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ORIGINAL PAPER

Comparison of parametric and nonparametric standardized precipitation index for detecting meteorological drought over the Indian region

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Abstract

In this study, Standardized Precipitation Index (SPI) derived from parametric and nonparametric methods using 0.25° gridded rainfall data from 1901 to 2013 (113 years) generated by India Meteorological Department (IMD) was compared for understanding drought conditions over the Indian region. The parametric SPI was computed using a three-parameter Gamma distribution function, whereas nonparametric SPI was computed using Gringorten, Weibull, and Hazen plotting positions, on a 4-month cumulative rainfall data of June–September (SPI-4) representing the southwest monsoon season. Nonnormality is a major concern if equal-sized intervals are drawn for interpretation, and SPI being a normalized index wherein classes are standard deviations from normal, its impact on drought assessment needs to be understood. Accordingly, in our study, normality tests were performed using the Shapiro-Wilk method on SPI derived from both parametric and nonparametric methods. The SPI showed 100% of grid cells conforming to normality in the case of nonparametric methods, whereas in the case of parametric approach it was only 80%. The remaining 20% of nonnormality in parametric SPI is spread over montane, tropical wet, and semi-arid regions of India. Furthermore, differences in the estimation of dryness are observed in the range of 1.0 to 2.5% between nonparametric and parametric SPI for the drought years considered this study. The quantile analysis on all grid cells for the drought year 2002 showed an important fact that at 0.025 quantile only 2.6% of grid cells are in the extremely dry condition as per parametric SPI, whereas in the case of nonparametric SPI it is 6.9%. For the drought year 1939 in grid cells where normality is not followed in parametric SPI, Cohen's kappa ($\kappa = 0.15$) under extreme dryness category indicates large disagreements between parametric and nonparametric SPI. The temporal analysis of Cohen's kappa computed for each grid cell over drought years shows that in 22.5% of cases the drought category between nonparametric and parametric SPI is not in perfect agreement. Hence, the nonparametric SPI can better categorize the drought classes, representing well the extent of dryness and normality conditions, it is highly recommended for drought assessment over India.

Keywords Drought assessment · Standardized precipitation index · Pearson-3 distribution · L-Moments · Cohen's kappa · Gringorten · Weibull · Hazen · Plotting position · Normality · Quantiles

1 Introduction

Drought is a normal recurring natural hazard capable of impacting at times the survival of human civilizations. Thus, understanding its characteristics would greatly help in developing better plans for mitigation. Historically, droughts have been grouped under four categories: (i) meteorological, (ii) agriculture, (iii) hydrological, and (iv) socio-economic (Wilhite and Glantz 1985; AMS 2013). Among them, meteorological drought is widely studied and is considered as a precursor to all other drought occurrences. Also, due to its direct relationship with agricultural crop production (Cruz-Roa et al. 2017; Deo et al. 2017), understanding its impacts is highly recommended.

Meteorological drought as the name suggests deals with precipitation and its anomalies. In general, one may define meteorological drought as the variability of precipitation over a region to its long-term average. Owing to its region-specific relations, meteorological droughts have a variety of definitions. The American Meteorological Society (AMS) defines meteorological drought in terms of the magnitude and duration of a precipitation shortfall

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(AMS 2013). The India Meteorological Department (IMD) defines drought as a situation occurring in any area when the deficiency in annual rainfall is greater than 26% of the long-term average for the season. Furthermore, droughts are classified as (i) severe when the deficiency in the annual rainfall exceeds 50% of the long-term average, and (ii) moderate when the deficiency in the rainfall is between 26 and 50% (Shewale and Kumar 2005). For more recent literature and studies on meteorological droughts, the readers are referred to Golian S et al. (2015), Guhathakurta P et al. (2017), Haslinger and Blöschl (2017), and Zhou H and Liu Y (2018).

In general, the impacts of droughts are measured using standardized indices as they provide a comprehensive understanding of its impacts in terms of severity, persistence, and spread. Some of these measures are deficiency of rainfall deviation from the normal (Shewale and Kumar 2005), China-Z index (Wu H et al. 2001), effective drought index (Byun and Wilhite 1999), rainfall deciles (Gibbs and Maher 1967), Palmer Drought Severity Index (PDSI) (Palmer WC 2006), and most popularly the Standardized Precipitation Index (SPI) (McKee et al. 1993). Even though PDSI is a popular index based on soil moisture (Briffa et al. 1994; Szinell CS et al. 1998), its sensitivity to the criteria for end times of established drought and precipitation of a month (Alley WM 1984) has become a major stumbling factor for use in operational drought assessment. However, the SPI has emerged as a more effective method for studying drought climatology (Lloyd-Hughes and Saunders 2002; Shukla S and Wood AW 2008; Hayes et al. 2011) due to its utility and flexibility. The computation of SPI requires one to choose a suitable statistical distribution that best fits the rainfall data of a location for a particular timescale to obtain precipitation probabilities which is then transforming into a standard normal variate. This makes the SPI comparable across space and time, thus providing an ability for a consistent interpretation of drought situation in a region (Farahmand A and AghaKouchak A 2015).

2 Literature review

SPI due to its computational simplicity, consistent interpretation, reliability, and adaptability to different timescales and climate conditions has been studied extensively for understanding droughts globally (Olukayode Oladipo 1985; Das S et al. 2016; Kumar R et al. 2016; Meroni et al. 2017; Elkollaly et al. 2018). Bordi I et al. (2001) analyzed the SPI time series (1948 to 1981) for drought patterns over the Mediterranean. Rodriguez-Puebla and Nieto (2009) analyzed the SPI over the Iberian Peninsula and were able to derive four regional regimes using empirical orthogonal functions. Sirdas and Sen (2003) characterized the drought intensity and magnitude in the Trakya region, Turkey, using the SPI. Vicente Serrano et al. (2004) observed a significant increase in the area under drought from mid to northern areas over Spain using SPI time series. Dinpashoh et al. (2004) studied droughts over Iran using regional precipitation data, factor analysis, and clustering. Pai et al. (2011) evaluated the district-wise drought climatology in India using SPI. SPI is extensively used in studies related to drought monitoring (Hayes et al. 1999; Tsakiris and Vangelis 2004), drought frequency analysis (Łabędzki L 2007), spatio-temporal impacts (Kumar Naresh et al. 2012), and climate change analysis (Mishra and Singh 2010; Jenkins and Warren 2015; Kostopoulou et al. 2017), thus covering various aspects that are related to droughts. Though SPI and PDSI indicate temporal changes in the proportion of area experiencing drought in Europe (Lloyd-Hughes and Saunders 2002), the latter is not comparable across the regions. Furthermore, it is not possible to extend/compute PDSI on multiple scales, thus making it infeasible to correlate with runoff and other hydrological drought parameters.

3 Motivation

Parametric methods of computing SPI are a widely adopted approach wherein the rainfall time series is fit to a statistical distribution and transformed into a standard normal variate. Several distributions such as Cohen's kappa, Log-normal, Weibull, Gamma, etc., have been used for generating SPI in the literature. These studies point out that the choice of distribution that best fits the rainfall data is critical in SPI computation (Farahmand A and AghaKouchak A 2015). It is observed in Kumar Naresh et al. (2009) that SPI is overestimated in some of the regions over India. Also, it is made quite evident that no single distribution fits the rainfall time series of different regions. However, the methods developed by Hosking and Wallis (1997) using the concept of regional rainfall were found to provide a better estimation of distribution parameters for computing SPI. Also, the parameter estimation using L-moments provided a better characterization of droughts using SPI over the Indian region (Kumar Naresh et al. 2012). Although, SPI is a widely used drought index, its reliability is based on two important computational issues: (i) length of time series data, and (ii) the type of probability distribution that fits a given data (Mishra and Singh 2010). The assumption of prior distribution in the computation of SPI limits its capability in interpreting droughts for various rainfall regimes and in particular when examining drought patterns that are of short duration. Therefore, alternative methods are sought after for computing the SPI.

In recent literature, probability plotting position techniques for computing SPI has generated quite an amount of interest in drought studies (Soláková T et al. 2014; Farahmand A and AghaKouchak A 2015). Being parameter-free, these methods are now being widely employed in drought assessment (Huang S et al. 2015; Chu 2018) and forecasting (Ma et al. 2018). This motivated us to employ these methods generally termed as nonparametric for computing SPI over the Indian region. Also, it became a matter of interest to compare its strengths and weakness with parametric approaches of computing SPI for assessing the drought conditions over India.

Accordingly, in this paper, we develop nonparametric SPI over the Indian region using methodology presented in Section 4 on the study area and dataset discussed in Section 5. An assessment of severity and extent of dryness using parametric and nonparametric SPI is carried out for the drought years given in Shewale and Kumar (2005). Our results are presented in Section 6, followed by a discussion in Section 7 and conclusions in Section 8.

4 The methodology

The SPI was first developed at Colorado State University by McKee et al. (1993) using a two-parameter Gamma distribution. Later, Farahmand A and AghaKouchak A (2015) proposed a generalized framework for deriving the nonparametric SPI. This study is novel in the sense that nonnormality issues in parametric SPI and its impact on drought assessment are being studied for the first time over the Indian region. Furthermore, an objective comparison is presented between parametric and nonparametric SPI through quantiles and statistical tests.

This section is organized as follows: In Section 4.1, we present the data model; the procedures for computing SPI in Section 4.2; statistical methods for comparing SPI time series in Section 4.3.

4.1 The data model

Let $Q_{k,l}(p,q)$ denote the daily gridded rainfall data over the Indian region, where $k \in \{1, 2, \ldots, 113\}$ is an index representing years from 1901 to 2013, $l \in \{1, \ldots, 366\}$ is the day number of the year if it is leap; otherwise, $l \in \{1, \ldots, 365\}$, $p \in \{1, 2, \ldots, 129\}$, $q \in \{1, 2, \ldots, 135\}$ are the indices for latitude $\{6.5°, 6.75°, \ldots, 38.5°\}$ and longitude $\{66.5°, 66.75°, \ldots, 100°\}$ respectively.

The monthly rainfall data $R_{k,m}(p,q)$ is obtained from $Q_{k,l}(p,q)$ as:

$$R_{k,m}(p,q) = \sum_{r=d}^{d+t} Q_{k,r}(p,q), \tag{1}$$

where $m \in \{1, 2, \ldots, 12\}$ is the index which represents months
from $\{January, \ldots, December\}$, d denotes the start day number of the month, it takes values as $d \in \{1, 32, 61, \ldots, 335\}$ if year is leap otherwise $d \in \{1, 32, 60, \ldots, 334\}$. The variable t denotes number of days in a month and takes values as $t \in \{31, 28, \ldots, 31\}$ for non-leap year and $t \in \{31, 29, \ldots, 31\}$ for leap year.

The total southwest monsoon season rainfall $X_k(p,q)$ occurs between June and September months of an year is represented by:

$$X_k(p,q) = \sum_{m=6}^{9} R_{k,m}(p,q) \tag{2}$$

and the mean seasonal rainfall is obtained as:

$$X(\bar{p},q) = \frac{\sum_{k=1}^{113} X_k(p,q)}{L}, \tag{3}$$

where L denotes length of the time series which in the present case is 113 years.

4.1.1 A toy example

As an example, for the year 2008 and March month, the variables k, m, t, r take values 108, 3, 31, and 61, respectively, and Eq. (1) can be written as:

$$R_{108,3}(p,q) = \sum_{r=61}^{61+31=92} Q_{108,r}(p,q). \tag{4}$$

The total seasonal rainfall $X_k(p,q)$ for grid cells p, q representing southwest monsoon from June to September months for the year 2008, i.e., ($k = 2008 - 1900 = 108$) and $m = \{6, 7, 8, 9\}$ is obtained as $X_{108}(p,q) = \{R_{108,6}(p,q) + R_{108,7}(p,q) + R_{108,8}(p,q) + R_{108,9}(p,q)\}$

4.2 SPI computation

Parametric techniques of estimating SPI involve identifying a candidate probability distribution that fits a given rainfall time series. Though there are many probability distributions such as Gamma, Gumbel, Logistic, Log-logistic, Lognormal, Normal, and Weibull distributions employed in computing standardized precipitation indices (Stagge et al. 2015), the two-parameter Gamma function and Pearson type III distribution are the ones that are widely used in drought assessment studies.

The probability density function(f_P) of Pearson type III distribution for the rainfall series X is written as:

$$f_P(X, \alpha, \psi, \xi) = \frac{(X-\xi)^{\alpha-1} e^{-(X-\xi)/\psi}}{\psi \Gamma(\alpha)} \tag{5}$$

where α represents the shape of rainfall distribution, ψ denotes the scale parameter, and ξ denotes the threshold parameter which is equal to the minimum value of rainfall series X. If μ, σ, and γ denote the mean, standard deviation, and skewness of rainfall X, then α, ψ, ξ parameters of the three-parameter Gamma function can be computed as $\alpha = \frac{4}{\gamma^2}$, $\psi = \frac{1}{2\alpha|\gamma|}$, and $\xi = \mu - \frac{2\sigma}{\gamma}$ provided $\gamma \neq 0$. The $\Gamma(\alpha)$ denotes the Gamma function which is a factorial on $(\alpha - 1)$, i.e., $(\alpha - 1)!$.

The cumulative probability distribution of Pearson III (F_P) is written as:

$$F_P(x) = \frac{G(\alpha, \frac{x-\xi}{\beta})}{\Gamma(\alpha)}, \tag{6}$$

where $G(\alpha, \frac{x-\xi}{\beta})$ is computed as $(\alpha - 1)! e^{-x} \sum_{k=0}^{\alpha-1} \frac{x^k}{k!}$ and is known as an incomplete Gamma function.

To obtain the above parameters, we employ the method of linearized moments (L-moments), which is more robust to outliers. The L-moments (Hosking 1990) are linearized functions of probability weighted moments (PWM) (Greenwood et al. 1979). Using rational approximation the PELPE3 (parameter estimation via L-moments for the Pearson type III distribution) computes the three parameters of the Gamma distribution. Furthermore, the CDFPE3 (Cumulative Distribution Function for Pearson Type III distribution) computes the cumulative probability of an observed precipitation event using the parameters obtained from PELPE3. For more details on the above methods, readers are referred to Hosking (1990).

The nonparametric methods of computing SPI involve obtaining the marginal probabilities of precipitation by calculating the cumulative frequencies through empirical plotting positions. These methods are parameter-free approaches found suitable in the assessment of drought (Cancelliere A et al. 2006; Hao and AghaKouchak 2014; Soláková T et al. 2014; Farahmand A and AghaKouchak A 2015; Ghamghami et al. 2017). There are several nonparametric plotting positions formulae (Hazen 1914; Weibull 1939; Gringorten 1963) to obtain the parametric free distribution models for a given rainfall series. These methods are widely employed in a variety of drought-related applications (Rad et al. 2017; Zhou H and Liu Y 2018; Vazifehkhah et al. 2019).

To compute the nonparametric cumulative distribution functions for the rainfall times series(X_k) of a given grid cell p, q $X_k = \{x_1, x_2, \ldots, x_{113}\}$, we first obtain the ordered statistics for a given grid cell by arranging the rainfall data in the ascending order. We then obtain the rank m for each precipitation value x from the ordered series. The cumulative distribution function (CDF) for a given precipitation value is obtained as $\frac{m-a}{n+1-2a}$ where n is the total number of years in the time series which is 113 in our case, a is a parameter which takes values 0.5, 0.44, 0 in the case of Hazen, Gringorten, and Weibull plotting positions methods respectively.

Accordingly, the CDF of Gringorten, Weibull and Hazen plotting positions F_G, F_W, and F_H respectively is computed as:

$$\begin{aligned} F_G(x_{(m)}) &= \frac{m - 0.44}{n + 1 - (2 * 0.44)} = \frac{m - 0.44}{n + 0.12}, \\ F_W(x_{(m)}) &= \frac{m - 0}{n + 1 - (2 * 0)} = \frac{m}{n + 1}, \\ F_H(x_{(m)}) &= \frac{m - 0.5}{n + 1 - (2 * 0.5)} = \frac{m - 0.5}{n}. \end{aligned} \tag{7}$$

4.2.1 A toy example

For example, let the rainfall data be $X = \{100, 150, 50, 500, 350, 70\}$, the ordered series would be $\{50, 70, 100, 150, 350, 500\}$, and the rank of each element of X would be $\{3, 4, 1, 6, 5, 2\}$, respectively. The CDF for the first element in X, i.e., 100 using Gringorten, Weibull, and Hazen plotting is obtained as $F_G(100) = \frac{3-0.44}{6+0.12} = 0.418$, $F_W(100) = \frac{3}{6+1} = 0.429$, and $F_H(100) = \frac{3-0.5}{6} = 0.417$. Likewise, the CDF for other elements in X can be obtained.

4.2.2 Obtaining SPI from cumulative distribution function

The rainfall being a random event takes a value zero on most of the occasions; hence, its probability mass function defined as number of zeroes in the time series (P_0) is one of its important characteristics. The final cumulative probability for each rainfall occurrence is obtained as $F_{(.)}(x) = P_0 + (1 - P_0) F_{(.)}(x|x > 0)$, where $F_{(.)}(x|x > 0)$ is the cumulative probability strictly for non-zero rainfall occurrences of x in X as $F_{(.)}$ is not defined for $x = 0$. The probability of zero P_0 is computed as $P_0 = N_0/n$, where N_0 is the number of observations with zeros in the rainfall data X having total number of records n.

We then obtain the SPI of X for a grid cell p, q, by fitting a inverse standard normal distribution ζ (zeta) to the CDFs F_P, F_G, F_W, F_H; i.e.:

$$\begin{aligned} S_P(X) &= \zeta(F_P(X)) \\ S_G(X) &= \zeta(F_G(X)) \\ S_W(X) &= \zeta(F_W(X)) \\ S_H(X) &= \zeta(F_H(X)) \end{aligned} \tag{8}$$

The approximation given in Abramowitz (1974) is used to obtain ζ:

$$\zeta(F_{(.)}) = \begin{cases} -(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}), & \text{if } 0 < F_{(.)} \leq 0.5 \\ +(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}), & \text{if } 0.5 < F_{(.)} \leq 1 \end{cases}, \tag{9}$$

where $c_0 = 2.515517$, $c_1 = 0.802583$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$:

$$t = \begin{cases} \sqrt{-2\ln(F_{(.)})}, & \text{if } 0 < F_{(.)} \leq 0.5 \\ \sqrt{-2\ln(1 - F_{(.)})}, & \text{if } 0.5 < F_{(.)} \leq 1, \end{cases} \tag{10}$$

where $F_{(.)}$ denotes the cumulative distribution function of parametric F_P and nonparametric F_G, F_W, F_H methods respectively.

4.3 Statistical methods for comparison of SPI time series

The SPI is a measure similar to standard deviation as it represents how much an event is above or below the mean. The cumulative probability of a SPI time series is a function of given rainfall events. McKee et al. (1993) categorized SPI into groups such that each of them is well separated by 0.5 standard deviation intervals which are well suited for variables that are normally distributed. Assuming the normality of SPI, we adopted a similar approach and arranged the drought classes as follows:

$$\begin{aligned} \text{Wet (WT)} &= S_{(.)} \geq 0, \\ \text{Near Normal (NN)} &= -1.0 < S_{(.)} < 0, \\ \text{Moderate Dryness (MD)} &= -1.5 < S_{(.)} \leq -1.0, \\ \text{Severe Dryness (SD)} &= -2.0 < S_{(.)} \leq -1.5, \\ \text{Extreme Dryness (ED)} &= S_{(.)} \leq -2.0, \end{aligned} \tag{11}$$

wherein $S_{(.)}$ represent parametric SPI (S_P) and nonparameteric SPI (S_G, S_W, S_H).

However, since the assumption of normality is especially critical when constructing reference intervals for variables (Royston 1991), there is a strong case to study the effects on drought interpretation due to nonnormality in SPI.

The Q-Q plot is a graphical method for matching the quantiles of a given data values to standard normal (Field A 2013). The normality tests such as Shapiro-Wilk (Shapiro and Wilk 1965) are supplementary to visual methods which is better than many other normality tests (Razali NM and Wah YB 2011). The Shapiro-Wilk test is based on the correlation between data and corresponding normal scores and is better than the Shapiro-Francia (Shapiro SS and Francia RS 1972) test for the platykurtic sample, whereas, for leptokurtic samples, the Shapiro-Francia test is found to be better. Accordingly, in the present study based on the sample being tested is leptokurtic or platykurtic, the normality test is performed by either Shapiro-Francia or Shapiro-Wilk method. In terms of climatology if the SPI time series is leptokurtic, then it implies that the given distribution is not normal and has tails on both sides. Also, it means that extreme values are present in the data as outliers which may impact certain assumptions made in the interpretation of droughts.

Cohen's kappa is a widely employed measure for assessing the inter-rater reliability between two sets of observations. This statistic is introduced in remote sensing applications by Congalton et al. (1983) and is a recommended measure in thematic accuracy analysis. It is a coefficient of agreement between classification and verification. Cohen's kappa accuracy is determined from the error matrix which gives information on the number of correctly classified along with the errors of commission and omission.

In the present study, parametric SPI (S_P) and nonparametric SPI (S_G) are considered as two raters of a given drought event whose agreements are assessed by first constructing the confusion matrix which gives the agreements or disagreement across different drought classes wet (WT), normal (NN), moderate (MD), severe (SD), and extreme (ED). Cohen's kappa statistic (κ) as given by Hudsoll and Ramm (1987) and Congalton RG and Green K (2009) is computed:

$$\kappa = \frac{(p_o - p_c)}{(n - p_c)} \tag{12}$$

wherein, n is the number of observations; p_o and p_c denote the total and chance agreements respectively between the two raters S_P and S_G. The p_o is the number of grid cells that show the same drought category for parametric or nonparametric SPI. A higher value of p_o indicates better agreement between S_P and S_G on the underlying drought condition. On the other hand, p_c is a measure of disagreement between the drought labels generated from S_P, S_G for each of the grid cells. The higher the value of p_c compared with p_o, the stronger is the disagreement between two raters S_P and S_G on the drought assessment. The κ value thus obtained is interpreted as (see Viera and Garrett (2005)):

$$\begin{aligned} \kappa \leq 0 &= \text{Less than chance agreement} \\ 0 < \kappa \leq 0.2 &= \text{Slight agreement} \\ 0.2 < \kappa \leq 0.4 &= \text{Fair agreement} \\ 0.4 < \kappa \leq 0.6 &= \text{Moderate agreement} \\ 0.6 < \kappa \leq 0.8 &= \text{Substantial agreement} \\ 0.8 < \kappa \leq 1.0 &= \text{Almost perfect agreement.} \end{aligned} \tag{13}$$

4.3.1 Toy example

Let:

$$M = \begin{bmatrix} 53 & 18 & 12 \\ 8 & 48 & 9 \\ 4 & 28 & 90 \end{bmatrix}$$

denote the confusion matrix pertaining to drought class moderate (MD), severe (SD), and extreme dryness (ED) categories obtained from the SPI values S_P, S_G. The diagonal elements of M, i.e., $\{53, 48, 90\}$, denote the number of grid cells that are in agreement between S_P and S_G when rating the drought situation as MD, SD, or ED. The total actual agreement $p_o = \{53+48+90\} = 191$. The row and column totals are $\{83, 65, 122\}$ and $\{65, 94, 111\}$ respectively. The total observations $n = \{83 + 65 + 122\} = 270$. The chance agreement is computed as $p_c = \{\frac{65\times83}{270}, \frac{94\times65}{270}, \frac{111\times122}{270}\} = \{19.98+22.63+50.16\} = 92.77$.

We now obtain $\kappa = \frac{191-92.77}{270-92.77} = \frac{98.23}{177.23} = 0.55$ which according to Eq. 13 denotes moderate agreement between the two raters S_P and S_G.

5 Study area and dataset

The present study area is the region extending from 6.5° north to 38.5° north in latitude, and from 66.5° east to 100° east in longitude covering India. We have utilized the new high spatial resolution (0.25 × 0.25 degree) daily gridded rainfall dataset (Pai DS et al. 2014) over the Indian region comprising of 135×129 grid points in longitude and latitude directions with a time span of 113 years from 1901 to 2013. This dataset obtained from the India Meteorological Department (IMD) has total grid cells of 4642 representing the landmass of India.

At first, the daily rainfall data were summed over the month to get the monthly rainfall data using Eq. 1. The total season precipitation is the sum of monthly rainfall data from June to September and is obtained using Eq. 2. The above 4-month period represents the southwest monsoon season, which is the prime rain occurring period over India. This dataset is further utilized for computing parametric and nonparametric SPI in the present study using Eq. 5 to Eq. 8. The years 1901, 1904, 1905, 1911, 1918, 1920, 1941, 1951, 1965, 1966, 1968, 1972, 1974, 1979, 1982, 1987, and 2002 are considered for analysis of all India drought based on two criteria: (i) when deficiency of area weighted rainfall having normal of 88 cm exceeds 10%, and (ii) area under drought is more than 20% of the total area corresponding to plains (Shewale and Kumar 2005). So, in our study, we propose to compare the efficacy of parametric and nonparametric SPI (S_P, S_G, S_W, S_H) in assessing actual drought situation over India.

6 Results

Utilizing the dataset discussed in Section 5 and implementing the methods in Section 4 over the study area, we obtain the parametric (S_P) and nonparametric (S_G, S_W, S_H) SPI. In order to understand the effectiveness of these techniques in detecting drought situation, we undertake the following investigations. In Section 6.1, a comparative study on the extent of skewness in S_P, S_G, S_W, S_H is done. A study on the extent of nonnormality in SPI is presented in Section 6.2. Analysis of the percentage area under dryness estimated by the parametric and nonparametric SPI is carried out in Section 6.3. A quantitative analysis on the SPI using quantiles is presented in Section 6.4 followed by spatial and temporal agreements in drought classes obtained from S_P and S_G discussed in Section 6.5 and Section 6.6.

6.1 Skewness in SPI-1 and SPI-4 time series (1901–2013)

The SPI-1 time series comprise SPI values for each month computed from monthly rainfall data for years 1901 to 2013. On the other hand, the SPI-4 time series comprise of SPI values computed from June to September cumulative rainfall data for each year from 1901 to 2013. Skewness is a measure to assess whether a given time series follow normal distribution. In general, drought classes are derived in steps of 0.5 deviation toward the left half of the normal distribution which has no skewness (McKee et al. 1993). Therefore, in the present context, the presence of skewness in the SPI time series may result in an erroneous interpretation of drought situation. Accordingly, we compute the left skewness in parametric and nonparametric SPI-1, SPI-4 time series, and choose grid cells that have skewness less than −0.5. Furthermore, we compute the percentage left skewness (Delta) Δ (see Table 1) as:

Table 1 Percentage left skewness in parametric SPI (Δ_P) and nonparametric SPI computed using Gringorten (Δ_G), Weibull (Δ_W), and Hazen (Δ_H) plotting position for time series (1901–2013)

Measure	June	July	August	September	June–September
Δ_P	5.1	5.9	3.4	4	6.3
Δ_G	0	0	0	0	0
Δ_W	0	0	0	0	0
Δ_H	0	0	0	0	0

$$\Delta_{(.)} = \frac{\sum_{p=1}^{129}\sum_{q=1}^{135}\delta_{(.)}(p,q)}{C} \times 100 \quad (14)$$
$$= \frac{\delta_{(.)}}{4642} \times 100$$
$$= 0.02 \times \delta_{(.)},$$

where δ represents:

$$\delta_{(.)}(p,q) = \begin{cases} 0, & \text{if } p,q \notin \{\text{grid cells over Indian region}\} \\ 1, & \text{if } skewness(S_{(.)}) < -0.5, \\ 0, & \text{otherwise} \end{cases}$$

C is the total number of grid cells (4642) covering the Indian region and $S_{(.)}$ is the SPI, $p \in \{1, 2, \ldots, 129\}$, $q \in \{1, 2, \ldots, 135\}$ are the indices for latitude $\{6.5°, 6.75°, \ldots, 38.5°\}$ and longitude $\{66.5°, 66.75°, \ldots, 100°\}$ respectively. In the above computation, only those grid cells that fall within the Indian region are considered.

From Table 1, it is evident that the nonparametric SPI (S_G, S_H, S_W) for SPI-1 and SPI-4 time series has no skewness, whereas the percentage left skewness in parametric SPI-4 (Δ_P) shows 6.3% when compared with lower percentages in August (3.4%) and September (4%) months. However, the percentage left skewness in parametric SPI-4 (Δ_P) in June (5.1%) and July (5.9%) are comparatively higher than August and September months. Therefore, any drought interpretation and assessment using SPI-4 (June–September) and SPI-1 (June and July) of parametric SPI are subjected to some anomalies.

6.2 Analysis on extent of nonnormality in SPI

To understand the nonnormality in SPI time series, Q-Q plot method discussed in Section 4.3 is obtained for the grid cell (12,49) corresponding to latitude 18.5° and longitude 72.75°. A plot of the standard normal and empirical quantiles of both S_P and S_G is plotted and shown in Fig. 1a and b. In Fig. 1a, the lower and upper regions show deviations from normal for the parametric SPI (S_P), whereas Fig. 1b shows no such deviations in S_G. It is observed that the deviations in S_P are more evident in the lower region as shown in Fig. 1a, which may lead to incorrect assessment of drought situation when using parametric SPI S_P.

The normality map obtained for S_P and S_G time series (1901–2013) using the Shapiro-Wilk test is shown in Fig.2a–b. Figure 2a clearly shows that all grid cells for nonparametric SPI are normal, whereas in some grid cells parametric SPI is not normal (see Fig. 2b). Out of 4642 total grid cells, 3731 are found to be normal in S_P and 911 did not follow normality. The percentage of nonnormality corresponding to S_P is shown in Table 2. The parametric SPI (S_P) for SPI-4 (June–September) has the highest nonnormality of 19.6%. The month of July has 17.2%, whereas June–September SPI has nonnormality in 15.3% of grid cells. The August month parametric SPI (S_P) has a nonnormality of 14.3% which is lowest when compared with all the months. This result is consistent with skewness measured on the parametric SPI (S_P) in Section 6.1. However, no such anomalies were seen in the nonparametric SPI (S_G). Hence, the nonparametric SPI can provide an unbiased assessment of the underlying drought situation.

6.3 Analysis on percentage area under dryness in SPI-4 time series

The percentage area under dryness measure provides an insight into the geographical spread and extent of drought severity as perceived from the SPI time series. Using the SPI classification scheme (McKee et al. 1993) given in Eq. 11, we compute the percentage area under dryness Θ (theta) as:

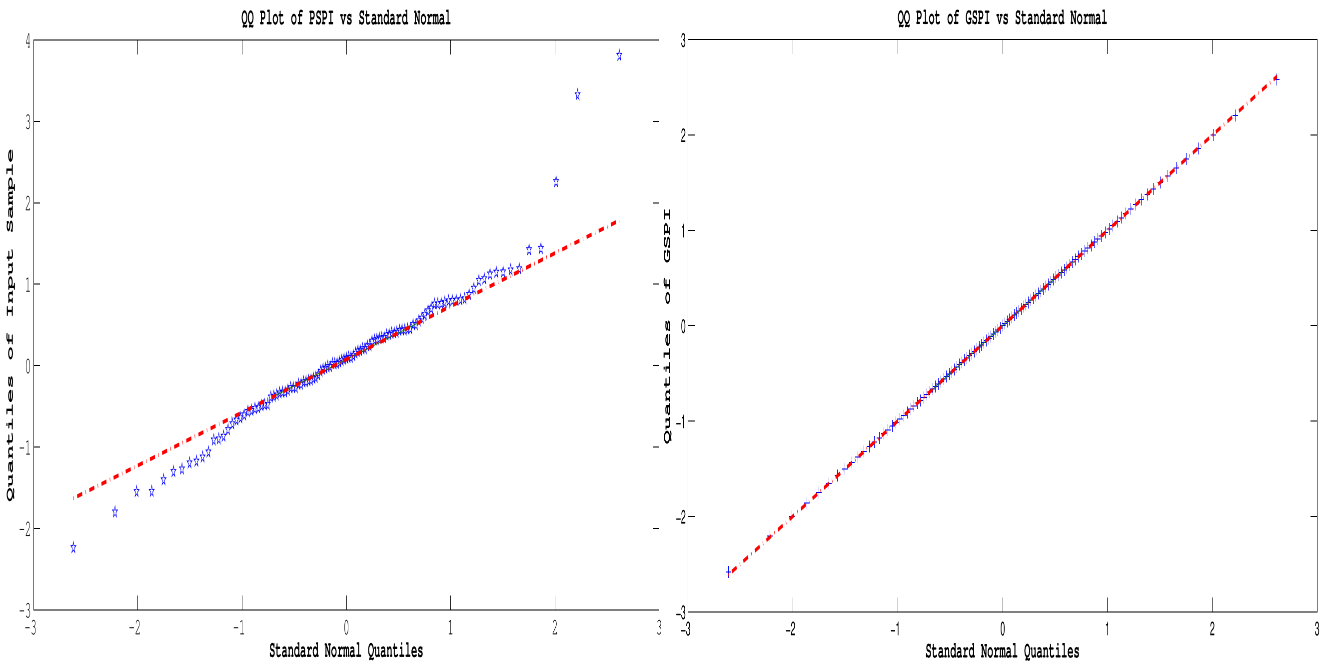
$$\Theta_{(.)} = \frac{\sum_{p=1}^{129}\sum_{q=1}^{135}\varepsilon_{(.)}(p,q)}{C} \times 100, \quad (15)$$
$$\Theta_{(.)} = \frac{\sum_{p=1}^{129}\sum_{q=1}^{135}\varepsilon_{(.)}(p,q)}{4642} \times 100,$$
$$\Theta_{(.)} = 0.02 * \sum_{p=1}^{129}\sum_{q=1}^{135}\varepsilon_{(.)}(p,q),$$

where

$$\varepsilon_{(.)}(p,q) = \begin{cases} 0, & \text{if } p,q \notin \{\text{grid cells over Indian region}\} \\ 1, & \text{if } S_{(.)}(p,q) \le -1 \\ 0, & \text{if } S_{(.)}(p,q) > 1 \end{cases}$$

and C is the total number of grid cells (4642), $p \in \{1, 2, \ldots, 129\}$, $q \in \{1, 2, \ldots, 135\}$ are the indices for latitude $\{6.5°, 6.75°, \ldots, 38.5°\}$ and longitude $\{66.5°, 66.75°, \ldots,$
$100°\}$ respectively. In the above computation, only those grid cells that fall within the Indian region are considered.

The values of Θ for drought years 1901, 1904, 1905, 1911, 1918, 1920, 1941, 1951, 1965, 1966, 1968, 1972, 1974, 1979, 1982, 1987, and 2002 given in Shewale and Kumar (2005) for parametric and nonparametric SPI-4 time series are shown in Table 3. The 1918 drought year was more pronounced due to the impact of El Niño and had area weighted rainfall deficiency from normal (80 cm) also known as the Indian Summer Monsoon Rainfall (ISMR) around −24.9%. This is very well captured by the percentage area under dryness nonparametric SPI Θ_G measure showing 52.5% in 1918 which is one of the worst year affected by drought as per the Table 3. Also, it is more



(a) Parametric SPI S_P (b) Nonparametric SPI S_G

Fig. 1 Q-Q plot of parametric and nonparametric SPI with standard normal deviations for grid cell (12, 49) corresponding to latitude 18.5° and longitude 69.25°

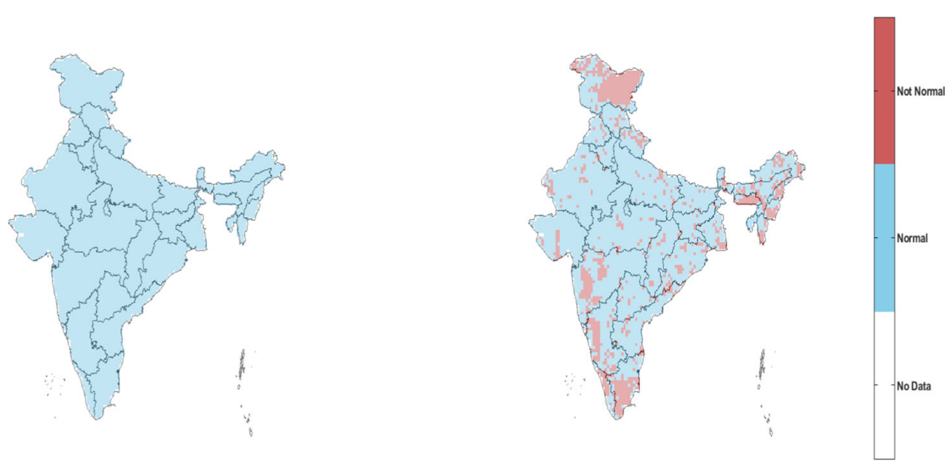
clear that from the percentage area under drought over India nonparametric SPI Θ_G given in Table 3 the dryness is more pronounced in the year 2002 as well.

The measure $\Theta_G - \Theta_P$ clearly shows that Θ_G exceeds Θ_P in all the 22 drought years considered in this study. Also, on average Θ_G exceeds Θ_P by around 1.6%, minimum being 1% in drought years 1911, 1941, and 1974 and a maximum of 2.5% in the year 2002. As the response to dryness is similar in all nonparametric methods (S_G, S_H, S_W), for all further investigations in this paper our comparisons will be only with nonparametric SPI (S_G) and parametric SPI (S_P).

6.4 Quantitative analysis of SPI-4 time series

To understand whether S_G is a better index than S_P, a quantitative analysis using quantiles is carried out in this section. For the drought year 2002, S_P, S_G is obtained

Fig. 2 Normality map obtained from Shapiro-Wilk test outcome for parametric and nonparametric SPI time series (1901–2013) for all grid cells over the Indian region



(a) NonParametric SPI (S_G) (b) Parametric SPI (S_P)

Table 2 Percentage of grid cells showing nonnormality in SPI

Method	June	July	August	September	June–September
S_P	15.3	17.2	14.3	15.3	19.6
S_G	0	0	0	0	0
S_W	0	0	0	0	0
S_H	0	0	0	0	0

for all grid cells and quantiles are computed for the intervals 0,0.025,0.25,0.5,0.75,0.975, and 1.0. These results are tabulated in Tables 4 and 5. In Table 4, quantiles of S_P and S_G time series are presented for those grid cells where S_P is not following normality. Out of 4642 grid cells covering India, 911 grid cells in S_P do not follow normality. From Table 4, we can see that the quantiles 0 and 0.025 the SPI values correspond to extreme dryness (ED) category as per both S_P and S_G. However, the total of grid cells in ED category as per S_P is only 23, i.e., 2.5%, whereas S_G is 63 grid cells, i.e., 6.9%. S_G shows a higher percentage of grid cells (4.4%) in the ED category compared with S_P. At 0.25 quantile, both S_P and S_G agree on the grid cells being under severe dryness (SD); however, S_P shows 3% more under this category than S_G. One possible reason could be S_P underestimating extreme dryness grid cells as belonging to the severe dryness category. At 0.5 quantile around the S_P value is -0.96 which is near normal category whereas S_G shows -1.27 which represents moderate dryness. The S_P values show near normal in 25.1% of grid cells but as per S_G, 24.9% of grid cells are under the moderate dryness category. The remaining quantiles from 0.75 to 1.0, the S_P and S_G agree on the drought category and the percentage of grid cells under that category.

In Table 5 where the grid cells are normal in both S_P and S_G, at the quantiles 0 and 0.025, 2.5% of the grid cells in S_P show extreme dryness, whereas 9.71% in S_G belong to this category. S_G shows higher percentages of grid cells up

Table 3 Comparison of percentage area under drought parametric SPI(Θ_P) and nonparametric SPI computed using Gringorten(Θ_G), Weibull (Θ_W), and Hazen (Θ_H) plotting position for drought years given in Shewale and Kumar (2005) using June–September rainfall from 1901 to 2013 over India

Year	Θ_P	Θ_G	Θ_W	Θ_H	$\Theta_G - \Theta_P$
1918	50.5	52.2	52.2	52.2	1.7
2002	48.6	51.1	51.1	51.1	2.5
1987	44.1	45.6	45.6	45.6	1.5
1972	40.3	42.1	42.1	42.1	1.8
1979	39.5	41.2	41.2	41.2	1.7
1974	35.7	36.7	36.7	36.7	1.0
1965	33.1	34.4	34.4	34.4	1.3
1905	30.6	31.8	31.8	31.8	1.2
1982	28.4	30.1	30.1	30.1	1.7
1951	28.2	30.0	30.0	30.0	1.8
1920	28.0	29.6	29.6	29.6	1.6
1911	26.1	27.1	27.1	27.1	1.0
1941	26.0	27.0	27.0	27.0	1.0
1968	25.2	26.9	26.9	26.9	1.7
2000	24.7	26.3	26.3	26.3	1.6
1985	24.0	26.2	26.2	26.2	2.2
1913	24.3	26.1	26.1	26.1	1.8
1966	24.1	25.7	25.7	25.7	1.6
1915	23.7	24.8	24.8	24.8	1.1
1939	21.8	23.2	23.2	23.2	1.4
1907	18.7	19.8	19.8	19.8	1.1
1925	13.7	14.8	14.8	14.8	1.1

Table 4 Quantile analysis for 2002 where the grid cells in S_P are not normal and S_G is normal

Quantile	S_P	$\#S_P$	S_G	$\#S_G$	$\%S_P$	$\%S_G$
0	− 9.17	1	− 2.58	63	0.1	6.9
0.025	− 4.12	22	− 2.58	0	2.4	0
0.25	− 1.77	205	− 1.86	173	22.5	19.0
0.50	− 0.96	228	− 1.27	227	25.1	24.9
0.75	− 0.12	227	− 0.2	223	24.9	24.5
0.975	1.4	205	1.38	203	22.5	22.3
1.0	3.85	23	2.58	22	2.5	2.4

to 7.2% are in extreme dryness than S_P. On the other hand, in the quantiles from 0.5 to 1.0, both S_P and S_G agree on the drought category and the percentage of grid cells in this category.

From Tables 4 and 5, one can see S_G can detect a higher percentage of grid cells being under extreme dryness category than S_P. The drought conditions in grid cells that do not follow normality in S_P are underestimated as severe dryness in place of extreme dryness and near normal instead of moderate dryness when compared with S_G. Even in grid cells where S_P follows normality, the underestimation of drought situation can be evidenced from Table 5.

6.5 Spatial analysis on agreements in drought classes

To understand the spatial agreement among drought classes corresponding to S_P and S_G, a confusion matrix is constructed for the drought year 2002 and tabulated in Table 6. Table 6 clearly shows substantial disagreement in the number of pixels supposed to be in severe dryness (SD) class. Out of 667 grid cells in SD class, 133 (19.9%) grid cells are misclassified as belonging to the ED class. Likewise, around 7% of grid cells are misidentified as moderate dryness (MD). Also, the ED cases, around 83 (12.3%) grid cells are incorrectly labeled as SD. One can see the gross incorrect estimation of dryness by parametric SPI (S_P) over nonparametric SPI (S_G). The spatial drought maps for all grid cells obtained from S_P and S_G for drought years 1982 and 2002 over the Indian region is shown in Figs. 3 and 4 respectively. The map clearly shows the spatial differences wherein underestimation of drought situation is more conspicuous in S_P compared with S_G. To see whether the normality of SPI is a reason for the overestimation of drought, confusion matrices were constructed for grids cells that show normality in both S_P and S_G (see Table 7) and those that do not follow normality (see Table 8). In the case of grid cells that are normal in both S_P and S_G (see Table 7), around 124 (20.5%) grid cells are estimated as ED and 39 (6.5%) as MD instead of SD. Also, around 55 (9.9%) grid cells in the ED category are misrepresented as SD. In contrast where the grid cells are not following normality (see Table 8) in S_P, around 13.84% is estimated as ED and 12.3% as MD instead of SD. Interestingly, around 22.9% of grid cells are incorrectly labeled as SD instead of ED when the normality condition is met in S_G but not in S_P. Clearly, in the case where there is nonnormality in parametric SPI (S_P), an increase in misrepresentation of grid cells up to 3% as extreme dryness category instead of severe dryness. Therefore, there is now strong evidence of drought underestimation in grid cells where S_P and does not follow normality.

The spatial maps of drought classes derived from parametric SPI (S_P) and nonparametric SPI (S_G) for all grid cells are shown in Figs. 3 and 4.

To understand the degree of agreement among drought classes derived from S_P and S_G, Cohen's kappa is computed using Eq. 12 as given in Section 4.3 for drought years

Table 5 Quantile analysis for 2002 where the grid cells in S_P and S_G follow normality

Quantile	S_P	$\#S_P$	S_G	$\#S_G$	$\%S_P$	$\%S_G$
0	− 4.37	1	− 2.58	205	0.0	5.5
0.025	− 2.76	92	− 2.58	0	2.5	0
0.25	− 1.55	840	− 1.57	750	22.5	20.1
0.50	− 0.97	933	− 0.98	955	25.0	25.6
0.75	− 0.3	932	− 0.3	899	25.0	24.1
0.975	1.19	840	1.22	833	22.5	22.3
1.0	3.28	93	2.58	89	2.5	2.4

Table 6 Confusion matrix between the drought classes obtained from S_P and S_G for drought year 2002

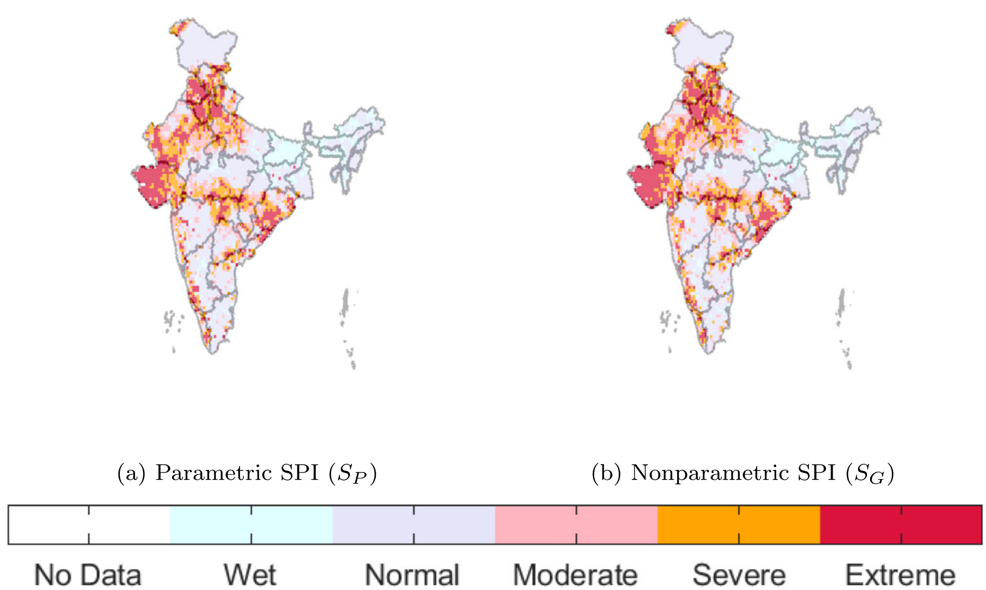
(S_P/S_G)	WT	NN	MD	SD	ED
WT	1228	34	0	0	1
NN	28	1206	89	3	5
MD	0	28	558	95	24
SD	0	0	47	487	133
ED	0	0	4	83	589

considered in this study. The results are tabulated in Tables 9 and 10. Table 9 shows Cohen's kappa (κ) for grid cells which are normal in S_G and do not follow normality in S_P. In Table 9, for the year 1939, κ is found to be 0.15 which means the two raters S_P and S_G have a slight agreement. The κ for years $2000, 1913, 2002, 1911$, and 1905 was found to be $0.21, 0.36, 0.38, 0.42$, and 0.44 respectively which is fair agreement as per Cohen's kappa classification given in Eq. 13. From Table 9, one can observe the disagreements between S_P and S_G are higher in the ED category. Table 10 shows Cohen's kappa (κ) for the grid cells where both S_P and S_G are normal. From Table 10, we observe the Cohen's kappa (κ) ranges from 0.71 to 0.99 which according to Eq. 13 indicates a substantial to perfect agreement among drought classes.

6.6 Temporal analysis on agreements in drought classes

To understand the temporal disagreement, Cohen's kappa is computed for each grid cell using S_P and S_G for drought years considered in this study. The results are tabulated in Table 11. From Table 11, one can see that in 95 grid cells there is only a slight agreement in the drought categories derived from S_P and S_G. In 307, i.e., 6.6% of grid cells, S_P and S_G have fair agreement on the drought situation, whereas in 642 grid cells. i.e., 13.8% there is moderate agreement. There is substantial to almost perfect agreement between S_P and S_G in 1480 and 2118 grid cells, i.e., 31.9% and 45.6% respectively. A spatial map of Cohen's kappa is shown in Fig. 5. In the Montane climate regions which are characterized by high rainfall variability, the agreement between S_P and S_G varies from slight to a moderate agreement, whereas in the tropical wet region, most of the grid cells show fair agreement between S_P and S_G. Even in the semi-arid and arid regions, the agreement between S_P and S_G ranges from slight agreement to moderate agreement. Therefore, one may conclude that in regions of high rainfall variability the agreements are low between S_P and S_G during the drought years.

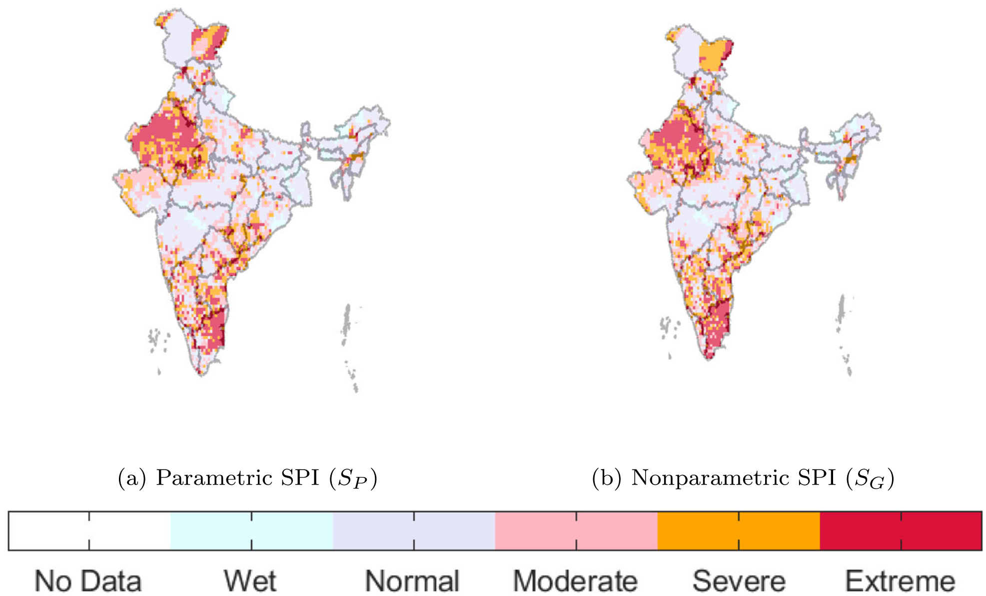
Therefore, there is clear evidence from the present work that parametric SPI deviates from normality in some of the grid cells which might have led to an underestimation of the drought situation. Also, in regions of high rainfall variability S_P and S_G, the agreements are not almost perfect. Moreover, there is an underestimation of the drought situation by S_P compared with S_G. Therefore, assessment on dryness by S_P may be erroneous especially



(a) Parametric SPI (S_P) (b) Nonparametric SPI (S_G)

Fig. 3 Spatial map showing extent of drought estimated by parametric and nonparametric SPI for drought year 1987

Fig. 4 Spatial map showing extent of drought estimated by parametric and nonparametric SPI for drought year 2002



in the grid cells where normality conditions are not met and in regions where there is a high degree of rainfall variability.

7 Discussion

The parametric SPI is a widely adopted measure to assess drought situation across the globe. This popularity is basically due to simplicity in its computation, and adaptability to different time scales and climate regions. The computation of parametric SPI requires a probability distribution function that fits the rainfall time series data (Lloyd-Hughes and Saunders 2002; Stagge et al. 2015). Several choices of distributions have been suggested in the literature for computing SPI from rainfall time series of different parts of the world (Livada and Assimakopoulos 2007; Zhang et al. 2009). However, it is now understood that whatever the chosen probability density function, SPI values will remain sensitive in the tail regions of the distribution (Farahmand A and AghaKouchak A 2015). That means, the fitted function upon transformation to standard normal, shows some residual skewness, i.e., non-conformity in the tail regions. This may distort SPI values and may affect drought interpretation. Also, studies in Kumar Naresh et al. (2009) and Kumar Naresh et al. (2012) pointed out that the SPI is sensitive to the choice of distribution; and in regions of high rainfall variability, it underestimates or overestimates the drought situation over India. On the other hand, nonparametric methods are found to be more flexible as there is no need to specify the probability distribution function (Hao et al. 2014) for computing the SPI. In the literature, Weibull and Gringorten formulae are the most extensively used nonparametric methods (Soláková T et al. 2014). When these techniques are applied to the computation of SPI, the time series did not show any marked difference with respect to the number of pixels deviating from the normality. Moreover, the effects of extrapolation normally encountered in nonparametric methods are not seen in our interpretation of SPI (Soláková T et al. 2014).

In the present study, we have computed the SPI both from parametric and nonparametric to understand which one of them would be suitable for drought interpretation. It is observed that the parametric SPI-4 showed negative skewness in 6.3% for the June to September rainfall,

Table 7 Confusion matrix between drought classes for grid cells normal in both (S_P) and (S_G) for drought year 2002

S_P/S_G	WT	NN	MD	SD	ED
WT	946	10	0	0	0
NN	26	914	56	0	1
MD	0	28	505	77	12
SD	0	0	39	439	124
ED	0	0	0	55	499

Table 8 Confusion matrix between drought classes for grid cells which are normal in S_G and not normal in S_P drought year 2002

S_P/S_G	WT	NN	MD	SD	ED
WT	282	24	0	0	1
NN	2	292	33	3	4
MD	0	0	53	18	12
SD	0	0	8	48	9
ED	0	0	4	28	90

whereas no skewness is found in nonparametric SPI. It is observed that in 19.6% of grid cells, the parametric SPI-4 time series do not follow normality compared with 0% in nonparametric SPI-4 time series. Quantitative analysis between parametric and nonparametric SPI-4 time series revealed that parametric SPI is underestimating dryness especially in the drought year 2002; in the grid cells where parametric SPI follows normality, only 2.5% show extreme dryness, whereas nonparametric SPI shows 6.9%. Even in the case where grid cells follow normality in parametric SPI, around 2.5% are under extreme dryness as per parametric SPI, whereas 9.7% of grid cells are under ED as per nonparametric SPI. The analysis of the confusion matrix between parametric- and nonparametric-derived SPI for the 2002 drought year showed incorrect categorization of the ED category by parametric SPI. More than 22.9% of grid cells are incorrectly labeled as SD instead of ED. The Cohen's kappa for years 2002, 1913, 2002, 1911, and 1905 was found to be under the fair agreement category. Around 19.4% of grid cells show less than chance agreement to moderate agreement between parametric SPI and nonparametric SPI. Most interestingly, the spatial map of Cohen's kappa showed that in climate regions of high rainfall variability the parametric and nonparametric SPI may tend to show slight to a moderate agreement only.

The present study demonstrates the computation issues in parametric and nonparametric SPI and attempts to bring out differences in interpretation of the drought situation. The parametric SPI had to be used with caution when being used in regions having high rainfall variability. It is found

Table 9 Cohen's kappa statistic arising out of intercomparison of drought class among grid cells not normal in S_P but normal in S_G for all India drought years

Year	WT	NN	MD	SD	ED
1905	0.88	0.82	0.80	0.83	0.44
1907	0.93	0.83	0.87	0.85	0.83
1911	0.88	0.88	0.86	0.82	0.42
1913	0.91	0.78	0.90	0.73	0.36
1915	0.90	0.86	0.86	0.70	0.70
1918	0.73	0.76	0.76	0.58	0.63
1920	0.56	0.82	0.75	0.72	0.70
1925	0.89	0.85	0.85	0.95	0.50
1939	0.90	0.85	0.81	0.77	0.15
1941	0.79	0.87	0.94	0.80	0.83
1951	0.90	0.84	0.79	0.85	0.63
1965	0.88	0.83	0.92	0.56	0.60
1966	0.92	0.83	0.82	0.69	0.58
1968	0.88	0.80	0.89	0.73	0.46
1972	0.93	0.77	0.78	0.75	0.75
1974	0.93	0.80	0.94	0.67	0.62
1979	0.95	0.73	0.92	0.67	0.55
1982	0.86	0.79	0.84	0.68	0.53
1985	0.86	0.74	0.86	0.62	0.60
1987	0.88	0.81	0.59	0.71	0.70
2000	0.94	0.76	0.54	0.66	0.21
2002	0.95	0.61	0.53	0.74	0.38

Table 10 Cohen's kappa statistic arising out of intercomparison among drought classes for pixels that are normal in both S_P and S_G for all India drought years

Year	WT	NN	MD	SD	ED
1905	0.96	0.92	0.82	0.76	0.88
1907	0.97	0.89	0.85	0.76	0.89
1911	0.97	0.91	0.80	0.74	0.83
1913	0.98	0.87	0.84	0.84	0.74
1915	0.96	0.91	0.83	0.78	0.84
1918	0.98	0.90	0.80	0.71	0.84
1920	0.97	0.90	0.84	0.72	0.82
1925	0.98	0.91	0.82	0.79	0.76
1939	0.97	0.88	0.81	0.79	0.75
1941	0.97	0.90	0.82	0.76	0.91
1951	0.96	0.86	0.84	0.76	0.93
1965	0.97	0.89	0.79	0.74	0.80
1966	0.97	0.90	0.84	0.77	0.89
1968	0.96	0.89	0.80	0.74	0.87
1972	0.97	0.89	0.84	0.74	0.88
1974	0.98	0.91	0.81	0.68	0.82
1979	0.98	0.90	0.83	0.78	0.86
1982	0.97	0.88	0.78	0.73	0.82
1985	0.97	0.88	0.86	0.74	0.83
1987	0.99	0.89	0.78	0.68	0.88
2000	0.96	0.91	0.85	0.78	0.83
2002	0.98	0.91	0.82	0.68	0.80

that nonparametric SPI is a good candidate index for better interpretation and understanding meteorological droughts over India.

8 Conclusions

This paper presents an objective comparison of the SPI derived from parametric and nonparametric approaches for meteorological drought assessment. The SPI is a standardized index wherein classes are drawn based on deviations from the mean (McKee et al. 1993), its impact on assessment of drought due to nonnormality is a major concern. The crux of this paper is to evaluate the parametric and nonparametric SPI especially in the regions where normality conditions are not met and its impact on drought interpretation and categorization. Accordingly, the skewness and normality of SPI from parametric and nonparametric methods were computed and compared using June–September southwest monsoon season rainfall data from 1901 to 2013. Higher nonnormality and skewness are observed in parametric SPI, whereas nonparametric methods did not show any such deviation.

One of the ways to assess the drought situation is to measure the degree and extent of dryness represented by the SPI. Accordingly, the comparison of percentage dryness revealed that in drought nonparametric SPI has better represented the dryness compared with parametric

Table 11 Cohen's kappa statistics for each grid cell computed using SPI for all drought years to assess agreement between S_P and S_G

Category	#grid cells	%grid cells
Less than chance agreement	0	0
Slight agreement	95	0
Fair agreement	307	6.6
Moderate agreement	642	13.8
Substantial agreement	1480	31.9
Almost perfect agreement	2118	45.6

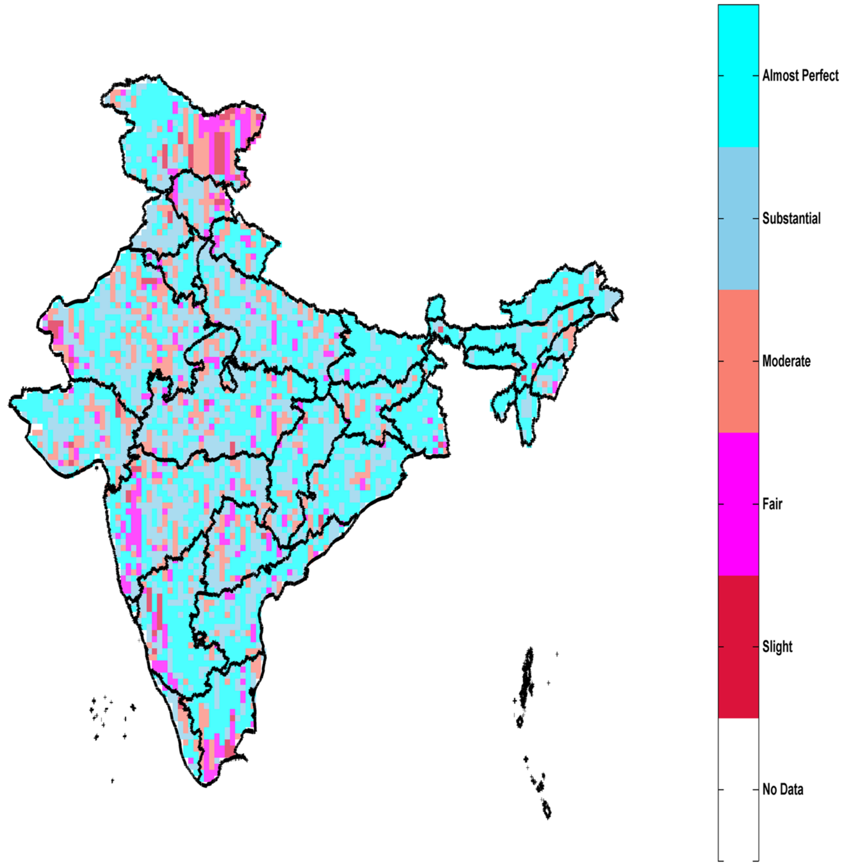


Fig. 5 Cohen's kappa category of each grid cell computed using S_P and S_G for drought years considered in this study

SPI. This is commensurate with the dryness represented by the rainfall deficit in all grid cells over the Indian region. Furthermore, our study on drought years 1901, 1904, 1905, 1911, 1918, 1920, 1941, 1951, 1965, 1966, 1968, 1972, 1974, 1979, 1982, 1987, and 2002 revealed that parametric SPI tends to overestimate the level of dryness at a location as it categorizes severe dryness as extreme in the case of grid cells following normality in both SPI, whereas in grid cells where parametric SPI does not follow normality, there is an underrepresentation of extreme dryness cases as severe dryness. A comparison of Cohen's kappa statistic for all drought years between the parametric SPI and nonparametric SPI for all drought classes revealed the disagreement between them is higher in ED class compared with other classes, and this observation is consistent in grid cells where parametric SPI does not follow normality.

This study thus concludes that the normality of SPI is an important aspect to be considered while assessing the drought situation. Furthermore, nonparametric SPI has provided an index that has zero skewness and 100% normality conditions met in all grid cells over the Indian region. Moreover, it is reported in the recent past on climate change phenomena that the reason for observation of rainfall variability is not consistent with historic patterns. Under such circumstances, the nonparametric approach of computing SPI can effectively capture the underlying drought conditions. Since the current study covers a larger geographic area characterized by high rainfall variability and longer time series, one may assume the results of this study to be stable. Furthermore, work needs to be oriented toward how the drought characteristics and frequency can be characterized using nonparametric SPI and multivariate drought indices. This would be the focus of our subsequent studies on drought over the Indian region.

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