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RESEARCH ARTICLE

Statistical Modeling of Extreme Drought Occurrence in Bellary District of Eastern Karnataka

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Abstract Drought is a natural hazard which may temporarily affect any region in the world by several means. In the present study frequency analysis of meteorological drought in the Bellary region of Karnataka has been investigated for 52 years (1961–2012) using the Standardized Precipitation Index (SPI) at short (SPI-1 and SPI-3), medium (SPI-6) and long (SPI-12) time scales. This method aims to provide a concise overall picture of drought, regardless of the actual probability distribution of the observed cumulative amount of rainfall for a given time scale. By applying the SPI methodology, results indicated that drought randomly affected a region and several drought events occurred during the period analyzed. The generalized extreme value (GEV) distribution was fitted to data from the location to describe the extremes of rainfall and to predict its future behavior. Minimum assured drought at 50 % probability level was observed to be a better representative of long-term average of drought (minimum SPI) in the region as depicted by the GEV distribution. The return period analysis indicate that the region experiences extreme drought (SPI < -2) every ten or less years for all time scales, whereas moderate to severe drought occurs every alternate year. There is thus a necessity to prepare contingency plans for the region and focus on the cultivation of those crops with a capacity of withstanding droughts of moderate intensity which will be used as a guide for water resource management in the region during droughts.

Keywords Auto-correlation · Drought risk · Generalized extreme value distribution · Return levels · Standardized Precipitation Index

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Introduction

During the last few decades water resource managers are facing severe challenges of ensuring water availability all over the world and increasing trends of higher temperature and decreasing precipitation have intensified the occurrence of drought [1]. Drought is a disastrous natural phenomenon that has significant impacts on the economy, environment, industries and the community. The absence of a precise and universal accepted definition of drought adds to the confusion about whether or not a drought exists and if it does what is its level of severity. Although Wilhite and Glantz [2] analyzed more than 150 definitions, many of them do not adequately define drought in meaningful terms for scientists and policy makers. Research has shown that the lack of a precise and objective definition in specific situations has been an obstacle to understand drought that has led to indecision and inaction on the part of managers, policy makers and others. Timely determination of the occurrence and level of drought will assist in the decision making process to reduce the impact of droughts. Some of the widely used drought indices are the Palmer Drought Severity Index (PDSI) [3], the Deciles [4], the Standardized Precipitation Index (SPI) [5] and the Reconnaissance Drought Index (RDI) [6]. All these indices have their own capability to assess drought under different situations. The Standardized Precipitation Index, known as SPI, seems to be the most popular among the existing simple indices for the estimation of drought because it is simple (low data requirements), spatially consistent in its interpretation, probabilistic so that it can be used in risk management and decision analysis, and can be tailored to time periods of user's interest [7].

Out of 329 m ha of total geographical area in India about 107 m ha of lands are subjected to different degrees of water stress and drought conditions [8]. Identification of drought prone areas provides useful information for planning and optimal operation of irrigation systems. Patel et al. [9] focused on investigation variability of seasonal drought events in Gujarat where it was concluded that SPI at a 3 month time scale was found effective in capturing seasonal drought patterns over space and time. Alam et al. [10] developed stochastic model for drought forecasting for one of the most drought affected area viz. Bundelkhnad region which can predict drought up to 3 months in advance with good accuracy using SPI as drought indicator.

Rainfed agriculture has a distinct place in India, occupying 58 % of the cultivated area, contributing 40 % of the food grain production, support 40 % of the human and 65 % of the livestock population [11]. The Bellary region falls in the state of Karnataka which has the second largest arid zone after Rajasthan in terms of total geographical area prone to drought [12]. The northern region of Karnataka bordering the neighboring state of Andhra Pradesh is classified as a semi-arid region falling in the rain shadow region with an annual average rainfall of 503 mm, received in 35 rainy days with a high variability (184–949 mm year^{-1}) [13]. Drought analysis indicates that 5 droughts of varying intensities occur in a decade. Low rainfall and a short growing season (8–14 weeks) restrict the choice of crops, limit ground water recharge and often lead to high soil erosion rates due to the nature of the soils, which are highly dispersible clays (Vertisols). In recent years the occurrence of drought in the Bellary region has been experienced with higher peaks and intensity. To the best of authors' knowledge, no systematic study has been conducted to analyze the extreme drought events using extreme value distribution in Indian condition. The present study aims to analyze temporal variation and frequency analysis of meteorological droughts using SPI in Bellary region and to undertake frequency analysis of drought using the generalized extreme value (GEV) distribution.

Material and Methods

Dataset

Daily rainfall recorded at the meteorological observatory of Central Soil and Water Conservation Research and Training Institute, Research Centre, Bellary was used in the analysis. The observatory is situated at 15°09′ N latitude and 76°51′ E longitude at an elevation of 445 m above MSL. Daily rainfall for the last 52 years (1961–2012) was computed and used for the study. The distribution of monthly rainfall over the study period has been shown in Fig. 1.

The Standardized Precipitation Index (SPI)

McKee et al. [5]. developed the SPI to quantify the precipitation deficit for multiple time scales, reflecting the impact of precipitation deficiency on the availability of various water supplies. The SPI provides a quick and handy approach to drought analysis. Other advantages of this approach are its relative simplicity and minimal data requirements.

Computation of the SPI involves fitting a gamma probability density function to a given time series of precipitation, whose probability density function is given by the following expression:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \tag{1}$$

where $\alpha > 0$ is a shape parameter, $\beta > 0$ is a scale parameter, and $x > 0$ is the amount of precipitation. $\Gamma(\alpha)$ is the gamma function, which is defined as under:

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \tag{2}$$

Fitting the distribution to the data requires α and β to be estimated. Using the approximation of Thom [14], these parameters can be estimated as follows:

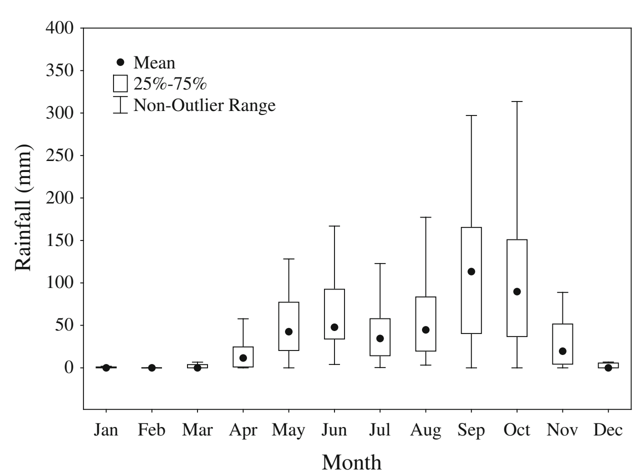


Fig. 1 Monthly distribution of rainfall in Bellary region for the period 1961–2012

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \beta = \frac{\bar{x}}{\alpha}, \quad \text{with } A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{3}$$

where n is the number of observations. Integrating the probability density function with respect to x yields the following expression G(x) for the cumulative probability:

$$G(x) = \frac{1}{\Gamma(a)} \int_0^x t^{\alpha-1} e^{-1} dt \tag{4}$$

It is possible to have several zero values in a sample set. In order to account for zero value probability, since the gamma distribution is undefined for $x = 0$, the cumulative probability function for gamma distribution is modified as:

$$H(x) = q + (1 - q)G(x) \tag{5}$$

where q is the probability of zero precipitation.

Finally, the cumulative probability distribution is transformed into the standard normal distribution to yield the SPI. Following the approximate conversion provided by Abramowitz and Stegun [15], it results:

$$z = \mathrm{SPI} = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \text{ for } 0 < \mathrm{H(x)} < 0.5 \tag{6}$$

$$z = \mathrm{SPI} = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad t = \sqrt{\ln\left(\frac{1}{(1.0 - H(x))^2}\right)} \text{ for } 0.5 < \mathrm{H(x)} < 1.0 \tag{7}$$

and $c_0 = 2.515517$; $c_1 = 00802853$; $c_2 = 0.010328$; $d_1 = 1.432788$; $d_2 = 0.189269$; $d_3 = 0.001308$.

Once standardized, the strength of the SPI, as given in Table 1 [16] can be visualized to categorize drought.

1-Month SPI and 3-month SPI reflect short term moisture condition and provides a seasonal estimation of precipitation. In primary agricultural regions, a 1- and 3-month SPI might be more applicable in highlighting available moisture conditions. A 6-month SPI indicates medium-term trends in precipitation and is considered to be more sensitive to conditions at this scale than the Palmer Index. A 12-month SPI reflects long-term precipitation patterns and is probably related to estimation of stream flows, reservoir levels, and even groundwater levels on longer time scales. In some locations, the 12 month SPI is most closely related with the Palmer Index, and the two indices (SPI-12 and Palmer Index) usually reflect similar conditions.

Table 1 Drought classification by SPI value and corresponding event probability

SPI value	Drought category
$-0.99 \leq \mathrm{SPI} < 0$	Mild-drought
$-1.49 \leq \mathrm{SPI} \leq -1.00$	Moderate drought
$-1.99 \leq \mathrm{SPI} \leq -1.5$	Severe drought
$\mathrm{SPI} \leq -2.00$	Extreme drought

The Generalized Extreme Value (GEV) Distribution

The GEV distribution is a family of continuous probability distributions that combines the Gumbel, Frechet and Weibull distributions. GEV makes use of 3 parameters- location, scale and shape. The location parameter describes the shift of a distribution in a given direction on the horizontal axis. The scale parameter describes how spread out the distribution is, and defines where the bulk of the distribution lies. The shape parameter strictly affects the shape of the distribution. The GEV distribution is derived from the characterization of extremal properties of random process. Denoting daily observations by X_1, X_2,…, the classical model for extremes is obtained by studying the behavior of $M_n = \max\{X_1;\ldots;X_n\}$ for large values of n. With n = 365, M_n corresponds naturally to the annual maximum. Asymptotic considerations suggest that the distribution of M_n should be approximately that of a member of the GEV family [17, 18], having distribution function.

$$F(z|\mu, \sigma, \xi) = exp\left(-\left[1 + \xi\left(\frac{z - \mu}{\sigma}\right)\right]^{-1/\xi}\right) \tag{8}$$

with parameter space $\{(\mu, \sigma, \xi) : \mu \in \mathbb{R}, \sigma > 0, \xi \in \mathbb{R}\}$.where, μ is the location parameter, σ is scale parameter and ξ is shape parameter. The three extremal types are determined by the sign of ξ arriving at the Weibull distribution for $\xi < 0$, the Gumbel for $\xi = 0$, and the Freechet for $\xi > 0$. Equation 1 assumes that data are maximum or minimum from block of times.

For the GEV distribution given in (1), the return level is given by the following equation:

$$\hat{z}_p = \begin{cases} \mu - \frac{\sigma}{\xi}\left[1 - y_p^{-\xi}\right] & \text{for } \xi \neq 0 \\ \mu - \sigma log y_p & \text{for } \xi = 0 \end{cases} \tag{9}$$

where $z_p = -\log(1 - p)$.Better estimates for parameters and return level are obtained from the profile likelihood. To obtain the profile likelihood for the shape parameter, one fixes $\xi = \xi_0$ and maximizes the log-likelihood with respect to the remaining parameters, μ and σ [19]. This is repeated for a range of values of ξ_0. The corresponding maximized values of the log-likelihood constitute the profile log-likelihood for ξ that is used to obtain approximate confidence intervals.

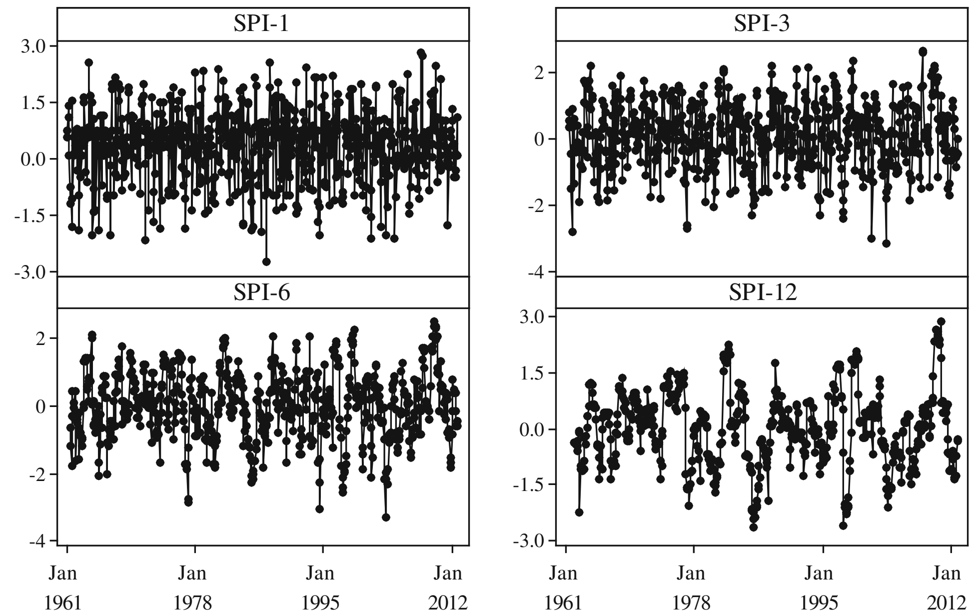


Fig. 2 Time series plot of SPI series at different time scale (1, 3, 6 and 12 month)

Anderson–Darling (A–D) Test for Goodness of Fit Test

In the present study for testing GEV fit of data sets, the Anderson–Darling test [20] has been used which tests the null hypothesis (H_0) that the data follow a normal GEV distribution. If the p value for the test is greater than the chosen α-level (0.05), then the null hypothesis is accepted and it can be concluded that the data follow GEV probability distribution.

Results and Discussion

Standardized Precipitation Index values have been computed for Bellary region at multiple time scales (1, 3, 6 and 12) using average monthly rainfall. The time series of SPI values computed for Bellary region for different time scale have been shown in Fig. 2. From the time series of monthly SPI series, it is clear that the region experienced frequent droughts and several severe and extreme drought events were detected at multiple time scale during the period under study [21]. It is also evident from the figure that drought frequency changes as the time scale changes. The summary statistic of different SPI series has been shown in Table 2. At a shorter time scale (SPI-1 and SPI-3) drought frequency increases with shorter duration whereas longer duration are less frequent but medium scale (SPI-6) and longer scale (SPI-12) drought has been observed on a higher time scale. The area experienced frequent drought for all months. But for higher time scale (SPI-12) maximum frequency of drought (most frequent negative SPI value) has been observed in the month of June. The most extreme drought was observed in July 1987 (SPI $= -2.80$) for SPI-1 and May 2003 (SPI $= -3.18$) for SPI-3, whereas for SPI-6 and SPI-12 extreme drought was observed during May, 2003 (SPI $= -3.32$) and October, 1985 (SPI $= -2.64$), respectively. Summary of occurrence of droughts of varying intensities based on SPI values has been presented in Table 3. The total number of moderate and higher drought months for 1, 3, 6 and 12 month time scale was 66, 83, 96 and 96, respectively.

The temporal variability of all the SPI series within the study area and their correlation structure were analyzed through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) [22]. The ACF and PACF plots, computed for the SPI-1 series are shown in Fig. 3a, b, respectively. In both the figures the autocorrelation values are exceeding the upper and lower limits. These results suggest the presence of a significant correlation over time, thus SPI-1 series have a marked temporal dependence. Replication of the same analysis on the remaining SPI series (SPI-3, SPI-6 and SPI-12) revealed approximately the same temporal pattern i.e. for all the three series the autocorrelation values exceeded the upper and lower confidence limit, indicating presence of dependence among the observations (data not shown).A strong dependence between observations would break one of the main assumptions upon which extreme value models are built. As the consequence, both parameter and return level estimates may be severely biased [23].

The block-maxima approach aims to build a statistical model exclusively for maxima/minima of a time series. The annual minima gives 52 observations from 52 years. Figure 4a, b shows that all the correlation values are within confidence interval bands. This result suggests that yearly minima have weak dependence overtime. Therefore, use of

Table 2 Summary statistic of block minima of different SPI series

Statistical parameter	SPI-1	SPI-3	SPI-6	SPI-12
Mean	−1.365	−1.500	−1.303	−0.934
SD	0.581	0.621	0.786	0.827
Minimum	−2.803	−3.180	−3.324	−2.643
Q_1	−1.875	−1.848	−1.818	−1.418
Q_3	−0.954	−1.052	−0.784	−0.344
Maximum	−0.287	−0.294	−0.090	0.700

Q_1 = Fist quartile, Q_3 = third quartile, SPI-1, -3, -6 and -12 indicate SPI at time scale 1-month, 3-month, 6 month and 12 month

Table 3 Summary of occurrence of number of drought months (annual and *rabi* season) of varying intensities at different time scales

Drought severity	Drought months (1961–2012)							
	Mild drought		Moderate drought		Severe drought		Extreme drought	
	Jan–Dec	Sep–Dec	Jan–Dec	Sep–Dec	Jan–Dec	Sep–Dec	Jan–Dec	Sep–Dec
SPI-1	126	45	43	24	15	6	8	2
SPI-3	194	75	42	29	31	8	10	5
SPI-6	206	76	45	27	32	11	19	6
SPI-12	199	68	54	31	22	10	20	8

Sept–Dec *rabi* season in this part of the state is common for rainfed areas which use the receeding monsoons for crop production

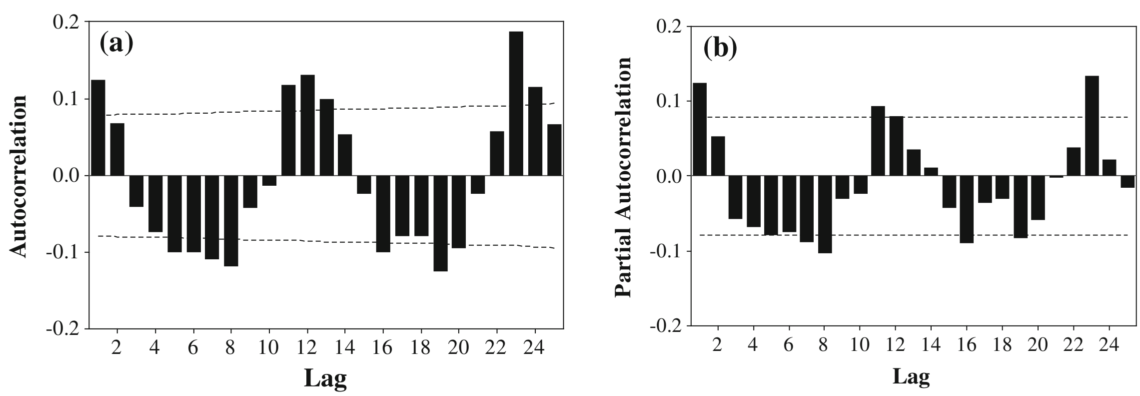


Fig. 3 Auto-correlation among monthly SPI-1 series of Bellary region

yearly minimum SPI data at different time scale is appropriate [23].

Frequency analysis was performed using GEV distribution for annual minimum values of SPI and drought severity at different return period. The data cover 52 minimum SPI series (i.e. minimum drought series) derived from the different SPI series. To fit a GEV distribution to the SPI series the usual method for maximum value applies by realizing that $\min(x_1, x_2, \ldots, x_n) = -\max(-x_1, -x_2, \ldots, -x_n)$ i.e., the GEV distribution was applied to the negative transformation of the data of minimum SPI series of each year.

The maximum likelihood estimate of GEV parameters of SPI-1, SPI-3, SPI-6, and SPI-12 has been presented in Table 4. According to the negative values of Shape parameter (ξ) it can be concluded that the Weibull distribution to SPI-1, SPI-3, SPI-6 and SPI-12 series is bounded above, meaning that there are finite values which the minimum SPI value cannot exceed [24].

Probability plots for assessing the accuracy of the GEV model fitted to different SPI series are represented in Fig. 5. If the probability distribution is a good fit for the data, the points form a straight line and fall within 95 % confidence interval (CI).The probability plots show the validity of the fitted model as each set of plotted points are close to linear. After fitting GEV distribution to different SPI series, testing the fit of the GEV probability density function was done using the Anderson–Darling (AD) goodness-of-fit test. The calculated

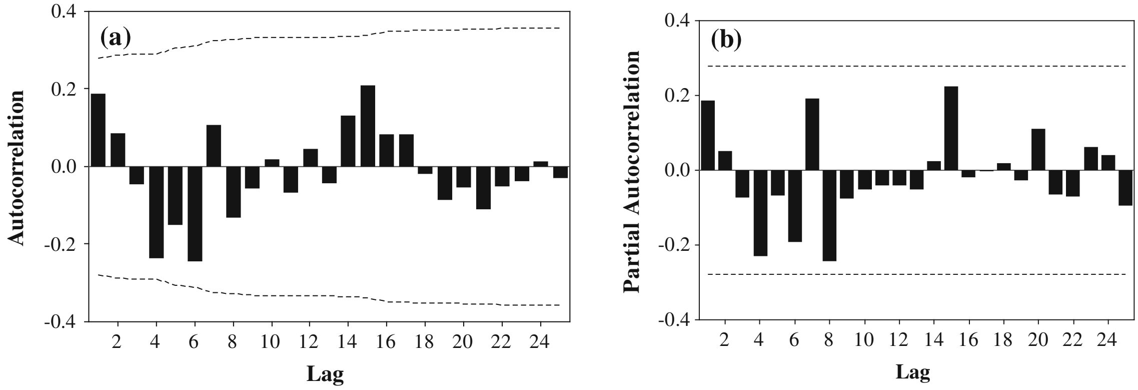
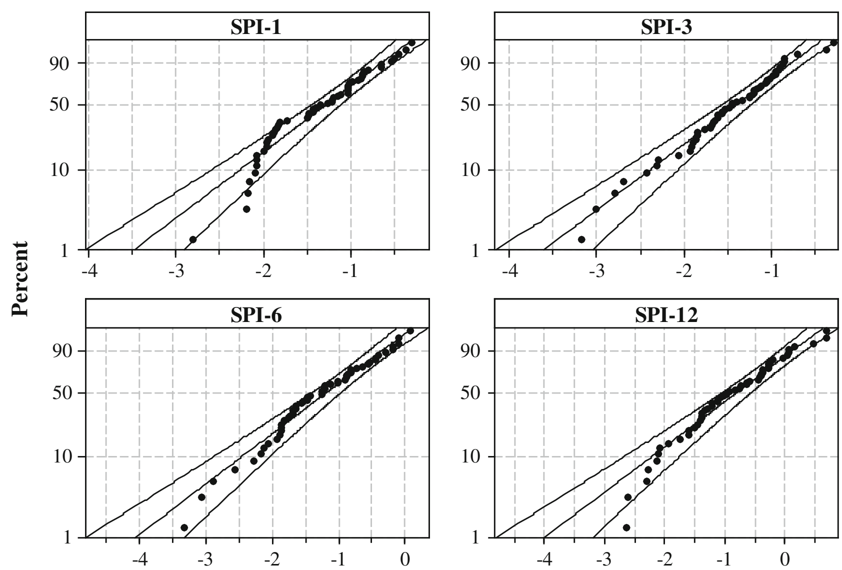


Fig. 4 Auto-correlation among yearly minimum SPI-1 series of Bellary region

Table 4 Maximum Likelihood Estimates (Standard error) of GEV distribution for different SPI series

Parameter	Maximum likelihood estimate			
	SPI-1	SPI-3	SPI-6	SPI-12
Location (μ)	1.149 (0.085)	1.239 (0.081)	0.988 (0.111)	0.639 (0.125)
Scale (σ)	0.554 (0.062)	0.529 (0.057)	0.714 (0.079)	0.800 (0.090)
Shape (ξ)	−0.239 (0.099)	−0.092 (0.091)	−0.162 (0.101)	−0.266 (0.108)

Fig. 5 Probability plot for the GEV fit to SPI-1, SPI-3, SPI-6 and SPI-12 series



test statistic (A^2) along with the probability value for SPI-1, SPI-3, SPI-6 and SPI-12 were determined to be 0.593 ($p = 0.97$), 0.315 ($p = 0.26$), 0.253 ($p = 0.52$) and 0.207 ($p = 0.32$), respectively which indicates that GEV distribution is an optimal choice for describing the underlying process.

The return level for each SPI series has been calculated using GEV distribution. The return level plot for all the three series has been presented in Fig. 6. As a consequence of the negative estimate of shape parameter (ξ) in all the SPI series, the return level curves are not linear [25]. From the figure it is clear that the region experiences long term extreme drought (SPI ≤ -2) every 10 years, whereas for medium term drought and short term drought the return period is <8 years. The most extreme droughts at short scale (SPI-1 $= -2.80$ and SPI-3 $= -3.18$) have been observed during July, 1987 and May, 2003 with return period of more than 100 and 70 years respectively, while the most extreme medium and longer scale extreme drought (SPI-6 $= -3.32$ and SPI-12 $= -2.64$) experienced in the region had a return period of 100 and 70 years, respectively.

Minimum assured drought amount (negative SPI) at different probability levels (0.1–0.9) was computed by

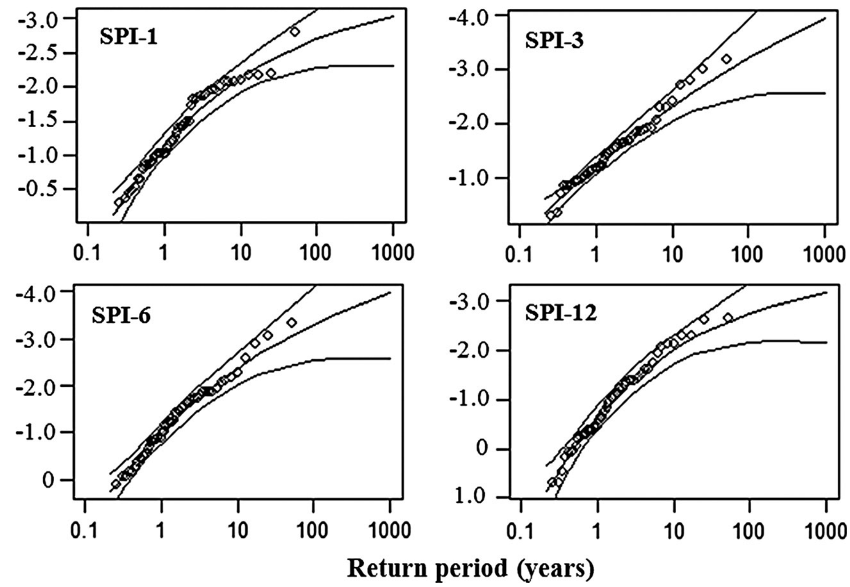


Fig. 6 Return level plots for GEV model of annual minima SPI-1, 3, 6 and 12 series

Table 5 Minimum assured drought at different time scale at different probability level employing GEV distribution

SPI series	Probability level									Normal SPI
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
SPI-1	−2.12	−1.85	−1.66	−1.49	−1.34	−1.20	−1.04	−0.89	−0.64	−1.36
SPI-3	−2.31	−1.98	−1.76	−1.58	−1.43	−1.29	−1.14	−0.98	−0.78	−1.50
SPI-6	−2.33	−1.93	−1.67	−1.44	−1.24	−1.05	−0.85	−0.63	−0.35	−1.30
SPI-12	−1.99	−1.63	−1.36	−1.13	−0.92	−0.71	−0.49	−0.23	−0.11	−0.93

using the GEV distribution for each of the SPI series and the results are presented in Table 5. It is evident from the analysis that for all the four SPI series, the estimated minimum drought is in close agreement with the long-term average weekly rainfall at 50 and 60 % probability levels.

Conclusion

The present study focused on analyzing frequency analysis of meteorological drought at a multiple time scale in the Bellary region using SPI as a drought indicator. For short, medium and longer time scale SPI-1, SPI-6 and SPI-12 has been used. Moderate, severe and extreme droughts are reasonably frequent in the region. Monthly SPI series at different time scale are highly correlated over time and return level estimates may be severely distorted. Yearly minima of SPI series, unlike monthly observations, are weakly correlated over time, justifying the choice of using the block-maxima approach, expressed by GEV models. The return level obtained using GEV suggests that the region experience extreme drought in every 10 years or less period for short, medium and long scale drought. Minimum assured drought at 50 % probability level was determined to be a better representative of long-term average SPI data in the region. Results and the conclusion reached in the present study can be an essential step toward addressing the issue to drought vulnerability in Bellary region and will be used as a guide for water resources management in the region during droughts.

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Conflict of interest The authors declare that there is no conflict of interest related to this study.

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