Belagavi district were found to have a significant ($p < 0.05$) lag-1 correlation; however, the mMK test showed an increasing trend for the post-monsoon season only. The MK and SR tests detected 14.63% of the time series ($(6/(43-2) = 0.1463)$) as significant trends. However, the ITA method could detect 93.02% ($(40/43=0.9302)$) of the total time series. The MK and SR tests could capture a significant trend for the winter season in Koppal and Raichur districts. The two tests could detect significant trend only in the Kalaburagi district for the summer season. No trend could be captured for the monsoon season. The significant trend in Bagalkot and Kalaburagi districts could be captured for the post-monsoon season. The tests could detect a significant trend in the Raichur district for annual rainfall; however, the ITA captured a significant trend for all the seasons in most districts.

The sub-trends (obscure) of each time series provided us with lots of information on how each sub-trend varies on varying degrees of trend magnitude. Out of all the districts studied for obscure trend analysis, the district of Belagavi experienced the highest increasing trend magnitude on an annual basis (20.27 mm/year). This means the district experienced the likelihood of more flood occurrences. On the other hand, the district of Haveri experienced almost similar trend magnitude (21.28 mm/year), but a decreasing one. That means the district had likely undergone drought to some extent.

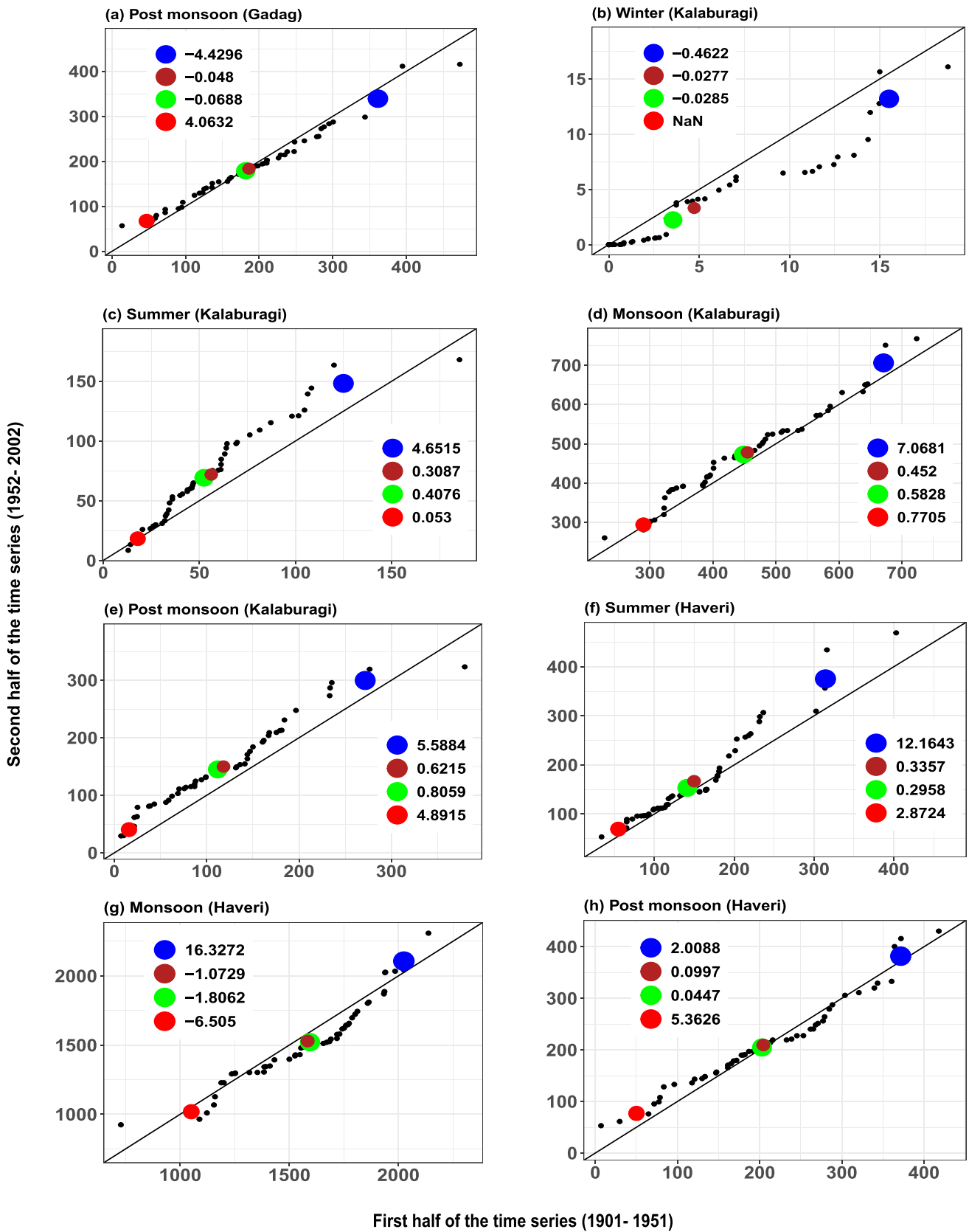


Fig. 10 Innovative trend analysis of Gadag, Kalaburagi and Haveri districts

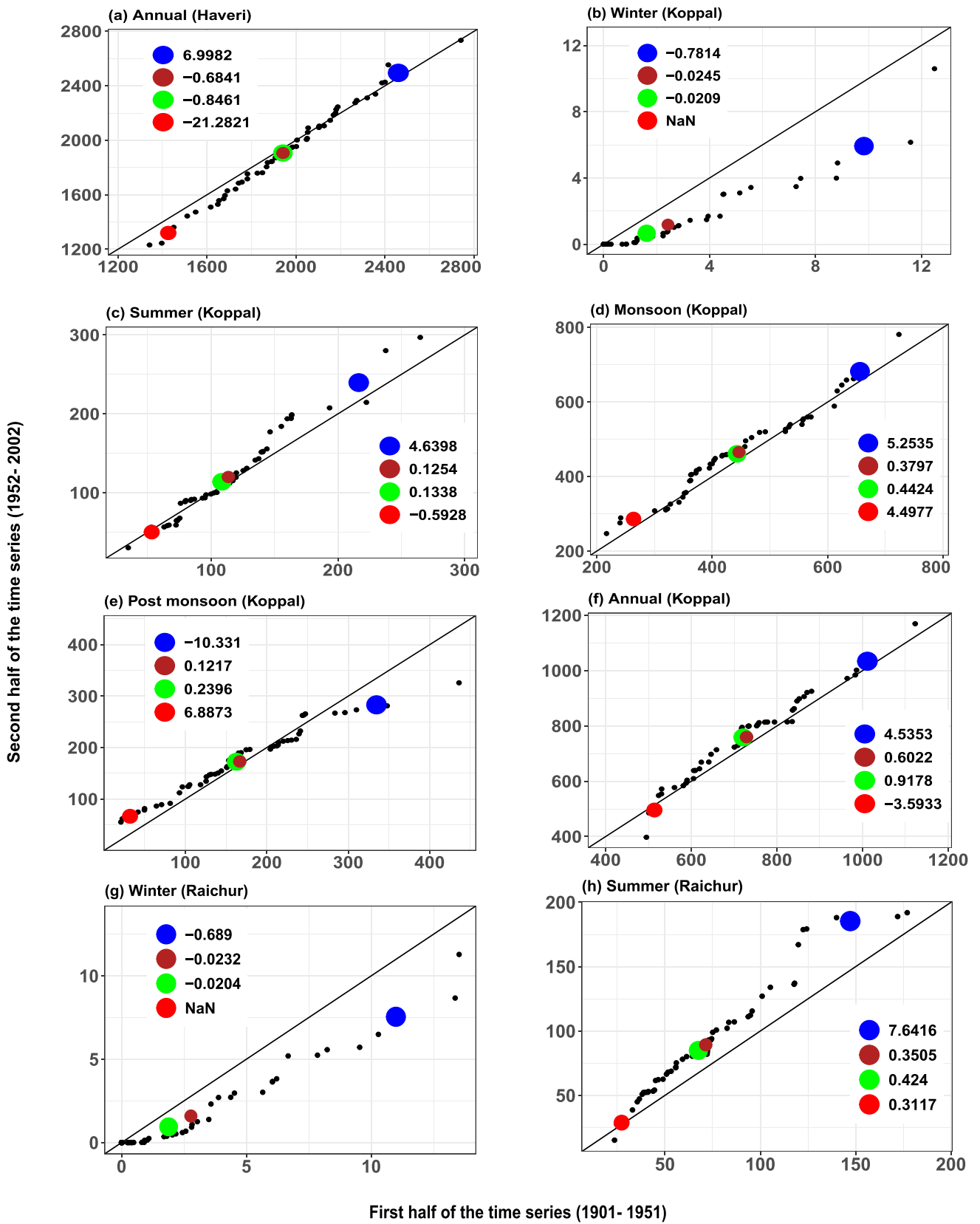


Fig. 11 Innovative trend analysis of Haveri, Koppal and Raichur districts

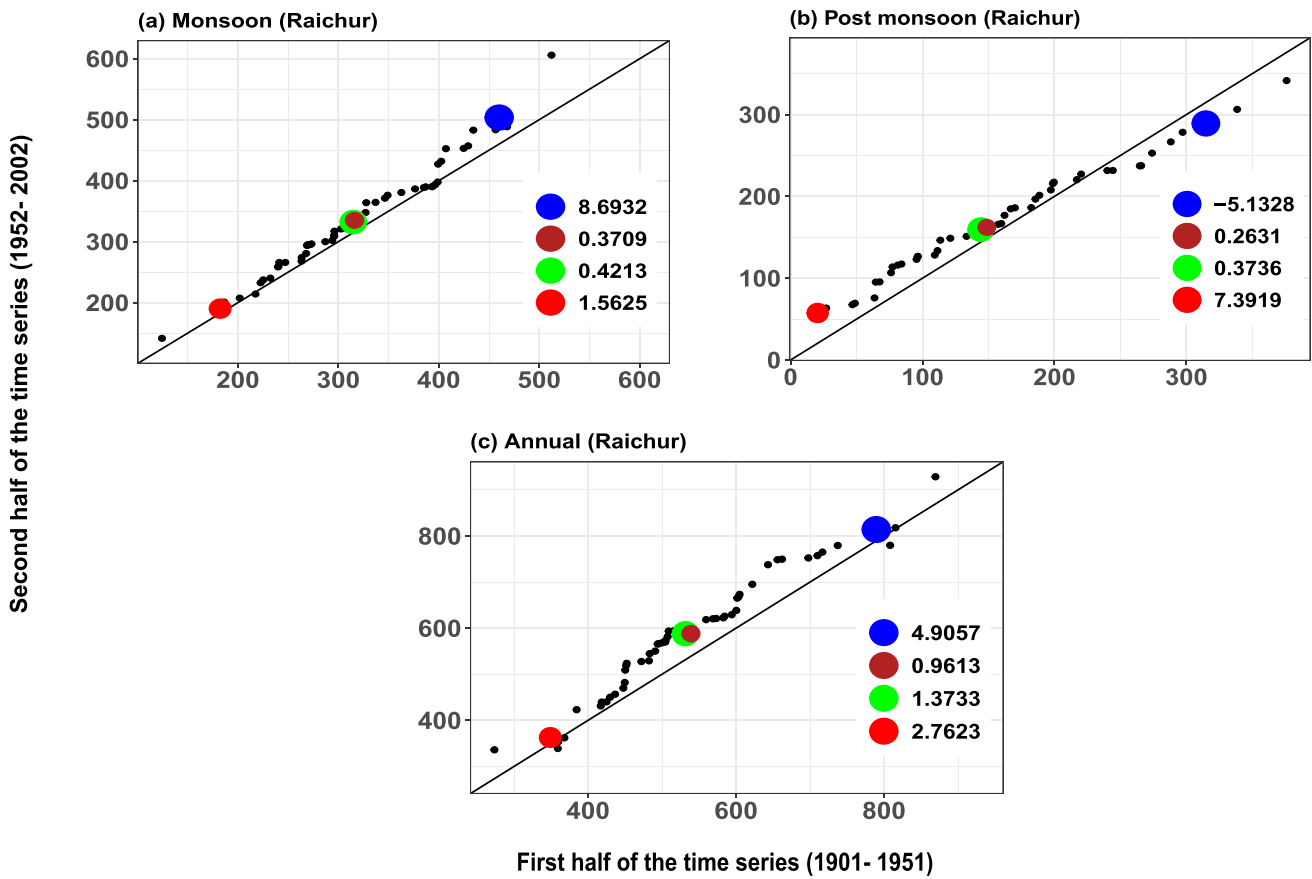


Fig. 12 Innovative trend analysis of Raichur district

Table 5 Magnitude of trends of the summer rainfall

District	Sen's slope	ITA slope	Slope of SD (SSD)	Correlation (r_{y_1, y_2})	Lower CL	Upper CL
Bagalkot	0.12	0.37*	0.034	0.96	-0.07	0.07
Belagavi	0.06	0.38*	0.02	0.99	-0.03	0.03
Ballari	-0.02	0.18*	0.02	0.98	-0.03	0.03
Bidar	0.09	0.16*	0.02	0.97	-0.03	0.03
Vijayapura	0.20	0.38*	0.03	0.96	-0.05	0.05
Dharwad	-0.21	0.17*	0.02	0.99	-0.05	0.05
Gadag	-0.25	-0.01	0.02	0.98	-0.05	0.05
Kalaburagi	0.18**	0.31*	0.02	0.96	-0.04	0.04
Haveri	-0.06	0.34*	0.04	0.98	-0.07	0.07
Koppal	-0.1	0.13*	0.02	0.99	-0.03	0.03
Raichur	0.14	0.35*	0.02	0.98	-0.03	0.03

A single asterisk indicates 5% significance level; a double asterisk indicates 10% significance level

Table 6 Magnitude of trends of the monsoon rainfall

District	Sen's slope	ITA slope	Slope of SD (SSD)	Correlation (r_{y_1, y_2})	Lower CL	Upper CL
Bagalkot	NA	NA	NA	NA	NA	NA
Belagavi	-0.77	0.86*	0.22	0.94	-0.43	0.43
Ballari	-0.009	-0.01	0.03	0.99	-0.07	0.07
Bidar	-0.02	0.20*	0.05	0.98	-0.1	0.1
Vijayapura	NA	NA	NA	NA	NA	NA
Dharwad	NA	NA	NA	NA	NA	NA
Gadag	-0.74	0.08	0.08	0.98	-0.16	0.16
Kalaburagi	0.16	0.45*	0.03	0.99	-0.07	0.07
Haveri	-1.53	-1.07*	0.16	0.96	-0.32	0.32
Koppal	0.2	0.38*	0.04	0.98	-0.08	0.08
Raichur	0.23	0.37*	0.03	0.99	-0.05	0.05

A double asterisk indicates 5% significance level; a single asterisk indicates 10% significance level; NA indicates no analysis was carried out

Table 7 Magnitude of trends of the post-monsoon rainfall

District	Sen's slope	ITA slope	Slope of SD (SSD)	Correlation (r_{y_1, y_2})	Lower CL	Upper CL
Bagalkot	0.47**	0.52*	0.03	0.97	-0.06	0.06
Belagavi	0.25	0.21*	0.04	0.97	-0.08	0.08
Ballari	0.09	0.06*	0.02	0.99	-0.04	0.04
Bidar	NA	NA	NA	NA	NA	NA
Vijayapura	NA	NA	NA	NA	NA	NA
Dharwad	0.003	-0.05	0.02	0.99	-0.04	0.04
Gadag	-0.04	-0.05	0.02	0.99	-0.04	0.04
Kalaburagi	0.63*	0.62*	0.03	0.98	-0.06	0.06
Haveri	0.08	0.10*	0.03	0.98	-0.06	0.06
Koppal	0.14	0.12*	0.03	0.98	-0.06	0.06
Raichur	0.34	0.26*	0.02	0.99	-0.03	0.03

A single asterisk indicates 5% significance level; a double asterisk indicates 10% significance level; NA indicates no analysis was carried out

Table 8 Magnitude of trends of the annual rainfall

District	Sen's slope	ITA slope	Slope of SD (SSD)	Correlation (r_{y_1, y_2})	Lower CL	Upper CL
Bagalkot	NA	NA	NA	NA	NA	NA
Belagavi	-0.44	1.44*	0.22	0.94	-0.44	0.44
Ballari	0.06	0.19*	0.05	0.98	-0.09	0.09
Bidar	0.86	1.12*	0.09	0.96	-0.19	0.19
Vijayapura	NA	NA	NA	NA	NA	NA
Dharwad	NA	NA	NA	NA	NA	NA
Gadag	NA	NA	NA	NA	NA	NA
Kalaburagi	NA	NA	NA	NA	NA	NA
Haveri	-1.31	-0.68*	0.05	0.99	-0.11	0.11
Koppal	0.36	0.6*	0.06	0.98	-0.11	0.11
Raichur	0.88*	0.96*	0.05	0.98	-0.11	0.11

A single asterisk indicates 5% significance level; a double asterisk indicates 10% significance level; NA indicates no analysis was carried out

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Code availability The “modifiedmk” and “trendchange” R packages were used for the trend analysis.

Author contribution CKK, SDB, and NB conceptualized, investigated, wrote, reviewed, and edited the draft. RG, KCG and AM supervised, reviewed, and edited the draft.

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Data availability The datasets generated during and/or analysed during the current study are available in the India water portal repository, <http://www.indiawaterportal.org/metdata>.

Declarations

Ethics approval Not applicable.

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Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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