

Long-term trend analysis of rainfall using hybrid Discrete Wavelet Transform (DWT) based Mann-Kendall tests in central Gujarat region, India

NIRAV V. RAJANI, MUKESH K. TIWARI*, S. S. CHINCHORKAR,

N. K. PAMPANIYA and SANJAY PARMAR

CAET, Anand Agricultural University, Godhra, Gujarat – 388 110, India

(Received 18 June 2018, Accepted 16 January 2020)

*email : tiwari.iitkgp@gmail.com

सार – वैज्ञानिक समुदाय द्वारा हाल ही के वर्षों में जलवायु परिवर्तन के कारण जल मौसम विज्ञान के परिवर्तों अध्ययन पर अधिक ध्यान दिए जाने के कारण इस प्रवृत्ति का विश्लेषण एक अत्यंत महत्वपूर्ण विषय बन गया है। प्रस्तुत अध्ययन में भारत के मध्य गुजरात क्षेत्र में स्थित अर्द्ध शुष्क आठ स्टेशनों पर हुई वर्षा की दीर्घकालिक प्रवृत्तियों का विश्लेषण किया गया है, जिसके लिए 116 वर्षों की समय श्रृंखला (1901 - 2016) के आंकड़ों को प्रयोग किया गया है। वर्षा की समय श्रृंखला के मासिक, वार्षिक और मॉनसून काल के समय मानों पर प्रवृत्ति तथा बारंबारता के विश्लेषण के लिए निरंतर तरंगिका रूपांतरण के रूप में विविक्त तरंगिका रूपांतरण (डी. डब्ल्यू. टी.) का व्यापक रूप से लागू और स्वीकार किए गए मान-कैंडेल (एम. के.) प्रवृत्ति विश्लेषण पद्धति का प्रयोग किया गया। एम.के. प्रवृत्ति परीक्षण को प्रयुक्त करने के पहले उच्च तथा निम्न बारंबारताओं पर उप-समय श्रृंखला प्राप्त करने के लिए डी. डब्ल्यू. टी. का उपयोग करके, आरंभ में इस अध्ययन में प्रयुक्त वर्षा की समय श्रृंखला को विघटित किया गया। इसके बाद प्रवृत्ति के बदलते बिंदुओं का पता लगाने के लिए क्रमिक मान-कैंडेल परीक्षण (SQMK) भी प्रयुक्त किया गया। परिणामों में देखा गया कि मासिक, वार्षिक और मॉनसून के समय मानों पर वर्षा की प्रवृत्ति में लगभग सभी स्थानों पर काफी कमी पाई गई। मासिक समय श्रृंखलाओं पर 4 माह तथा 8 माह के तथा मॉनसून की समय श्रृंखलाओं पर 2 वर्ष और 4 वर्ष के घटक प्रमुख रूप से पाए गए जबकि वार्षिक समय-मान पर 2 वर्ष के घटक प्रमुख रूप से पाए गए।

ABSTRACT. Trend analysis has become one of the most important issues in hydro-meteorological variables study due to climate change and the focus given to it in the recent past from the scientific community. In this study, long-term trends of rainfall are analyzed in eight stations located in semi-arid central Gujarat region, India by considering time series data of 116 years (1901-2016). Discrete wavelet transform (DWT) as a dyadic arrangement of continuous wavelet transformation combined with the widely applied and acknowledged Mann-Kendall (MK) trend analysis method were applied for analysis of trend and dominant periodicities in rainfall time series at monthly, annual and monsoonal time scales. Initially, rainfall time series applied in this study were decomposed using DWT to generate sub-time series at high and low frequencies, before applying the MK trend test. Further, the Sequential Mann-Kendall (SQMK) test was also applied to find out the trend changing points. The result showed that at the monthly annual and monsoon time scales, the trends in rainfall were significantly decreasing in most of the station. The 4-month and 8-month components were found as dominant at the monthly time series and the 2-year and 4-year component were found as dominant at the monsoon time series, whereas the 2-year components were observed as dominant in the annual time scale.

Key words – Trend analysis, Periodicity, Rainfall, Mann-Kendall test, Discrete wavelet transform.

1. Introduction

Global warming has caused the problem of climate change which is drastically accelerated much faster in last few decades. Climate is warmed up of 0.89 °C (0.69 to 1.08) over the period 1901-2012, whereas in last 25 years it has increased with a rate of 0.18% per decade in the last 25 years, which is mainly attributed to anthropogenic activities (Grover, 2013; IPCC, 2013). Climate change and climate variability are associated with the trends in

hydro-climatic variables such as temperature, rainfall, relative humidity, evapotranspiration, runoff, etc. (Birsan *et al.*, 2005). The assessment of climate change in terms of trend detection is generally carried out using historical data (Trenberth *et al.*, 2007; Adamowski *et al.*, 2010; Nalley *et al.*, 2013; Nourani *et al.*, 2018). Understanding of significant trends and periodicities in hydro-meteorological dataset plays an important role for sustainable water resources planning and management (Yenigun *et al.*, 2008; Nourani *et al.*, 2018).

The impacts of changing climate varied spatially through the world and it has been studied by several researchers. For instance, Partal and Kahya (2006) conducted one study applying long-term annual mean and monthly total precipitation time series data of 96 gauging stations in Turkey using nonparametric methods. It was found in the study that there is a decreasing trend in the annual mean precipitation in western and southern areas of Turkey. Basistha *et al.* (2007) carried out a study for assessment of spatial trends in rainfall over Indian subdivisions during the period from 1872 to 2005 and result findings revealed a decreasing trend of rainfall in over North India with an exception to the states of Punjab, Haryana, West Rajasthan, and Saurashtra, whereas an increasing trend was observed mostly in South India with an exception to the states of Kerala and Madhya Maharashtra. Ramesh and Goswami (2007) analysed rainfall trend and presented a decreasing trend for early and late monsoon period. Number of rainy days over India also depicted a decreasing trend. In another study, Jain *et al.* (2013) analysed trends in monthly, seasonal, and annual scale for rainfall and temperature for the northeast region of India. The study reported no trend in the rainfall data series during 1871-2008, although some hydro-meteorological subdivisions depicted significant seasonal trends for some seasons. Pingale *et al.* (2014) presented variation in spatial and temporal trends for mean and extreme rainfall and temperature time series data for the 33 urban centers in Rajasthan, India. Results showed significant decreasing trends of annual rainfall with significant spatial variation. Murumkar and Arya (2014) conducted a study to assess trend and periodicity in the four stations in Nira basin, Central India, using more than 100 years of seasonal and annual rainfall dataset. An increasing trend during monsoon and post-monsoon seasonal rainfall was observed in the study, whereas a falling trend in the rainfall time series was reported during the summer and winter season. Moreover, dominant periodicities were observed in the rainfall time series after year 1960, that was ranging from 2-8 years for all the stations. Sharma *et al.* (2016) conducted one study for assessment of trends in precipitation and temperature and its spatial variation in eastern India using time series data from 1970 to 2004 applying MK test, Sen's slope estimator, Spearman rank correlation, Least square linear regression, and SQMK test. It was observed in the study that in the regions of north-east, south-east, and west parts, there is an increasing trend in annual rainfall distribution, whereas the north-west, central, and south regions of eastern India depicted a decreasing trend in annual rainfall distribution. Further maximum rainfall depicted decreasing and increasing trend in eastern region, western region, respectively, excepting during monsoon season). Kumar and Jain (2011) applied daily gridded rainfall data for trend analysis for the duration of 1951-

2004 over 22 river basins of India. Six river basins showed increased annual and monsoonal rainfall trend, whereas fifteen river basins showed decreasing trend for monsoon season rainfall. In this study rainfall and rainy days both showed similar trend direction in most of the basin area for both the annual and seasonal scale. Bisht *et al.* (2017) carried out a study for trend analysis for seasonal, annual and maximum cumulative rainfall for 1-5 days maximum rainfall using gridded data for the duration 1901 to 2015. An upward trend was reported for most of the basin areas for 1-5 days maximum cumulative rainfall in the post-urbanization era. An increasing trend in the extreme events for most of the river basins during the post-urbanization era was also reported in the study. In the Gujarat state of India, only a few studies were carried out on trend analysis for rainfall and temperature (Lunagaria *et al.*, 2015; Chinchorkar *et al.*, 2016; Patel *et al.*, 2016). *e.g.*, Chinchorkar *et al.* (2016) assessed the long-term change in rainfall by linear trend analysis. The result implied that in Junagadh, the August month had a highest increasing trend at the rate of 1.463 mm during the last 32 years. The annual rainfall showed an increasing trend at 0.482 mm per year.

Even though there are several statistical methods frequently applied for trend analysis, fluctuations, and change point detection, non-parametric methods are widely applied over parametric methods (Sonali and Kumar, 2013; Wang *et al.*, 2013). It is due to the reason that parametric tests are generally appropriate for normally distributed data, whereas non-parametric methods are less affected by the existence of outliers in the data series (Lanzante, 1996). The MK test is found to be robust as its output is not affected by the assumptions of uniform distribution of data as well as that of need of skewed distribution of data (Onoz and Bayazit, 2003). Moreover, MK test can also be applied with non-stationary and non-linear dataset and even if there are missing values. One of the actual limitations of MK test is that it cannot be applied to the time series data possessing serial correlation that is generally a case with hydro-climatic data (Yue *et al.*, 2002). As a solution to the above issues Hamed and Rao (1998) proposed a modified MK test having capabilities to handle auto correlated data. In another study Sneyers (1990) proposed the sequential MK test to further enhance the trend analysis by detecting the change point in the trend.

Wavelet transformation is a relatively recent development in signal processing for time series analysis in both the time and frequency domain. Wavelet transform is used to decompose a time series data into different sub time series data of different periodicities applying different scales and amplitude and is a very powerful tool for time series data analysis. In the decomposed time

series data, lower periodicities (high frequency) components present rapidly changing events, whereas higher periodicities (low frequency) component presents slowly changing events. Wavelet analysis have been proved as an advanced tool to extract some of the physical characteristics inherent in the time series data such as trends, periodicity, discontinuities and change points (Labat, 2005; Wang *et al.*, 2009; Partal, 2010; Raj and Azeez, 2012; Araghi *et al.*, 2015).

Combination of wavelet analysis with MK test has also been reported recently for non-linear trend analysis in hydro-climatic time series dataset. Partal and Kucuk (2006) applied wavelet-MK test conjunction model to identify non-linear trends time series data of annual total rainfall in Turkey. It was reported in the study that the 16 year periodic component was the dominating component for trend analysis of annual rainfall data. Xu *et al.* (2009) applied wavelet analysis and MK test for analysed non-linear trends in climatic variables such as annual temperature, precipitation, and relative humidity in the Tarim River basin, China. It was found in the study that all the variables showed non-linear trends with the dominant periodicities at the 4-year and 8-year scales. Nalley *et al.* (2012) applied a wavelet-MK test conjunction model for trend analysis in the time series data of annual, seasonal, monthly precipitation and stream flow in southern Ontario, Quebec, Canada. The positive trends were reported in the study starting during the mid-1960s to early 1970s. 32-months, 24-48 months (2-4 years) and 2-4 years, dominant periodicities were observed, respectively, for annual, seasonal and monthly precipitation. Adarsh and Reddy (2015) applied MK test in conjunction with discrete wavelet transform (DWT) for the analysis of long-term trend subdivisions of southern India. A short-term periodicity of less than a decade was observed as dominant periodicity for the post-monsoon rainfall in the study area. Joshi *et al.* (2016) analyzed seasonal trends and periodicities of drought variables using discrete wavelet transform and Mann-Kendall test. A total of 30 rainfall subdivisions in India were considered in the study with over 141 years (1871-2012) of dataset. The results obtained from the study indicated increment in frequency of drought occurrences significantly in subdivisions of northeast and central India. Moreover, the dominant periodicities observed were both short-term (2-8y) and decadal (16-32y) influencing the trend. Pandey *et al.* (2017) analyzed the trend for monthly, annual and monsoon total precipitation series over India. In this study three methods namely linear regression, Mann-Kendall (MK) test and discrete wavelet transformation (DWT) were applied. The results found indicated the positive trend for monsoon series, over North Mountainous India and North East India with dominant periodicities at 2-, 4- and 8-year. Nourani *et al.* (2018)

applied hybrid wavelet Mann-Kendall test and Sen's methodologies for investigation of potential trends and their dominant periodicity in rainfall, streamflow, temperature, and humidity on monthly, seasonal, and annual scale. It was observed in the study that water level and streamflow series have significant decreasing trends, rainfall and relative humidity presents moderately decreasing trend, whereas temperature presents increasing trends. Wavelet analysis helped to find out the dominant periods as 8-, 12-month, and 2-year for the time series in monthly, seasonal, and annual timescales, respectively.

The aim of this study is to investigate trend in rainfall dataset in central Gujarat region by analyzing their monthly, annual and monsoon time series. The analysis of monthly to yearly data would allow this study to analyse the rapidly and slowly changing events in the datasets used in this study. The discrete wavelet transform (DWT) is initially applied to decompose the time series data into different lower resolution sub time series components; the MK test was applied to whole as well as each sub time series in order to investigate trend and their dominant periodicity with statistical significance. The dyadic arrangement in terms of DWT facilitates to analyse the dominance of periodic events in the range varying from 2 months to 32 years applying time series data over the 100 year study period.

2. Theoretical background

2.1. Discrete wavelet transform

The wavelet transform (WT) is mathematical techniques recently developed for signal processing for time frequency representation of a time series (Hernandez and Weiss, 1996; Torrence and Compo, 1998). A wavelet function is a function having a wave like shape with flexible length having a mean value equal to zero, and is localized in both time and frequency domains. WT apply high and low pass filter using a wavelets called as mother wavelet (ψ) to mathematically decompose a signal into multiple sub time series by controlling the scaling and shifting factors of a particular mother wavelet.

As the mother wavelet moves with different scaling and shifting factors across the time series under consideration, several wavelet coefficients are generated representing the similarity between the time series and the mother wavelet. The wavelet coefficients are then utilized in analyzing the short as well as long-term fluctuations (*i.e.*, trends) (Adamowski *et al.*, 2009). It gives information not only about the dominant modes or periodicities, but also about how it fluctuates in time (Torrence and Compo, 1998).

The basic application of the wavelet transform is performed through the continuous wavelet transformation (CWT), but as it generates a large number of coefficients, a dyadic arrangement simplify it and is called as the discrete wavelet transformation (DWT), which still provides a very effective and precise wavelet analysis very useful for time series having sharp jumps or shifts (Partal and Kucuk, 2006; Olkkonen, 2011). The mathematical equation for generation of wavelet coefficients (W) using the discrete wavelet transformation approach for the time series (with dyadic grid arrangement) is calculated as follows (Partal and Kucuk, 2006) is presented as:

$$W_{\psi}(a, b) = \frac{1}{(2)^{a/2}} \sum_{t=0}^{n-1} x_t \Psi\left(\frac{t}{2^a} - b\right) \quad (1)$$

where, 2^a represents the dyadic scale of the DWT.

Applying the above equation disintegrate the signal into two ancillary sub signal components, one is the detail (D) component obtained applying the high pass filter and another is the approximation (A) components obtained by subtracting D components from the original time series data. Therefore, approximation (A) components represents the large-scale/low-frequency component, whereas detail (D) component represents the small-scale/ high-frequency component. In general, component A shows long-term variations, and is very important component for trend analysis studies. The decomposition process can further be extended by decomposing the A into another approximation A and decomposition D components (Nalley *et al.*, 2012, 2013; Nourani *et al.*, 2018).

2.2. Mann-Kendall (MK) trend test

The Mann-Kendall (MK) test is a non-parametric test (Mann, 1945; Kendall, 1975) and has widely been applied for trends analysis in a time series. The MK statistic (S) is computed as follows (Hirsch and Slack, 1984; Jain *et al.* 2013):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad (2)$$

where,

X_i and X_j = Data points in the time series,

n = Length of the dataset,

and

sign (t) is defined as:

$$\text{Sign}(X_j - X_i) = \begin{cases} +1 & X_j > X_i \\ 0 & X_j = X_i \\ -1 & X_j < X_i \end{cases} \quad (3)$$

The Mann-Kendall statistics, Z is then given as:

$$\text{Var}(S) = \frac{1}{18} [n(n-1)(2n+5) - \sum_{i=1}^n t_i(i-1)(2i+5)] \quad (4)$$

where,

n = The number of tied groups

t_i = The size of the i^{th} tie groups

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} f & \text{or } S > 0 \\ 0 & \text{or } S < 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} f & \text{or } S = 0 \end{cases} \quad (5)$$

The significance of trend is analysed by comparing the MK-Z value with the standard normal variant at the pre-specified significance level (Hamed and Rao, 1998). A positive value of Z presents an 'upward or positive trend' whereas a negative value of Z presents a 'downward or negative trend'. The statistical significance of MK Z-value or significance of trend is analysed applying the probability value (p -value) generally at 5% significance level or 95% confidence level.

The presence of seasonality and autocorrelation limits the performance of MK test. To deal with the seasonality pattern issues Hirsch and Slack (Hirsch and Slack, 1984) modified MK test is used, whereas if there is presence of significant lag-1 autocorrelation, then the modified MK test is applied as proposed by Hamed and Rao (1998).

2.3. Modified Mann-Kendall (MK) test by Hirsch and Slack (1984) for data with seasonality patterns and autocorrelation

The matrix X of data set collected over v seasons and u years, without any missing or tied values, is presented as (Hirsch and Slack, 1984):

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1v} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2v} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3v} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{u1} & x_{u2} & x_{u3} & \dots & x_{uv} \end{pmatrix}$$

The ranks of the data in matrix X are represented by matrix r (Hirsch and Slack, 1984):

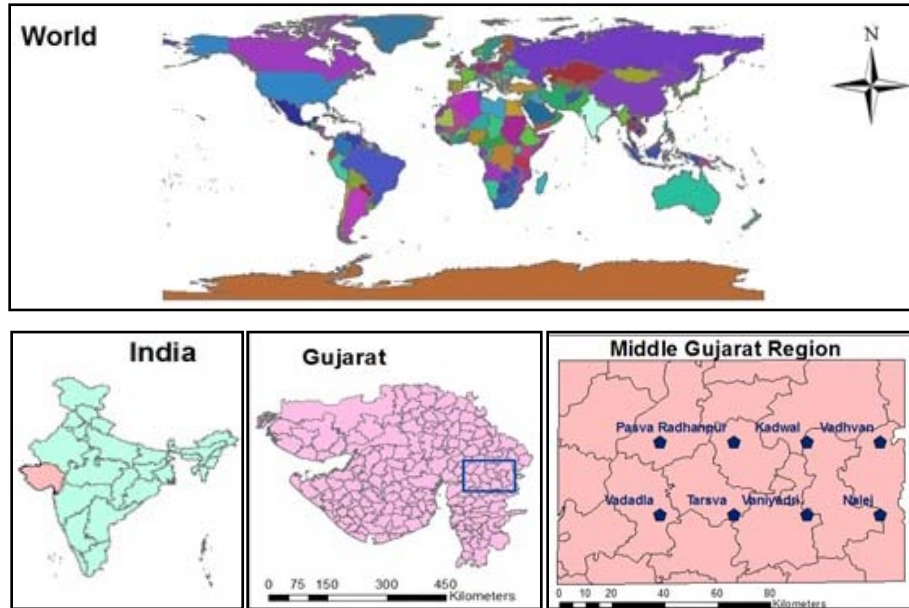


Fig. 1. A location map of the rainfall stations used in this study

$$r = \begin{pmatrix} r_{11} & r_{12} & r_{13} & \dots & r_{1v} \\ r_{21} & r_{22} & r_{23} & \dots & r_{2v} \\ r_{31} & r_{32} & r_{33} & \dots & r_{3v} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{u1} & r_{u2} & r_{u3} & \dots & r_{uv} \end{pmatrix}$$

The seasonal Kendall test statistic is then calculated as the sum of test statistic for each season and the variance of the seasonal Kendall test statistic as the sum of the variance for each season with the estimate covariance of two seasons. It was demonstrated by Hirsch and Slack (1984) that by using this procedure, the assumption of independence is not required. For the further details interested readers are directed to refer the modified version of the MK test in Hirsh & Slack (1984).

2.4. Sequential Mann-Kendall (SQMK) test

The sequential MK test is recommended by the World Meteorological Organization (WMO) for analysing progressive trends or detecting the start or change point in a trend (Sneyers, 1990). The procedure SQMK test involves the following steps:

- (i) The magnitudes of x annual mean time series ($i = 1, \dots, n$) are compared with X_j ($j = 1, \dots, i-1$). The number of events where $X_i > X_j$ are counted and denoted by n_i .
- (ii) The test statistic (t_i) is then calculated as follows as follows:

$$t_i = \sum_{j=1}^i n_i \quad (6)$$

- (iii) The first and second moment of t_i for large number of n values is presented as:

$$\bar{t}_i = \frac{n(n-1)}{4} \quad (7)$$

and

$$\text{Var}(t_i) = [i(i-1)(2i+5)]/72 \quad (8)$$

- (iv) The standardized value of the SQMK test statistic $u(t_i)$ is then calculated as below:

$$u(t_i) = \frac{|t_i - \bar{t}_i|}{\sqrt{\text{Var}(t_i)}} \quad (9)$$

Finally, by plotting $u(t_i)$ versus t_i , will present progressive trend variations. Analysing the plotted line $u(t_i)$ and the upper and lower confidence limits at a particular significance level (*e.g.*, $\alpha = 5\%$ significance level), the significant change in trend can be observed at that point of time.

3. Study area and data

The monthly, annual and monsoon rainfall data of eight stations for the period of 1901-2016 were analyzed. These stations are located in central Gujarat region, India. Gujarat state is geographically divided into five regions: (i) North Gujarat (ii) Central Gujarat (iii) South Gujarat

TABLE 1

Key features of the station used in this study

Station	Latitude (°N)	Longitude (°E)	Elevation (m)	Average annual rainfall (mm)
Vadadla	22.25	73.25	31	951.62
Tarsva	22.25	73.5	60	1075.48
Vaniyadri	22.25	73.75	85.7	995.96
Nalej	22.25	74	197.4	1015.33
Pasva	22.5	73.25	49	978.63
Radhanpur	22.5	73.5	130.1	1042.26
Kadwal	22.5	73.75	181.8	1048.65
Vadhvan	22.5	74	200.6	1012.73

and (iv) Saurashtra and (v) Kuchchh. The middle Gujarat region is generally characterized by a semi-arid climate. The mean annual precipitation of central Gujarat is about 950 mm/year, of which nearly 88% falls in the monsoon season. In this study eight stations namely Vadadla, Tarsva, Vaniyadri, Nalej, Pasva, Radhanpur, Kadwal and Vadhvan were selected located in the middle Gujarat region. The location details of study area are shown in Fig. 1.

In the present study monthly, annual and monsoonal precipitation data comprising of 116 year period (1901-2016) are applied. Monthly data were applied to estimate the short-term fluctuations, whereas annual precipitation data were used to investigate the long-term fluctuations, and monsoonal precipitation data were used to identify the variation in seasonality. Gridded rainfall data sets have widely been applied in many earlier hydro-climatological studies, for hydro-climatic variable forecasting, climate variability, climate attribution studies and for performance evaluation of climatic models (Dash *et al.*, 2013; Bisht *et al.*, 2017; Nourani *et al.*, 2018). Long-term precipitation data series were obtained from the Indian Meteorology Department (IMD), Pune. Daily gridded high-resolution rainfall data at 0.25° spatial resolution of 116 years (1901-2016) was used for trend analysis. Details of the stations used in this study are given in Table 1.

4. Methodology

In this study monthly, annual and monsoon rainfall datasets have been analyzed to identify the existence of trends, seasonality and periodicities. The wavelet decomposition was applied to the different data types used in order to analyze the high- and low-frequency events that affect the rainfall fluctuations over the study area. The data analysis was carried out using procedures summarized as follows:

(i) To select the appropriate MK test, test were carried out to identify if there is any seasonality patterns or significant lag-1 auto-correlations existed in the time series data for each of the stations for each of the time scales (*i.e.*, monthly, seasonal, annual).

(ii) Each time series data at each scale was decomposed using the DWT with Daubechies family of wavelets, by decomposing the time series into its approximation (A) and detail (Ds) components.

(iii) The appropriate MK test (original or modified MK test) was applied to the original time series, decomposed components (*i.e.*, A and D components) and a combination of approximate and detailed components.

(iv) The SQMK test was performed for all the time series dataset including the original actual, the decomposed sub time series components, and for the different combinations of A and D components.

(v) The most common periodicities that mostly affect the observed trends were determined by examining the sequential MK graphs and the MK Z-values of the detail (plus approximation) components, and then comparing them to that of the original data.

4.1. Estimation of autocorrelation and seasonality patterns

The presence of autocorrelation makes some implications in estimation of some standard statistical methods for climatic data (Wilks, 2011). Lag-1 ACF is commonly used to determine whether a time series exhibit non-random characteristics (*e.g.*, Partal and Kahya, 2006; Mohsin and Gough, 2010). Lag-1 ACFs were computed using the following equations (Yue *et al.*, 2002):

$$R = \frac{\left(\frac{1}{n-1}\right) \sum_{t=1}^{n-1} (x_t - \bar{x}_t)(x_{t+1} - \bar{x}_t)}{\left(\frac{1}{n}\right) \sum_{t=1}^n (x_t - \bar{x}_t)^2} \quad (10)$$

$$= \frac{-1 - 1.645 \sqrt{n-2}}{n-1} \leq R \leq \frac{-1 + 1.645 \sqrt{n-2}}{n-1} \quad (11)$$

R is the lag-1 autocorrelation coefficient of the sample data $\bar{x}_t$ is the sample mean, and n is the number of observations in the data. If the calculated R is found to be outside of the range defined by equation (11), the corresponding dataset is assumed to exhibit a significant autocorrelation at the 5% significance level.

The correlogram depicting the ACFs of the time series data at different lags were used to determine the presence of seasonality patterns. The presence of a sinusoidal-like oscillating pattern in the ACFs graph presents a seasonality pattern in the time series data.

4.2. Decomposition of data using DWT

DWT was used to decompose the rainfall data at different time scale and at different level using Daubechies (db) wavelets as the mother wavelet. Daubechies wavelets are widely applied in the time series decomposition due to their ease of use, wide suitability for meteorological data, and orthogonality (Ma *et al.*, 2003; Vonesch *et al.*, 2007). Once the type of mother wavelet is selected another components is the number of decomposition level to be considered for decomposition of the time series. To determine the number of decomposition levels (L) the following equation was applied (De Artigas *et al.*, 2006):

$$L = \frac{\log\left(\frac{n}{2^v-1}\right)}{\log(2)} \quad (12)$$

where,

v = the number of vanishing moments of the Daubechies (db) wavelet,

L = the maximum number of decomposition levels, and

n = the number of data pattern in the time series.

As the DWT has a dyadic form and therefore, each of the decomposed component or sub time series data represents a different period of 2 base powers (2^n)

making D1 components as a 2-unit, D2 as a 4-unit, D3 as 8-unit time scale and so on. The time unit mentioned here depends upon the time scale under study, for example, D2 represents a 4-month time period if the time series data are monthly, whereas it represents 4-year time period if the time series data is an annual data series.

The most common periodicities that mostly affect the observed trends were determined by comparing the results of common statistical trend tests (*e.g.*, the MK test) for the original data with those for combinations of the WT-decomposed components.

4.3. Mann-Kendall (MK) and sequential MK trend tests

The original MK test was applied to those monthly, seasonal and annual rainfall datasets that didn't present any significant lag-1 autocorrelations. The modified MK test was applied on the monsoon and annual datasets because they exhibit seasonality patterns. The significant level used was $\alpha = 5\%$ (or 95% confidence level) for a two-sided probability. The absolute value of this Z-score was then compared to the critical two-tailed Z-value (area under the normal curve) of $\alpha/2$. The Z values in a two-tailed test for $\alpha = 5\%$ are ± 1.96 . If the calculated MK Z-score is outside the range of -1.96 and +1.96, the trends are statistically significant.

The SQMK test is also applied for monthly, seasonal and annual rainfall datasets to identify how the trend gets fluctuated over the study period. To determine the most prominent periodic component(s), the following two approaches were considered *viz.*, : (i) the MK Z-values of detail components separately and along with its approximation and compared with the MK Z-value of the respective original data; and (ii) the sequential Mann-Kendall values of different combinations of detail and approximations components were plotted along with the sequential Mann-Kendall values of the original time series data. The periodic components that are considered the most dominant in affecting the trends in rainfall over the study area are the ones whose MK Z-values were close to that of the original data and whose sequential MK graphs were observed to be harmonious with the sequential MK of the original series.

5. Results and discussion

5.1. Autocorrelations and seasonality patterns

Autocorrelation analysis was performed to check for the presence of seasonality and autocorrelation in the time

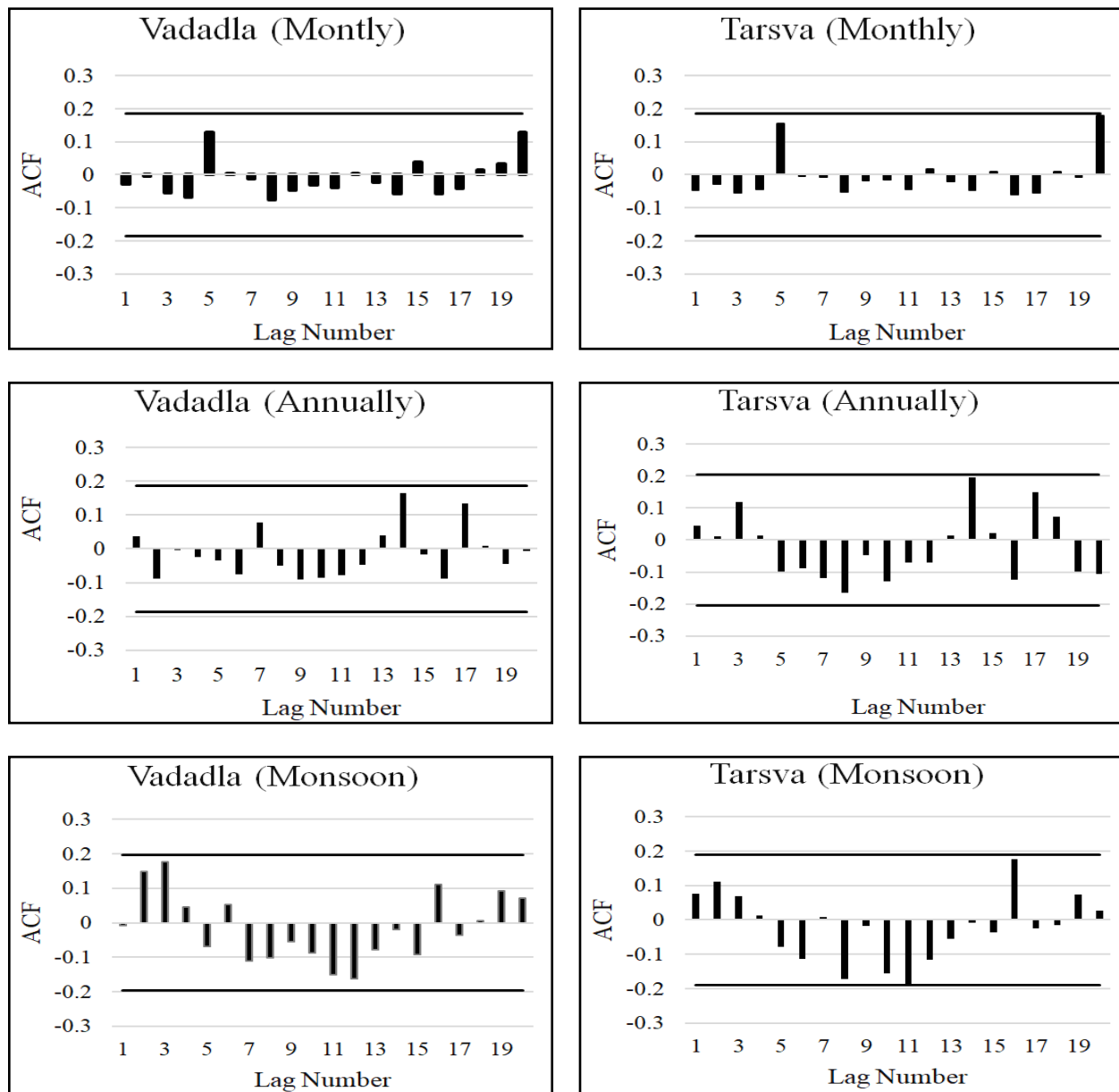


Fig. 2. Lag-1 correlogram of monthly, annual and monsoon rainfall datasets for Vadadla and Tarsva station

series of monthly, annual and monsoon rainfall for all the 8 stations. Out of the 8 stations considered in this study, Lag-1 autocorrelation for monthly, annual and monsoon rainfall datasets only for Vadadla and Tarsva station is presented here as an example and is shown in Fig. 2. It was observed from the ACF analysis for monthly, seasonal and annual rainfall datasets that for all the stations, lag-1 autocorrelation was insignificant. It was also observed from the ACF that only annual and monsoon rainfall time series exhibit's seasonality patterns whereas it was insignificant in case of monthly time series.

5.2. Mann-Kendall (MK) test for monthly, seasonal and annual rainfall series

5.2.1. Monthly rainfall trend analysis

Initially MK test was applied to all the individual components such as A and Ds and then for different combinations of A and Ds. MK Z-values for monthly rainfall time series for the original data, approximation (A) component, detail (D) components and for different combinations of A and D components is presented in Table 2. The most dominant periodic components for

TABLE 2

MK Z-values of the monthly rainfall series for the original data, Approximation (A), detail (D) and combination of D and A component for the monthly rainfall datasets

Station	Vadadla	Tarsva	Vaniyadri	Nalej	Pasva	Radhanpur	Kadwal	Vadhvan
Original	-0.024	-0.043*	-0.037	-0.033	-0.029	-0.042*	-0.051*	-0.041*
A8	-0.293*	-0.096*	-0.113*	-0.496*	-0.161*	-0.259*	-0.293*	-0.253*
D1	0.000	-0.003	0.000	-0.001	-0.001	0.001	0.002	0.001
D2	0.000	0.003	0.003	-0.004	-0.001	-0.001	0.001	0.000
D3	0.001	0.000	-0.003	0.006	0.001	0.002	0.001	0.002
D4	0.010	0.009	0.006	0.006	0.008	0.010	0.008	0.008
D5	-0.002	-0.005	-0.007	-0.001	-0.006	-0.008	-0.003	0.001
D6	0.033	0.037*	0.034	0.036*	0.027	0.026	0.030	0.034
D7	0.029	0.040*	0.036*	0.036*	0.019	0.018	0.025	0.021
D8	0.224*	0.078*	0.217*	0.209*	0.119*	0.132*	0.208*	0.219*
D1 + A	-0.122*	-0.066*	-0.064*	-0.171*	-0.092*	-0.104*	-0.103*	-0.110*
D2 + A	-0.086*	-0.043*	-0.044*	-0.119*	-0.066*	-0.073*	-0.069*	-0.080*
D3 + A	-0.051*	-0.032	-0.033	-0.065*	-0.039*	-0.042*	-0.041*	-0.047*
D4 + A	-0.126*	-0.059*	-0.058*	-0.182*	-0.092*	-0.105*	-0.100*	-0.118*
D5 + A	-0.214*	-0.106*	-0.112*	-0.299*	-0.186*	-0.209*	-0.182*	-0.192*
D6 + A	-0.203*	-0.060*	-0.091*	-0.322*	-0.156*	-0.194*	-0.203*	-0.181*
D7 + A	-0.245*	-0.145*	-0.139*	-0.392*	-0.168*	-0.177*	-0.209*	-0.221*
D8 + A	-0.389*	0.067*	-0.082*	-0.521*	-0.194*	-0.232*	-0.226*	-0.302*

trends are indicated in bold format and significant value are denoted by an asterisk sign (*). From the MK test analysis of original rainfall values and different wavelet components, it was found that detail (D) components did not show any significant MK Z-values, also these MK Z-values were not very close to the MK Z-values of the original rainfall data. Further investigation using the MK test was made using different combinations of A and D component for finding out the most prominent component(s).

Further it can be observed from the Table 2 that all the different components and combinations of A and D show a negative trend having values lower than 0. Out of 8 stations, 4 stations showed statistically significant downward or negative trend with $Z = -0.043$, -0.042 , -0.051 and -0.041 , respectively, for Radhanpur, Kadwal, Vadhvan and Tarsva stations.

Detail components D1 to D5 didn't show any significant trend even though some of their respective original time series data exhibits significant negative trend, whereas some of the remaining detail components D6-D8 showed significant negative trend even though

their respective original time series data didn't show any significant negative trend. But it was also observed that though some of the detail components presented significant MK Z-values but those were not very close to the MK Z-values of respective original time series data. Then, significance of MK Z-values for different combinations of A and D were investigated and it was observed that all the different combinations showed significant negative trend except only a few values. Though most of these combinations exhibits significant negative trend but it is only the combinations of D2+A and D3+A which presented the closest MK Z-values to that of the original series, which indicate 4 and 8-month components are the most dominant components affecting the monthly rainfall trends, respectively. The dominance of high-frequency components for all of the station suggests that lower periodic modes have the greatest impact on monthly rainfall variation patterns.

5.2.2. Annual rainfall trend analysis

MK Z-values of the annual rainfall series for the original data, approximation (A), detail (Ds) and different combinations of Ds and A components is presented in

TABLE 3

MK Z-values of the original data, approximation (A), detail (D) and different combinations of D & A components of annual rainfall datasets

Station	Vadadla	Tarsva	Vaniyadri	Nalej	Pasva	Radhanpur	Kadwal	Vadhvan
Original	-0.060	0.019	0.018	-0.162*	-0.051	-0.097	-0.037	-0.023
A4	-0.528*	0.130	-0.236*	-0.556*	-0.167*	-0.236*	-0.222*	-0.306*
D1	0.037	0.000	-0.023	0.019	0.042	0.009	0.032	0.032
D2	0.014	-0.014	-0.023	0.014	-0.005	0.005	-0.005	-0.023
D3	-0.023	-0.111	-0.019	-0.019	-0.023	-0.028	-0.032	-0.023
D4	0.083	0.079	0.056	0.093	0.120	0.130	0.125	0.088
D1 + A	-0.065	0.088	0.060	-0.199*	-0.028	-0.079	-0.014	-0.051
D2 + A	-0.106	0.056	0.069	-0.213*	-0.102	-0.148	-0.051	-0.093
D3 + A	-0.227*	-0.023	0.065	-0.352*	-0.065	-0.153	-0.111	-0.144
D4 + A	-0.148	0.153	0.093	-0.431*	-0.093	-0.093	-0.037	-0.111

TABLE 4

MK Z-values for original rainfall, approximation (A), detail (Ds) and different combinations of D & A components of monsoon rainfall datasets

Station	Vadadla	Tarsva	Vaniyadri	Nalej	Pasva	Radhanpur	Kadwal	Vadhvan
Original	-0.048	0.056	0.060	-0.135*	-0.041	-0.075	-0.028	-0.033
A4	-0.554*	0.069	-0.152*	-0.501*	-0.176*	-0.210*	-0.135*	-0.315*
D1	-0.009	0.011	-0.003	0.009	-0.001	-0.004	0.015	0.017
D2	0.048	0.016	0.017	0.007	0.026	0.024	0.017	0.008
D3	-0.009	-0.021	0.000	-0.007	-0.041	-0.034	-0.040	-0.034
D4	0.069	0.071	0.089	0.061	0.079	0.075	0.087	0.077
D1 + A	-0.106	0.045	0.057	-0.193*	-0.074	-0.102	-0.030	-0.089
D2 + A	-0.106	0.049	0.058	-0.206*	-0.066	-0.111	-0.036	-0.085
D3 + A	-0.171*	0.025	0.032	-0.261*	-0.134*	-0.149*	-0.127	-0.134*
D4 + A	-0.122	0.134*	0.095	-0.366*	-0.081	-0.091	-0.011	-0.086

Table 3. The most dominant periodic components for trends are indicated in bold format and significant value are denoted by an asterisk (*). The annual original rainfall series showed that only two out of eight stations exhibited a positive trend having values lower than 0 with non-significant Z values as 0.019 and 0.018 for Tarsva and Vaniyadri stations, respectively. All the remaining stations exhibited negative trend but it was only the Nalej station which showed significant negative trend ($Z = -0.162$) over the study area. None of the individual Detail components (D1 to D4) showed any significant trend.

5.2.3. Monsoon rainfall trend analysis

Each monsoon rainfall time series was decomposed into four lower resolution levels (*i.e.*, A4 and D1-D4

components) *via* the DWT approach. The detail components represent the 2-year, 4-year, 8-year and 16-year periodicity, respectively. MK Z-values for original rainfall, approximation (A), detail (Ds) and different combinations of Ds and A components is presented in Table 4. The most dominant periodic components for trends are indicated in bold format and significant value are denoted by an asterisk (*). It can be observed from the Table 4 that for monsoonal rainfall time series all the different components and combinations of A and D show a negative trend having values lower than 0. The monsoonal rainfall time series in most of the stations depict a negative trend except for Tarsva and Vaniyadri stations where trends are positive. Only Nalej station experienced statistically significant trends ($Z = 0.135$). Detail components D1 to D4 didn't show any significant

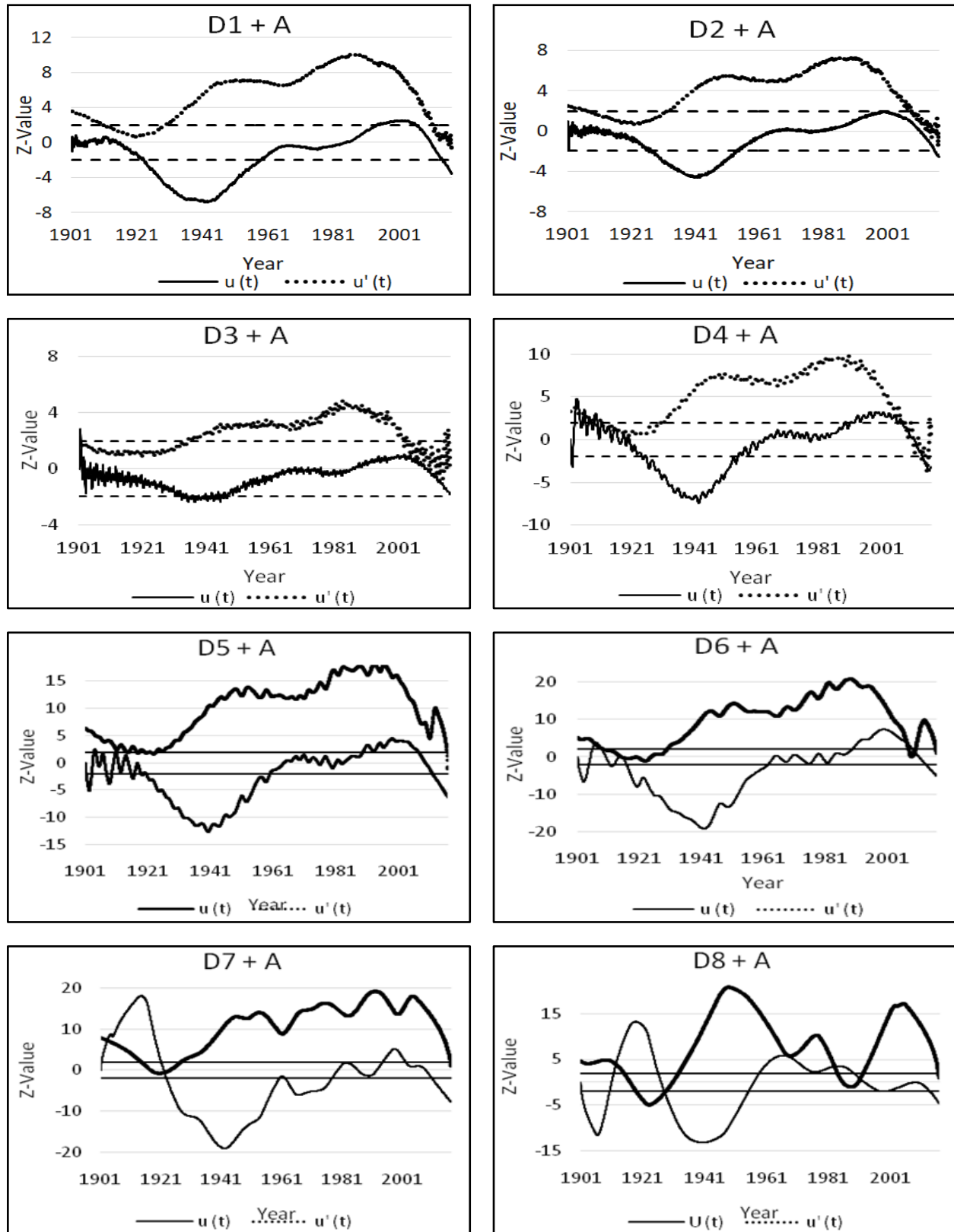


Fig. 3. Sequential MK graphs for monthly rainfall time series of the combinations of A and D components for Vaniyadi station (The upper and lower dashed lines represent the confidence limits ($\alpha = 5\%$); the solid and dotted progressive lines are the original time series and component combinations)

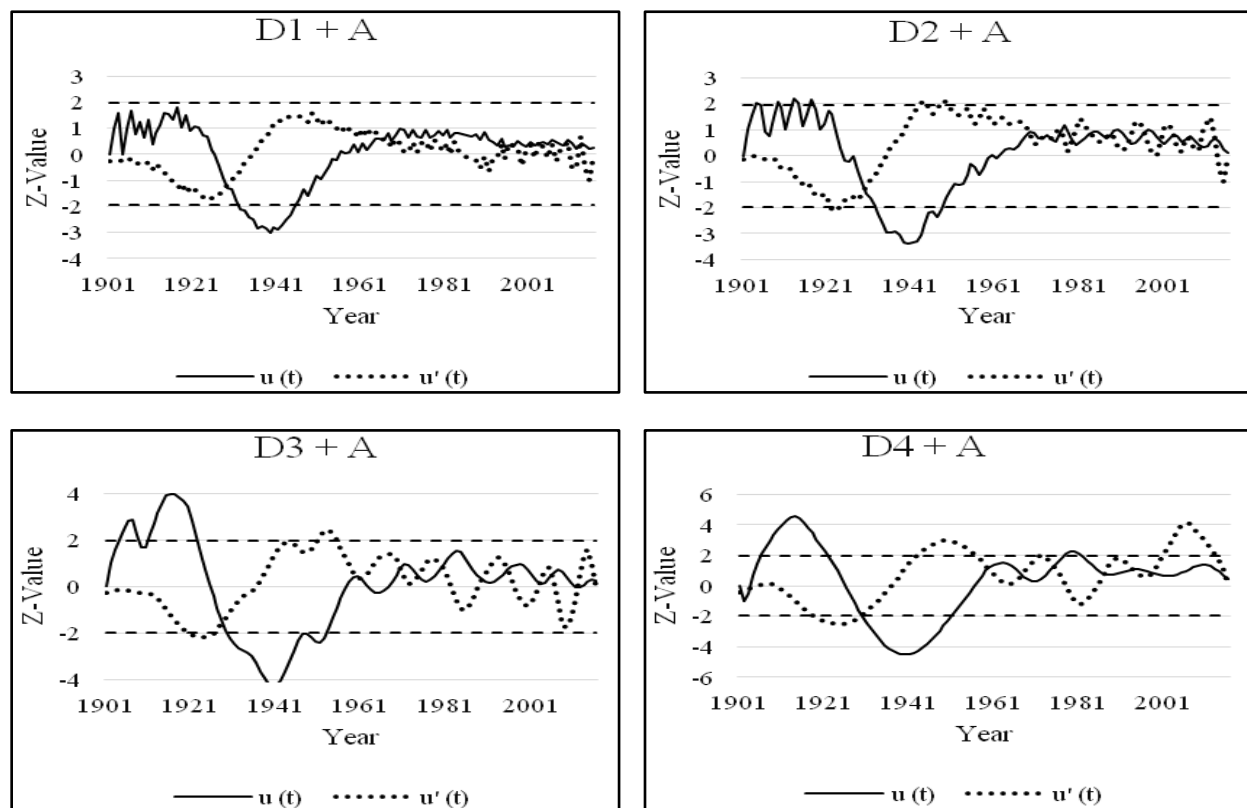


Fig. 4. Sequential MK graphs for original annual rainfall time series and the combinations of A and D components for Vaniyadri station (The upper and lower dashed lines represent the confidence limits ($\alpha = 5\%$); the solid and dotted progressive lines are the original time series and component combinations)

trend even though some of their respective original time series data exhibits significant negative trend. Further, it can also be observed that though some of the detail components presented significant MK Z-values but those were not very close to the MK Z-values of their respective original time series data except for Vadhvan station. Then, significance of MK Z-values for different combinations of A and D were investigated and it was observed that all the different combinations showed significant negative trend excepting a few values.

Further analysis revealed that though most of these combinations exhibits significant negative trend but it is only the combinations of D1+A and D2+A components which presented the closest MK Z-values to that of the original series, which indicate a 2-year and 4-year components are the most dominant components affecting the monsoon rainfall trends, while in Radhanpur and Vadhvan stations the lower frequency components (D3 and D4) were identified as the dominant time scales affecting the monsoon rainfall. The dominance of high-frequency components for all of the station suggests that lower periodic modes have the greatest impact on monthly rainfall variation patterns.

5.3. Sequential MK test

The SQMK test is investigated for annual and monsoon rainfall datasets of the eight station to identify how the trend gets fluctuated over the study period. The sequential MK graphs of monthly rainfall series for Vaniyadri station are presented as an example in Fig. 3. It can be observed from the figures that the combination of D3+A components showing the much better behaviour to the sequential MK Z-values of the original rainfall time series. It is to be highlighted here that the sequential MK Z-values were investigated for any combination of components or individual components only if the MK Z-values were identified as very similar to that of the original rainfall time series data. The progressive MK graph of the annual data for Vaniyadri station are presented in Fig. 4. As seen in these figure, the D1+A combination are the most similar to the sequential MK graph of the original rainfall series. The progressive MK graph of the monsoon data for Vaniyadri station are presented in Fig. 5. As seen in these figure, the D1+A combination are the most similar to the sequential MK graph of the original rainfall series.

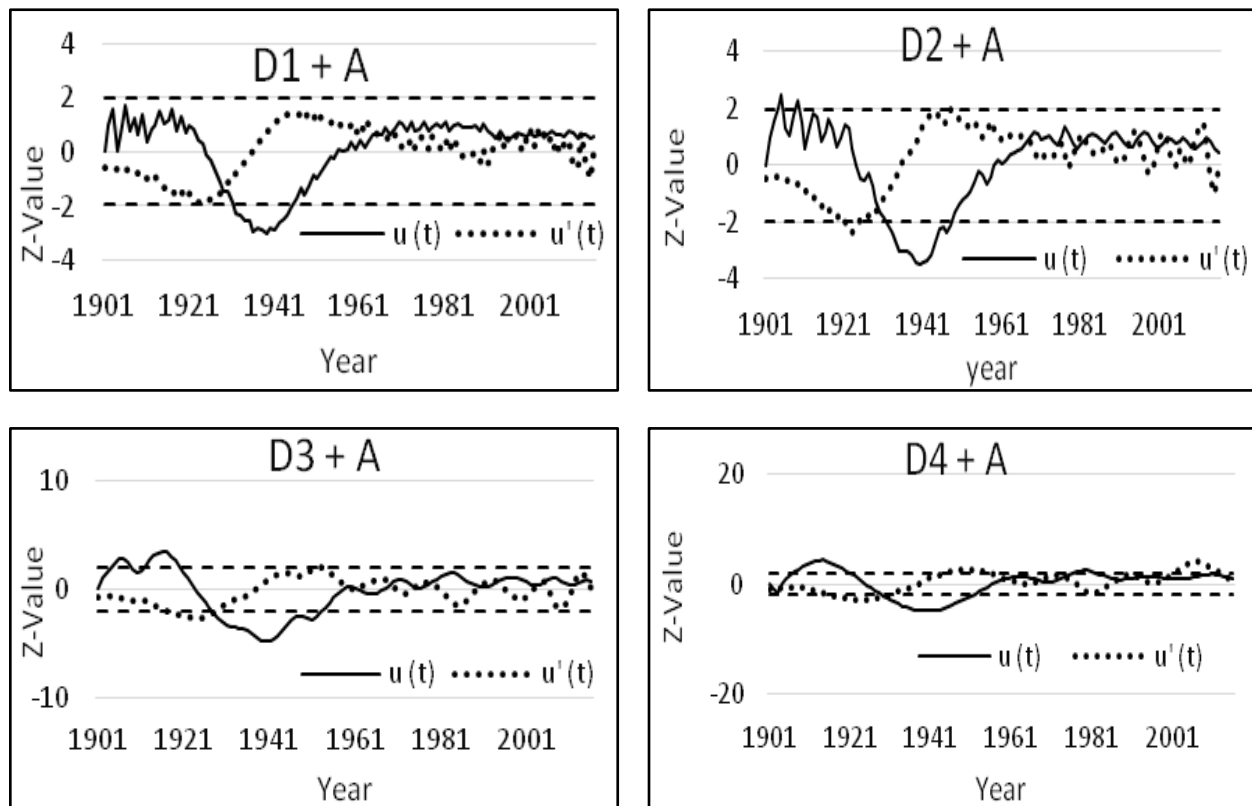


Fig. 5. Sequential MK graphs for monsoon rainfall time series of the combinations of A and D components for Vaniyadi station (The upper and lower dashed lines represent the confidence limits ($\alpha = 5\%$); the solid and dotted progressive lines are the original time series and component combinations)

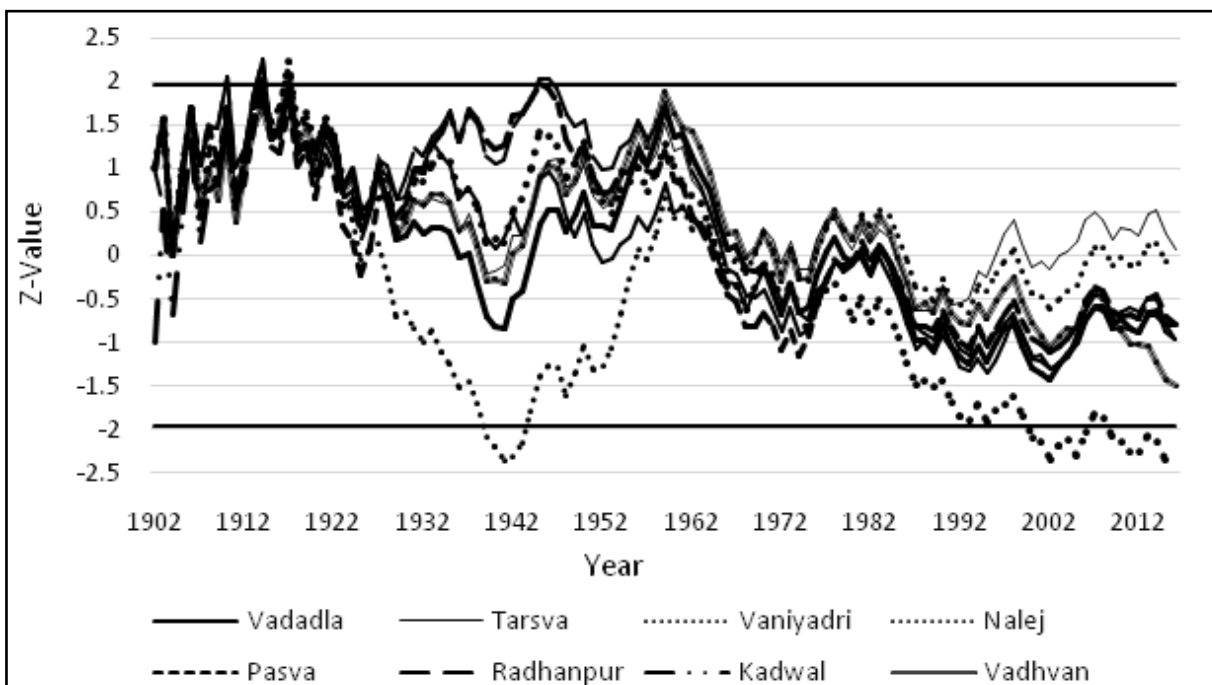


Fig. 6. Sequential MK graphs for original annual rainfall time series of all the station [The upper and lower dashed lines represent the confidence limits ($\alpha = 5\%$)]

The progressive MK graphs of the annual data from 1901 to 2016 of eight station are showed in Fig. 6. It is observed that all station were downward trends that started between 1915 and 1920 and stopped between 1940 and 1945. Vaniyadri station showed a significant negative trend during 1940 to 1945. The positive trend started around 1940 at six out of the eight stations. The downward trend again started from 1960. It can be noted that the Nalej station showed a negative trend during the last decade and the trend was significant for the period 2000 to 2016. Only two stations showed a slightly increasing trend in last decade otherwise, six stations showed a decreasing trend.

6. Summary and conclusions

Climate change has become a very challenging issue causing significant variation in hydro-meteorological variables with extreme events. In the present study long term trends and dominant periodicities for rainfall are estimated using Mann-Kendall (MK) test coupled with discrete wavelet transform (DWT) considering time series data over a period of 116 years (1901-2016) in the semi arid middle Gujarat region, India. Not only the original rainfall data but also the decomposed time series data into approximation and detail components were analyzed using the MK test. The most common periodicities that mostly affect the observed trends were determined by examining the sequential MK graphs and the MK Z-values of the detail (plus approximation) components, and then comparing them to that of the original data. The result showed that at monthly scale, the short term periods of 2-month and 4-month time series are involved in the production of the trend. The period of 2-year and 4-year were obtained for monsoon time series, while 2-year and 16-year found as the most effective periodicity components that produce significant trend. A sequential Mann-Kendall analysis is applied for identifying the potential starting point and the temporal variability of trends over a period of time. It is observed in this study that most of the trends started during the mid-1960s. This study provides some baseline information about the periodic components that affect the trends in the original time series data. It is found in this study that the trends in rainfall were significant decreasing in most of the station at the monthly annual and monsoon time scales. The 4-month and 8-month components were dominant at the monthly time series, the 2-year and 4-year component dominant at the monsoon time series, whereas the 2-year components were found as dominant in the annual time scale. In the present study a baseline information is established about the different periodicities influencing the rainfall trends and it can be useful in the future work to relate the information with different climatic scenarios and rainfall trends in the middle Gujarat region, India.

Acknowledgements

The study was funded by ITRA, Digital Corporation India, Meity, Government of India. Authors would also like to thank Indian Meteorological Department (IMD), Pune. The help and guidance provided by Mr. Deepak Singh Bisht and Dr. Ashok Mishra, Department of Agricultural and Food Engineering, Indian Institute of Technology, Kharagpur, West Bengal, India, is duly acknowledged.

The contents and views expressed in this research paper/article are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

References

- Adamowski, J., Adamowski, K. and Bougadis, J., 2010, "Influence of trend on short duration design storms", *Water Res. Manage.*, **24**, 401-413.
- Adamowski, K., Prokoph, A. and Adamowski, J., 2009, "Development of a new method of wavelet aided trend detection and estimation", *Hydrol. Processes.*, **23**, 18, 2686-2696.
- Adarsh, S. and Reddy, J., 2015, "Trend analysis of rainfall in four meteorological subdivisions of southern India using nonparametric methods and discrete wavelet transforms", *Int. J. Climatol.*, **35**, 6, 1107-1124.
- Araghi, A., Baygi, M. M., Adamowski, J., Malard, J., Nalley, D. and Hasheminia, S. M., 2015, "Using wavelet transforms to estimate surface temperature trends and dominant periodicities in Iran based on gridded reanalysis data", *Atmos. Research.*, **155**, 52-72.
- Basistha, A., Goel, N. K., Arya, D. S. and Gangwar, S. K., 2007, "Spatial pattern of trends in Indian sub-divisional rainfall", *Jalvigyan Sameeksha*, **22**, 47-57.
- Birsan, M. V., Molnar, P., Burlando, P. and Pfaundler, M., 2005, "Streamflow trends in Switzerland", *J. Hydrol.*, **314**, 1-4, 312-329.
- Bisht, D. S., Chatterjee, C., Raghuwanshi, N. S. and Sridhar, V., 2017, "Spatio-temporal trends of rainfall across Indian river basins", *Theor. Appl. Climatol.*, **132**, 419-436.
- Chinchorkar, S. S., Trivedi, M. M., Patel, G. R., Paradava, D. M. and Ram, B., 2016, "Evaluation of Temperature and Rainfall Trends using Mann-Kendall Test in Saurashtra Region (Junagadh) of Gujarat, India", *Advances in Life Sci.*, **5**, 12, 4935-4948.
- Dash, S. K., Saraswat, Vaishali, Panda, S. K. and Sharma, N., 2013, "A study of changes in rainfall and temperature patterns at four cities and corresponding meteorological subdivisions over coastal regions of India", *Global Planet Change*, **111**, 3, 801-817.
- De Artigas, M. Z., Elias, A. G. and De Campra, P. F., 2006, "Discrete wavelet analysis to assess long-term trends in geomagnetic activity", *Phys. Chem. Earth*, **31**, 77-80.
- Grover, V. I., 2013, "Impact of Climate Change on Water and Health", CRC Press, NY, p428.

- Hamed, K. H. and Ramachandra Rao, A., 1998, "A modified Mann-Kendall trend test for auto correlated data", *J. Hydrol.*, **204**, 182-196.
- Hernandez, E. and Weiss, G., 1996, "A First Course on Wavelets", CRC press, USA, p489.
- Hirsch, R. M. and Slack, J. R., 1984, "A nonparametric trend test for seasonal data with serial dependence", *Water Resour. Res.*, **20**, 727-732.
- IPCC, 2013, "Climate Change 2013 - The Physical Science Basis", Cambridge.
- Jain, S. K., Kumar, V. and Saharia, M., 2013, "Analysis of rainfall and temperature trends in Northeast India", *Int. J. Climat.*, **33**, 968-978.
- Joshi, N., Gupta, D., Suryavanshi, S., Adamowski, J. and Madramootoo, C. A., 2016, "Analysis of trends and dominant periodicities in drought variables in India: A wavelet transform based approach", *Atmos. Res.*, **182**, 200-220.
- Kendall, M. G., 1975, "Rank Correlation Methods", Griffin, London, UK.
- Kumar, V. and Jain, S. K., 2011, "Trends in rainfall amount and number of rainy days in river basins of India (1951-2004)", *Hydrol. Res.*, **42**, 4, 290-306.
- Labat, D., 2005, "Recent advances in wavelet analyses: Part 1. A review of concepts", *J. Hydrol.*, **314**, 1-4, 275-288.
- Lanzante, J. R., 1996, "Resistant, robust and non-parametric techniques for the analysis of climate data: Theory and examples, including applications to historical radiosonde station data", *Int. J. Climatol.*, **16**, 11, 1197-1226.
- Lunagaria, M. M., Dabhi, H. P. and Pandey, V., 2015, "Trends in the temperature and rainfall extremes during recent past in Gujarat", *J. Agrometeor.*, **17**, 1, p118.
- Ma, J., Xue, J., Yang, S. and He, Z., 2003, "A study of the construction and application of a Daubechies wavelet-based beam element", *Finite Elem. Anal. Des.*, **39**, 965-975.
- Mann, H. B., 1945, "Nonparametric tests against trend", *Econometrica*, **13**, 3, 245-259.
- Mohsin, T. and Gough, W., 2010, "Trend analysis of long-term temperature time series in the Greater Toronto Area (GTA)", *Theor. Appl. Climatol.*, **101**, 3, 311-327.
- Murumkar, A. R. and Arya, D. S., 2014, "Trend and periodicity analysis in rainfall pattern of Nira basin, Central India", *American Journal of Climate Change*, **3**, 1, 60-70.
- Nalley, D., Adamowski, J. and Khalil, B., 2012, "Using discrete wavelet transforms to analyse trends in streamflow and precipitation in Quebec and Ontario (1954-2008)", *J. Hydrol.*, **475**, 204-228.
- Nalley, D., Adamowski, J., Khalil, B. and Ozga-Zielinski, B., 2013, "Trend detection in surface air temperature in Ontario and Quebec, Canada during 1967-2006 using the discrete wavelet transform", *Atmos. Res.*, **132**, 375-398.
- Nourani, V., Mehr, A. D. and Azad, N., 2018, "Trend analysis of hydroclimatological variables in Urmia lake basin using hybrid wavelet Mann-Kendall and Sen tests", *Environ. Earth Sci.*, **77**, 5, p207.
- Olkkonen, J. T. and Olkkonen, H., 2011, "Discrete wavelet transform algorithms for multi-scale analysis of biomedical signals", In: *Discrete Wavelet Transforms-Biomedical Applications*, In Tech.
- Onoz, B. and Bayazit, M., 2003, "The power of statistical tests for trend detection", *Turk. J. Engg. Environ. Sci.*, **27**, 4, 247-251.
- Pandey, B. K., Tiwari, H. and Khare, D., 2017, "Trend analysis using discrete wavelet transform (DWT) for long-term precipitation (1851-2006) over India", *Hydro. Sci. J.*, **62**, 13, 2187-2208.
- Partal, T. and Kahya, E., 2006, "Trend analysis in Turkish precipitation data", *Hydrol. Processes*, **20**, 9, 2011-2026.
- Partal, T. and Kucuk, M., 2006, "Long-term trend analysis using discrete wavelet components of annual precipitations measurements in Marmara region (Turkey)", *Phys. Chem. Earth*, **31**, 18, 1189-1200.
- Partal, T., 2010, "Wavelet transform-based analysis of periodicities and trends of Sakarya basin (Turkey) streamflow data", *River Res. Appl.*, **26**, 6, 695-711.
- Patel, A. J., Suryanarayan, T. M. V. and Parekh, F., 2016, "Trend and variability of climatic parameters in Vadodara district", *Recent Adv. Civil Engg. Global Sustain.*, **22**, 121-127.
- Pingale, S. M., Khare, D., Jat, M. K. and Adamowski, J., 2014, "Spatial and temporal trends of mean and extreme rainfall and temperature for the 33 urban centers of the arid and semi-arid state of Rajasthan, India", *Atmos. Res.*, **138**, 73-90.
- Raj, P. P., Nikhil and Azeez, P. A., 2012, "Trend analysis of rainfall in Bharathapuzha River basin, Kerala, India", *Int. J. Climatol.*, **32**, 4, 533-539.
- Ramesh, K. V. and Goswami, P., 2007, "The shrinking Indian summer monsoon", CSIR report RR CM, p709.
- Sharma, C. S., Panda, S. N., Pradhan, R. P., Singh, A. and Kawamura, A., 2016, "Precipitation and temperature changes in eastern India by multiple trend detection methods", *Atmos. Res.*, **180**, 211-225.
- Sneyers, R., 1990, "On the Statistical Analysis of Series of Observations", Secretariat of the World Meteorological Organization, p192.
- Sonali, P. and Kumar, D. Nagesh, 2013, "Review of trend detection methods and their application to detect temperature changes in India", *J. Hydrol.*, **476**, 212-227.
- Torrence, C. and Compo, G. P., 1998, "A practical guide to wavelet analysis", *Bull. Am. Meteorol. Soc.*, **79**, 1, 61-78.
- Trenberth, K. E., Jones, P. D., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., Parker, D., Rahimzadeh, F., Renwick, J. A., Rusticucci, M., Soden, B. and Zhai, P., 2007, "Observations: Surface and atmospheric climate change", In: *Climate Change 2007: The Physical Science Basis*, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 235-336.
- Vonesch, C., Blu, T. and Unser, M., 2007, "Generalized Daubechies wavelet families", *Sig. Process. IEEE Trans.*, **55**, 9, 4415-4429.
- Wang, H., Chen, Y., Xun, S., Lai, D., Fan, Y. and Li, Z., 2013, "Changes in daily climate extremes in the arid area of northwestern China", *Theor. Appl. Climatol.*, **112**, 1-2, 15-28.

- Wang, N. and Lu, C., 2009, "Two-dimensional continuous wavelet analysis and its application to meteorological data", *Journal of Atmospheric and Oceanic Technology*, **27**, 4, 652-666.
- Wilks, D. S., 2011, "Statistical Methods in the Atmospheric Science", 3rd ed., Academic Press, USA, p704.
- Xu, J., Chen, Y., Li, W., Ji, M., Dong, S. and Hong, Y., 2009, "Wavelet analysis and nonparametric test for climate change in Tarim River Basin of Xinjiang during 1959-2006", *Chin. Geogr. Sci.*, **19**, 4, 306-313.
- Yenigun, K., Gumus, V. and Bulut, H., 2008, "Trends in streamflow of the Euphrates basin, Turkey", In Proceedings of the Institution of Civil Engineers-Water Management, **161**, 4, 189-198.
- Yue, S., Pilon, P., Phinney, B. and Cavadias, G., 2002, "The influence of autocorrelation on the ability to detect trend in hydrological series", *Hydrol. Process.*, **16**, 9, 1807-1829.
-