

# Identification of Relationship Between Precipitation and Atmospheric Oscillations in Upper Ganga Basin



Lalit Pal and C. S. P. Ojha

**Abstract** The hydrology of a region is directly or indirectly dependent on atmospheric variables. Identification of large-scale climate circulations dominating temporal pattern in regional atmospheric variables becomes crucial for improved precipitation forecasting for the region. The livelihood of a large population living in the downstream reaches of Ganga basin is dependent on snow melt and precipitation received in the Upper Ganga basin. Therefore, the aim of this study is to identify trends along various precipitation time series (monthly, seasonally-based, seasonal and annual) over Upper Ganga basin using discrete wavelet transform (DWT) approach for the period of 116 years (1901–2015). Relationship between large-scale atmospheric oscillations and regional scale trends in precipitation series are analysed. In the results, insignificant increasing trend is observed in monthly, annual, monsoon and pre-monsoon time series. On the other hand, winter time series is found to be following significant decreasing trend. The temporal trend in monthly and seasonally-based precipitation series are found to be dominated by seasonal variations in Inter-Tropical Convergence Zone (ITCZ). Overall, El Niño-Southern Oscillations (ENSO) is having a dominant effect on most of the precipitation time series over UGB (monsoon, annual, and pre-monsoon). The study outcomes are particularly beneficial for hydro-meteorological analyses and climate impact assessment based studies in the region.

**Keywords** Precipitation · Atmospheric oscillations · Wavelet transform · MK test · Upper Ganga basin

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## 1 Introduction

Over the last 100 years, the global average surface temperature has experienced an increase of  $0.85\text{ }^{\circ}\text{C}$  which has altered the precipitation patterns and other hydrological systems, globally (Pachauri et al. 2015). As climatic variables directly or indirectly defines the hydrologic response of a catchment, changes in parameters such as temperature, precipitation, evaporation are influencing the streamflow and flow regimes, substantially. Hydrologic variables (streamflow, precipitation, evapotranspiration, etc.) are particularly driven by atmospheric variables (temperature, relative humidity, pressure, perceptible water, etc.) (Sonali and Kumar 2013). Analysing trends in hydrological variables can provide valuable insights for identifying alteration in relationship between atmospheric and hydrologic variables within a region. Identification of trends in time series of hydrologic variables is of significant scientific and practical importance in order to plan and implement an efficient and sustainable management practice in a river basin. In the recent past, considerable number of studies have been focused on analysing the hydrological response to climate variability and climate change through identifying trends in hydrologic time series. Most of these studies have employed trend detection methods such as Sen's slope test, least square linear regression, Mann-Kendall test, Seasonal Mann-Kendall test, etc. All of the above mentioned techniques hold a common assumption that the hydrologic variable is stationary during observed period of record. However, substantial anthropogenic climate change and various other human disturbances have compromised the assumption of stationarity (Milly et al. 2007). Changes in basin climate are altering the mean and extremes of hydrologic variables resulting in tempering of probability density function established from instrumental records. These changes in climate are non-monotonic and non-uniform in nature, making trend detection complicated in a non-stationary environment (Franzke 2010). Therefore, identification of trends using conventional methods with stationarity assumption may result in erroneous conclusions and there needed a technique independent of such assumption.

A spectral analysis method called the wavelet transform (WT) has found its application in the analysis of non-stationary geophysical time series (Lau and Weng 1995; Lindsay et al. 1996). The WT decomposes one-dimensional non-stationary time series into multiple low and high frequency components to represent intra-annual, inter-annual and decadal fluctuations. The method has been acknowledged to be superior to other conventional signal analysis techniques, for example, Fourier transform (FT). In FT, a signal is decomposed into sine wave functions with infinite duration, whereas, WT decomposes signals using wavelet functions with limited duration and zero means. In recent times, the WT method has gained popularity for analysing the time series of geophysical variables under climate change scenario (Nalley et al. 2012, 2013). The method provide insight to the different periodic components that dominates the trend in hydrologic variables which can later be inferred to large and regional scale climate circulations. It provides a complete picture of dynamics contained in the signal being analysed. The present study aims to investigate relationship between atmospheric circulations and trends in monthly, seasonal, and annual

precipitation over Upper Ganga basin, India using the discrete wavelet transform (DWT) approach. Different lower resolution (low frequency) components can be derived from a time series using the DWT approach. DWT simplifies the decomposition process as it is based on dyadic discretization (integer power of two) and generates one-dimensional signal which is easier to analyse. MK trend test is applied to the decomposed time series to assess their statistical significance. The decomposed series having MK-Z value closest to that of original time series is considered to be the dominant periodic component. Later, climate system(s) with similar periodicity as that of dominant periodic component are identified in order to investigate the relationship between the trends in precipitation and dominant climate system.

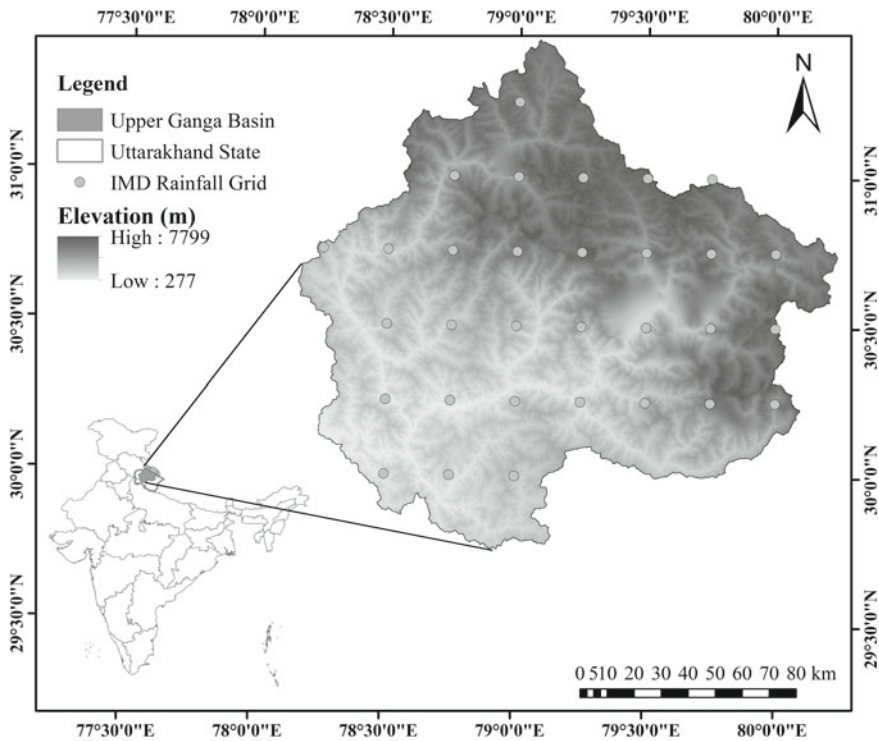
## 2 Study Area

The Ganga River is the longest east flowing river in India which forms at the confluence of Bhagirathi and Alaknanda River in Uttarakhand state of India within the mountain range of the Himalayas. The entire Ganga River basin is divided into three zones namely Upper Ganga basin, Middle Ganga basin and Lower Ganga basin. The present study is carried out over the Upper Ganga basin (up to Haridwar) situated in northwest Himalayan region in India. The areal extent of the region lies within  $29^{\circ} 38' - 31^{\circ} 24' N$  latitude and  $78^{\circ} 09' - 80^{\circ} 22' E$  longitude covering an area of about 22,292 km<sup>2</sup> up to Haridwar. The Upper Ganga basin extends from snow/glacier covered greater Himalayas in the north to forest covered Himalayan foothills in the south. Runoff generated from snow melt and monsoon rainfall nurtures the population living in the downstream reaches of the basin. The elevation in the river basin ranges from 7799 m in the Himalayan mountain peaks to 277 m in the plains. In the western Himalayas, rainfall distribution responds to moist monsoon winds from the Bay of Bengal and moisture bearing westerlies during winters. A major fraction of rainfall in Upper Ganga basin is received from the Indian summer monsoon (ISM) extending from June to September, thus, monsoon rains have vital social and economic consequences. Location map of study area along with topographic details is shown in Fig. 1.

## 3 Materials and Methods

### 3.1 Data Collection

The daily precipitation gridded dataset developed by India Meteorological Department (IMD) (Pai et al. 2014) at  $0.25^{\circ} \times 0.25^{\circ}$  resolution has been used to generate basin average precipitation time series for the period from 1901 to 2015. A



**Fig. 1** Location of study area and topography of the Upper Ganga basin with IMD rainfall grid points

total of seven time series viz. monthly, seasonally-based, pre-monsoon (March–May), monsoon (June–September), post-monsoon (October–November), winter (December–February) have been generated from the available daily precipitation data to carry out various analyses. Each dataset has been tested for the presence of seasonality and autocorrelation.

### 3.2 Wavelet Transform

A wavelet is a small piece of wave having zero mean and finite length in space. Wavelet transform (WT) is a mathematical function which scales a signal into high frequency (low pass filter) and low frequency components (high pass filter) (Adarsh and Janga Reddy 2015). It utilises a variable-size window function which can be enlarged and shifted in the time and frequency domain (Lau and Weng 1995). High frequency components are captured by narrow window whereas low frequency components are resolved by a wide window. In the process of time series decomposition using WT, mother wavelet is shifted along the signal in multiple steps in order

to generate wavelet coefficients. Wavelet coefficients store the information regarding position and extent of different events at various scales. Different dilated versions of the mother wavelet represent different scales. In signal decomposition, the WT is considered advantageous over conventional signal processing technique like Fourier transform (FT) as FT uses sine function resulting in loss of time information of the signal being processed. The WT can be applied in two ways: continuous and discrete wavelet transform. In the present study, discrete wavelet transform (DWT) is applied to decomposed precipitation time series into various periodic components.

### 3.2.1 Discrete Wavelet Transform

Various studies have employed DWT for trend analysis and forecasting (Karthikeyan and Kumar 2013; Nalley et al. 2013). In DWT, window function scales and translates on dyadic scales i.e. in integer power of 2 (Adarsh and Janga Reddy 2015). The mother wavelet function ( $\psi$ ) in DWT is described as:

$$\psi_{(a,b)}\left(\frac{t - \gamma}{s}\right) = \frac{1}{(s_0)^{\frac{a}{2}}} \psi\left(\frac{t - by_0s_0^a}{s_0^a}\right) \tag{1}$$

where,  $\psi$  represents the discrete mother wavelet,  $a$  and  $b$  are integers representing the magnitude of enlargement (stretching) and translation (shifting) of the wavelet, respectively,  $\gamma_0$  defines the location along the signal having value greater than zero and  $s_0$  is the dilation length with value greater than 1. The wavelet coefficients of time series  $x_t$  at discrete integer time step is given as:

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

with the values of  $s_0$  and  $\gamma_0$  are 2 and 1, respectively (Mallat 1989; Daubechies 1992).

### 3.3 Test for Serial Correlation

Lag-k autocorrelation coefficient (ACF) can be computed as (Partal and Kahya 2006):

$$R = \frac{\left(\frac{1}{n-1}\right) \sum_{t=1}^{n-k} [x_t - \bar{x}_t][x_{t+k} - \bar{x}_t]}{\left(\frac{1}{n}\right) \sum_{t=1}^n [x_t - \bar{x}_t]^2} \tag{3}$$

$$\frac{\{-1 - 1.645\sqrt{n} - 2\}}{n - 1} \leq R \leq \frac{\{-1 + 1.645\sqrt{n} - 2\}}{n - 1} \tag{4}$$

where,  $R$  = autocorrelation coefficient (ACF) at lag- $k$  of the time series  $x_t$ , and  $\bar{x}_t$  = mean of the data. Lag-1 autocorrelation coefficients (ACFs) are used to identify the presence of significant autocorrelation. The time series is said to be independent of serial correlation if the value of lag-1 ACF is found to be within the interval computed using Eq. (2). Autocorrelation coefficients (ACFs) are analysed at various lags to obtain correlograms using MATLAB®.

### 3.4 Mann-Kendall Test

The MK test (Mann 1945; Kendall 1975) is a non-parametric trend test widely employed to test the significance of trend in a time series. The test statistic  $S$  is given as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (5)$$

where  $x_j$  and  $x_i$  are data values in sequence  $i$  and  $j$  ( $j > i$ ),  $n$  is the length of data series, and  $\text{sgn}(x_j - x_i)$  is sign function as:

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & \text{for } (x_j - x_i) > 0 \\ 0, & \text{for } (x_j - x_i) = 0 \\ -1, & \text{for } (x_j - x_i) < 1 \end{cases} \quad (6)$$

For identically distributed random variable with  $n \geq 8$ , test statistics closely follow normal distribution with the mean and variance given by:

$$E(S) = 0 \quad (7)$$

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18} \quad (8)$$

where,  $t_i$  denotes the number of ties of extent,  $i$  and  $m$  are the number of tie groups. The standardized normal variate of test statistics  $Z_S$  is computed as:

$$Z_S = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{for } S > 0 \\ 0, & \text{for } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{for } S < 0 \end{cases} \quad (9)$$

The positive values of  $Z_S$  indicate increasing trend while negative  $Z_S$  indicates decreasing trend. At a given level of significance ' $\alpha$ ', the null hypothesis  $H_0$  of no trend is rejected if  $|Z_S| > Z_{1-\alpha/2}$ , where  $Z_{1-\alpha/2}$  is the value of standard normal variate

corresponding to a probability of  $\alpha/2$ . In present study, the hypothesis is tested at 5% significance level, i.e.,  $\alpha = 0.05$ . At 5% significance level, the null hypothesis of no trend is rejected, if  $|Z_S| > 1.96$ .

Hamed and Rao (1998) proposed a modified version of MK test in which effect of autocorrelation is taken into account by using a modified variance of the test statistic. The modified variance is described as:

$$V^*(S) = Var(S) \cdot \frac{n}{n_s^*} = \frac{n(n-1)(2n-5)}{18} \cdot \frac{n}{n_s^*} \tag{10}$$

where,  $\frac{n}{n_s^*}$  represents a correlation in the data due to the presence of serial correlation. The  $\frac{n}{n_s^*}$  is evaluated using:

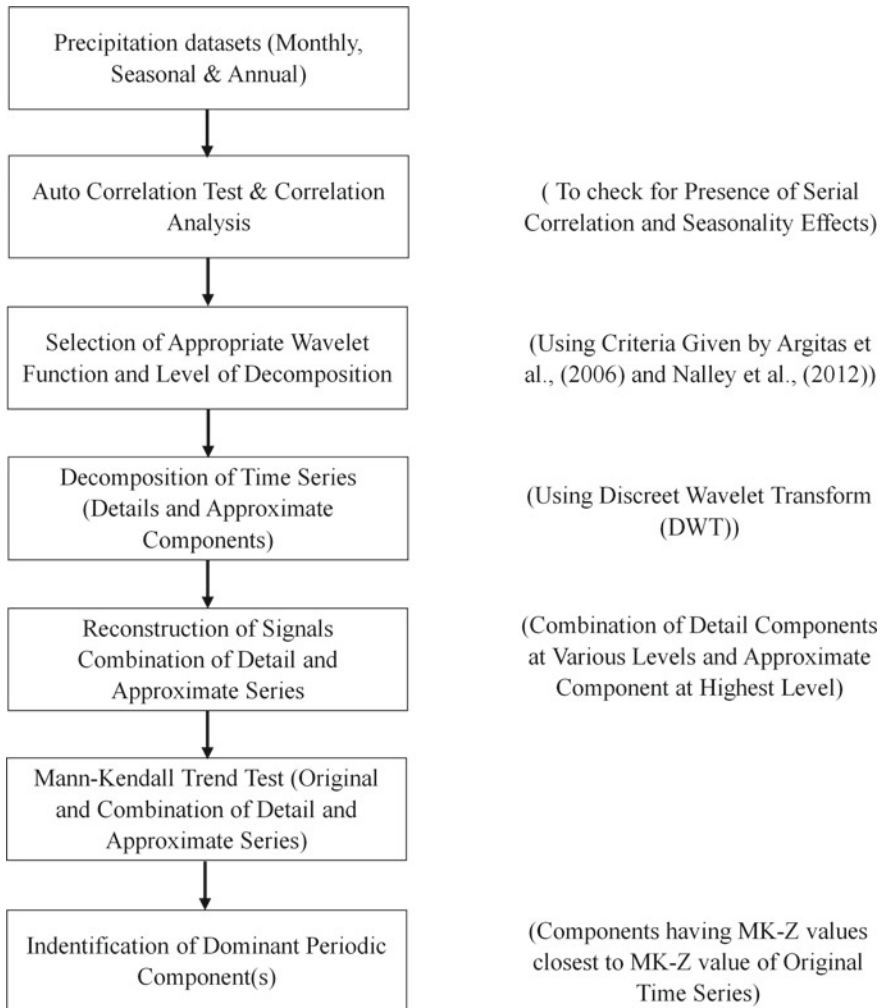
$$\frac{n}{n_s^*} = 1 + \frac{2}{n(n-1)(n-2)} \sum_{i=1}^{n-1} (n-i)(n-i-1)(n-i-2)\rho_s(i) \tag{11}$$

where  $n$  denotes number of observations, and  $\rho_s(i)$  is the autocorrelation function values computed for the rank of the observations. The standardized test statistics  $Z$  is computed as:

$$Z = \frac{S}{[V^*(S)]^{0.5}} \tag{12}$$

## 4 Methodology

Prior to decomposition using WT, various time series of precipitation are analysed for presence of autocorrelation and seasonality effect at 5% significance level. To identify trends in the time series, Mann-Kendall test is applied if no serial correlation exists and Modified Mann-Kendall test is applied if there exist significant autocorrelation. A flow chart of methodology adopted in the present study is shown in Fig. 2. Various monthly, seasonal and annual precipitation time series are analysed for inherent periodic components using DWT. All the computations were performed in MATLAB®. The first step in the methodology involves selection of an appropriate mother wavelet function, level of decomposition and border extension method. Among various families of mother wavelet, the Haar, Symlets and Daubechies families of wavelets have found their application in analysis of trends in geophysical time series (Nalley et al. 2013; Sang 2013; Adarsh and Janga Reddy 2015; Araghi et al. 2015). In particular, past studies have used Daubechies (db) family of wavelets owing to its ease of application. It provides full scaling and translation orthogonal properties with non-zero basis function over a finite interval (Ma et al. 2003; de Artigas et al. 2006).



**Fig. 2** Flowchart of methodology

Different forms of db wavelets (db1, db2, ..., db45) are available in wavelet transform package of MATLAB<sup>®</sup>. For selection of appropriate mother wavelet for signal decomposition, db1–db10 wavelets are considered in the study. To check for the border distortion effect introduced during decomposition of signal with finite length, three types of border extension are available in MATLAB<sup>®</sup> viz. periodic extension, zero padding and boundary value replication (symmetrization). Symmetrization is the default extension mode in MATLAB which ensure signal recovery by symmetric boundary replication. For identifying the adequate combination of the above mentioned three parameters, de Artigas et al. (2006) and Nalley et al. (2012) have proposed two different approaches, each of which are summarized in the



following section. The method proposed by de Artigas et al. (2006) involves minimization of mean relative error (MRE) between the original and approximate (A) series corresponding to last decomposition level as:

$$MRE = \frac{1}{n} \sum_{j=1}^n \frac{|a_j - x_j|}{|x_j|} \quad (13)$$

where  $x_j$  is the original time series with  $n$  number of data points and  $a_j$  is the approximate component of  $x_j$ .

In the second approach proposed by Nalley et al. (2012), the combination producing minimum  $RE$  is selected, where  $RE$  is calculated as:

$$RE = \frac{|Z_{op} - Z_{or}|}{|Z_{or}|} \quad (14)$$

$Z_{or}$  represents the MK Z-value of original time series; and  $Z_{op}$  is the MK Z-value of the approximation component of the last decomposition level of DWT. The combination of mother wavelet type, level of decomposition and border decomposition producing minimum value of MRE and RE are selected for further analyses. To calculate the number of decomposition levels, de Artigas et al. (2006) proposed the following equation:

$$L = \frac{\text{Log}\left(\frac{n}{2^v-1}\right)}{\text{Log}(2)} \quad (15)$$

where  $n$  is the number of records in monthly time series,  $v$  is the number of vanishing moments and  $L$  is maximum decomposition level. In MATLAB, the number of vanishing moments for a Daubechies (db) wavelet is half of the length of its starting filter.

The *multilevel one-dimensional wavelet analysis* function in MATLAB® has been employed to decompose precipitation time series using discrete wavelet transform (DWT). The approximation (A) and detail (D) components are generated through convolving the time series with low-pass and high-pass filters, followed by a dyadic scale discretization. The detail component at each decomposition level is added with approximate component corresponding to last level of decomposition as important characteristics of original time series such as trend are stored in last the approximate component. Decomposed time series are reconstructed into one dimensional signal using *multilevel one-dimensional wavelet reconstruction* function in MATLAB. The original signal is decomposed using window of scale varying by integer powers of 2 i.e. the signal is broken down in halves, then in quarters, and it continues onward (Dong et al. 2008). The original signal (time series) is decomposed at various levels by power of 2 and at each level, approximation (A) components of previous level are decomposed. The periodic component dominating the trend in original time series is identified by comparing the MK-Z value of original series with MK-Z value of detail

component at different decomposition levels. As each detail component represents a time series of defined periodicity (in integer power of 2), the component having MK-Z value closest to that of original series defines the dominance of variable with corresponding periodicity. Lastly, the existing atmospheric processes directly or indirectly controlling the precipitation patterns in southern Asia are identified.

## 5 Results and Discussion

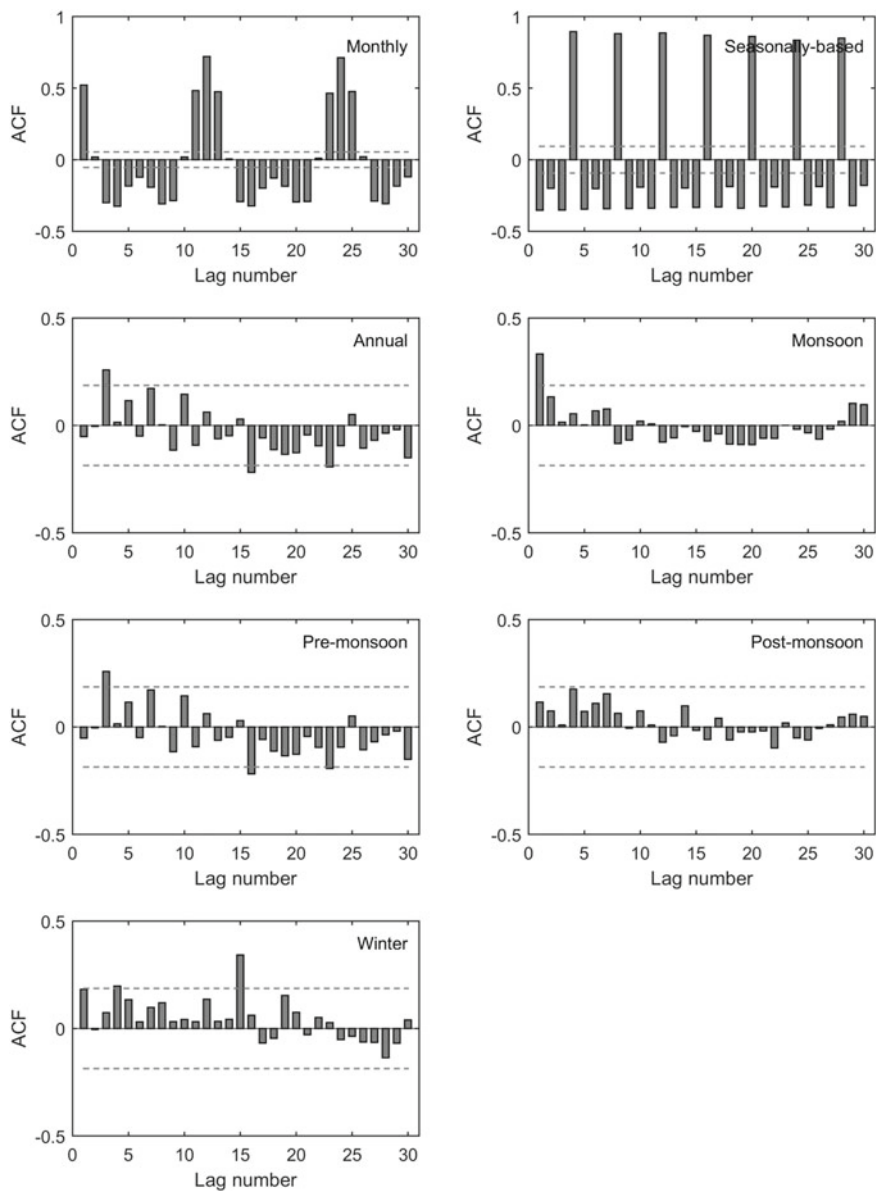
### 5.1 Serial Correlation and Seasonality

All seven precipitation time series (monthly, seasonally-based, annual, monsoon, pre-monsoon, post-monsoon and winter) have been tested for the presence of serial correlation. The computed lag-1 autocorrelation coefficients along with their upper and lower bounds are given in Table 1. As evident from the table, significant lag-1 autocorrelation has been observed in monthly, seasonally-based and monsoon time series, whereas, annual, post-monsoon, winter and pre-monsoon time series are found to be independent of serial correlation. In general, monthly time series are expected to have stronger autocorrelation than the annual data series (Hamed and Rao 1998). Also, strong effect of seasonality has been observed in the monthly time series as repeated patterns of semi-annual and annual cycles can be seen in its correlograms (Fig. 3). Similarly, the correlograms of seasonally-based time series are presenting an evidence of annual to inter-annual cyclic patterns (Fig. 3). No clear effect of seasonality can be observed in the rest of time series. The trends in time series following strong seasonality pattern are identified using Modified Mann-Kendall test as discussed in previous section and time series independent of the effect of autocorrelation are employed with Mann-Kendall test.

**Table 1** Lag-1 autocorrelation coefficients for various precipitation time series for Upper Ganga basin

Time series	ACF (lag-1)	Upper limit	Lower limit
<b>Monthly*</b>	<b>0.521</b>	<b>0.054</b>	<b>-0.054</b>
<b>Seasonally-based*</b>	<b>-0.353</b>	<b>0.093</b>	<b>-0.093</b>
Annual	-0.052	0.187	-0.187
<b>Monsoon*</b>	<b>0.333</b>	<b>0.187</b>	<b>-0.187</b>
Post-monsoon	0.116	0.187	-0.187
Winter	0.183	0.187	-0.187
Pre-monsoon	-0.052	0.187	-0.187

\*Significant at 5% significance level



**Fig. 3** Correlograms of monthly, seasonally-based, annual, monsoon, post-monsoon, pre-monsoon and winter time series

**Table 2** Best combination of mother wavelet, decomposition level and border extension type for different precipitation data series

Time series	Daubechies wavelet	Decomposition level	Border extension
Monthly	'db4'	6	Symmetrization
Seasonally-based	'db4'	4	Symmetrization
Annual	'db5'	4	Symmetrization
Monsoon	'db6'	4	Symmetrization
Post-monsoon	'db5'	4	Symmetrization
Winter	'db3'	2	Zero padding
Pre-monsoon	'db7'	4	Symmetrization

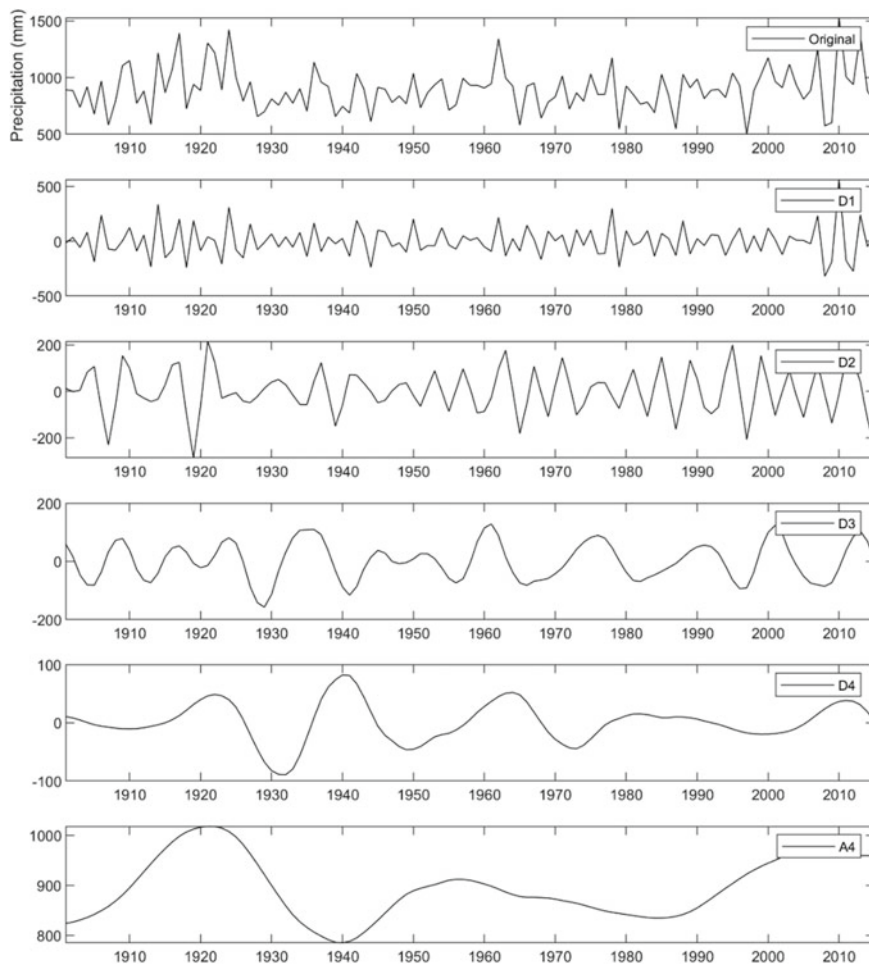
## 5.2 Wavelet Transform of Different Time Series

In the present study, wavelet transform has been carried out using discrete wavelet transform (DWT) with Daubechies (db) family of wavelets as mother wavelet. For each time series, the best combination of Daubechies (db) mother wavelet, level of decomposition and type of border extension are identified using criteria proposed by de Artigas et al. (2006). The combination giving minimum value of MRE has been selected for decomposition of respective time series. The best combination satisfying the above mention criteria for different time series are given in Table 2.

In DWT, the scales are organized in dyadic format (integer powers of two) from the lowest scale to which time series are decomposed to as 2-unit periodic components at D1 level, 4-unit components at D2 level, 8-unit components at D3 level, and so on (Nalley et al. 2012). For each time series, MK Z-values are computed for detail (D) component series at each level of decomposition, approximation (A) component series at last decomposition level, and sum of detail components at each level with approximation components (D + A). An example of WT of monthly precipitation time series using Daubechies (db4) as mother wavelet, at six decomposition levels with 'symmetrization' border extension mode is shown in Fig. 4.

## 5.3 Identification of Dominant Periodic Component Affecting Trend

The modified version of Mann-Kendall (MMK) test has been applied to the monthly, seasonally-based and monsoon time series as all these are effected by strong autocorrelation. The original Mann-Kendall (MK) test has been applied to the remaining time series independent of the effect of autocorrelation. The results of both MK and MMK test are presented in Table 3. As evident from the table, monthly, annual, monsoon and pre-monsoon precipitation is exhibiting an insignificant increasing trend at 5% significance level, whereas, precipitation time series of seasonally-based, post-monsoon



**Fig. 4** Monthly precipitation time series and its decomposition using DWT with db4 wavelet into six levels

**Table 3** MK Z-values for different original precipitation time series

Time series	S	Z	Z <sub>n</sub>	Trend
Monthly	7129	0.42	1.96	+
Seasonally-based	-210	-0.06	1.96	-
Annual	209	0.5	1.96	+
Monsoon	313	0.75	1.96	+
Post monsoon	-245	-0.59	1.96	-
<b>Winter*</b>	<b>-941</b>	<b>-2.01</b>	<b>1.96</b>	<b>-</b>
Pre-monsoon	623	1.5	1.96	+

\*Significant at 5% significance level

and winter is showing falling trend in which trend in winter season are significant. It should also be noted that trend in seasonally-based time series are so weak that it can be regarded as to be following no trend.

In order to determine the dominant periodic component controlling trend in given time series, the approximation component of last decomposition is added to detail component of each decomposition level as the approximation component captures the lowest frequency components of the signal. The strength of trend (MK Z-value) of each detail component (approximation component added) is compared with strength of trend (MK Z-value) in original time to assess the dominance of a particular periodic component on the overall trend in original time series. Table 4 represents the MK Z-values computed for original and various decomposed series of monthly precipitation in Upper Ganga basin. For monthly precipitation time series, MK-Z value of detail component at third level of decomposition is closest to the that of original series. Therefore, component having periodicity of  $2^3$  i.e. 8 months is found to be dominating the trend in monthly precipitation. Seasonal shifts in Inter-Tropical Convergence Zone (ITCZ) is considered to be one of the responsible factors for manifestation of monsoon over Indian sub-continent (Gadgil 2003). Since, major fraction of rainfall over Indian sub-continent is received during monsoon months, variations in onset of monsoon may cause change in monthly rainfall received in the region. Therefore, seasonal variations in ITCZ may be considered as dominant climatic phenomenon for temporal patterns in monthly rainfall over Upper Ganga basin.

Trends in original and decomposed components for seasonally-based time series are shown in Table 5. Seasonally-based time series was decomposed using db4 mother

**Table 4** MK Z-values for monthly precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	7129	0.42	1.96	+
D1	1884	0.11	1.96	+
D2	-2304	-0.13	1.96	-
D3	-244	-0.01	1.96	-
D4	-2830	-0.17	1.96	-
D5	-882	-0.05	1.96	-
D6	-18,980	-1.11	1.96	-
A6	-11,626	-0.68	1.96	-
A6 + D1	-17,466	-1.02	1.96	-
A6 + D2	-17,604	-1.03	1.96	-
<b>A6 + D3<sup>a</sup></b>	<b>8918</b>	<b>0.52</b>	<b>1.96</b>	<b>+</b>
A6 + D4	-18,844	-1.10	1.96	-
A6 + D5	-18,578	-1.09	1.96	-
A6 + D6	48,496	2.84	1.96	+

<sup>a</sup>Dominant periodic component

**Table 5** MK Z-values for seasonally-based precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	Z <sub>n</sub>	Trend
Original	-210	-0.06	1.96	-
D1	-154	-0.05	1.96	-
D2	-558	-0.17	1.96	-
D3	-672	-0.20	1.96	-
D4	3130	0.95	1.96	+
A4	506	0.15	1.96	+
<b>A4 + D1<sup>a</sup></b>	<b>-32</b>	<b>-0.01</b>	<b>1.96</b>	<b>-</b>
A4 + D2	72	0.02	1.96	+
A4 + D3	-514	-0.16	1.96	-
A4 + D4	3026	0.92	1.96	+

<sup>a</sup>Dominant periodic component

wavelet up to four decomposition level with ‘symmetrization’ border extension. From the table, the seasonally based series has been observed to be following practically no trend. Subsequently, different trend can be seen in various decomposed components with no series presenting any significant trend. As evident from Table 5, MK-Z value of level-1 detail component (D1) is closest to that of original time series, therefore, level-1 periodic component with a periodicity of 2<sup>1</sup> seasons i.e. about 8 months may be adopted as dominant for seasonally-based precipitation. Again, shifts in ITCZ have seasonal periodicity which corresponds to that of identified dominant component. Therefore, trends in seasonally-based precipitation over Upper Ganga basin may be attributable to the seasonal variations in ITCZ.

The MK Z-value for different decomposed components of annual time series are shown in Table 6. As evident from the table, a positive trend exists in the annual precipitation in UGB. Further, trends in all detail and approximation components are observed to be positive in nature which shows that almost all physical processes with various periodicities are contributing to the overall annual time series. The level-2 detail component representing 2<sup>2</sup> years i.e. 4-year periodic component may be adopted as dominant periodic component for annual precipitation as MK-Z value of D2 + A component is 0.41 which is closest to that of original time series. Among various existing atmospheric process, El-Niño Southern Oscillations (ENSO) have periodicity of 4–7 years (Webster et al. 1998; Gadgil et al. 2004). In addition, trends observed in observed and decomposed time series of monsoon rainfall are same as that of annual rainfall. These results are evident as monsoon rainfall constitutes major portion of total annual rainfall received in the region. Subsequently, 4-year periodic component corresponding to D2 + A periodic component is found to the dominant periodic component for monsoon rainfall also (Table 7). Moreover, various past studies have documented the dominance of ENSO on Indian summer monsoon rainfall (Sikka 1980; Pant and Parthasarathy 1981; Rasmusson and Carpenter 1983;

**Table 6** MK Z-values for annual precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	209	0.50	1.96	+
D1	111	0.27	1.96	+
D2	-31	-0.07	1.96	-
D3	163	0.39	1.96	+
D4	439	1.06	1.96	+
A4	459	1.11	1.96	+
A4 + D1	295	0.71	1.96	+
<b>A4 + D2<sup>a</sup></b>	<b>169</b>	<b>0.41</b>	<b>1.96</b>	<b>+</b>
A4 + D3	281	0.68	1.96	+
A4 + D4	693	1.67	1.96	+

<sup>a</sup>Dominant periodic component

**Table 7** MK Z-values for monsoon precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	313	0.75	1.96	+
D1	11	0.02	1.96	+
D2	-133	-0.32	1.96	-
D3	97	0.23	1.96	+
D4	247	0.59	1.96	+
A4	587	1.42	1.96	+
A4 + D1	5	0.01	1.96	+
<b>A4 + D2<sup>a</sup></b>	<b>271</b>	<b>0.65</b>	<b>1.96</b>	<b>+</b>
A4 + D3	455	1.10	1.96	+
A4 + D4	1231	2.97	1.96	+

<sup>a</sup>Dominant periodic component

Webster et al. 1998; Ashok and Saji 2007). Therefore, ENSO may be adopted as the dominant climate cycle controlling the temporal patterns in monsoon and annual rainfall over Upper Ganga basin.

Post-monsoon precipitation in UGB is found to be dominated by 2-year periodic component as MK-Z value of D1 + A component is closest to that of the original time series (Table 8). Among key atmospheric processes identified to have influence on rainfall over Indian sub-continent, periodic cycle of seasonal variations in ITCZ, Indian Ocean Dipole (IOD) movement and ENSO varies between 2 and 7 years. Although, various attempts have been made by researchers to understand the physics behind rainfall occurrence over Indian sub-continent, the interaction between these



**Table 8** MK Z-values for post-monsoon precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	-245	-0.59	1.96	-
D1	151	0.36	1.96	+
D2	-223	-0.54	1.96	-
D3	-173	-0.42	1.96	-
D4	37	0.09	1.96	+
A4	-1931	-4.67	1.96	-
<b>A4 + D1<sup>a</sup></b>	<b>-247</b>	<b>-0.56</b>	<b>1.96</b>	<b>-</b>
A4 + D2	-1075	-2.60	1.96	-
A4 + D3	-1119	-2.70	1.96	-
A4 + D4	-893	-2.16	1.96	-

<sup>a</sup>Dominant periodic component

individual process is not yet well understood. Therefore, attribution of change in precipitation patterns specifically among these climate patterns is difficult. As, 2-year periodic component is found to be dominant in post-monsoon period, variability of rainfall during this period may be due to interaction between the processes with bi-annual periodicities.

As obtained for post-monsoon period, precipitation patterns in winter season are also dominated by 2-year periodic component (Table 9). Subsequently, variability and temporal in precipitation during winter season may also be attributable to climate processes with 1–2-year periodicity such as IOD, seasonal variation in ITCZ or ENSO. In addition, the original precipitation time series for winter season is exhibiting a significant decreasing trend with MK-Z value being  $-2.01$ . Lastly, MK Z-values computed for original and decomposed time series of pre-monsoon precipitation are given in Table 10. Combination of detail and approximation components at all four decomposition level has been observed to following significant increasing

**Table 9** MK Z-values for winter precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	-941	-2.01	1.96	-
D1	11	0.02	1.96	+
D2	-13	-0.03	1.96	-
A2	-985	-2.38	1.96	-
<b>A4 + D1<sup>a</sup></b>	<b>-761</b>	<b>-1.84</b>	<b>1.96</b>	<b>-</b>
A4 + D2	-669	-1.61	1.96	-

<sup>a</sup>Dominant periodic component

**Table 10** MK Z-values for pre-monsoon precipitation series (original, detail, approximation, detail + approximation)

Time series	S	Z	$ Z_n $	Trend
Original	623	1.50	1.96	+
D1	27	0.06	1.96	+
D2	95	0.23	1.96	+
D3	-383	-0.92	1.96	-
D4	-35	-0.08	1.96	-
A4	1651	3.99	1.96	+
A4 + D1	937	2.26	1.96	+
<b>A4 + D2<sup>a</sup></b>	<b>717</b>	<b>1.70</b>	<b>1.96</b>	<b>+</b>
A4 + D3	1285	3.10	1.96	+
A4 + D4	1463	3.53	1.96	+

<sup>a</sup>Dominant periodic component

trend. However, MK-Z value of D2 + A component (1.70) is closest to that of original time series (1.50). This indicates that a climate process with 4-year periodicity is dominating the trend observed in pre-monsoon series. Evidently, the insignificant increasing trend observed in pre-monsoon rainfall over UGB may fairly be attributable to ENSO (4–7-year periodicity).

## 6 Conclusion

The wavelet transform (WT) approach which is conventionally been used for signal processing has been applied to precipitation time series in Upper Ganga basin to analyse trends and dominant periodic component controlling the trends. The application of DWT to the precipitation time series is found to provide useful information regarding inherent controlling processes. The methodology presented in the present study can be applied to other hydro-meteorological variables also. In the results, monthly, annual, monsoon and pre-monsoon precipitation series are found to be exhibiting an insignificant increasing trend at 5% significance level. Whereas significant decreasing trend are observed in winter precipitation series. A fair amount of rainfall in the region is also received during winter season from retreating north-east monsoon in southern foothills of Himalayas and westerlies in northern Great Himalayas. The significant decreasing trend observed in winter precipitation reveals the drying tendency of region in western Himalayas.

The atmospheric oscillations dominating temporal trends in various seasonal and annual precipitation series are identified by comparing the dominant periodic components with periodicity of known atmospheric patterns. The temporal trend in monthly

and seasonally-based precipitation series are found to be dominated by seasonal variations in Inter Tropical Convergence Zone (ITCZ). The cycles of ENSO are found to be dominating the trends observed in pre-monsoon, monsoon and annual precipitation over Upper Ganga basin. Further, temporal variations in precipitation during remaining two seasons i.e. post-monsoon and winter are found to be influenced by the combined effect of inter-annual scale climate processes namely ENSO, IOD and ITCZ.

Overall, ENSO climate circulation is having a dominant effect on most of the precipitation time series which is also supported by various past studies. The summer monsoon rainfall over Indian subcontinent is a combined results of various climate processes occurring simultaneously at different temporal scale. The interaction between these processes, however, is not well studied yet. Therefore, the relationship established between monsoon precipitation trends and various global climate circulations need to be verified by carrying out correlation studies. Further, such relationships may be helpful in identifying linkages between precipitation and different climate processes and improved precipitation forecast at regional scale.

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