Predicting Long Term Regional Drought Pattern in Northeast India using Advanced Statistical Technique and Wavelet-Machine Learning Approach

Abstract

Understanding drought and its multifaceted challenges is crucial for safeguarding food security, promoting environmental sustainability, and fostering socio-economic well-being across the globe. As a consequence of climate change and anthropogenic factors, the occurrence and severity of drought has risen globally. In India, droughts are regular phenomenon affecting about 16% area of country each year which leads to a loss of about 0.5 – 1% of country's annual GDP. Hence, the study aims to analyse and predict the meteorological drought in northeast India during 1901 to 2015 using standardised precipitation index (SPI) and analytical techniques such as Mann-Kendall test (MK), innovative trend analysis (ITA), and wavelet approach. In addition, the periodicity of the drought was estimated using Morlet wavelet technique, while discrete wavelet transform (DWT) was applied for decomposing the time series SPI-6 & SPI-12. Study shows that the northeast India experienced moderate drought conditions (SPI-6) in short term and two significant severe droughts (SPI-12) in long term between 1901 and 2015. The trend analysis shows a significant increase in SPI-6 & SPI-12 (p-value 0.01). Further, the combination of parameters i.e. approximation and levels result in the best drought prediction model with higher correlation coefficient and lower error. By using PSO-REPTtree, this study pioneers the use of decomposed parameters to detect trends and develop a drought prediction model. The study is the first step towards establishing drought early warning system that will help decision-makers and farmers to mitigate the impact of drought at the regional level.

***Keywords*:** Meteorological drought pattern; Particle Swarm Optimization; Innovative Trend Analysis; Standardized Precipitation Index; Sequential Mann-Kendall test; Reduced Error Pruning Tree.

1. Introduction

One of the most complex and significant threats to society is drought, which is a persistent risk in several parts of the world (Dunne and Kuleshov 2022; Swain et al. 2021; Zhang et al. 2016; Wilhite 2000). In the age of climate change and increase of global temperature about 1°C since pre-industrial times (Allen et al. 2018) may have significantly increased the severity and occurrence of drought across the globe (Sheffield Wood, 2008; Gyamfi et al. 2019; Saharwardi et al. 2022). This has resulted in reduction in agricultural productivity, loss of ecology and ecosystem services, water scarcity, compromised food security, increasing risk of wildfires, etc. (Anderegg et al. 2013; Lesk et al. 2016; Wang et al. 2022; Qtaishat et al. 2023). Hence, the concern about the frequency, intensity, and occurrence of drought events have grown in recent past throughout the world (Wilhite et al. 2014; Pham et al. 2022). Consequently, researches are being carried out worldwide to understand the causes and consequences of drought to mitigate its consequences on the society and economy (Zhang et al. 2016; Ault 2020; Wang et al. 2022; Elbeltagi et al. 2023).

In India, more than half of the population relies on agriculture for living, the majority of whom are from low-income families, and when a drought happens, it impacts agricultural production, affecting the livelihood of these people (Rao et al. 2016; Roy et al. 2022). Droughts damage approximately 16% of India's total land area each year (Sarkar et al. 2020; Saini et al. 2022). The Central Water Commission (CWC) of India describes drought as the condition in which rainfall falls below 75% of the average, with the severity of the drought depends on the extent of the rainfall deficit (Rahman and Lateh, 2016; Singh et al. 2021). According to the World Bank (2006), India experiences frequent droughts and stood second only after China in terms of the occurrences of drought. Sam et al. (2020) observed the frequency of droughts had increased in India with prolonged since 1990. Bandyopadhyay et al. (2016) noted that many parts of India frequently witness drought due to the rainfall deficit from south-west monsoon. Further, Talukdar et al. (2022) observed that during last two decades, the intensity of drought has increased by more than 30% in the western parts of India. Hence, there is a possibility that the occurrence and severity of droughts may rise with climate change and thus, the analysis of droughts over the past decades is of great value (Poornima et al. 2023; Roy et al. 2023).

Studies have been performed to evaluate and anticipate droughts in many parts of the world using a variety of tools and approaches as the frequency and severity of droughts have grown (Zhang et al. 2016; Kisi et al. 2019; Dikshit et al. 2021; Swain et al. 2021; Mishra et al. 2022). Although several indices have been proposed for characterizing drought, the Standardized Precipitation Index (SPI) is most applied index for drought monitoring (McKee et al, 1993), as it can assess drought severity while being less complex than other indices (Jain et al. 2015). The SPI is easy to use because it only needs monthly rainfall data, and its results can compare droughts in different regions, even if they have different climates (Rahman and Lateh, 2016; Elbeltagi et al. 2023). Furthermore, trend analysis of past droughts is essential to take long-term and sustainable action to reduce the impact of droughts (Dai 2011). There are several techniques for trend detection for example Mann-Kendall (MK) test (Mann 1945; Kendall 1955), Sequential MK (SQMK) test (Sneyers et al. 1998), Modified MK (MMK) test (Yue and Wang 2004), Innovative Trend Analysis (ITA) of (Şen 2012) and others. The MK test has certain complications in trend detection such as serial correlation and need of an essential sample size for trend detection which ITA solves and hence it has been extensively used for trend analysis (Almazroui and Şen 2020; Owolabi et al. 2021; Katipoğlu 2023). More recently, machine learning models like support vector machine (SVM) and artificial neural networks (ANN) (Morid et al. 2007; Borji et al. 2016), Random Forest (RF) (Lotfirad et al. 2022), Rotation Forest (Saha et al. 2023), and Reduced Error Pruning Tree (REPTree) (Elbeltagi et al. 2023) have been used for building a better predictive model for prediction and forecasting the drought. Nowadays, machine learning models combined with particle swarm optimisation (PSO) are frequently applied for time series forecasting (Kisi et al. 2019; Souza et al. 2022).

Meteorological droughts have been studied in India (Sharma and Mujumdar 2020; Sharma et al. 2022; Kumar and Middey 2023; Alam et al. 2023), but there is currently a lack of studies focusing on the northeastern regions of the country. Further, no study has been conducted by using wavelet approach and POS-based machine learning for studying drought in India. An analysis of meteorological drought PSO-based machine learning models may provide better outcomes with higher accuracy which may be beneficial for the planning and policy making. Hence, in this study, the short and long terms (6 and 12 months) meteorological drought is assessed using SPI-6 and SPI-12 along with drought periodicity analysis using Morlet's Wavelet Transformation (MWT). The MWT proposed by Grossmann and Morlet (1984) disables the limitation of dynamic time series and is used for recurrence features, detection of long-term scale trends and identification of authoritative drought years, which makes it more acceptable for drought analysis (Byun et al. 2008). The findings of this research may be helpful for researchers to analyse and predict drought using a novel approach and planners will plan according to the results to address the impacts of meteorological drought in northeast India.

2. Materials and methodology

2.1 Study area

For this study, Nagaland, Manipur, Mizoram & Tripura (NMMT) meteorological division is situated in the northeastern region of India (Figure 1). NMMT meteorological division has an area of about 70,447 square kilometres and covers four Indian states, namely Nagaland, Manipur, Mizoram, and Tripura. The Tropic of Cancer passes through the meteorological division NMMT; hence the climate of region is tropical monsoon type. With a monsoon-like climate, the region experiences heavy rainfall during June – September because of southwest monsoon. The rainfall has been collected by the meteorological departments of India from 1901 to 2017. The vast area covers only one meteorological department, which cannot be realistic. Due to scarcity of data and inaccessible topography, there is only one station in this vast region. However, the data does not show any missing data and the data quality has been successfully addressed (for details, please follow Praveen et al. 2019). The mean annual rainfall in NMMT meteorological division is about 2000 mm (Mohapatra et al. 2021). The region is topographically very uneven and all major physio-graphic structures i.e. plains, plateaus, hills and valleys are found in the region. Due to the uneven physio-graphic structure and inland location, there are climatic contrasts in the region and the climate in the hilly areas is different from that in the valleys and plains. The average summer temperature of the region varies between 30 and 33 °C, while the average winter temperature is 15 °C. At the same time, the temperature in the hilly areas rarely reaches 20 °C and drops to below freezing.

Insert figure 1 here

2.2 Standardized Precipitation Index

McKee et al. (1993) proposed the SPI for anaylzing the precipitation discrepancy in a region and wet and dry periods at multiple time scale using precipitation data alone. The SPI was calculated using equation 1 to represent the sum of standard deviations by which precipitation is above or below a climatological average.

$$SPI = \left(\frac{X_{i,j} - X_{i,m}}{\sigma} \right) \quad [1]$$

Where *Xij* is precipitation at the *ith* station over a time (i.e., from one month to 12-months with SPI-12) and *jth* observation, while *Xi, m,* and σ are for long-term average of precipitation and the standard deviation, respectively, at the *ith* station over the same period (Omondi 2014), the negative SPI value represents a precipitation deficit, while the positive value refers to a wet period.

The SPI is calculated in the following ways (Guttman 1999): 1. the density function of the probability reflecting long-term time series of the precipitation observation is determined, 2. based on the interest of the time scale, the time series of the precipitation observation can be chosen. In this study, moving series of total precipitation analogous to 6 and 12 months were used. The identical SPI values were quantified: SPI 6 and SPI 12, 3. The observed rainfall amount, 4, is used to estimate the collective probability at a given time, and opposite ordinary function (Gaussian), with variance 1 and average 0, is used to calculate the distribution function of the collective probability resulting in the SPI.

Values of the SPI can range from less than -2 to greater than +2. A value of below -2 and above +2 describes dry as well as extremely wet scenarios, respectively, while values between -0.5 to +0.5 represent near-normal conditions (Table 1).

Insert table 1 here

Short-term changes in the SPI reflect changes in soil moisture levels, while long-term changes reflect changes in water flow and availability within reservoirs and aquifers. To account for the differential effects of the duration of a rainfall deficit on water availability, McKee et al. (1993) proposed and applied the SPI at scales of 3-, 6-, 12-, 24- as well as 48-months. In this research, we quantified the severity of a drought using the 6- and 12-month SPI using rainfall data for 1901-2015. The SPI-6 represents anomalous conditions in river discharge and reservoir storage and is related to medium-term trends in precipitation. SPI-12 characterises long-term precipitation patterns and can be associated with changes in groundwater levels in addition to longer-term changes in river and reservoir discharge. We used this index in this study to assess drought severity.

2.3 Morlet wavelet transformation

The two most commonly used methods for identifying periodicities in a time series are Fourier and wavelet analyses. Wavelet analyses have advantages over the Fourier transform because, as with the Fourier transform, they allow the identification of values of specific frequencies in a time series and the determination of their location in time (Pisoft et al. 2004). Wavelet transforms can be divided into continuous and discontinuous transforms, with the continuous wavelet transform often being performed using the Morlet approach, referred to as MWT for Morlet Wavelet Transform, as it was suitable for hydrology. The MWT is used to identify periodicities on various time scales and is applied in various fields, e.g. to identify recurring features in a time series hydro-meteorological datasets, to analyse the temporal structure of ENSO (Torrence and Compo 1998), to detect inhomogeneities in a time series and to detect long-term trends (Byun et al. 2008). The wavelet transforms due to a time series xn (n = 0... N - 1) is found out as the complication of xn with a translated and scaled wavelet (η) (eq. 2).

$$W_n(\xi) = \sum_{\gamma=0}^{N-1} X_\gamma (\psi)^* \left[\frac{(\gamma - n)\delta t}{\xi} \right] \quad [2]$$

The Morlet wavelet equation is described as equation 3 (Torrence and Compo 1998).

$$\psi(\eta) = \pi^{-1/4} e^{i\omega_0 \eta} e^{-\eta^2/2} \quad [3]$$

Where, ξ represents the time scale, ω0 indicates the non-dimensional frequency, η denotes time, δt indicates time interval. The complex compound of the wavelet function is written as $\psi^*[(\gamma - n)/\xi]$. The actual section of ξ and modulus square of the MWT (spectral power) are broadly employed to select the original trembling periodicities. The actual section of the MWT exhibits signal severity and stage of several properties in various time scales, while wavelet spectral power shows the signal's power on the feature time scales. Wavelet spectral strength at several scales (ξ) can be quantified by using equation 4.

$$P_n(\xi) = \left|W_n(\xi)\right|^2 \qquad [4]$$

The total of the square of wavelet coefficients can assess wavelet variance in the time field.

$$Var(\xi) = \sum_{n=0}^{N-1} \left|W_n(\xi)\right|^2 \qquad [5]$$

The present study used this method for periodicity analysis of drought.

2.4 Discrete wavelet transforms (DWT)

DWT has gained popularity in many parts of the world for monitoring of drought (Chong et al. 2022; Roushangar and Ghasempour 2022). The DWT is ideally suited for analysing non-stationary time-series datasets because it can capture localised variations and abrupt changes in data at various scales and resolutions. It can explore the localized frequency and time information of non-stationary datasets. While the hydro-climatic data is typically non-stationary, it can successfully extract helpful information. It generates a set of high (approximations) and low (details) pass versions from original time series datasets at a different resolution. We express the critical theme of DWT in equation 6.

$$\psi_{(a,b)}\left(\frac{t-\gamma}{S}\right) = \frac{1}{S_0^{a/2}}\psi\left(\frac{t-b\gamma_0 S_0^{\,a}}{S_0^{\,a}}\right) \qquad [6]$$

2.5 Trend analyses

2.5.1 Innovative trend analysis

Sen (2012) developed the ITA which is a non-parametric technique which do not need inspection of the normality of the observations. First, two equal parts of the time series are separated, and each is then independently categorised in increasing order. Then, the X- and Y-axis are set up with the first half as well as remaining time series, respectively. If the data are gathered on the zero line (45° line/1:1 line), the time series exhibits no trend. The data displays an upward trend when it lies above the 1:1 line. The decreasing trend is indicated if the data are aggregated below the 1:1 line (Naikoo et al. 2022). Equation 7 expresses the method ITA.

$$\varnothing = \frac{1}{n}\sum_{1}^{n}\frac{10X_j - X_i}{\mu} \quad [7]$$

Where, n refers to total number of observations; X_i and X_j describes first & second sub-series; μ represents value of X_i and Ø refers to trend indicator.

2.5.2 Sequential Mann-Kendall test

SQMK test is utilized to identify trend turning points and the approximate timing of the trend's onset in a time series (Sneyers 1998). To estimate the sequential version of the MK test, each value in a time series xj (j = 1, ..., n) was associated with all previous values xk (k = 1, ..., j-1) and the number of instances xj > xk is recorded as nj . The statistic test tj was then calculated using equation 8.

$$tj = \sum_{i}^{j} n_j \quad [8]$$

with *e(t)* and *var (t_j)* representing the mean and variations and are calculated using equations 9 and 10, respectively.

$$e(t) = \frac{n(n-1)}{4} \quad [9]$$

$$var(t_j) = \frac{(j(j-1)(2j+5))}{72} \quad [10]$$

The sequential MK test creates forward *u(t)* & backward *u'(t)* time series, which can be calculated using the outcomes of equations 8, 9 and 10 according to the equation 11.

$$u(t) = \frac{t_j - e(t)}{\sqrt{var(t_j)}} \quad [11]$$

If the progressive and regressive time series cross and then diverge and exceed the threshold of ±1.96, there is a statistically significant trend with 95% confidence, with the crossing point of the progressive and regressive lines being an estimate of the beginning of the trend.

2.6 Development of wavelet-based particle swarm optimization (PSO) embedded REPtree algorithm

2.6.1 Particle Swarm Optimization

The PSO has its origin in researches on activity of organisms in a flock of birds or fish and describes the study by a swarm (population) of particles (individuals) that are changing from iteration to iteration (Pedrycz et al. 2009). The method protects the local optimum and, in each iteration, compares its values to those of the global (best-yet) optimum. The standards for selecting an optimal state are determined by suitability of the impartial function in each case. Remember the suitability of any set of particles' solutions (decision variables). The following equations accelerate the position of each particle for the optimal global situation (Wu 2010). At every outcome stage t, particle i is used to expand the current location Xi, j (t) of its candidate solution by the best local location Pi, j (t) and the best location Pg, j (t) (Eq. 12 and 13).

$$V_{i,j}\left(t+1\right)=\omega v_{i,j}\left(t\right)+c_1 r_1\left[p_{i,j}-x_{i,j}\left(t\right)\right]+c_2 r_2\left[p_{g,j}-x_{i,j}\left(t\right)\right] \qquad [12]$$

$$x_{i,j}\left(t+1\right)=x_{i,j}\left(t\right)+v_{i,j}\left(t+1\right), \qquad j=1,2,\ldots..,d \qquad [13]$$

where Vi,j is the velocity magnitude for the particles; ω is the inertial weight that monitors the velocity direction; the acceleration coefficients are represented by C1 and C2; r1 & r2 denotes identical random numbers amongst (0, 1). Xi, j refers to the situation of the particles.

2.6.2 Machine learning algorithm

In current research, the REPTree algorithm was used to forecast drought conditions. It is a fast decision learning algorithm which merges Reduced Error Pruning with Decision Tree. Despite a DT's massive output, it is used to categorise the simulation course for training data. The error reduction algorithm was used to reduce the structural complexity of the trees (Jayanthi and Sasikala, 2013). The pruning process was executed in this research to overcome the problem of backward overfitting. REPTree applies to discover the smallest representation of the most accurate subtree, depending on the post-pruning procedure.

2.6.3 Development process

The PSO algorithm is used in this study to determine the best structural parameters of the MLAs used. The ensemble method of the planned PSO-REPTree should be as: Parameter initialization of the PSO model→ Training as well as testing of the MLA with the original parameters→ Computing the suitability function→ Suitability of particle swarms over global and local best values→ Corresponding update of the velocity as well as position of each particle swarm→ Reaching the highest number of iterations? These would be the ideal parameters for the MLAs once the maximum number of iterations has been reached. The parameter initialization of PSO itself was chosen. Detailed initialized parameters and optimized parameters for the MLAs were made available:

Maximum depth of tree:- 1, Total lowest weight of the occurrence in leaf-2, least the quantity of the variance-0.001, no pruning-FALSE, sum of data used for the pruning-3, seed-1, Swarm size-25, Iteration-100, probability of mutation - 0.01, mutation type-bit-flip, inertia weight- 0.33, discrete weight- 0.34, social weight- 0.33, report frequency-20, seed-1.

2.7 Performance evaluation

Various indicators were applied to examine the accomplishment of model, notably Pearson's correlation (r) (Kumar and Chong, 2018); Mean Absolute Error (MAE), RMSE (Despotovic et al. 2015); MAPE (Kim and Kim 2016); RMSPE (Chen et al. 2003); Spearman's rho (rspm) (Spearman, 1961) and Kendall's tau (τKen,) (Kendall 1938). The equation 14-20 express the seven statistical indicators used:

$$r = \frac{\sum_{i=1}^{n}\left(A_{i,m} - A'_{i,m}\right)\times\left(A_{i,e} - A'_{i,e}\right)}{\sqrt{\sum_{i=1}^{n}\left(A_{i,m} - A'_{i,m}\right)^2}\times\sqrt{\sum_{i=1}^{n}\left(A_{i,e} - A'_{i,e}\right)^2}} \quad [14]$$

where, $A_{i,m}$, $A_{i,e}$ and n, respectively, describes the detected and predicted ith meteorological drought and total observations. $A'_{i,m}$, $A'_{i,e}$ refers to average detected and projected meteorological drought. Higher r values mean more validity of the models.

$$RMSE = \sqrt{\left(\frac{\sum_{i=1}^{n}\left(Y_o - Y_p\right)^2}{n}\right)} \quad [15]$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_o - Y_p\right| \quad [16]$$

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{I}=1}^{\mathrm{n}} \left| \frac{\mathrm{Y_o} - Y_p}{\mathrm{Y_o}} \right| \times 100\% \quad [17]$$

$$RMSPE = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{Y_p}{Y_o} \right)^2}{n}} \times 100 \quad [18]$$

where, Y_o refers to observed value; Y_p is the projected value and n indicates the sum of data points.

$$r_{spm} = \frac{\sum \left(R_{Y_{m \cdot i}} - \bar{R}_{Y_m} \right) \left(R_{Y_{est \cdot i}} - \bar{R}_{Y_{est}} \right)}{\sqrt{\sum \left(R_{Y_{m \cdot i}} - \bar{R}_{Y_m} >^2 \right) (\sum \left(R_{Y_{est \cdot i}} - \bar{R}_{Y_{est}} \right)}} \quad [19]$$

where, rank of the measured inhibitory denotes by $R_{Ym\text{-}i}$ for compound i. Average of the measured inhibitory activity denoted by R_{Ym}. MDF-SAR inhibitory activity provided rank denotes by $R_{Yest\text{-}I}$ for compound I and is the average of the estimated inhibitory activity denoted by R_{Yesti}.

$$\tau_{Ken,} = \left(C - D \right) / \sqrt{\left[\left(\mathrm{n} \left(\mathrm{n} - 1 \right) / 2 - \mathrm{t} \right) \left(\mathrm{n} \left(\mathrm{n} - 1 \right) / 2 - \mathrm{u} \right) \right]} \quad [20]$$

where, number of tied Y_m and Yest values are denoted by t and u respectively.

3. Results

3.1 Characteristics of meteorological droughts

In this study, both the medium-term and long-term meteorological droughts in northeast India are examined using SPI-6 & SPI-12, respectively, during 1901-2015. The SPI-6 time series shows that northeast India has experienced moderate drought during the 115-year study period (Figure 2 and Table 1). Nearly 13 identical significant moderate droughts and two significant severe droughts occurred in the study area. The short-term observation (SPI-6) in 1967 (SPI value: 2) examined one significant extreme drought. The long-term observation (SPI-12) shows two significant severe droughts. Both the SPI-6 and SPI-12 showed that there were significant moderate droughts in the study area.

Insert figure 2 here

3.2 Trend detection and periodicity analysis

Figure 3a shows ITA results of the SPI-6 and the SPI-12, which show a 99% significant increasing drought trend in northeast India. The SPI-12 shows a monotonically increasing drought trend. There was an increasing drought trend at low, medium, and high levels (Figure 3a). As far as the sequential MK test is concerned, the forward line in both cases meets the criterion of 1.960 and shows substantial rising trends in SPI- and SPI-12. The rate of increasing trend in drought ranges from -0.142 to -0.249 (SPI value) per decade.

Insert figure 3 here

The sequential MK test results show statistically significant SPI trends that began in the early 1990s in SPI-6 & SPI-12 (Figure 3b). Figure 3c shows the wavelet spectrum of SPI-6 and SPI-12. The cone of action of the areas devoid of edge effects is depicted by the white contours. The wavelets' high power is represented by the deep red tone, while their low strength is shown by the blue colour. Two substantial droughts within the cone of influence in SPI-6 occurred in 1950-2015 (from 11 to 25) and 1970-1988 (from 2 to 7). Three significant droughts (1950-2015; 1965-1981 and 1972-1993) were observed within the cone of influence and one significant drought (2008-2015) outside the cone of influence in the SPI-12 observation.

3.3 Decomposition of SPI-6 & SPI-12.

Long-term past SPI-6 & SPI-12 series were decomposed into four lower levels of resolution using DWT, where d1, d2, d3 and well as d4 represent the 2-month, 4-month, 8-month and 16-month periodicity of drought, respectively. While a1, a2, a3 and a4 represent the approximate decomposed components at levels 1-4. Figure 4 shows the SPI-6 values and their decomposed components, while Figure 5 shows the SPI-12 values and their decomposed components. Higher frequencies with lower levels of detail show the frequently fluctuating components of the SPI series. Lower frequencies with higher level of detail of the component series.

Insert figure 4 here

Insert figure 5 here

3.4 Trend detection using wavelet-based ITA and the sequential MK test

For this study, we used wavelet-based ITA in all decomposed parameters (or strata) (a1 to d4) of the SPI to detect the drought trend (Figure 6 and 7). The significant monotonic increasing drought trend (SPI-6) was found in parameters a3 and a4 (Figure 6). All parameters from a1 to d4 of SPI-6 exhibited a substantial rising trend of dryness in low stages. In the middle stage, d1-d3 showed no significant trend; d4 showed a significant increasing trend and a1-a4 showed a significant decreasing trend of dryness in the short-term observation (Figure 6). In contrast, parameters d1-d2 (strata) showed no significant trend in the high level; in the short-term (SPI-6) observations, parameter d3 showed a significant decreasing trend, while parameters a1-a4 and d4 showed a significant increasing trend (Figure 6). Overall, all decomposed strata of SPI-6 showed 99% ($p < 0.01$) substantial rising trend (the value of trend detector D ranged from -16.590 to -21.370) of drought in region between 1901 and 2015.

Insert figure 6 here

Insert figure 7 here

The trend (all decomposed parameters of SPI-6) ranged from -1.224 to 0.001 (SPI value) per year. Similarly, SPI-6 showed a monotonically increasing trend of meteorological dryness in layer a4 decomposed by SPI-12 (Figure 7). All the decomposed layers (a1 to d4) showed a significant increasing trend of dryness in low levels. Strata d1-d2 showed no significant trend; d3-d4 showed a significant decreasing trend; finally, a1-a4 showed a substantial increasing trend of meteorological dryness in the middle stage. At a high stage of long-term observation, D2-d4 showed a significant decreasing trend and a1-d1 showed a substantial increasing drought trend (Figure 7). Like SPI-6, all decomposed strata SPI-12 also showed a 99% ($p < 0.01$) substantial rising trend (the value of trend detector D ranged from -5.810 to -28.780) of drought in the region during 1901-2015. The rate of change of trend (all decomposed parameters of SPI-12) ranged from -0.014 to 0.001 (SPI value) per year.

We applied the sequential MK test to all decomposed strata (a1-d4) of SPI-6 & SPI-12 to detect the abrupt change in drought (Figures 8 and 9). Several trends of turning years (abrupt change) were found in layers d1-d4 in the short- and long-term observations. Strata a1-a3 and a4 showed only one trend turning year in 1998 and 2002, respectively (Figure 8). In contrast, layers a1-a4 of SPI-12 experienced an abrupt trend reversal to drought in the same year 2012 (Figure 9).

Insert figure 8 here

Insert figure 9 here

3.5 Prediction of meteorological droughts

Short-term and long-term drought forecasts for northeast India were conducted using PSO embedded REPTree hybrid algorithms from 1901 to 2015. 20% of the data was utilised for testing and 80% of the data was used for prediction. Only a1, the decomposed parameter, was used in a single for prediction. Except for a1, we combined all other parameters with the previous parameter one by one (e.g. a1, then a1+a2, then a1+a2+a3,... and so on, finally a1+a2+......+d4) to investigate whether the single parameter or the combined parameter is best for drought prediction. The statistical results evaluating the performance of the single and combined decomposed parameters for both the training and testing phases are presented in tables 1-4. The two parameters SPI-6 & SPI-12 a1 showed the lowest performance with higher error values (RMSE, MAE, MAPE, RMSPE) and lower correlation coefficients (Spearman's rho, Kendall tau and r values) (Tables 1-2). The best parameter for predicting drought was the combined parameter a1+a2+a3+a4+d1+d2+d3+d4, which gave higher correlation coefficient (Spearman's rho, Kendall tau and r values) and lower error values (RMSE, MAE, MAPE, RMSPE) (Tables 2 & 3).

The visual (graphical) illustration of the correlation (SPI-6 & SPI-12) between the real SPI and the projected SPI during the training phase can be noticed in Figure 10 and Figure 11. The ascending order of drought prediction parameters during the training phase is a1+a2+a3+a4+d1+d2+d3+d4 > a1+a2+a3+a4+d1+d2+d3 > a1+a2+a3+a4+d1+d2 > a1+a2+a3+a4+d1 > a1+a2+a3+a4 > a1+a2+a3 > a1+a2 > a1 based on the performances. After the training phase, the parameter a1 showed the lowest performance in the test phase with higher error values (RMSE, MAE, MAPE, RMSPE) and lower correlation coefficients (Spearman's rho, Kendall tau and r values) in both the short- and long-term (SPI-6 & SPI-12) observations (Tables 4 & 5). a1+a2+a3+a4+d1+d2+d3+d4 showed higher performance accuracy in the training phase with a higher correlation coefficient (Spearman's rho, Kendall tau and r-values) and lower error values (RMSE, MAE, MAPE, RMSPE) (Tables 3-4). The visual illustration of correlation (SPI-6 & SPI-12) between the actual SPI and the projected SPI during the test phase can be found in Figure 12 and Figure 13. The ascending order of the parameters for predicting drought in the test phase is similar to that in the training phase a1+a2+a3+a4+d1+d2+d3+d4 >

a1+a2+a3+a4+d1+d2+d3 > a1+a2+a3+a4+d1+d2 > a1+a2+a3+a4+d1 > a1+a2+a3+a4 > a1+a2+a3 > a1+a2 > a1 based on the performances. Thus, we have concluded that the combination of a1+a2+a3+a4+d1+d2+d3+d4 are the best parameters for predicting drought in northeast India using PSO-REPTree algorithms.

Insert figure 10 here

Insert figure 11 here

Insert figure 12 here

Insert figure 13 here

Insert table 2 here

Insert table 3 here

Insert table 4 here

Insert table 5 here

4. Discussion

The drought condition in northeast India was examined in this study with the help of medium-term (SPI-6) and long-term (SPI-12) precipitation data from 1901 to 2015. To examine the drought, researchers have applied SPI, Standardized Precipitation Evapotranspiration Index (SPEI) and Palmer Drought Severity Index (PDSI) in different parts of the world (Palmer 1965; McKee et al. 1993; Vicente-Serrano et al. 2010). This study employed SPI-6 & SPI-12 along with ITA, MK test, Morlet wavelet and discrete wavelet transform (DWT) techniques for examining the trend and periodicity of drought in northeast India. Study shows a considerable moderate drought at both medium and long terms in the northeast India. This result is identical to Kumar et al. (2012) and Mallenahalli (2020). Researchers have extensively used MK test for analysis of drought trend in India while ITA has been rarely used. Therefore, the use of the ITA technique in the present study makes it different and novel. Trend analysis of drought using ITA shows a significant increasing ($P < 0.01$) drought trend in the region during 1901-2015. Das et al (2016) also noted an increasing drought trend in northeast India using MK test. Further, Sharma and Mujumdar (2017) also noted an increasing drought trend in India.

Like ITA, the SQMK test is also not common and rarely sued technique for analysing the drought trend in India. Adinehvand and Singh (2017) applied SQMK test for analysing the drought trend in Jaisalmer district of Rajasthan and found no significant trend in drought trend. In this study, the SQMK test shows significant drought trend of SPI-6 & SPI-12 in the year 1996 and 1990, respectively. The increasing drought in northeast India may be linked to the climate change and variability in monsoon rainfall (Parida and Oinam 2015). The analysis of SPI-6 & SPI-12 using Morlet wavelet shows two (within 2–25-month band) and four (within 2–29-month band) significant droughts in the region, respectively. This is identical to the result of Sharma and Goyal (2020) who found a significant drought influence in northeast India within a 4–8-year period from 1901 to 2002. Further, Joshi et al. (2016) also noted a significant periodicity of drought within the 2–8-year band of the SPI-6 in India. Similarly, Gyamfi et al. (2019) who noted significant periodicity in meteorological drought in the Olifants Basin in South Africa within the 2–8-year band (1991-2004).

This study utilizes DWT to decompose both SPI-6 & SPI-12 at four lower levels of resolution (a1-a4 and d1-d4). In comparison, components a1-a4 showed an abrupt trend change only once. Joshi et al. (2016) also used DWT to decompose both parametric and non-parametric SPI at six lower levels of resolution (a1-d6) to analyse drought variability in India for the period 1871-2012. Similarly, Chen et al. (2016) used DWT, to decompose streamflow and rainfall series in the Yellow River basin in China at 7 and 6 lower resolution levels. All decomposed components (SPI-6 & SPI-12) showed a 99% significant increasing drought trend studied using ITA. Furthermore, SQMK investigated abrupt trend changes in components d1-d4 of both SPI-6 & SPI-12, which occurred several times during the study period. Sezen and Partal (2020) used ITA for assessing the rainfall trend in the Euphrates-Tigris catchment in Turkey using decomposed wavelet parameters. PSO-REPTree has been applied to predict the drought scenarios. The result exhibited that single decomposed component (a1) had the lowest performance in predicting drought while massive combined component a1+a2+a3+a4+d1+d2+d3+d4 showed the best performance with higher correlation coefficient and lower error values for drought prediction. Maity et al. (2016) also created multiple models by coupling different decomposed parameters for drought prediction in India, and noted that the coupled decomposed parameters provide the best prediction accuracy for drought as this study.

Although, northeast India is one of the wettest parts of India which receives more than 250 cm rainfall annually (Mahanta et al. 2013), the study shows a significant rising drought trend in the region. Northeastern part of India has an agrarian economy where more than 50% population is engaged in agriculture, horticulture, and related activities (Darlong et al. 2020). In this regard, increasing drought trend may significantly affect the economy and livelihood of the people of northeast, which is one of the least developed regions of India. Thus, there is an urgent need to make effective plans and policies to lessen the impact of drought. The trend analysis of drought using ITA, SQMK and PSO-REPTree with decomposed SPI-6 & SPI-12 has produced reliable and accurate results. Therefore, it may be utilized for the analysis of drought trend in other regions.

5. Conclusions

This study deals with the analysis of trend and periodicity of meteorological drought in northeast India using ITA, SQMK test and wavelet approach. Study shows moderate drought in northeast India at both medium term and long-term during 1901-2015. Trend analysis using ITA showed an upward trend in drought in the region, while SQMK test showed an abrupt change in the drought trend in the later part of first half (around 1958) of study period. The upward trend in drought in the region may be linked with the variability in monsoon rainfall as well as the changes in global climate pattern. The original SPI-6 & SPI-12 series were decomposed into four lower resolutions using DWT. All decomposed parameters of SPI-6 & SPI-12 showed an increasing drought trend in the region. Decomposed parameters d1-d4 showed multiple trend reversal years, while a1-a4 showed only one trend reversal year in the past 115 years, as determined by the SQMK test. A single decomposed component proved to be the least powerful with higher error values and a lower correlation coefficient. The most coupled decomposed component performed best, coupled with lower error values and a higher correlation coefficient using hybrid PSO-REPTree algorithms. Hence, this study advocates to use a combination of the decomposed components for the drought monitoring and prediction at short- and long-terms. Moreover, the increasing drought trend indicates that there is a need to formulate effective management plans to deal with the consequences of drought as well as to mitigate the effects of drought on economy and society. Although, the study produced good result using SPI, ITA, SQMK and wavelet approaches, it deals only with the meteorological drought. Thus, in the future studies, researchers may incorporate SPEI along with SPI and other techniques to study the drought to get an idea of hydrological drought along with the meteorological drought. Understanding hydrological drought in addition to meteorological drought may be more beneficial for agriculture because it may help farmers to gain an understanding of rainfall deficiency and its impact on surface water availability, allowing them to plan irrigation and water management strategies properly for better agricultural output.

References

1. Adinehvand M, Singh BN (2017) Monitoring drought status using precipitation factor: a case study of Jaisalmer Meteorological Station in Rajasthan, India. Forum Geografic, 16(2): 119.
2. Alam J, Saha P, Mitra R, Das J (2023) Investigation of spatio-temporal variability of meteorological drought in the Luni River Basin, Rajasthan, India. Arabian Journal of Geosciences, 16(3): 201.
3. Allen MR, O.P. Dube, W. Solecki, F. Aragón-Durand, W. Cramer, S. Humphreys, M. Kainuma, J. Kala, N. Mahowald, Y. Mulugetta, R. Perez, M. Wairiu, and K. Zickfeld (2018) Framing and Context. In: *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.*
4. Almazroui M, Şen Z (2020) Trend analyses methodologies in hydro-meteorological records. Earth Systems and Environment, 4: 713-738.
5. Anderegg WR, Kane JM, Anderegg LD (2013) Consequences of widespread tree mortality triggered by drought and temperature stress. Nature climate change, 3(1): 30-36.
6. Ault TR (2020) On the essentials of drought in a changing climate. Science, 368(6488), 256-260.
7. Bandyopadhyay N, Bhuiyan C, Saha AK (2016) Heat waves, temperature extremes and their impacts on monsoon rainfall and meteorological drought in Gujarat, India. Natural Hazards, 82: 367-388.
8. Borji M, Malekian A, Salajegheh A, Ghadimi M (2016) Multi-time-scale analysis of hydrological drought forecasting using support vector regression (SVR) and artificial neural networks (ANN). Arabian Journal of Geosciences, 9: 1-10.
9. Byun HR, Lee SJ, Morid S, Choi KS, Lee SM, Kim DW (2008) Study on the periodicities of droughts in Korea. Asia-Pacific Journal of Atmospheric Sciences, 44(4): 417-441.
10. Chen RJ, Bloomfield P, Fu JS (2003) An evaluation of alternative forecasting methods to recreation visitation. Journal of Leisure Research, 35(4): 441-454.
11. Chen Y, Guan Y, Shao G, Zhang D (2016) Investigating trends in streamflow and precipitation in Huangfuchuan Basin with wavelet analysis and the Mann-Kendall test. Water, 8(3): 77.
12. Chong KL, Huang YF, Koo CH, Ahmed AN, El-Shafie A (2022) Spatiotemporal variability analysis of standardized precipitation indexed droughts using wavelet transform. Journal of Hydrology, 605: 127299.
13. Dai A (2011) Drought under global warming: a review. Wiley Interdisciplinary Reviews: Climate Change, 2(1): 45-65.
14. Darlong V, Hore DK, Barma SD (2020) Gender, food security and rice farming in Tripura. In Agriculture and a Changing Environment in Northeastern India (pp. 184-211). Routledge India.
15. Das PK, Dutta D, Sharma JR, Dadhwal VK (2016) Trends and behaviour of meteorological drought (1901–2008) over Indian region using standardized precipitation–evapotranspiration index. International Journal of Climatology, 36(2): 909-916.

16. Despotovic M, Nedic V, Despotovic D, Cvetanovic S (2015) Review and statistical analysis of different global solar radiation sunshine models. Renewable and Sustainable Energy Reviews, 52: 1869-1880.
17. Dikshit A, Pradhan B, Huete A (2021) An improved SPEI drought forecasting approach using the long short-term memory neural network. Journal of environmental management, 283: 111979.
18. Dunne A, Kuleshov Y (2022) Drought risk assessment and mapping for the Murray–Darling Basin, Australia. Natural Hazards, 115: 839–863.
19. Elbeltagi A, Kumar M, Kushwaha NL, Pande CB, Ditthakit P, Vishwakarma DK, Subeesh, A (2023) Drought indicator analysis and forecasting using data driven models: Case study in Jaisalmer, India. Stochastic Environmental Research and Risk Assessment, 37(1): 113-131.
20. Grossmann A, Morlet J (1984) Decomposition of Hardy functions into square integrable wavelets of constant shape. SIAM journal on mathematical analysis, 15(4): 723-736.
21. Guttman NB (1999) Accepting the standardized precipitation index: a calculation algorithm. Journal of the American Water Resources Association, 35(2): 311-322.
22. Gyamfi C, Amaning-Adjei K, Anornu GK, Ndambuki JM, Odai SN (2019) Evolutional characteristics of hydro-meteorological drought studied using standardized indices and wavelet analysis. Modeling Earth Systems and Environment, 5: 455-469.
23. Jain VK, Pandey RP, Jain MK, Byun HR (2015) Comparison of drought indices for appraisal of drought characteristics in the Ken River Basin. Weather and Climate Extremes, 8: 1-11.
24. Jayanthi SK, Sasikala S (2013) Reptree classifier for identifying link spam in web search engines. IJSC, 3(2): 498-505.
25. Joshi N, Gupta D, Suryavanshi S, Adamowski J, Madramootoo CA (2016) Analysis of trends and dominant periodicities in drought variables in India: a wavelet transform based approach. Atmospheric Research, 182: 200-220.
26. Katipoğlu OM (2023) Revealing the trend and change point in Hargreaves equation based on potential evapotranspiration values with various statistical approaches. Environmental Science and Pollution Research, 1-17.
27. Kendall MG (1938) A new measure of rank correlation. Biometrika, 30(1/2): 81-93.
28. Kendall MG (1955) Rank correlation methods. 1955. Griffin, London.
29. Kim S, Kim H (2016) A new metric of absolute percentage error for intermittent demand forecasts. International Journal of Forecasting, 32(3) 669-679.
30. Kisi O, Gorgij AD, Zounemat-Kermani M, Mahdavi-Meymand A, Kim S (2019) Drought forecasting using novel heuristic methods in a semi-arid environment. Journal of Hydrology, 578: 124053.
31. Kumar NM, Murthy CS, Sesha Sai MVR, Roy PS (2012) Spatiotemporal analysis of meteorological drought variability in the Indian region using standardized precipitation index. Meteorological Applications, 19(2): 256-264.
32. Kumar S, Chong I (2018) Correlation analysis to identify the effective data in machine learning: Prediction of depressive disorder and emotion states. International journal of environmental research and public health, 15(12): 2907.
33. Kumar N, Middey A (2023) Extreme climate index estimation and projection in association with enviro-meteorological parameters using random forest-ARIMA hybrid model over the Vidarbha region, India. Environmental Monitoring and Assessment, 195(3): 380.
34. Lesk C, Rowhani P, Ramankutty N (2016) Influence of extreme weather disasters on global crop production. Nature, 529(7584): 84-87.

35. Lotfirad M, Esmaeili-Gisavandani H, Adib A (2022) Drought monitoring and prediction using SPI, SPEI, and random forest model in various climates of Iran. Journal of Water and Climate Change, 13(2): 383-406.
36. Mahanta R, Sarma D, Choudhury A (2013) Heavy rainfall occurrences in northeast India. International Journal of Climatology, 33(6): 1456-1469.
37. Maity R, Suman M, Verma NK (2016) Drought prediction using a wavelet-based approach to model the temporal consequences of different types of droughts. Journal of Hydrology, 539: 417-428.
38. Mallenahalli NK (2020) Comparison of parametric and nonparametric standardized precipitation index for detecting meteorological drought over the Indian region. Theoretical and Applied Climatology, 142(1-2): 219-236.
39. Mann HB (1945) Non-parametric tests against trend. Econometrica, 13: 245–259.
40. McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration to time scales. In Proceedings of the 8th Conference on Applied Climatology, 17(22): 179-183.
41. Mishra D, Goswami S, Matin S, Sarup J (2022) Analyzing the extent of drought in the Rajasthan state of India using vegetation condition index and standardized precipitation index. Modeling Earth Systems and Environment, 8: 601–610.
42. Mohapatra G, Rakesh V, Purwar S, Dimri AP (2021) Spatio-temporal rainfall variability over different meteorological subdivisions in India: analysis using different machine learning techniques. Theoretical and Applied Climatology, 145(1): 673-686.
43. Morid S, Smakhtin V, Bagherzadeh K (2007) Drought forecasting using artificial neural networks and time series of drought indices. International Journal of Climatology: A Journal of the Royal Meteorological Society, 27(15): 2103-2111.
44. Naikoo MW, Talukdar S, Das T, Rahman A (2022) Identification of homogenous rainfall regions with trend analysis using fuzzy logic and clustering approach coupled with advanced trend analysis techniques in Mumbai city. Urban Climate, 46: 101306.
45. Owolabi ST, Madi K, Kalumba AM (2021) Comparative evaluation of spatio-temporal attributes of precipitation and streamflow in Buffalo and Tyume Catchments, Eastern Cape, South Africa. Environ Dev Sustain 23: 4236–4251.
46. Omondi OA (2014) Analysis of Meteorological Drought in North Eastern Province of Kenya. Journal of Earth Science & Climatic Change, 5(8): 219.
47. Palmer WC (1965) Meteorological drought. US Department of Commerce, Weather Bureau. 45:58.
48. Parida BR, Oinam B (2015) Unprecedented drought in North East India compared to Western India. Current Science, 109(11): 2121-2126.
49. Pedrycz W, Park BJ, Pizzi NJ (2009) Identifying core sets of discriminatory features using particle swarm optimization. Expert Systems with Applications, 36(3): 4610-4616.
50. Pham MP, Nguyen KQ, Vu GD, Nguyen NT, Tong HT, Trinh LH, Le PV (2022) Drought risk index for agricultural land based on a multi-criteria evaluation. Modeling Earth Systems and Environment, 8(4): 5535–5546.
51. Pisoft P, Kalvova J, Brazdil R (2004) Cycles and trends in the Czech temperature series using wavelet transforms. International Journal of Climatology 24: 1661–1670.
52. Poornima S, Pushpalatha M, Jana RB, Patti LA (2023) Rainfall Forecast and Drought Analysis for Recent and Forthcoming Years in India. Water, 15(3): 592.

53. Qtaishat T, El-Habbab MS, Bumblauskas DP, Tabieh M (2023) The impact of drought on food security and sustainability in Jordan. GeoJournal, 88(2): 1389-1400.
54. Rahman MR, Lateh H (2016) Meteorological drought in Bangladesh: assessing, analysing and hazard mapping using SPI, GIS and monthly rainfall data. Environmental Earth Sciences, 75(12): 1026.
55. Rao CS, Gopinath KA, Prasad JVNS, Singh AK (2016) Climate resilient villages for sustainable food security in tropical India: concept, process, technologies, institutions, and impacts. Advances in Agronomy, 140: 101-214.
56. Roy S, Hazra S, Chanda A (2023) Changing characteristics of meteorological drought and its impact on monsoon-rice production in sub-humid red and laterite zone of West Bengal, India. Theoretical and Applied Climatology, 151(3): 1419-1433.
57. Roy P, Pal SC, Chakrabortty R, Chowdhuri I, Saha A, Shit M (2022) Climate change and groundwater overdraft impacts on agricultural drought in India: Vulnerability assessment, food security measures and policy recommendation. Science of The Total Environment, 849: 157850.
58. Roushangar K, Ghasempour R (2022) Multi-temporal analysis for drought classifying based on SPEI gridded data and hybrid maximal overlap discrete wavelet transform. International Journal of Environmental Science and Technology, 19(4): 3219-3232.
59. Saha S, Kundu B, Paul GC, Pradhan B (2023) Proposing an ensemble machine learning based drought vulnerability index using M5P, dagging, random sub-space and rotation forest models. Stochastic Environmental Research and Risk Assessment, 1-28.
60. Saharwardi MS, Kumar P, Dubey AK, Kumari A (2022) Understanding spatiotemporal variability of drought in recent decades and its drivers over identified homogeneous regions of India. Quarterly Journal of the Royal Meteorological Society, 148(747): 2955-2972.
61. Saini D, Singh O, Sharma T, Bhardwaj P (2022) Geoinformatics and analytic hierarchy process based drought vulnerability assessment over a dryland ecosystem of north-western India. Natural Hazards, 114(2): 1427-1454.
62. Sam AS, Padmaja SS, Kächele H, Kumar R, Müller K (2020) Climate change, drought and rural communities: Understanding people's perceptions and adaptations in rural eastern India. International Journal of Disaster Risk Reduction, 44: 101436.
63. Sarkar H, Soni S, Ahmad I, Verma MK (2020) Assessment of Agricultural Drought in Upper Seonath Sub-Basin of Chhattisgarh (India) Using Remote Sensing and GIS-Based Indices. Journal of the Indian Society of Remote Sensing, 48(6): 921-933.
64. Şen Z (2012) Innovative trend analysis methodology. Journal of Hydrologic Engineering, 17(9): 1042-1046.
65. Sezen C, Partal T (2020) Wavelet combined innovative trend analysis for precipitation data in the Euphrates-Tigris basin, Turkey. Hydrological Sciences Journal, 65(11): 1909-1927.
66. Sharma A, Sharma D, Panda SK (2022) Assessment of spatiotemporal trend of precipitation indices and meteorological drought characteristics in the Mahi River basin, India. Journal of Hydrology, 605: 127314.
67. Sharma A, Goyal MK (2020) Assessment of drought trend and variability in India using wavelet transform. Hydrological Sciences Journal, 65(9): 1539-1554.
68. Sharma S, Mujumdar P (2017) Increasing frequency and spatial extent of concurrent meteorological droughts and heatwaves in India. Scientific reports, 7(1): 1-9.

69. Sheffield J, Wood EF (2008) Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. Climate dynamics, 31: 79-105.
70. Singh TP, Nandimath P, Kumbhar V, Das S, Barne P (2021) Drought risk assessment and prediction using artificial intelligence over the southern Maharashtra state of India. Modeling Earth Systems and Environment, 7: 2005-2013.
71. Sneyers R, Tuomenvirta H, Heino R (1998) Observations Inhomogeneities and Detection of Climate Change The case of the Oulu (Finland) air temperature series, Transportation Research Record Journal of the Transportation Research Board, 34(3): 159–178.
72. Souza DP, Martinho AD, Rocha CC, da S Christo E, Goliatt L (2022) Hybrid particle swarm optimization and group method of data handling for short-term prediction of natural daily streamflows. Modeling Earth Systems and Environment, 8(4): 5743-5759.
73. Spearman C (1961) The proof and measurement of association between two things. Am J Psychol. 15(1):72–101.
74. Swain S, Mishra SK, Pandey AA (2021) A detailed assessment of meteorological drought characteristics using simplified rainfall index over Narmada River Basin, India. Environ Earth Sci 80: 221.
75. Talukdar S, Ali R, Nguyen KA, Naikoo MW, Liou YA, Islam ARMT, Mallick J, Rahman, A. (2022) Monitoring drought pattern for pre-and post-monsoon seasons in a semi-arid region of western part of India. Environmental Monitoring and Assessment, 194(6): 1-19.
76. Torrence C, Compo G (1998) A practical guide to wavelet analysis, Bull. Am. Meteorol. Soc., 79: 61-78.
77. Vicente-Serrano SM, Beguería S, López-Moreno JI (2010) A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of climate, 23:1696 – 1718
78. Wang T, Tu X, Singh VP, Chen X, Lin K, Lai R, Zhou Z (2022) Socioeconomic drought analysis by standardized water supply and demand index under changing environment. Journal of Cleaner Production, 347: 131248.
79. Wilhite DA (2000) Drought as a natural hazard: concepts and definitions. In: Wilhite DA (Ed) Drought: a global assessment. Routledge, New York, pp. 3–18.
80. Wilhite DA, Sivakumar MV, Pulwarty R (2014) Managing drought risk in a changing climate: The role of national drought policy. Weather and climate extremes, 3: 4-13.
81. World Bank (2006). Natural disaster hotspots. Case studies. Washington, DC: World Bank. www.indiastat.com(https://www.indiastat.com/odishastate/19/meteorologicaldata/22/rainfall/238/stats.aspx. [Last accessed in October 2021]
82. Wu Q (2010) A hybrid-forecasting model based on Gaussian support vector machine and chaotic particle swarm optimization. Expert Systems with Applications, 37(3): 2388-2394.
83. Yue S, Wang CY (2004) The Mann-Kendall Test Modified by Effective Sample Size to Detect Trend in Serially Correlated Hydrological Series. Water Resources Management, 18: 201-218.
84. Zhang Q, Han L, Jia J, Song L, Wang J (2016) Management of drought risk under global warming. Theoretical and applied climatology, 125: 187-196.