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Assessment of drought trend and variability in India using wavelet transform

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ABSTRACT
This paper presents an analysis of trends in six drought variables at 566 stations across India over the period 1901–2002. Six drought variables were computed using standardized precipitation index (SPI). The Mann-Kendall (MK) trend test and Sen's slope estimator were used for trend analysis of drought variables. Discrete wavelet transform (DWT) was used to identify the dominant periodic components in trends, whereas the significance of periodic components was examined using continuous wavelet transform (CWT) based global wavelet spectrum (GWS). Our results show an increasing trend in droughts in eastern, northeastern and extreme southern regions, and a decreasing trend in the northern and southern regions of the country. The periodic component influencing the trend was 2–4 years in south, 4–8 years in west, east and northeast, 8–64 years in central parts and 32–128 years in the north; however, most of the periodic components were not statistically significant.

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1 Introduction

Drought is a well-known but highly complicated and least understood natural hazard, which frequently occurs in different parts of the world (Wilhite 2000). It is defined by the constant shortage of water in meteorological, hydrological, agricultural or groundwater systems for an extended period such as a season or year. Drought is considered as a common feature of climate, and its recurrence is inevitable (Wilhite 2000). The phenomenon is not limited to the arid regions (i.e. the areas with less precipitation), but it occurs in all climate zones (i.e. in areas of high as well as low precipitation) (Mishra and Singh 2010). Drought is different from other natural hazards (e.g. floods, earthquakes and cyclones) as its effect accumulates slowly over a significant period and may persist for years after the termination of the event (Wilhite 2000, Mishra and Singh 2010). The complexity in drought modeling also arises because it is difficult to determine the onset and end of a drought event due to the progressive nature of reduction in precipitation, streamflow or soil moisture. The geographical area affected by a drought event is much larger compared to other natural hazards. The rapid increase in population and the expansion in industrialization and agriculture have resulted in a rise in water demand in different parts of the world, especially in developing countries like India (Amarasinghe *et al.* 2007). Therefore, the available water resources have been exploited above the sustainable limits, which is eventually leading to anthropogenic droughts (Van Loon *et al.* 2016). As discussed by Wilhite (2000), the drought severity is not only dependent on the duration, intensity, and geographical extent of a specific drought episode but also on the demands made by human activities and vegetation on a region's water supplies. Drought is not only a natural or physical event, but there is a social component associated with it. The drought risk is the compound effect of both the region's exposure to the event (i.e. the probability of occurrence at various severity levels) and the vulnerability of society to the event (Wilhite 2000). Due to the continuous increase in the concentration of CO_2 in the atmosphere, climate change is now seen as one of the major threats for the planet earth in the twenty-first century (IPCC 2014). Climate change is believed to enhance the frequency and severity of drought in different parts of the world (IPCC 2007, Dai 2011, Trenberth *et al.* 2014). Based on the historical records of precipitation, streamflow and drought indices, Dai (2012) showed the increased aridity in different parts of the world since 1950. Trenberth *et al.* (2014) highlighted that global warming might not result in an increased number of droughts, but the droughts could become quicker and more intense. On the other hand, some studies have found an increasing trend in precipitation as well. For example, Westra *et al.* (2013) found statistically significant increasing trends in total precipitation at the global scale over the period 1900–2009 using data from 8326 high-quality land-based observing stations globally. Based on observations and climate models, Donat *et al.* (2016) found an increase in both total precipitation and extreme daily precipitation averaged over both dry and wet regimes since 1950s. It is believed that the wet regions will be wetter and arid regions will be drier under climate change. The uneven distribution of precipitation changes is expected to enhance the frequency and severity of drought in many regions.

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India is a developing country, which relies mainly on the agricultural sector for its economic growth. Rainfed agriculture is predominant in India as about 60% of the total net sown area comes under rainfed lands, which makes agriculture in the country highly dependent on climatic conditions, primarily on precipitation. India ranks first among the countries that practice rainfed agriculture both in terms of extent (86 Mha) and the value of production (Sharma *et al.* 2010). Droughts affect plant growth and food production and can pose a severe threat to food security (Zhang *et al.* 2017). The Indian subcontinent has encountered many droughts in the past, some of which have created a massive deficit in food production (Mishra and Singh 2010, Aadhar and Mishra 2018, Mishra *et al.* 2019). Many studies carried out in different parts of Indian sub-continent found an increase in droughts frequency under climate change (e.g. Alamgir *et al.* (2015), Ahmed *et al.* (2018), Bisht *et al.* (2019)). Indian Meteorological Department (IMD) reported that India experienced 27 drought years between 1875 and 2005 (Shewale and Kumar 2005). A year is considered as a "drought year" if more than 20% area in the country is affected by droughts in that year. Mishra *et al.* (2019) used station-based observations and simulations of soil moisture to identify seven major drought periods during 1870–2016. Spatiotemporal assessment of drought occurrence plays a vital role in a better understanding of drought patterns, forecasting, and preparedness. Many studies have been carried out for the evaluation of spatiotemporal patterns of drought and precipitation in India (Kumar *et al.* 1999, Shewale and Kumar 2005, Pai *et al.* 2011, 2014, Jain and Kumar 2012, Deka *et al.* 2013, Kumar and Rao 2013, Mondal *et al.* 2014, Jain *et al.* 2015, Joshi *et al.* 2016, Mallya *et al.* 2016, Mishra *et al.* 2016, 2019, Aadhar and Mishra 2018). Few studies have also investigated the relation between monsoon droughts in India and El Nino Southern Oscillation (ENSO) (Kumar *et al.* 1999, 2006, Kumar and Rao 2013).

Though there are many studies available in the literature on trend analysis of droughts in India, most of these studies were carried out on coarser resolution (e.g. Bisht *et al.* (2019), Joshi *et al.* (2016)) or using conventional trend/change analysis techniques (e.g. Aadhar and Mishra (2018), Mallya *et al.* (2016), Mishra *et al.* (2019)). Mallya *et al.* (2016) carried out an investigation of trends and variability in the droughts over the Indian monsoon region using datasets from two sources, namely IMD and University of Delaware (UD), and four drought indices, namely, standardized precipitation index (SPI), standardized precipitation-evapotranspiration index (SPEI), Gaussian mixture model-based drought index (GMM-DI), and hidden Markov model-based drought index (HMM-DI) over the period 1901–2014. The study found an increase in the frequency and severity of drought events in the period 1972–2004. Bisht *et al.* (2019) carried out an investigation of the drought characteristics for six major homogenous monsoon regions in India for projected climate (2010–2099) using SPEI and found an increasing trend in the occurrence, duration and severity of droughts. Aadhar and Mishra (2018) used SPEI for the analysis of drought occurrence under climate change in India for the period 2011–2100. The study suggested an increase in the frequency of severe droughts in the warmer and wetter climate. These studies used conventional techniques of trend and change analysis using climate model outputs and climate indices. However, these conventional methods are not efficient for hydro-climatological variables that contain multiple signals and consist of fragments of different trends (Adamowski *et al.* 2009). Some studies have found wavelet-based methods efficient in trend analysis of non-stationary series of hydro-climatological variables (Torrence and Compo 1998). For example, Adamowski *et al.* (2009) reported that the wavelet-based methods offer a useful tool for the detection and estimation of complicated signals present in timeseries. Araghi *et al.* (2015) used the discrete wavelet transform (DWT) along with the Mann-Kendall (MK) trend test for finding out the long-term temperature trends and dominant periodicities in Iran. The continuous wavelet transform (CWT) is also found useful in trend detection and finding the dominant periodic components (Adamowski *et al.* 2009, Joshi *et al.* 2016, Goyal and Sharma 2017a). Joshi *et al.* (2016) studied the trend and dominant and significant periodicities of different drought variables in India using wavelet transform (WT). The study was carried out at 30 rainfall subdivisions for the period 1871–2012.

In this study, we present a WT-based high-resolution analysis of trend and drought variability in India. The analysis is performed at 566 stations in India using long-term observed precipitation data over the period 1901–2002. SPI based six drought variables, namely annual drought severity (ADS), annual drought duration (ADD), annual drought peak (ADP), annual-SPI (A-SPI), monsoon-SPI (M-SPI) and non-monsoon SPI (N-SPI), were computed (Joshi *et al.* 2016). DWT, along with the MK test, was used for trend analysis and identification of periodic component at the station level. CWT was used for finding significant periods of variability. This study provides a high-resolution analysis of drought variability using DWT based improved approach. This study will help in improving our understanding of drought occurrence and variability in India. This study also aims to help the scientific community to understand the limitations of conventional trend analysis techniques and will encourage them to adopt a wavelet-based approach to understand the underlying frequencies not only for the drought but also for other hydrologic processes.

2 Study area and data used

This study was carried out at 566 stations in India, which represent districts of India. The data used in this study is available from India Water Portal[1] at a monthly time step for the period 1901–2002 (102 years). Figure 1 shows the location of 566 stations on the map of India and the spatial variation of mean annual precipitation (MAP). Complete time series of precipitation were available at all stations, and hence no preprocessing or gap-filling was done on the data. The spatial distribution of MAP in Fig. 1 was generated using inverse distance weighted interpolation (IDWI) of precipitation data of 566 stations. The northeastern region of the country and the

[1]http://www.indiawaterportal.org/met_data/.

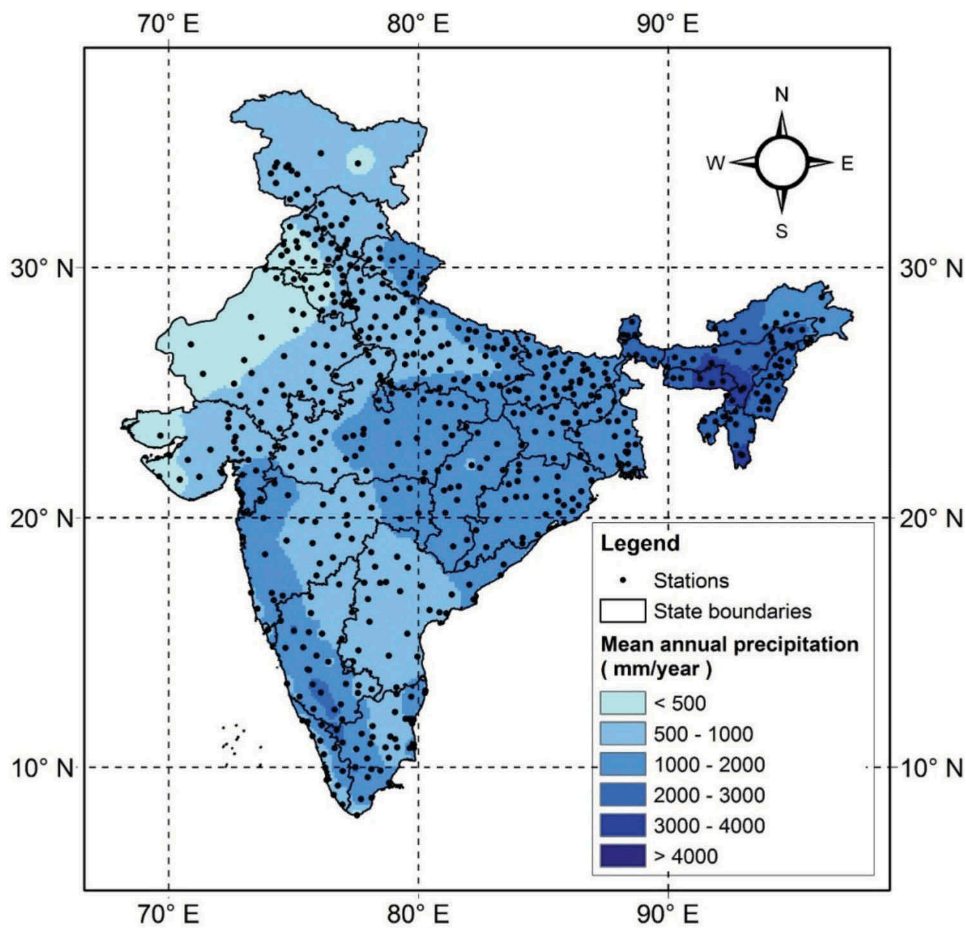

Figure 1. Location of 566 stations in India and the spatial representation of mean annual precipitation in India.

Western Ghats receive high precipitation (>2000 mm/year), whereas the western regions receive less precipitation (<500 mm/year). The localized annual precipitation at some stations in the northeast and Western Ghats is higher than 5000 mm. Western India is one of the most drought-affected areas in the country (Shewale and Kumar 2005, Goyal and Sharma 2017b).

3 Methodology

3.1 Standardized precipitation index (SPI)

The SPI is one of the most widely used drought indices, which is also recommended by the World Meteorological Organization (WMO) (Zargar *et al.* 2011, WMO 2012). It was proposed by Mckee *et al.* (1993) and has been used in many drought studies (Kumar *et al.* 2009, Ahmed *et al.* 2019). It represents the actual precipitation in terms of the standardized departure from probability distribution function (pdf) of precipitation. It can effectively be used for comparisons of drought conditions across space and time. The SPI is computed based on long-term precipitation data, which is required to determine the best-fit PDF (Mishra and Singh 2009, Mishra and Cherkauer 2010). The pdf is then transformed to a standardized normal distribution. In this way, SPI represents the standard deviations of precipitation values. The positive values of SPI indicate precipitation higher than the median value, whereas the negative values indicate precipitation less than the median value. Advantages of the use of SPI are: (a) it requires only precipitation data, which make it applicable for regions with scarce hydro-meteorological data; (b) it can be used for different timescales such as 1, 3, 6, 12, 24 or 48 months; (c) it is not adversely affected by topography; and (d) it can be used to compare stations in different climate zones due to the use of standard normal distribution (Kumar *et al.* 2009). The negative values of SPI represent the dry conditions, whereas the positive values represent the wet conditions. For more details about SPI, its computation, and applications, the reader is referred to Mckee *et al.* (1993), Mckee *et al.* (1995), Mishra and Desai (2005) and Goyal and Sharma (2016).

3.2 Drought variables

Using SPI, six drought variables were calculated at each station (Joshi *et al.* 2016). The drought variables are:

3.2.1 Annual drought duration (ADD)

The ADD represents the duration of a year (in terms of the number of months) having drought conditions. Six-month SPI (SPI6) was used to identify drought conditions. For every year, the number of months having SPI6 value less than the threshold was considered as the ADD. The threshold limit was taken as a 20th percentile SPI6 value, which was – 0.84 in the present case.

3.2.2 Annual drought peak (ADP)

The ADP represents the minimum value SPI6 for the drought months *j* (1, . . ., 12) in year *i*:

$$ADP_i = \min\left[SPI6_{i,j}\right] \tag{1}$$

3.2.3 Annual drought severity (ADS)

The ADS represents the cumulative value of SPI6 during droughts months *j* (1, . . ., 12) for every year *i* and is calculated as follows:

$$ADS_i = \sum\nolimits_{j=1}^{12} SPI6_{i,j} \tag{2}$$

3.2.4 Annual SPI (A-SPI)

The A-SPI is computed using the aggregated total precipitation for the year.

3.2.5 Monsoon-SPI (M-SPI)

The M-SPI is computed based on the aggregated total precipitation for the monsoon months, which for India are from June to September. In this case, total monsoon rainfall was computed as the sum of precipitation for the monsoon months for calculation of the SPI as above.

3.2.6 Non-monsoon-SPI (N-SPI)

This was computed based on the aggregated total precipitation for the non-monsoon months, i.e. January–May and October–December.

3.3 Wavelet transform (WT)

Wavelet transform, introduced by Grossmann and Morlet (1984), is an advanced mathematical tool, which is capable of providing the time–frequency representation of a signal (Daubechies 1990, Torrence and Compo 1998, Partal and Kişi 2007). In the field of hydro-climatology, WT is used in time-series forecasting, cluster and trend analysis (Partal and Kişi 2007, Adamowski *et al.* 2009, Araghi *et al.* 2015, Joshi *et al.* 2016). In contrast to Fourier transform (FT), which segregates the signal into smooth sinusoids of infinite duration, WT splits the signal into wavelets of finite duration and zero mean (Torrence and Compo 1998). These wavelets are localized in both frequency and time domains. There are two forms of WT, CWT and DWT. In the case of DWT, WT is implemented using a discrete set of the wavelet scaling and shifting, whereas, in the case of CWT, WT is implemented for continuous scaling and shifting. CWT is relatively complicated as it generates a large number of coefficients, which are mostly not required (Araghi *et al.* 2015). DWT is generally used for trend analysis and forecasting (Kim and Valdes 2003, Adamowski *et al.* 2009). DWT decomposes the signal into high and low-frequency components called detail (D) and approximation (A) components, respectively. The A component provides information about the important characteristics of the signal and is important for the trend analysis. Several studies have used DWT for trend analysis and the identification of dominant periodic components (Araghi *et al.* 2015, Joshi *et al.* 2016, Pathak *et al.* 2016).

The wavelet function $\psi(t)$ is defined as $\int_{-\infty}^{\infty} \psi(t)\mathrm{d}t = 0$. The term $\psi_{a,b}(t)$ is obtained by compression and expansion of $\psi(t)$ (Nason and von Sachs 1999):

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \quad b \in R, a \in R, a \neq 0 \tag{3}$$

where R represents real numbers, $\psi_{a,b}(t)$ is the successive wavelet, and a and b are the dilation (scale) parameter and translation (position). When the term $\psi_{a,b}(t)$ satisfies Equation (3) for a finite energy signal (Rosso *et al.* 2004, Zhou *et al.* 2008, Kisi 2009), the successive WT of f(t)is:

$$W_\psi f(a,b) = |a|^{-1/2} \int_R f(t)\bar{\psi}\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{4}$$

where $\overline{\psi(t)}$ represents the complex conjugate function of $\psi(t)$; and $f(t)$ is decomposed at a different resolution level (scale) in Equation (4). In the forecasting application, DWT is used instead of CWT due to the complexity and long computation time of CWT (Nason and von Sachs 1999). For an original signal $x(t)$, the smoother versions of the signal for different scales are given by:

$$c_0(t) = x(t) \tag{5}$$

$$c_j(t) = \sum\nolimits_{l=-\infty}^{\infty} h(l)c_j\left(t + 2^{j-1}l\right) \tag{6}$$

where j varies from 1 to J; J is the level of decomposition; and h is the low pass filter. The detail component of the signal is obtained by subtracting the smoothed form of the signal from the coarser signal that preceded it:

$$d_j(t) = c_{j-1}(t) - c_j(t) \tag{7}$$

A wide range of literature is available on WT and its application in the field of hydrology, for example, it is discussed in detail in Grossmann and Morlet (1984), Mallat (1989), Daubechies (1990) and Torrence and Compo (1998), while its applications in hydrology and meteorology are discussed in Nason and von Sachs (1999), Adamowski *et al.* (2009), Belayneh and Adamowski (2013), Nourani *et al.* (2014) and Araghi *et al.* (2015).

3.4 Estimation of dominant periodic components

The dominant periodicities within the time series can be identified 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 (Araghi *et al.* 2015). The dominant periodic components in the time series are determined based on the time scale of the dominant component. For example, for an annual time series, if the component combination of A + D1 is found to be the dominant timescale, then one may conclude that the 2-year time scale is dominant in the timeseries (Araghi *et al.* 2015). A similar approach was adopted by Araghi *et al.* (2015) and Joshi *et al.* (2016).

3.5 Trend analysis

3.5.1 Mann-Kendall (MK) trend test

The MK trend test (Mann 1945, Kendall 1975) is a non-parametric test that is widely used for the identification of the presence of trend in a timeseries (Yue *et al.* 2002, Jain and Kumar 2012). The S-statistics in the MK test is computed as:

$$S_t = \sum_{a=1}^{n-1} \sum_{b=a+1}^{n} \operatorname{sgn}(X_b - X_a) \tag{8}$$

where X_b and X_a are the data points in the timeseries; n is the length of the timeseries; and $\operatorname{sgn}(X_b - X_a)$ is defined as:

$$\operatorname{sgn}(X_b - X_a) = \begin{cases} +1 & X_b > X_a \\ 0 & X_b = X_a \\ -1 & X_b < X_a \end{cases} \tag{9}$$

For $n \geq 8$, the test statistic S is approximately normally distributed with a mean and variance as follows:

$$E(S) = 0 \tag{10}$$

$$\operatorname{var}(S_t) = \frac{n(n-1)(2n+5) - \sum_{a=1}^{m} t_a(t_a - 1)(2t_a + 5)}{18} \tag{11}$$

where m is the number of tied groups, and t_a is the size of the ath tie group. The MK statistic (Z) may be obtained by:

$$Z = \begin{cases} \frac{S_t - 1}{\sqrt{\operatorname{var}(S_t)}} & S_t > 0 \\ 0 & S_t = 0 \\ \frac{S_t + 1}{\sqrt{\operatorname{var}(S_t)}} & S_t < 0 \end{cases} \tag{12}$$

The presence of autocorrelation in the time series affects the MK Z value. If there exists a positive (negative) autocorrelation in time-series, the variance is estimated less (more) than the actual value (Hamed and Rao 1998, Hamed 2008). To counter this effect, a modified MK test was given by Hamed and Rao (1998), in which the variance of the test was modified to take into account the autocorrelation in the time series. The modified variance calculation is as follows:

$$\operatorname{var}^*(S) = \operatorname{var}(S)\left(\frac{n}{n_e^*}\right) = \left(\frac{n(n-1)(2n+5)}{18}\right)\left(\frac{n}{n_e^*}\right) \tag{13}$$

where n/n_e^* represents the correlation due to correlation in time series and is calculated as:

$$\frac{n}{n_e^*} = 1 + \left(\frac{2}{n(n-1)(n-2)}\right) \sum_{i=1}^{n-1} (n-i)(n-i-1)(n-i-2)\rho_e(i) \tag{14}$$

where n is the actual sample size; n^* is the effective sample size required to account for the autocorrelation factor in the data; and $\rho_e(i)$ is the autocorrelation function of the ranks of the observations and can be calculated by the inverse of the following equation (Hamed and Rao 1998):

$$\rho(i) = 2\sin\left(\frac{\pi}{6}\rho_e(i)\right) \tag{15}$$

In this study, the modified MK trend test was used to analyse trends present in drought variables. Based on the Z statistic value, the null hypothesis of no trend is accepted or rejected at a 95% confidence level.

3.5.2 Sen's slope estimator

The magnitude of the trend in a time series is determined using the non-parametric method, Sen's estimator of slope (Sen 1968). According to this method, Sen's slope is calculated as:

$$S_i = \frac{x_j - x_k}{j - k} \quad i = 1, \ldots, N \tag{16}$$

where x_j and x_k are the values of timeseries at times j and k ($j > k$), respectively. The median of N values of S_i gives the Sen's slope estimator. A positive value of Sen's slope estimator indicates an upward trend and a negative value indicates a downward trend in the time series.

3.6 Procedure

Based on the methods discussed above, the following steps were adopted to carry out this study:

- First, 6-month SPI (SPI6) was computed for all 566 stations using the monthly precipitation data. SPI6 was used to identify the beginning and end of drought events.
- SPI was used to compute ADD, ADP and ADS. Further, A-SPI, M-SPI and N-SPI were computed based on aggregated precipitation for the year, monsoon season and non-monsoon season, respectively.
- MK trend test and Sen's slope estimator were used for trend analysis of six drought variables at all stations. A significance level of 0.05 (i.e. p value ≤ 0.05) was used to check the statistical significance of the trend. Further, the dominant period components in different drought variables were identified at each station. The time series of drought variables were decomposed using DWT to get the A and D components. The MK trend test was used to analyse the presence of trend in decomposed components and the combinations of A and D components.
- Dominant periodic components were identified based on the comparison of the MK test Z statistic of the original time series and A + D components.
- CWT-based global wavelet spectrum (GWS) was used to find out the significant periods of variability.

4 Results and discussion

4.1 Trend analysis of drought variables

Figure 2 shows the results of trend analysis, and Fig. 3 shows the number of stations with increasing or decreasing trends for different variables. A-SPI showed a significant increasing trend ($p < 0.05$) in the northwest and southern parts of the country (Fig. 2(a)). Of 566 stations, 84 showed a significant increasing trend (mainly in northwestern and southern parts), whereas 188 stations had a non-significant increasing trend. In contrast, 79 stations had a significant decreasing trend, which were

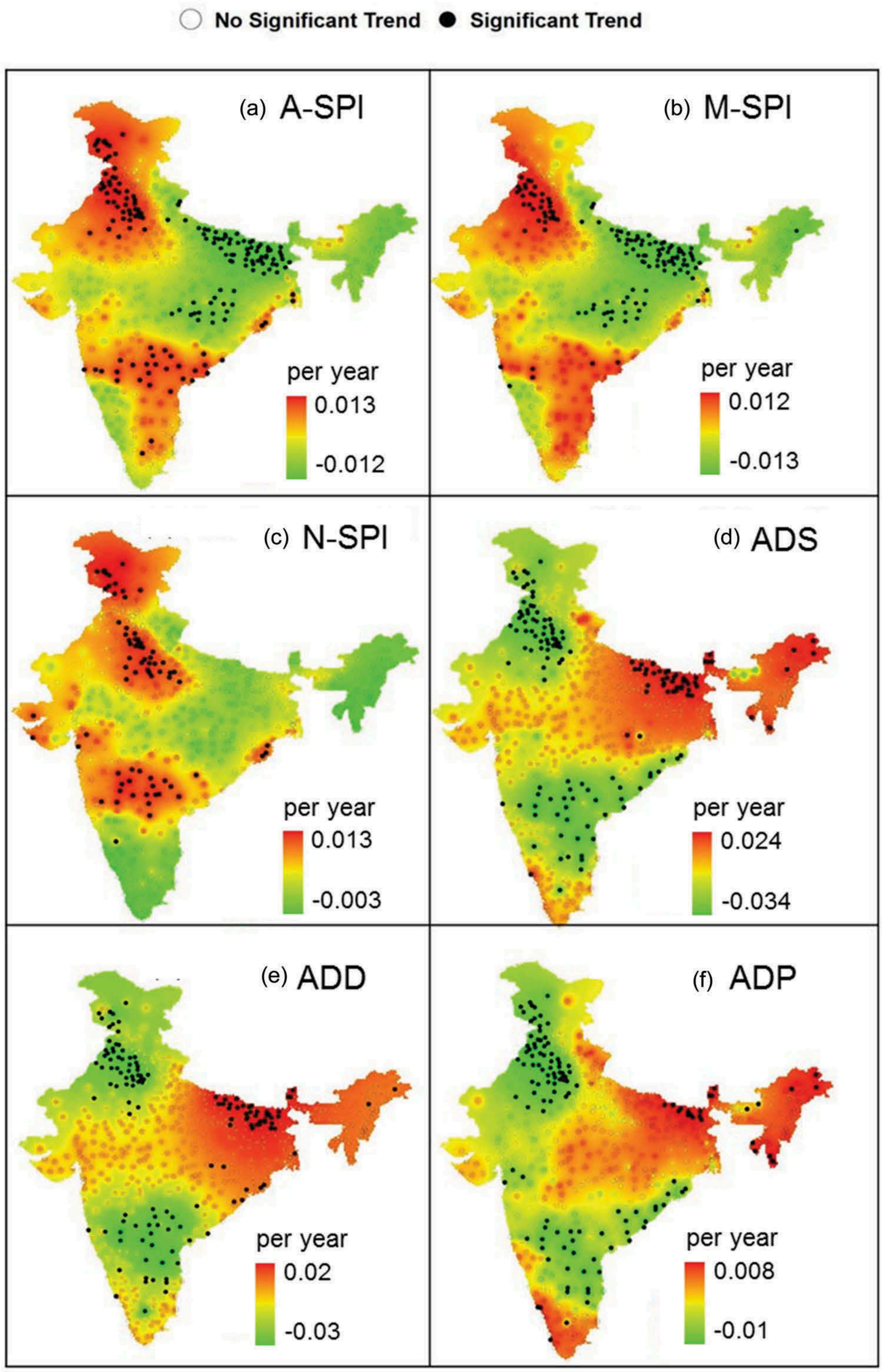

Figure 2. Trend analysis (Sen's slope values) for different drought variables for the period 1901–2002. The statistical significance of the trend was examined using Mann-Kendall trend test at 5% significance level. The dots show the stations with significant trend ($p < 0.05$), whereas the circles show the stations with a non-significant trend ($p > 0.05$).

mainly located in the northern and eastern regions of the country. Two hundred fifteen stations (about 40%) showed a non-significant decreasing trend. The magnitude of the trend, i.e. the Sen's slope, was between – 0.012 and 0.013 - per year. The spatial pattern of the trend in M-SPI (which was calculated using the aggregated precipitation for monsoon season) was similar to the trend in A-SPI (Fig. 2(b)), which may be due to the large contribution of monsoon precipitation to total annual precipitation. There was an increasing trend in M-SPI in the northwest and southern parts of the country, whereas a decreasing trend was found in the eastern and northern parts. Most of the stations in the south had non-significant increasing trends in M-SPI. The magnitude of the trend in M-SPI was similar to that in A-SPI, and it ranged

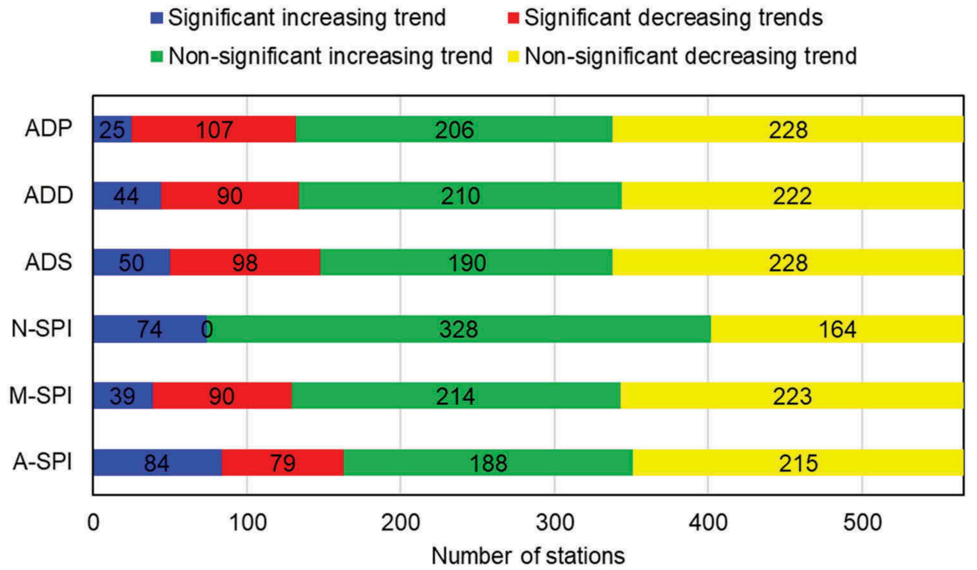

Figure 3. Number of stations having increasing and decreasing trends for different drought variables. The statistical significance of trend is evaluated based on the Mann-Kendall trend test at a significance level of 0.05.

between – 0.013 and 0.012/year. The number of stations having a significant increasing trend in M-SPI was 39 compared to 84 for the A-SPI, whereas the number of stations with a significant decreasing trend in M-SPI was 90 compared to 79 for A-SPI. The number of stations with increasing monsoon droughts is more than stations with increasing annual droughts. It should be noted that the negative values of SPI indicate the dry condition; therefore, decreasing (increasing) trend in SPI implies an increase (decrease) in drier conditions (droughts). The decreasing trend in M-SPI indicates an increase in monsoon droughts, especially in northern, eastern, and north-eastern regions. In the case of N-SPI, the spatial pattern of the trend was similar to that of A-SPI and M-SPI; however, there was a substantial difference in the magnitude and the statistical significance of trend (Fig. 2(c)). There was no station with a significant decreasing trend in N-SPI, which indicates that there was no increase in non-monsoon droughts anywhere in the country. About 71% stations (454/566) had an increasing trend in N-SPI (74 with significant and 328 with non-significant trend), indicating an overall decreasing trend in non-monsoon season droughts.

The remaining three drought variables, ADS, ADD and ADP, had similar spatial variations in trend (Fig. 2(d)–(f)). Increasing trend in these variables was found in eastern, northeastern and extreme southern parts of the country, whereas a decreasing trend was observed in northwestern and southern regions. ADS was observed increasing in the north and northeast India, whereas the decreasing trend

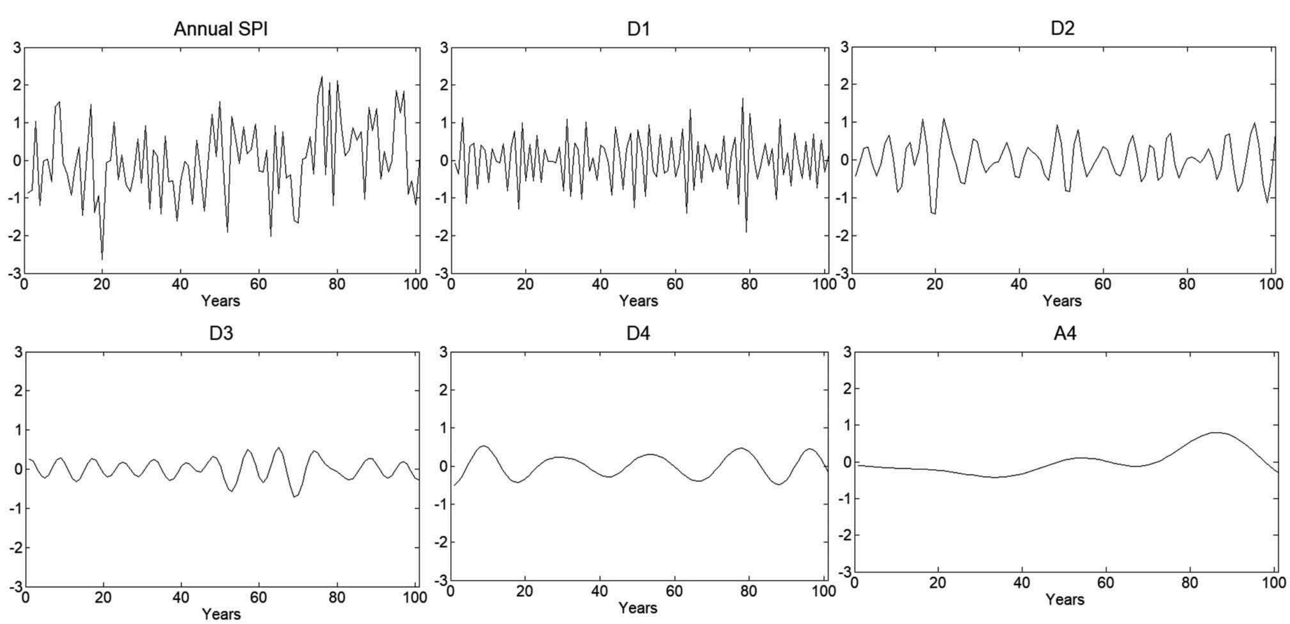

Figure 4. Annual SPI series with the decomposed components (up to four decomposition levels) for Station no. 1.

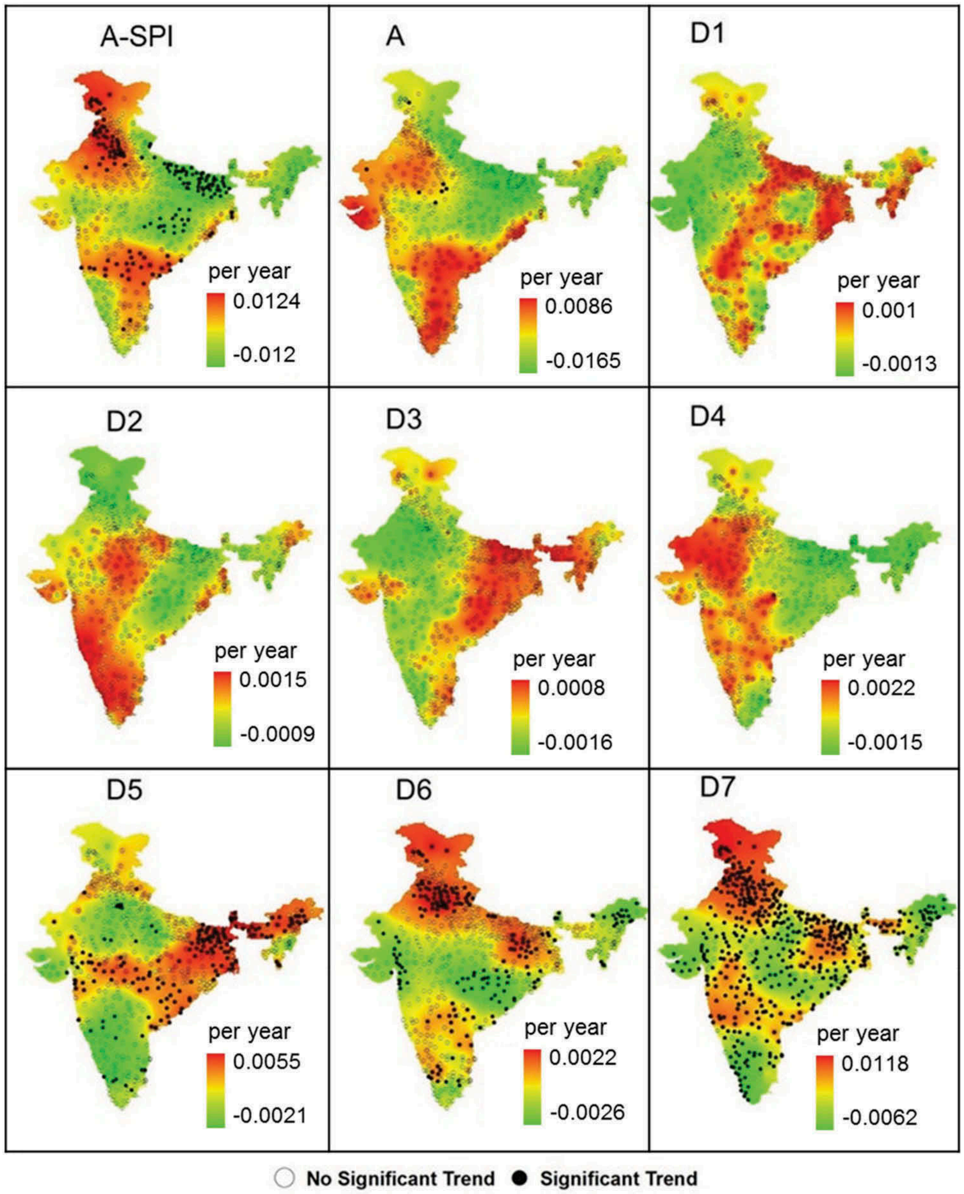

Figure 5. Trend analysis (Sens's slope values) for the decomposed A and D components of A-SPI (Annual SPI). The statistical significance of the trend was examined using MK trend test at 5% significance level. The dots show the stations with a significant trend ($p < 0.05$), whereas the circles show the station with a non-significant trend ($p > 0.05$).

was found in the northwest and southern India. The number of stations with a significant decreasing trend (98) was about two times the number of stations with a significant increasing trend (50) (Fig. 3). There was no significant trend found in the western states. The magnitude of the trend in ADS was found between – 0.034 and 0.024/year (Fig. 2(d)). The number of stations with a significant increasing trend further decreased to 44 for ADD, which were mainly located in the state of Bihar in eastern India. On the other hand, stations in the northwestern and southern parts had a significant decreasing trend (Fig. 2(e)). In the case of ADP, the number of stations with significant increasing and decreasing trends were 25 and 107, respectively. There were a few stations in the south and northeast with an increasing trend. Some stations in the western parts (in the state of Maharashtra) had a significant decreasing trend. The magnitude of the trend was found between – 0.01 and 0.008/year. Overall, it can be summarized that the increasing trend in droughts was found for eastern and north-eastern regions, whereas a decreasing trend was found for north-western and mid-southern parts. No significant trends were found for western and central India. Based on two different datasets, Mallya *et al.* (2016) also found an increasing trend in drought over the eastern Indo-Gangetic plain and parts of south-India. Previous studies have also found an increase in droughts in these regions (Kumar *et al.* 2013, Joshi *et al.* 2016).

4.2 Data decomposition using DWT

The drought variables were decomposed using DWT, as described in the methodology. For decomposition,

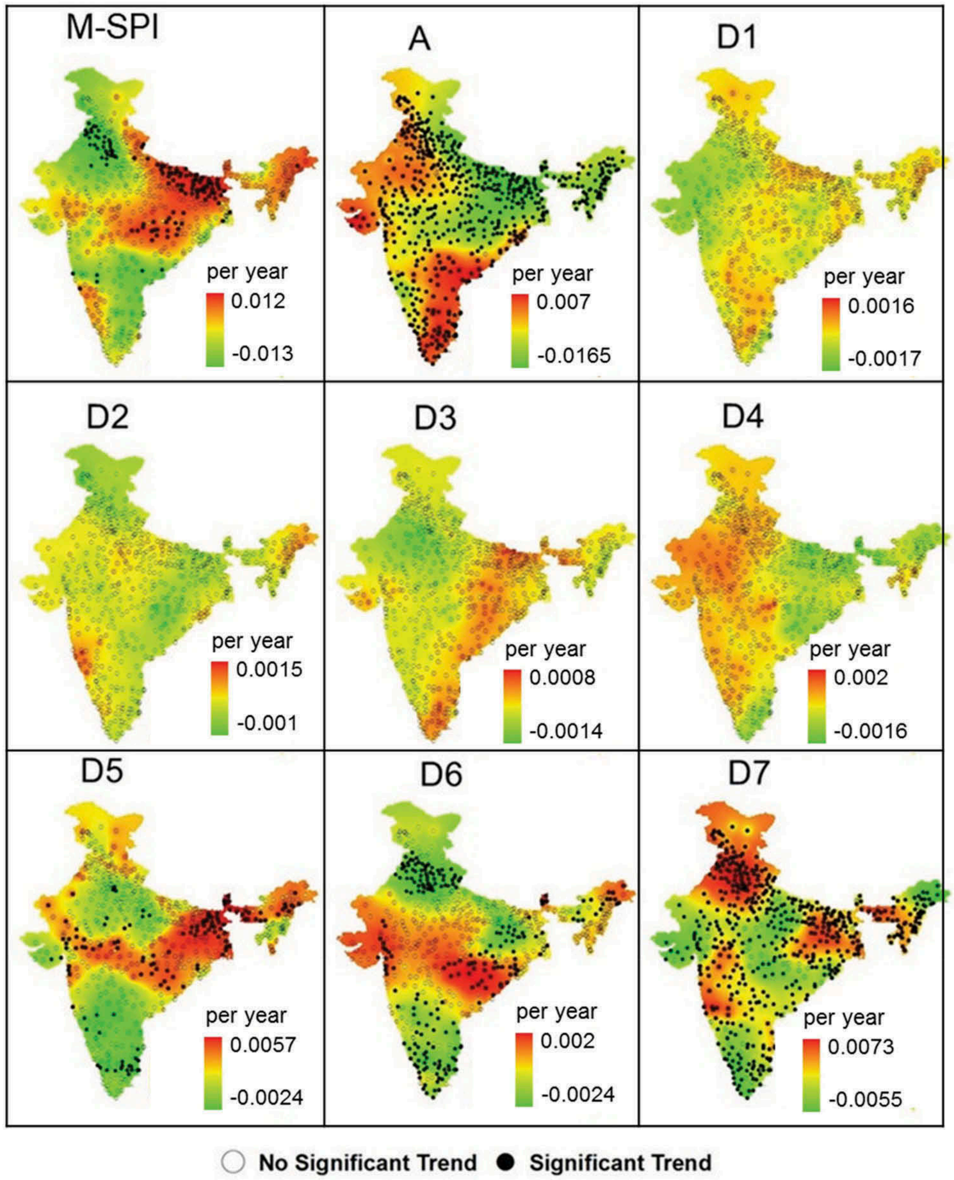

Figure 6. Same as Fig. 5 but for M-SPI (Monsoon SPI).

Daubechies wavelet (db10) was used for seven levels of decompositions. The level of decomposition and mother wavelet were chosen based on a trial-and-error approach and review of the literature (Joshi *et al.* 2016, Sachindra *et al.* 2019). For illustration purpose, Fig. 4 shows A-SPI for a station with its A and D components up to four levels of decomposition. It can be seen that as the level of decomposition increases, the frequency of the D component decreased. DWT was used to decompose all six variables into A and D components for all stations.

4.3 DWT-based trend analysis

Trend analysis was carried out on all A and D components and their combinations, which were further analysed to estimate the dominant periodic components (Araghi *et al.* 2015, Joshi *et al.* 2016). The results of the trend analysis of A and D components of six drought variables are shown in Figs. 5–10; however, the results of the trend analysis of the combination of A and D components are not shown here.

The general observations from the analysis are:

- A significant trend was not found in the first four D components for most of the drought variables. The reason could be that the first few D components contain high-frequency components, which do not exhibit any gradual trend. This can be observed in Fig. 4, as all D components have high frequency and lack any gradual trend.

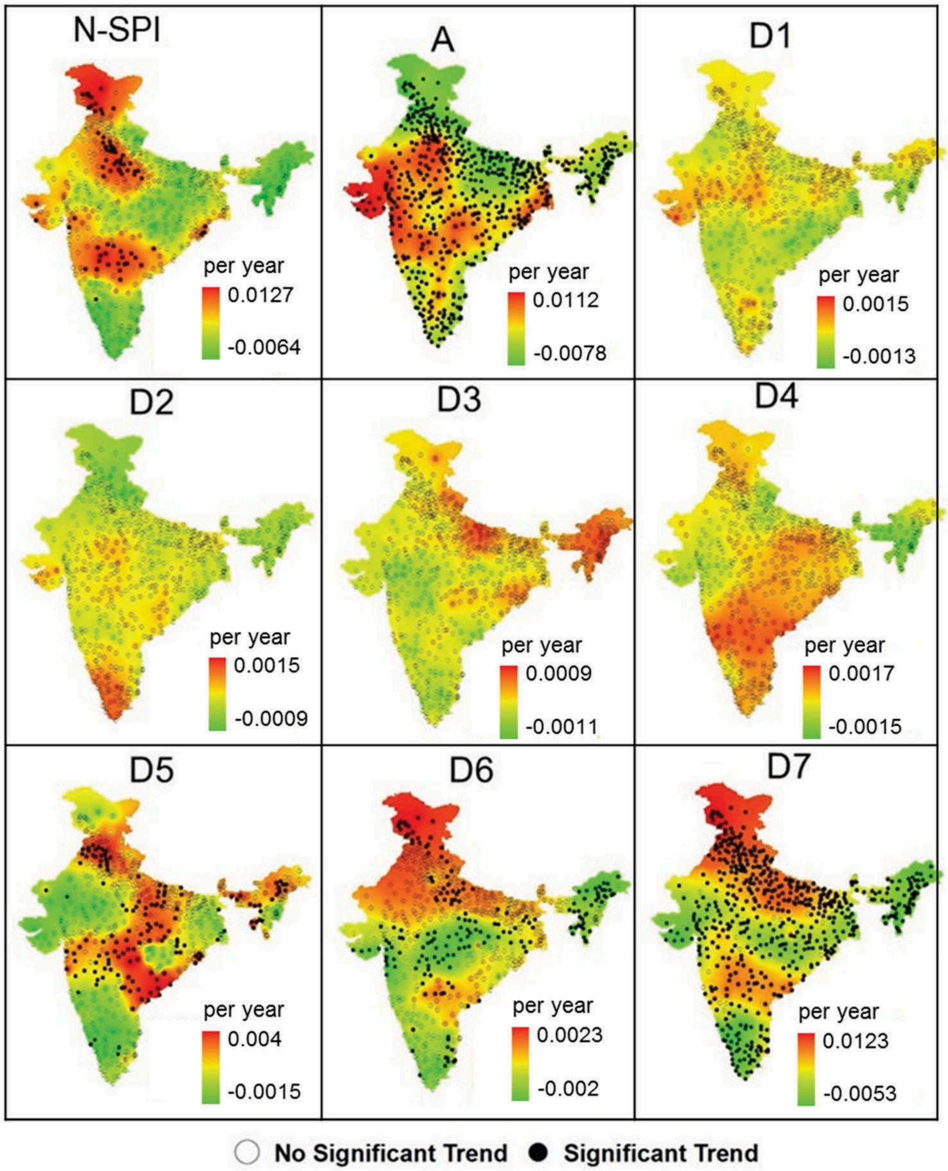

Figure 7. Same as Fig. 5 but for N-SPI (Non-monsoon SPI).

- Most of the stations had a significant increasing trend in A component of all drought variables except for A-SPI. The A component is the low-frequency component after the high-frequency components have been removed from the signal. This component tends to follow the underlying trend in the actual signal. For example, in Fig. 4, the A component of the signal shows a slightly rising trend.
- The spatial variation in trend in drought variable and respective A component was same for A-SPI, ADS, ADP, whereas it was different for other variables.
- The last D component (i.e. D7) had significant trends at most of the stations for all drought variables.

4.4 Identification of dominant periodic components

The dominant periodic components were identified based on the comparison of the MK Z statistics of the A + D components with the Z statistic for the original series (Joshi *et al.* 2016). Figure 11 shows the results for dominant periodic components of the trend in different drought variables. The procedure was carried out for all the stations and for six variables separately. Following are the observations for different drought variables:

- The trend in A-SPI at most of the stations was influenced by the dominant periodicities of 4–16 years. However, the trend in A-SPI in some parts of northern and north-eastern India was influenced by long-term periodicities (i.e. 16–64 years).
- Short-term periodic components influenced the trend in M-SPI. The 2- to 8-year period components were dominant at most of the stations in the country.
- For N-SPI, though most of the stations were influenced by short-term periodic components, long-term periodic

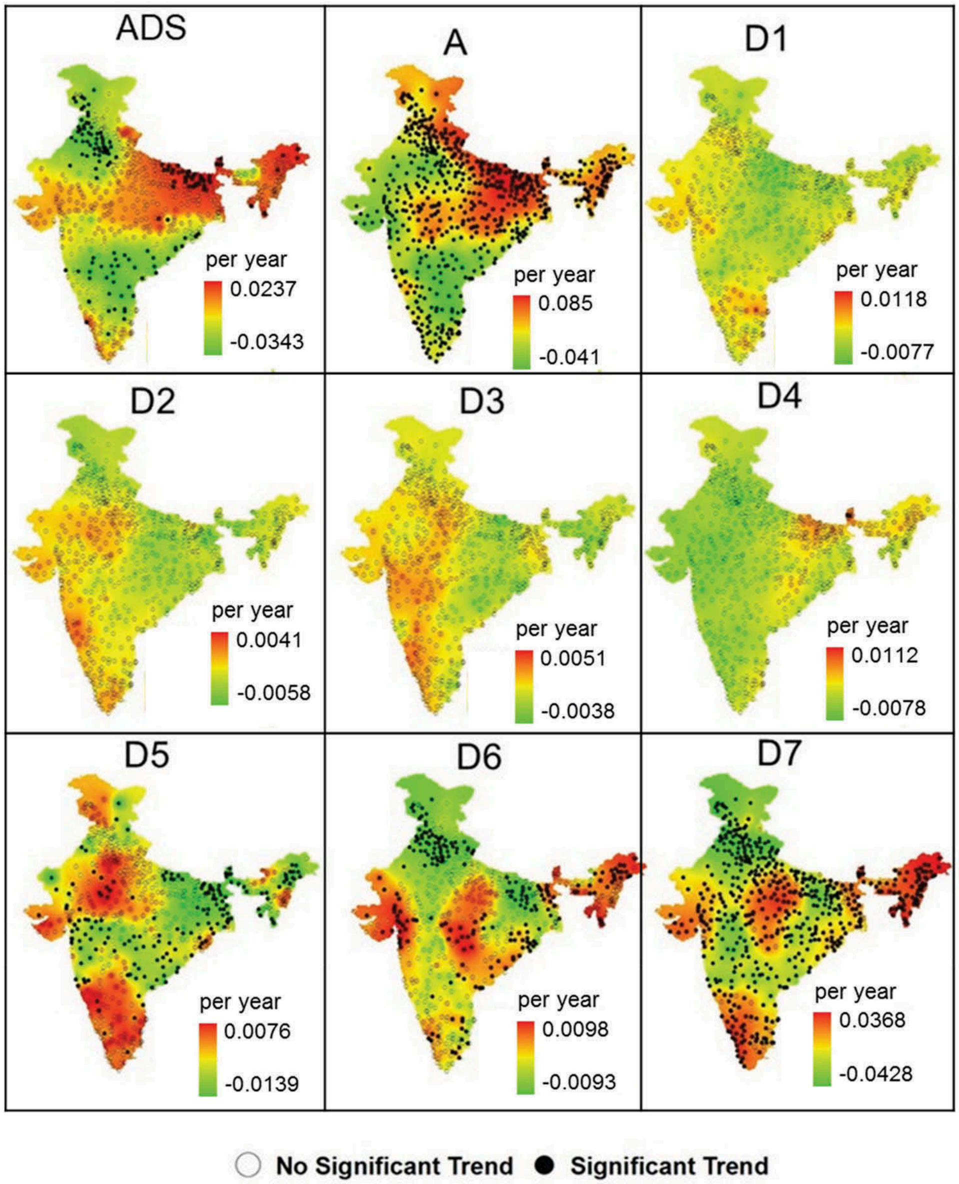

Figure 8. Same as Fig. 5 but for ADS (Annual Drought Severity).

component (e.g. 32–64 years) was dominant at few stations in northern and extreme southern India.

- Periodicity of 2–4 years was dominant in the trend in ADS in most parts of the country except in some parts of central and northern India where higher periodic components (32–64 years) were found dominating.
- The trend in ADD in northern regions and some parts of central regions were mainly dominated by 32–64 years periodic components.
- Low periodic components (2–8 years) influenced the trend in ADP in most parts of the country except for some regions in the north and central parts.

In general, low periodic components (e.g. 2–4 and 4–8 year) influenced the trend in drought variables at most of the stations in western and southern parts of the country. The trend in drought variables was influenced by long-term periodic components (e.g. 8–32 years) in north-eastern and central regions, whereas in some parts of northern India, 32–128 years periodic component was also found dominating.

To investigate the significance of the periodic components, CWT-based GWS was used to identify the significant periodic component in the time series of drought variable. The number of stations with a significant periodic component for different drought variables is shown in Fig. 12. The results show that the periodic component influencing the trend in drought variables at most of the stations was not statistically significant at a 5% significance level. The highest number of stations with significant periodic components was found for M-SPI (117), whereas the least number of stations with significant periodic component was found for N-SPI. The trend in M-SPI was influ-

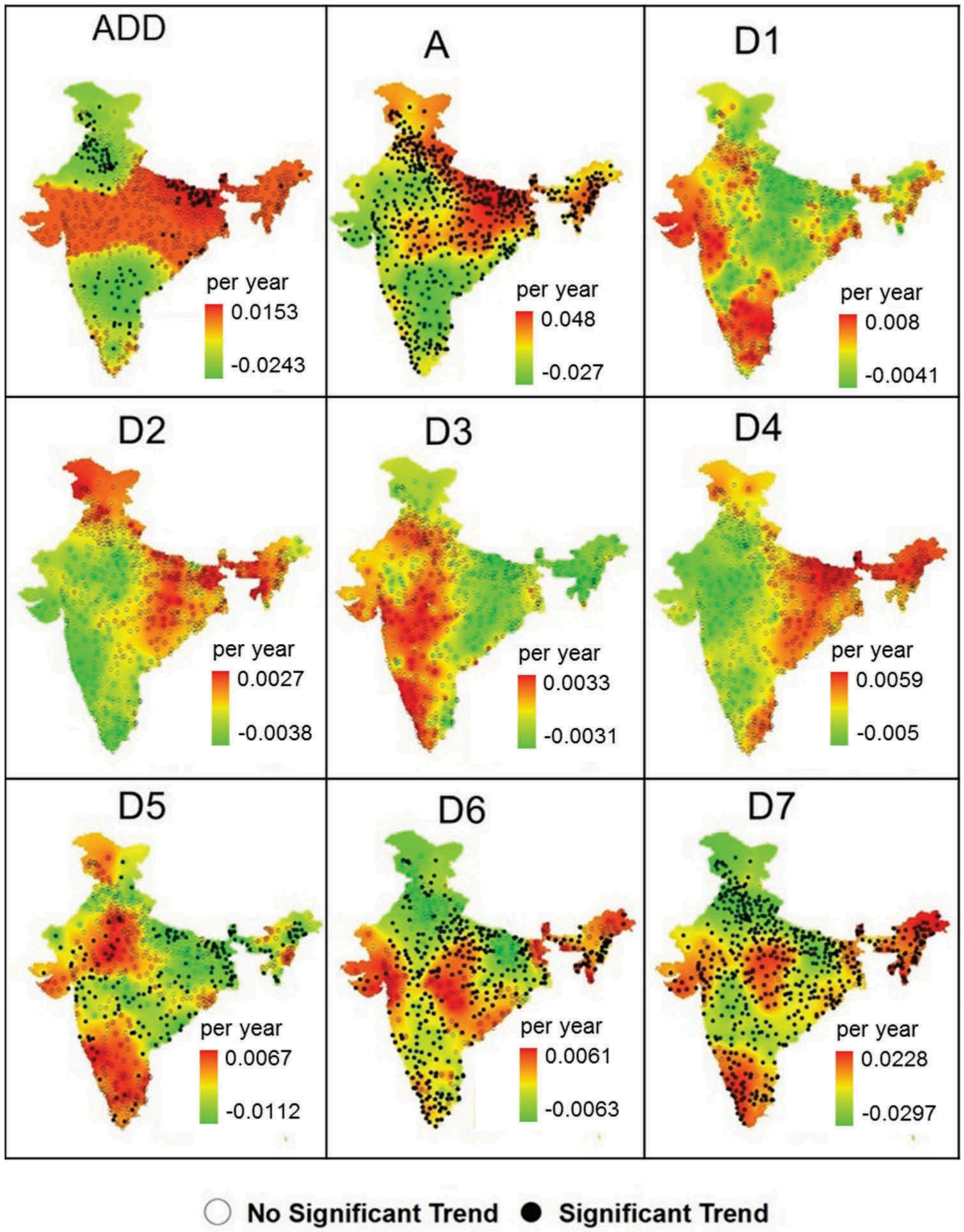

Figure 9. Same as Fig. 5 but for ADD (Annual Drought Duration).

enced by short-term periodicities (2–8 years) at most of the stations.

4.5 Comparison with previous studies

A similar investigation was carried out by Joshi *et al.* (2016) for 30 rainfall subdivisions in India over the long-term period 1871–2012. The results of our study at high-resolution are consistent with the work of Joshi *et al.* (2016). The increasing trend in droughts in the northeast and central India was reported by Joshi *et al.* (2016), which is consistent with our results. Mallya *et al.* (2016) also reported a rise in droughts in these regions. Joshi *et al.* (2016) reported both short-term (2–8 years) and long-term (16–64 years) periodicities influenced the trend in drought variables in India. Our station scale periodicity analysis is consistent with the subdivision scale analysis (Joshi *et al.* 2016). Similarly, they also reported that most of the periodic components were not statistically significant.

5 Conclusions

Trend analysis of six drought variables was carried out at 566 stations in India over the period 1901–2002 using the Mann-Kendall (MK) trend test and Sen’s slope estimator.

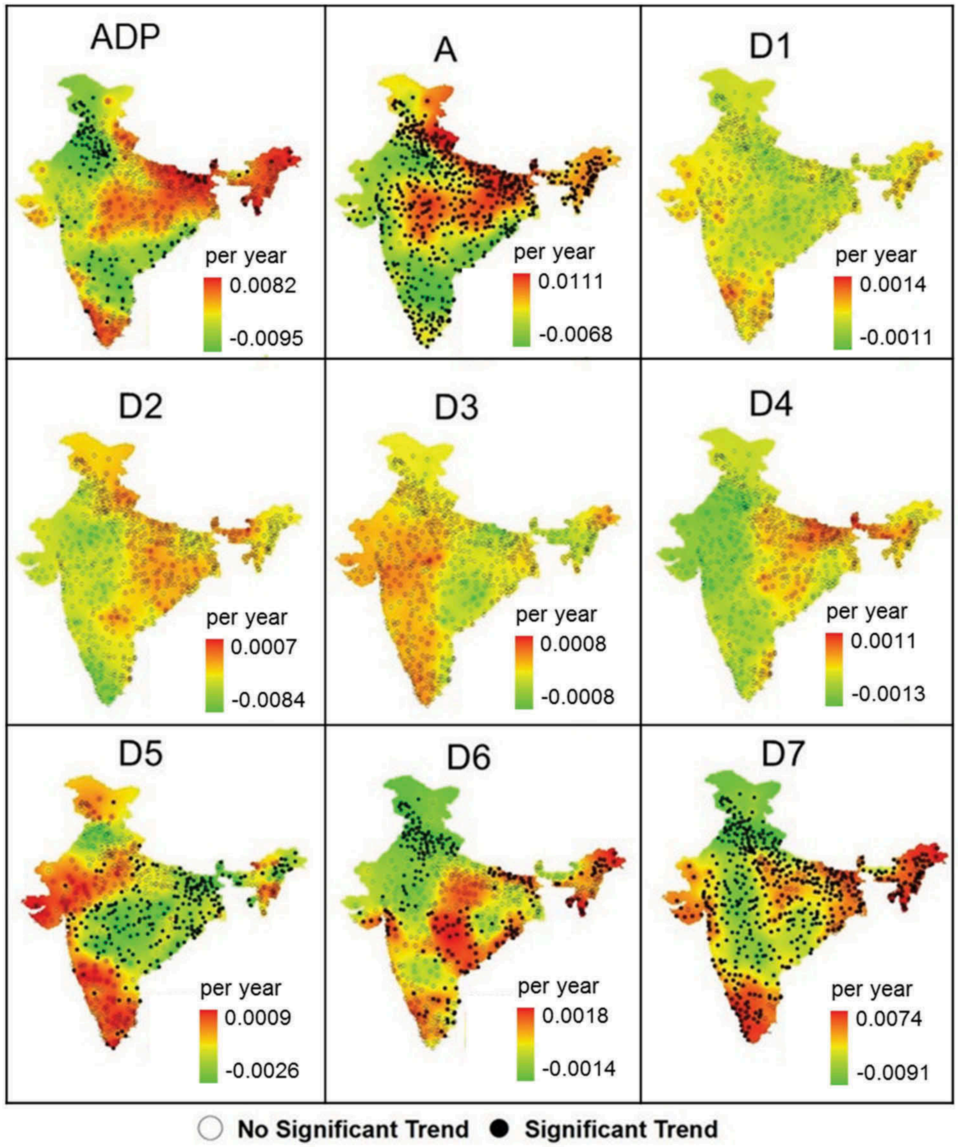

Figure 10. Same as Fig. 5 but for ADP (Annual Drought Peak).

The standardized precipitation index (SPI) was used for computing six drought variables, namely annual SPI (A-SPI), monsoon-SPI (M-SPI), non-monsoon-SPI (N-SPI), annual drought severity (ADS), annual drought duration (ADD) and annual drought peak (ADP), at every station. An increasing trend in droughts was found in eastern, northeastern and extreme southern regions, whereas there was a decreasing trend in parts of northern and southern regions; however, the trend at most of the stations was not statistically significant. Discrete wavelet transform (DWT), along with the MK test, was used to identify the dominant periodic components in trend for different drought variables at all stations. The analysis revealed that the trend in drought variables was influenced by 2- to 4-year periodic components in southern India, 4- to 8-year periodic components in western, eastern and northeastern India, and 8- to 64-year periodic components in central India and 32–128 years periodic components in northern India. Continuous wavelet transform (CWT) based global wavelet spectrum (GWS) revealed that the periodicities influencing trend at most of the stations were not statistically significant.

This study presents an analysis of drought periodicities using wavelet, which aims at improving our understanding of the complex phenomenon of drought. Through the analysis of a large number of stations, this study indicates that the different periodicities influence the trends in drought in different parts of India. Further research will help establish a more reliable statistical likelihood of the occurrence of droughts in the future. Further investigation on the impact of climate change on drought periodicities can also benefit in making long-term climate policies.

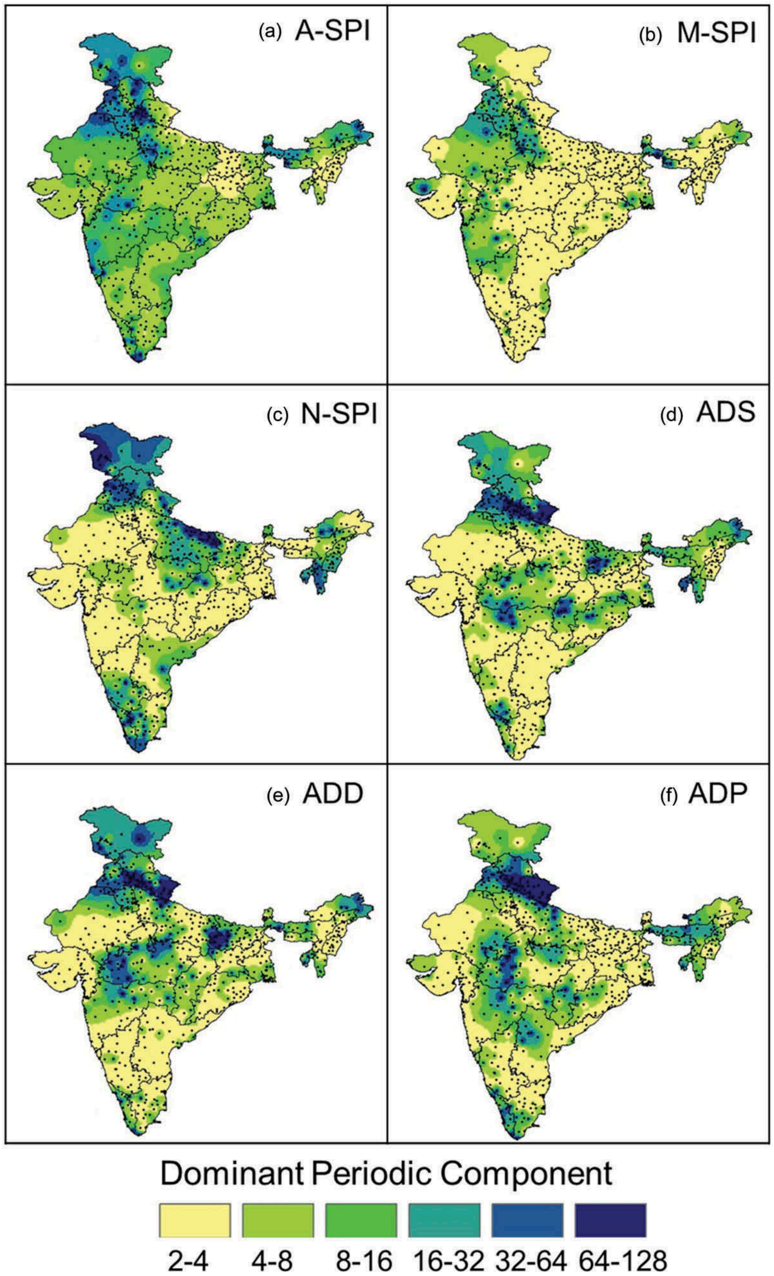

Figure 11. Dominant period component for different drought variables at 566 stations in India obtained using discrete wavelet transform (DWT) and the Mann-Kendall (MK) trend test.

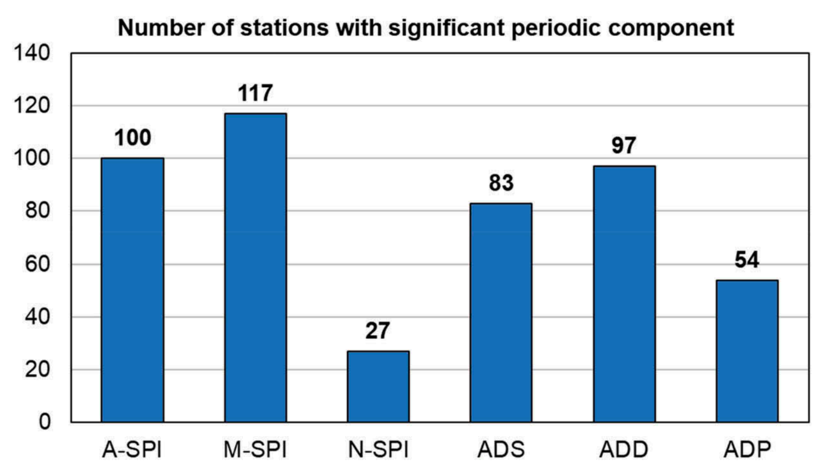

Figure 12. Number of stations with a significant periodic component for different drought variables based on the continuous wavelet transform (CWT) based global wavelet spectrum (GWS).

Disclosure statement

No potential conflict of interest was reported by the authors.

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