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Development of drought severity–duration–frequency curves for identifying drought proneness in semi-arid regions

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ABSTRACT

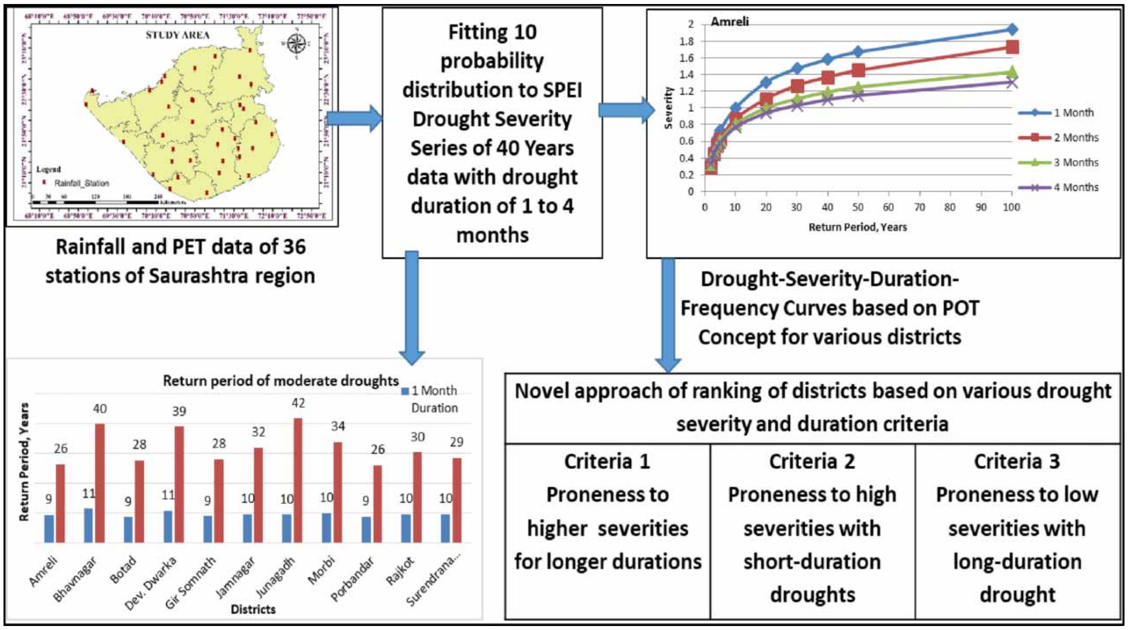
The effectual estimation of meteorological drought parameters such as severity, duration and frequency to plan suitable drought mitigation measures is challenging owing to the complex relationship among these parameters. The present study endeavored to assess the drought proneness of various districts of chronic drought prone Saurashtra region of Gujarat state (India). The district wise Drought Severity Duration Frequency (DSDF) curves were developed using Standardized Precipitation Evapotranspiration Index (SPEI) based on 40 years (1980 to 2019) data. The monthly drought severities of SPEI for various return periods ranging from 2 to 100 years were estimated by testing 10 probability distributions. The DSDF curves revealed that severe droughts were more prominent for shorter durations and identical severities were observed for 1 to 4 month drought duration for smaller rerun periods. As drought mitigation measures vary according to drought severity and duration, the study employed a novel approach of ranking the districts based on three criteria as proneness to higher severities for longer drought durations, high severities with short drought duration, and low severities with long drought duration. Rather than relying on rainfall or drought index-based judgement, the present study demonstrated the better alternative for drought risk assessment, resilience planning, and mitigation.

Key words: drought, drought severity–duration–frequency curve, evapotranspiration index, probability distribution, standardized precipitation

HIGHLIGHT

- Considering high spatial rainfall variability in semi-arid regions, the district-wise drought severity–duration–frequency curves were developed. The districts were ranked based on drought proneness in terms of high/low severity and longer-/shorter-duration droughts. The methodology established in the study will play a significant role in drought mitigation measures for agricultural and water resource management.

GRAPHICAL ABSTRACT



INTRODUCTION

Drought is a recurrent natural hazard and climate extreme affecting humans, plants, animals, and the environment. The occurrence of drought first triggers as metrological drought in terms of deficient rainfall and high evapotranspiration rates. The meteorological drought leads to agricultural drought in terms of soil moisture depletion and reduced crop acreage and yields, to hydrological drought in terms of depletion of surface and groundwater resources, and to socioeconomic drought in terms of economic loss and social distress. The meteorological drought cannot be avoided; however, its impacts on agriculture, water resources, and society can be minimized by taking the proper monitoring, risk assessment, and mitigation measures. Meteorological drought characterization involves the identification of drought onset, severity, duration, frequency, and spatial extent. Being a relative phenomenon, it is difficult to formulate a globally acceptable definition of drought for that reason, the drought assessment criteria are diverse and vary with regional climatic conditions (Todmal 2022). Therefore, comprehensive quantification of meteorological drought is very difficult owing to complex interactions among its characteristics. The efficient characterization of droughts and their proneness among the various regions is more crucial for countries like India where about 70–90% of its annual rainfall occurs during the southwest monsoon, i.e. from June to September (Kumar *et al.* 2021) and any failure in the southwest monsoon puts the country at high risk of socio-economic distress as a large portion of the population is agricultural dependent. Identification of drought proneness plays a key role in water management as droughts have the potential to affect a huge area over a long period (Won & Kim 2020).

There are a variety of approaches to modeling the drought starting from simplistic to more complex models (Mishra & Singh 2010). The region-oriented assessment of drought risk is the core of drought risk management, as well as the main means of regional sustainable development and combating global climate change (Xu *et al.* 2022). Mishra & Singh (2010) critically reviewed the drought modeling approaches and stated that probabilistic characterization of droughts is extremely important, primarily in those regions where accurate water resources planning and management requires detailed knowledge of water shortages. The probabilistic drought characterization includes (i) estimation of return periods for drought parameters and univariate drought analysis, (ii) bivariate drought analysis which deals with two drought parameters, (iii) multivariate drought analysis using copulas which include more than two drought parameters, and (iv) spatiotemporal drought analysis (Mishra & Singh 2010).

It is a generally accepted principle that the duration of a dry period and the degree of its severity are the two most important factors to determine meteorological drought resilience and preparedness. At present, there are three modes of regional drought assessment (Jin *et al.* 2016): the first is the curve assessment method based on the analysis of historical drought loss frequency, the second is the curve assessment method based on the physical genetic process of drought loss risk and the third is the assessment of drought risk based on the components of drought risk loss which is referred to as the weighted comprehensive assessment method (WCA). Tiwari *et al.* (2007) developed a methodology to characterize meteorological drought and drought frequency curves by fitting various frequency distributions and determining standardized drought severity indices. Many investigators have studied individual characteristics of drought using a probabilistic methodology; however, analysis of individual characteristics does not reveal the joint behavior of multiple attributes (Gupta *et al.* 2020). Presently, several operational drought monitoring systems in India treat them individually. Using the frequency of drought events alone is insufficient unless it is numerically related to the duration, severity, or intensity (Aksoy *et al.* 2021). A more rational approach to drought risk assessment is to compound both variables, based on multivariate relationships, such as S–D–F drought curves. However, the development of DSDF across various regions in India is limited (Sahana *et al.* 2021).

The rainfall intensity–duration–frequency (IDF) curves are graphical representations of the probability that a given average rainfall intensity will occur within a given period (Dupont & Allen 1999). The frequency (IDF) curve that is obtained after the frequency analysis can be used to estimate the magnitude of a hydrological event against various recurrence intervals. Similar to the approach of the IDF curve, drought severity–duration–frequency (DSDF) curves can be utilized to identify key relationships between the severities of drought for various recurrence intervals. To develop drought severity/IDF curves, frequency analysis is applied to the critical drought severity to determine the best-fit probability distribution function (Cavus & Aksoy 2020). The DSDF curves were explored by scientists to assess the relationship between the severity of drought with its duration and the recurrence interval (Halwatura *et al.* 2015; Won & Kim 2020). The task of ascertaining drought severity for various recurrence intervals assists in planning suitable measures to mitigate the ill effects of drought on agriculture, water resources, as well as the socioeconomic condition of the region.

Globally, various regional studies have been carried out to assess regional drought risk and via multivariate modeling to quantify the interrelationship between drought severity, duration, and frequency (Kumar *et al.* 2021; Sahana *et al.* 2021). For instance, Samantaray *et al.*(2019) carried out drought hotspot analysis and risk assessment using probabilistic drought monitoring and drought SDF analysis of mid-Mahanadi River Basin in Odisha using crop water stress as a drought indicator. Bazrafshan *et al.* (2020) analyzed the regional risk analysis and derivation of copula-based drought for the severity–duration curve in arid and semi-arid regions of Iran using the SPI index. Kumar *et al.* (2021) carried out a regional analysis of drought severity–duration curves in the Godavari River Basin, India. Aksoy *et al.* (2021) developed site-specific IDF curves furnished with an empirical relationship between the intensity and return period.

Some alternate approaches were used to assess the drought frequency and severity, e.g. Won *et al.*(2020) quantified Korean drought frequency based on copula function using partial duration series and bivariate exponential distribution, and application to climate change. They pointed out that to use the copula function, several drought events sample data representing various drought severities and various durations observed over a relatively long period should be secured. Therefore, when the number of drought events used in the analysis is only a few tens, it is difficult to secure the reliability of the result. Band *et al.* (2022) evaluated the effect of time series on modeling different monthly scales of SPI using the differencing approach. Shamshirband *et al.* (2020) predicted a standardized streamflow index for hydrological drought using machine learning models and the performance of the three models in forecasting the Standardized Streamflow Index using SPI and SPEI.

DSDF curves allow the drought to be determined not by the value of the drought index but by linking the severity, duration, frequency, and return period which is much more valuable for assessing the drought risk. Moreover, the present study introduced a novel approach to classify the various districts of the region not by only drought severity but by the proneness considering various scenarios, e.g. short-term drought with low severities, short-term drought with high severity, long-term drought with low severity, etc., to characterize the drought. This kind of representation of drought proneness is expected to be more useful and easier to understand for stakeholders and decision-makers for taking various decisions regarding drought proofing and mitigation.

There are several available indices to characterize meteorological droughts in terms of severity, duration, intensity, and frequency as well as linking them with agriculture and water resources. The rainfall is the sole parameter of several commonly used meteorological drought indices like the standardized precipitation index (SPI) (McKee *et al.* 1993), rainfall anomaly index (RAI) (Van Rooy 1965), drought area index (DAI) (Bhalme & Mooley 1980), decile index (DI) (Gibbs & Maher 1967), percent of normal precipitation index (PNPI) (Willeke *et al.* 1994), *Z*-score, China Z Index (CZI) (Ju *et al.* 1997), etc. The DSDF curves corresponding to 5-, 10-, 20-, 50-, and 100-year return periods have been derived by researchers using various indices. Dalezios *et al.* (2000) used palmer drought severity index (PDSI) in Greece; Halwatura *et al.* (2015) used reconnaissance drought index (RDI) and standardized precipitation evapotranspiration index (SPEI) in Eastern Australia; Rhee & Im (2017) used SPEI in Korea; Aksoy *et al.* (2018) used SPI in Turkey; Sahana *et al.* (2020) and Gupta *et al.* (2020) used SPEI in selected areas of India; Won *et al.* (2020) used SPI in Korea. The PDSI used historically for drought quantification in several studies is not as popular as SPI as it requires more detailed information and is complicated to calculate (Quiring 2009). Shamshirband *et al.* (2020) also warned against the use of PDSI as it did not consist of multi-scale characteristics and is not a standard index. The SPI developed by McKee *et al.* (1993) is the most widely used rainfall-based drought index owing to several advantages of being simple to calculate, based only on precipitation, capability to analyze the drought at various time scales, etc., which are highlighted in the literature (Rajasivaranjan *et al.* 2019; Cavus & Aksoy 2020; Pandya *et al.* 2020). However, a general increase in the intensity and percent area affected by moderate droughts during the recent decades is attributed to an increase in surface air temperatures and thus drying of the atmosphere (Kumar *et al.* 2013). For examining the future droughts in the global warming scenario, drought indices that consider precipitation only will not be sufficient as extreme drought would be more likely to occur due to rising temperatures (Jang 2018). Considering global warming, the role of temperature and potential evapotranspiration (PET) cannot be ignored for drought quantification (Vicente-Serrano *et al.* 2010). To acquire the diversity of drought prediction, evapotranspiration is deemed necessary for calculating meteorological droughts. Moreover, the IPCC report (IPCC 2022) indicated that owing to global warming Asian countries could experience an increase in drought conditions of 5–20% by the end of this century. Hence, incorporating role of temperatures and evapotranspiration will be more crucial. Since SPI does not take into account changes in other climate variables such as surface air temperature, there is a limitation that does not reflect the effects of climate (Won & Kim 2020). The resonance drought index (RDI) developed by Tsakiris & Vangelis (2005) and the SPEI developed by Vicente-Serrano *et al.* (2010) consider not only supply, i.e. rainfall, but also the climatic water demand by incorporating PET. Between SPEI and RDI, SPEI shows the largest sensitivity to ETo variation, with clear geographic patterns mainly controlled by aridity in comparison to RDI which is only sensitive to the variance but not to the average of P and ETo (Sergio *et al.* 2015). Despite carrying more information, the RDI was reported to have similar drought sensitivity characteristics concerning drought identification in many cases (Yaseen & Osamah 2016; Pandya 2023). The study in the Saurashtra region of Gujarat, India showed that SPEI was superior to quantify temporal and spatial patterns of meteorological droughts as compared to SPI, RAI, RDI, DAI, DI, and RDI (Pandya 2023) as well as better linked with agricultural drought (Pandya *et al.* 2022). The application of a multivariate drought index like SPEI is rather limited (Gupta *et al.* 2020). The SPEI retains all its advantages of SPI which is additional information on PET and hence gaining popularity in drought quantification (Adarsh *et al.* 2018). While developing DSDF curves using SPI in Kerala, India (Adarsh *et al.* 2018) and Korea (Won *et al.* 2020), the researchers recommended SPEI for better results in terms of drought risk analysis. Above-mentioned facts motivated us to use SPEI for the development of DSDF curves in the present study.

Gujarat is a chronic drought-prone state of India with substantial portions of the state being arid and semi-arid and suffering from recurrent droughts and perennial water scarcity problems (Bandyopadhyay *et al.* 2020). The Saurashtra region of Gujarat state is located at the peripheral boundary of the southwest monsoon; hence, the distribution of rainfall is extremely uneven and irregular. The region was reported as one of the three major drought-prone regions of India in the Manual of drought Management (2020), the Government of India as variability in rainfall exceeds 50% in these regions compared to the long period average along with quite high evaporation (250 cm or more). The occurrence of chronic drought conditions in Saurashtra has led to serious degradation and depletion of natural resources (Singh & Mondal 2020). The year 1987 was an extreme drought year, while 1972, 1974, 1985, and 1986 were severe and 1966, 1991, 2000, and 2012 were moderate drought years in Saurashtra with little variation in different districts (Pandya *et al.* 2020). The Saurashtra region has exceptionally high irrigation needs and limited surface and groundwater resources (Bandyopadhyay *et al.* 2020). Declining water tables in Saurashtra have exacerbated water stress on crops. Out of the total irrigated area, a major portion, i.e. a 73% area of Saurashtra, is irrigated by groundwater (Anonymous 2020), therefore any deviation in seasonal rainfall significantly affects crop production and water resources. The falling water tables in the Saurashtra region have added stress to crops and water supplies.

Considering these facts, the study was conducted with the objectives to develop DSDF curves using the SPEI and assess the drought proneness of various districts of the Saurashtra region of Gujarat.

MATERIALS AND METHODS

Study area

The present study was carried out in the Saurashtra region of Gujarat State (India), located in the western coastal region of India. The region is located between 20°30′ and 23° N latitude and 69° and 72° E longitude covering 11 districts. The monsoon commences usually in June and continues until September. The majority of the region falls under semi-arid and arid categories. The distribution of rainfall is erratic as the region is located at the peripheral boundary of the southwest monsoon. The average annual rainfall was observed to be 544 mm (Patel *et al.* 2020). About 95% of the rainfall occurs from June to September. Rainy days vary from 20 to 37 across the region. During the summer season, the maximum temperature goes up to 42 °C and the minimum temperature falls below 25 °C. In the winter season, the minimum temperature occasionally goes below 8 °C and the maximum temperature up to 34 °C. The lowest temperature is recorded in January and the highest in May. The region is blighted by the occurrence of frequent droughts for several decades (Pathak *et al.* 2016; Koyel & Lunagaria 2020).

The daily rainfall and minimum and maximum temperature data of 36 stations for the duration of 1980–2019 (40 years) were used for computing the drought index. The 36 weather stations are spread over 11 districts of the Saurashtra region as shown in Figure 1.

Standardized precipitation evapotranspiration index

The SPEI was developed by Vicente-Serrano *et al.* (2010) to quantify the risk of droughts using the approach of water balance. This index also allows the monitoring of droughts at different time scales. The difference between rainfall and PET is taken as the input in the determination of SPEI. The rainfall data of the required duration can be obtained from the weather stations while PET can be derived using the rainfall and temperature dataset. The Thornthwaite method was used in the study to estimate PET as shown in Equation (1). The mean monthly temperature data are sufficient to estimate PET using this method (Thornthwaite 1948). The procedure of computing SPEI is similar to the calculations of SPI; however, SPEI requires a monthly difference between precipitation (P) and PET.

$$\mathrm{PET} = 16 \times \left(\frac{N}{12}\right) \times \left(\frac{\mathrm{NDM}}{30}\right) \times \left(\frac{10T}{H}\right)^{m} \tag{1}$$

N is the mean hours of sunshine.
NDM is the number of days in a month.
H in the above equation is the heat index which can be calculated using the following equation.

$$H = \sum_{j=1}^{12} \left(\frac{T_i}{5}\right)^{1.514} \tag{2}$$

T is the average temperature of each month in °C.
m is a coefficient used whose value depends on H.

The coefficient m can be obtained using the following equation.

$$m = 6.75 \times 10^{-7} H^3 - 7.71 \times 10^{-5} H^2 + 1.79 \times 10^{-2} H + 0.492 \tag{3}$$

The difference between monthly precipitation and PET is used for obtaining SPEI as given in the following equation.

$$D_i = P_i - \mathrm{PET}_i \tag{4}$$

Here, $\underline{i}$ represents the month. The D_i values so obtained are combined at various time scales. To standardize the original series, the log-logistic distribution function is applied following the approach of Vicente-Serrano *et al.*

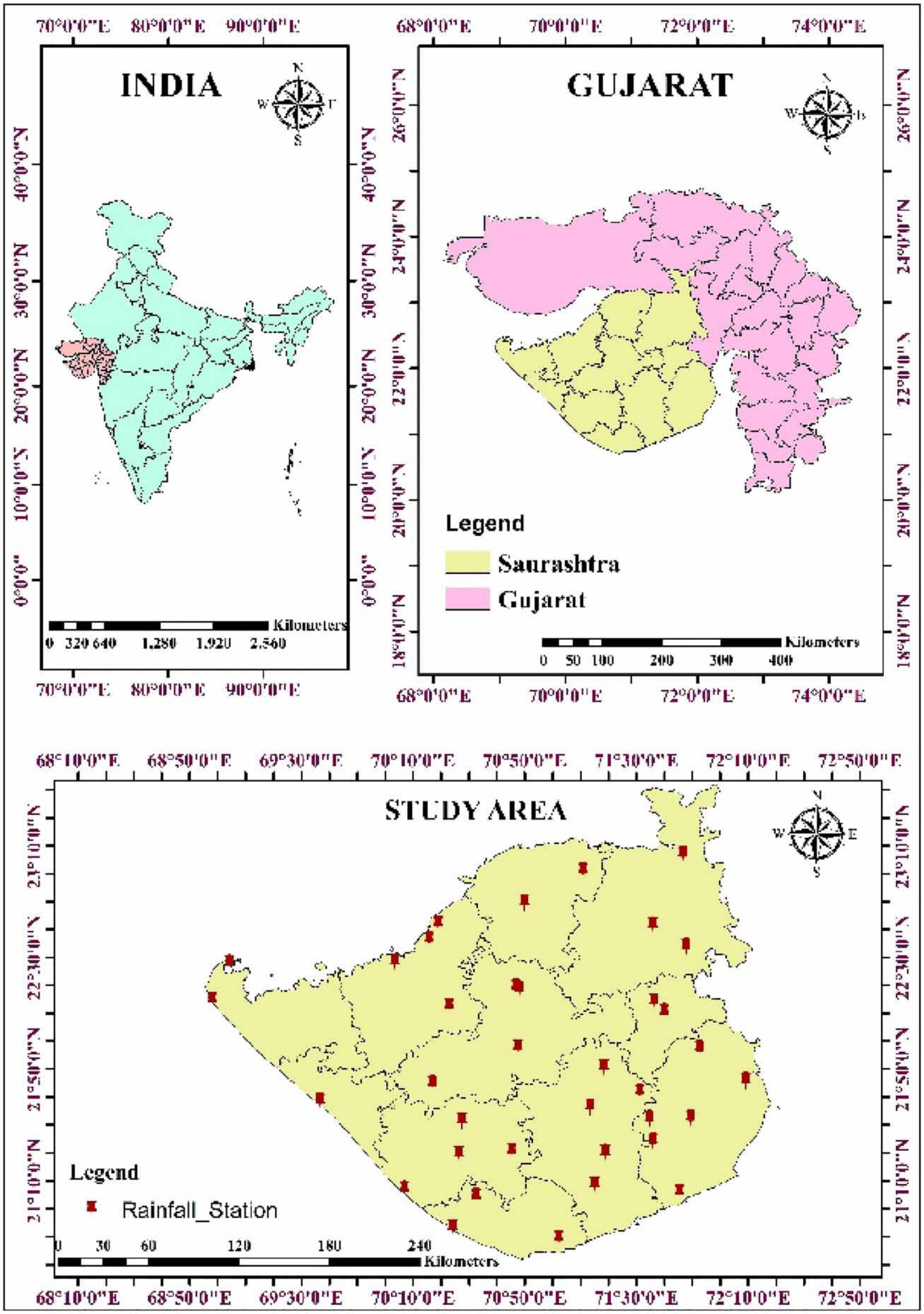


Figure 1 | Location study area and rain gauge stations.

(2010). The probability density function used for characterizing the log-logistic function is provided in the following equation.

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \tag{5}$$

Here α is the scale parameter, β is the shape parameter, and γ is the origin parameter. Also, $\gamma > D < \infty$. The distribution parameters were determined using the L-moments procedure in Equations (6)–(8). The L-moments method is considered an easy but robust method (Ahmad *et al.* 1988).

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\lceil\left(1+\frac{1}{\beta}\right)\lceil\left(1-\frac{1}{\beta}\right)} \tag{6}$$

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \tag{7}$$

$$\gamma = (w_0 - \ \alpha\lceil\left(\frac{1+1}{\beta}\right)\lceil\left(\frac{1-1}{\beta}\right) \tag{8}$$

Here, $\lceil(\beta)$ is the gamma function of β.

The D series follows the log-logistic distribution whose probability distribution function is expressed in the following equation.

$$F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{9}$$

Now, SPEI can be obtained using the following equation

$$\mathrm{SPEI} = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 \ + d_3 W^3} \tag{10}$$

where $W = \sqrt{-2\ln(P)}$ for $P \le 5$ and P is the probability of exceeding a determined D value.

The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

The SPEI has a mean and standard deviation of 0 and 1, respectively, as it is a standardized variable. The positive SPEI values indicate the wet condition and negative SPEI values indicate the drought condition. The value of SPEI less than −2 indicates extreme drought, between −2 and −1.5 indicates severe drought, between −1.0 and −1.49 indicates moderate drought and between −0.5 and −0.99 indicates mild drought.

Steps to derive DSDF curves

The following steps were involved in the development of DSDF curves:

1. Computation of monthly drought severity with long-duration meteorological data using SPEI
2. Defining the threshold of drought occurrence (which is zero in this case)
3. Constructing the drought severity series using a defined threshold
4. Fitting various probability distributions to drought severity series
5. Evaluating best-fit distribution based on various tests
6. Estimating severities of a specific duration for various return periods using best-fit distribution

The severity, duration, and frequency or return periods are important parameters of meteorological drought. Unlike rainfall, droughts do not occur every year, and long-term droughts continue into the next year, so the annual maximum time series may not be suitable for drought frequency analysis. Therefore, we constructed the drought severity time series by applying the peak-over-threshold (POT) concept (Won & Kim 2020). The concept is based on the theory of runs adopted to measure the characteristics of drought (severity and duration; Yevjevich 1967) which was also followed by Gupta *et al.* (2020). The definition of runs can be understood as: suppose, X_t is a drought variable with a time series t, then a run is a portion of the time series where all the values are either above or below a fixed threshold X_0. Therefore, the value above (below) the threshold is denoted as a positive run (negative run (Kumar *et al.* 2021). As the threshold level may vary or remain constant with time, the drought properties mainly depend on the chosen threshold (Mishra & Singh 2010).

The threshold was set to define the start of the drought event when SPEI becomes negative and the end of the drought when SPEI becomes positive, hence zero value of SPEI is the threshold in the present study. The identified drought events consisted of drought severity and drought duration. As expected, no drought might be observed in some years for the selected drought duration which means the severity is zero. In many studies using SDF curves, a drought severity time series has been constructed by extracting drought severity and duration from drought events by this method (Halwatura *et al.* 2015; Won & Kim 2020; Aksoy *et al.* 2021; Kumar *et al.* 2021). The average drought severity during the duration of each drought event was calculated to construct a drought severity time series. Based on the constructed drought severity series, a frequency analysis was conducted and the SDF curve was derived for various durations and return periods.

The drought severity time series was prepared using the peak over the threshold concept (Halwatura *et al.* 2015; Won & Kim 2020) by estimating the district-wise average drought severity for various time scales from the constructed drought events. Considering I (drought index) as SPEI values, the duration of any drought D was defined as the period of rainfall deficit, i.e. the cumulative time of negative SPEI index values (I), preceded and followed by positive I values. The severity of any drought period S starting at the ith month is expressed in the following equation:

$$S = \sum_{i=1}^{D} |-I_i| \tag{11}$$

Fitting probability distribution to drought severity series

It is important to test the type of probability distribution which fits the available data well, as the distribution is likely to vary, depending on the pattern of hydro-meteorological variables. The time series of S was fitted to various 10 cumulative probability distributions, namely normal, log normal (2P), log normal (3P), gamma (2P), gamma (3P), generalized extreme value (GEV), logistic, Gumbel maximum, Weibull (2P), Weibull (3P) distribution. These distributions were tested by several researchers to predict drought characteristics like severity, duration, and frequency across India and the globe (Adarsh *et al.* 2018; Aksoy *et al.* 2018; Won & Kim 2020; Aksoy *et al.* 2021). The normal distribution, also known as the Gaussian distribution, is one of the most frequently used distributions to model the linear function of a random variable. The log-normal distribution is a transformed normal distribution in which the variable is replaced by its logarithmic value. Therefore, if a variable is log-normally distributed, its logarithm is normally distributed. The log-normal distribution has positive skewness which increases with its scale parameter. A more general three-parameter form of the lognormal includes an additional waiting time parameter sometimes called a shift or location parameter. Gumbel distribution (GEV distribution Type-I) is used to model the distribution of the maximum (or the minimum) of several samples of various distributions. The gamma distribution is a flexible distribution with a wide variety of shapes. The function used in the gamma distribution is a generalization of the factorial. This distribution has a smoothly varying form and it is useful for describing skewed hydrologic variables without the need for logarithmic transformation. GEV distribution is also known as Fisher–Tippet type I distribution in which the parent distribution is unbounded in the direction of the desired extreme and all the moments of the distribution exist. Weibull distribution is extreme value type III distribution in which the parent distribution is bounded in the direction of the desired extreme.

Various goodness-of-fit tests are employed to decide the best-fit distribution out of various candidate distributions. The most popularly used tests to check the goodness of fit of probability distributions of hydrological quantities are the Chi-square test, Kolmogorov–Smirnov (K–S) test, and Anderson–Darling (A-D). Aksoy *et al.* (2018), Cavus & Aksoy (2020) and Aksoy *et al.* (2021) used the A-D test, Won & Kim (2020) used the Chi-square test and K–S test while Kumar *et al.* (2021) used K–S and A–D tests for probability distribution fitting of drought characteristics. The K–S is the largest vertical difference between theoretical and empirical cumulative distribution function (ECDF). This test is used to decide if a sample comes from a hypothesized continuous distribution. The A-D test compares the fit of an observed cumulative distribution function (CDF) to an expected CDF which gives more weight to the tails than the K–S test. The Chi-square (χ^2) test compares the observed frequency (f_0) of different classes with the expected frequency (fc). The probability with which the random variable lies in each class interval was determined using the probability distribution function. To take advantage of the outcomes of all three tests, we employed the method of ranking distribution suggested by Olofintoye *et al.* (2009) to decide the best-fit distribution by using all three tests, i.e. Kolmogorov–Smirnov (K–S) test, Anderson–Darling (A-D) and Chi-square test combined. The best distribution out of 10 candidate distributions is the one with the lowest test statistic value. The distributions were assigned a score from 1 to 10 for each of the three tests with the distribution having the lowest test statistic value as a score of 10, the second-lowest as 9, and so on. Scores for all three tests were summed up and the distribution with the highest combined score was designated as the best-fit distribution (Olofintoye *et al.* 2009).

RESULTS AND DISCUSSION

The first step to drive DSDF curves was to prepare the data series of drought severities for various durations. The occurrence, progression, and distribution of droughts are highly dependent on the Indian summer monsoon (ISM) spread over June to September (Gupta *et al.* 2020). More than 90% of annual rainfall in Saurashtra occurs from June to September, therefore these 4 months were considered for constricting SPEI time series. The period from the arrival of water inputs to the availability of a given usable resource differs considerably. Short time scales of 1, 2, and 3 months are mainly related to soil water content and river discharge in headwater areas, medium time scales are related to reservoir storage and discharge in the medium course of the rivers, and longtime scales are related to variations in groundwater storage. Many studies have indicated that relatively short reference periods (e.g. 1, 3, or 6 months) are more appropriate to describe the drought effects on soil moisture conditions and vegetation growth (Mallya *et al.* 2016). As indicated by Band *et al.* (2022), the 1-month time scale is a short-term drought index and can be a better indicator of monthly precipitation for a given region compared to other time steps. Aksoy *et al.* (2021) fitted the probability distribution functions to drought severities of durations of 1–5 months while Won & Kim (2020) used 1–6 months to derive DSDF. Considering these facts, DSDF curves were developed for a duration of 1–4 months.

The negative drought severity of SPEI was transformed to positive values (Loukas & Vasiliades 2004) to prepare the monthly drought severity series for a duration of 1–4 months. Hence, constructed SPEI severity series contained a total of 40 years (1980–2019) $\times$ 4 months, i.e. 160 months SPEI for each of the 11 districts. The observed drought severity time series of 40 years were subjected to 10 probability distributions, i.e. normal, log normal (2P), log normal (3P), gamma (2P), gamma (3P), GEV, logistic, Gumbel maximum, Weibull (2P), Weibull (3P) distribution. Several past studies generally used a single best-fit distribution for various durations for the entire region. However, considering the high rainfall variability and different characteristics of climate, water resources, and agriculture, the district-wise DSDF curves were developed in the present study by evaluating the best-fit distribution for each district and each duration of 1–4 months. The best-fit distributions based on three goodness-of-fit tests, namely, the Chi-square test, Kolmogorov–Smirnov (K–S) test, and Anderson–Darling (A-D) test, can be observed in Table 1.

It can be observed from Table 1 that out of 10 distributions under test, two distributions, Gumbel maximum distribution and GEV distribution, emerged as the best fit for various districts. Precisely, Gumbel maximum distribution was found as the best-fit distribution for all districts for 1 month and eight districts in the case of 2 months duration. For 3 and 4 months of duration, GEV distribution was found to be the best fit for a majority of districts. Sahana *et al.* (2020) also found GEV distribution to be best for critical drought severities at durations of 1–3 months, while Won & Kim (2020) adopted the Gumbel distribution as a result of the goodness-of-fit test for estimating drought severity time series. The Gumbel and GEV distributions were found to be superior compared to several candidate distributions for fitting drought severities in various regions across the globe including India (Dalezios *et al.* 2000; Loukas & Vasiliades 2004; Tiwari *et al.* 2007; Aksoy *et al.* 2018; Cavus & Aksoy 2020; Won *et al.* 2020). Each distribution has its pros & cons and one cannot fit in all locations, so examination of best-fit models owing to their peculiar location is essential. The literature highlights that other distributions like Gamma, Log-normal, and Weibull were also found to be suitable for deriving DSDF (Reddy & Ganguli 2012; Adarsh *et al.* 2018; Sahana *et al.* 2021).

Based on the best-fit distributions, the estimated drought severity values were applied to develop DSDF relationships for return periods of 2, 3, 4, 5, 10, 20, 30, 40, 50, and 100 years. The developed DSDF curves are plotted in Figure 2(a)–2(c).

For all the return periods, as observed in Figure 2, a common trend was observed whereby the drought severities were decreasing with an increase in drought duration and increased with an increase in the return period. Severe droughts for

Table 1 | Best-fit distribution based on SPEI for districts of Saurashtra

District	1 Month	2 Months	3 Months	4 Months
Amreli	GUBM	GEV	GEV	GEV
Bhavnagar	GUBM	GUBM	GEV	GEV
Botad	GUBM	GEV	GUBM	GEV
Dwarka	GUBM	GUBM	GEV	GUBM
Gir Somnath	GUBM	GUBM	GEV	GEV
Jamnagar	GUBM	GUBM	GEV	GEV
Junagadh	GUBM	GEV	GEV	GEV
Morbi	GUBM	GUBM	GEV	GEV
Porbandar	GUBM	GUBM	GEV	GEV
Rajkot	GUBM	GUBM	GEV	GEV
Surendranagar	GUBM	GUBM	GEV	GEV

GUBM, Gumbel maximum distribution; GEV, generalized extreme value distribution.

longer durations occurred less frequently as compared to shorter-duration droughts. As stated by Cavus & Aksoy (2020), when the return period increases, the drought severity is expected to increase owing to the physics of the drought process which is also comparable with the findings of Sahana *et al.* (2020), Adarsh *et al.* (2018), Samantaray *et al.* (2019), Gupta *et al.* (2020), Kumar *et al.* (2021), and others. This implies that consecutive higher drought severities of monthly rainfall are less prominent and severe droughts are more prominent for shorter durations. Samantaray *et al.* (2019) pointed out that the severity of short-term droughts worsens as the return period increases. For shorter time scales dry and moist periods change with a high frequency while for longest time scales the droughts are less frequent but their duration is higher; the number of studies also confirmed this fact (Yang *et al.* 2019).

With respect to changes in drought severities with various durations, a different behavior was observed for different return periods. Among various districts, the drought severities of various duration droughts were almost identical for lower return periods while for higher return periods of 50 and above, higher differences between drought severities for various durations were observed. This implies that droughts for smaller return periods and even longer-duration droughts tend to have severity as high as short-duration droughts, but this is not true for droughts with higher return periods. In other words, the rate of decrease in severity with an increase in duration is higher for longer-duration droughts as compared to that of shorter-duration droughts. For example, for return periods of 2–10 years, the difference in drought severities for 1 and 4 months of duration ranged from 0.10 to 0.11 whereas, in the case of return periods of 20–50 years, the difference in drought severities for 1 and 4 months of duration, the difference ranged from 0.42 to 0.63 for all the districts. The highest difference in drought severities was found for 100-year return periods with SPEI values ranging from 0.59 to 0.80 for 1 and 4 months duration. The DSDF curves reveal that the 1-month duration drought curve is well above and separated clearly from the curves at higher duration droughts. Also, the difference in drought severities between 3 and 4 months duration droughts was not much as compared to that of 1- and 2-month duration droughts. The precipitation deficit increases for all drought durations as the return period increases; however, it is more obvious when the drought duration becomes shorter (Cavus & Aksoy 2020). The results of our study confirmed the findings of Dalezios *et al.* (2000) that low-frequency events, i.e. events with return periods of 50 and 100 years, have a much larger uncertainty than more frequent events. Malakiya & Suryanarayana (2016), while assessing the drought using SPI and RDI in the Amreli district of Saurashtra, also judged that at shorter time scales, the SPI and RDI values fluctuated frequently above and below the zero line, and there was no extended dry or wet period. Adarsh *et al.* (2018) also confirmed while deriving DSDF relationships in Kerala, India that between severity and return period showed larger differences for a longer duration. However, the contradicting results were reported by Palchaudhuri & Biswas (2013) during the study in West Bengal, stating that there exists no relation between the droughts of short and longer time scales as well as among the severity classes of each period. Gupta *et al.* (2020) developed SDF relationships for the Indian regions using 12-month SPEI and observed a constant rate of change of severity with the change in duration for peninsular India (except the Western Ghats). Whereas in the present study, DSDF curves were developed using monthly SPEI and showed

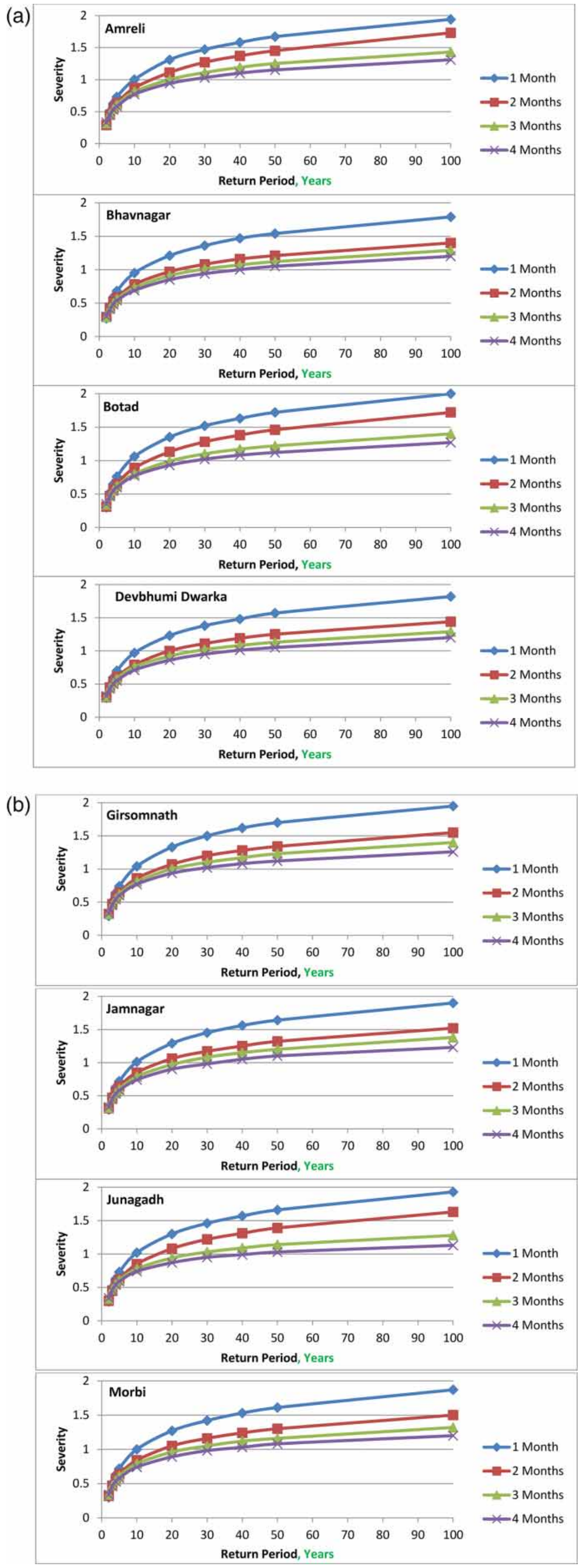


Figure 2 | (a) Drought SDF curves for Amreli, Bhavnagar, Botad, and Devbhumi Dwarka Districts. (b) Drought SDF curves for Gir Somnath, Jamnagar, Junagadh, and Morbi Districts. (c) Drought SDF curves for Porbandar, Rajkot, and Surendranagar Districts. (*continued.*).

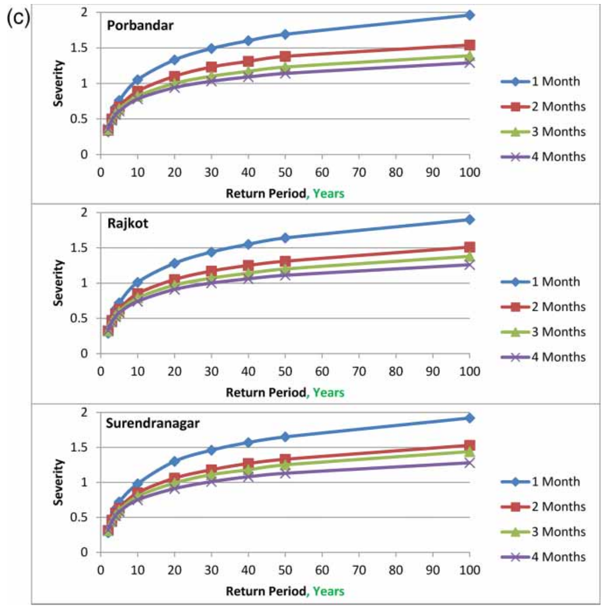


Figure 2 | Continued.

a different rate of change of severity with the change in duration. This fact discloses that the choice of the time scale of drought is important to evaluate the drought characters. The longer time scales may not be able to capture the variation in drought severity with duration. This important finding is also supported by Xu *et al.* (2022) who that with the improvement of the spatiotemporal attributes of statistical data, we can choose a shorter time scale and build a more refined risk assessment indicator system.

The districts Junagadh and Botad were among those with a high rate of drought severity reduction with increasing duration while Amreli, Bhavnagar, Dwarka, Rajkot, and Surendranagar were among the districts with a very low rate of drought severity reduction with an increase in duration. The difference of severities of 1 and 4 months duration were 0.63 and 0.60 for 50-year return periods and 0.80 and 0.73 for 100-year return period for districts Junagadh and Botad, respectively, whereas, for Amreli, Bhavnagar, Dwarka, Rajkot, and Surendranagar districts, the difference in severities of 1 and 4 months duration was 0.49–0.53 for 50-year return periods and 0.59–0.64 for 100-year return periods. As stated earlier, the drought severity decreased with an increase in duration, but the low rate of severity reduction at Amreli, Bhavnagar, Dwarka, Rajkot, and Surendranagar suggests that these districts are prone to be hit by frequent severe droughts, while Junagadh and Botad are comparatively less prone to face such frequent events.

The drought conditions should be analyzed based on multivariate complexity and spatial variations (Kumar *et al.* 2021). As far as the spatial variations of drought severity values across is concerned, it is obvious that the lowest drought severity for a 1-month duration drought was observed for 2-year return period with SPEI severity ranging from 1 to 1.2, i.e. almost equal for all districts. The severity of the various districts of Saurashtra for a 1-month duration ranged from 1.5 to 1.7 in the case of the 50-year return period and from 1.8 to 2.0 for the 100-year return period. For 1-month duration, Botad, Gir Somnath, and Porbandar showed higher drought severities as compared to the rest of the districts, i.e. 1.69–1.72 for 50-year return periods and 1.95–2.0 for 100-year return periods. Comparatively low severities for Bhavnagar and Dwarka districts were observed, i.e. 1.54 and 1.57 for the 50-year return period and 1.79 and 1.82 for the 100-year return period, respectively. The greater drought magnitudes are expected to occur for higher return periods (Halwatura *et al.* 2015; Aksoy *et al.* 2018; Sahana *et al.* 2021), which is also established in the current study.

Considering the 4-month drought duration which can lead to the most devastating drought effects, the drought severities ranged between 0.7 and 0.8, 1.03 and 1.15, and 1.1 and 1.3 for 10, 50, and 100-year return periods, respectively. For both 50- and 100-year return periods, Amreli, Porbandar, Surendranagar, Botad, and Gir Somnath are expected to face higher severities of consecutive monthly droughts with SPEI between 1.12 and 1.15 for 50-year return periods and 1.26 and 1.31 for 100-year return periods. The districts Morbi, Bhavnagar, Dwarka, and Junagadh are less prone to consecutive severe droughts with expected severities of 1.08, 1.05, 1.05, and 1.03 for the 50-year return period and 1.20, 1.20, 1.20, and 1.13 for the 100-year return period. It was also reflected from the graphs that the average difference in drought severity value of SPEI between the lowest (2-year return period) and highest (100-year return period) droughts severity was 0.81, 0.63, 0.52, and 0.45 for 1-, 2-, 3-, and 4-month drought durations, respectively, i.e. for longer-duration droughts, the difference in drought severities was less for higher return periods. A study by Adarsh *et al.* (2018) in Kerala also confirmed this fact while observing constant severity values corresponding to different return periods for a longer duration.

The above discussion reflects that drought severity, duration, frequency, and spatial variations among different parts of the region possess complex relations. A spatial comparison of SDF curves allows identifying drought-prone regions where mitigation measures are more important than in regions where such measures are not critically needed (Sahana *et al.* 2020). Ecosystem rehabilitation may fail if management actions are based only on the annual rainfall without considering the nature of drought events (i.e. the rate of recurrence of prolonged and severe droughts (Cavus & Aksoy 2020). The demarcation of various districts based on drought characterization helps with better planning, resource allocation, efficient drought proofing mechanism, and prioritization.

Meteorological drought is a rainfall deficit for a specified period and its ill effect on soil moisture, surface water resources, and groundwater resources varies according to the degree of deficit (drought severity) and the period of deficit (drought duration). The short periods like 1 month are expected to affect crop development. The medium duration of 2–3 months will affect crops as well as surface water resources. The longer droughts of 4 or more months will effect result in complete crops, and surface and groundwater resources. Thus mitigation measures towards droughts differ according to the drought duration and severity. Sahana *et al.* (2020) argued that different drought severity, duration, and return period should be considered for various short-term or non-structural measures such as crop management or water harvesting and conservation structures. As developed DSDF curves possess this critical information by exploring the interrelations among high/low drought severities, short/long drought duration, and high/low drought frequencies, the demarcation of various districts based on this characterization is expected to prove valuable for planning, resource allocation, and prioritization for drought mitigation. The novel feature of this study is the ranking of the districts of the study area based on three criteria, i.e. proneness to higher severities for longer durations, proneness to high severities with short-duration droughts, and proneness to low severities with long-duration drought based on developed DSDF curves (Table 2). The methodology is expected to provide the end-users the information needed for taking short-, medium-, and long-term actions in drought risk management, irrigation planning, and water resources development strategies.

As indicated in Table 2, Bhavnagar, Dwarka, Amreli, Surendranagar, and Rajkot have greater susceptibility towards persistent higher drought severities for longer durations as compared to the rest of the districts. If the past trends continue, Gir Somnath, Botad, and Junagadh may not face persistent higher severity droughts as frequently. However, as per criteria

Table 2 | Ranking of districts based on various drought severity and duration criteria

Criteria 1 Proneness to higher severities for longer durations		Criteria 2 Proneness to high severities with short-duration droughts		Criteria 3 Proneness to low severities with long-duration drought	
1	Bhavnagar	1	Botad	1	Amreli
2	Dwarka	2	Porbandar	2	Porbandar
3	Amreli	3	Gir Somnath	3	Surendranagar
4	Surendranagar	4	Junagadh	4	Botad
5	Rajkot	5	Jamnagar	5	Gir Somnath
6	Jamnagar	6	Rajkot	6	Rajkot
7	Porbandar	7	Amreli	7	Jamnagar
8	Morbi	8	Morbi	8	Bhavnagar
9	Gir Somnath	9	Surendranagar	9	Dwarka
10	Botad	10	Dwarka	10	Morbi
11	Junagadh	11	Bhavnagar	11	Junagadh

2, short-term droughts were most severe and prolonged in districts Botad, Porbandar, Gir Somnath, Junagadh, and Jamnagar. The highest value of equilibrium severity for longer drought duration for all return periods was observed in Amreli, Porbandar, Surendranagar, Botad, Gir Somnath, and Rajkot districts. It was also evident from the result that a common trend regarding rainfall variability and drought severity was not observed in SDF curves by SPEI. The districts Porbandar, Dwarka, and Junagadh were among those with very high monthly rainfall variability, however, the same trend was not observed in the drought severity. Since the DSDF curves are based on multivariate SPEI which captures the concurrent deficit in rainfall as well as PET with respect to a threshold, the combined effect of these two variables has generated a different trend than only rainfall variations. Sahana *et al.* (2021) also observed such diversified trends by DSDF curves for various regions in India using a multivariate drought index incorporating rainfall as well as soil moisture. While developing DSDF curves with SPI in Kerala, Adarsh *et al.* (2018) also advocated that estimation of drought should be performed by incorporating SPEI or other multivariate drought indices for a clearer picture of subsequent risk from droughts. Moreover, the SDF curves are derived based on probabilistic frequency analysis of SPEI which reflects precipitation – PET and not necessarily using the magnitude of precipitation alone.

Interestingly, it has been observed that there was a noticeable contrast in behavior in terms of long-term droughts between the geographically neighboring stations. For example, Botad district showed remarkably different drought severity and frequency as compared to neighboring districts Amreli and Bhavnagar. Such a difference in drought characteristics is not unexpected considering the diversity in topographical features and noticeable spatial and temporal variations in the rainfall patterns (Sahana *et al.* 2021). Drought possesses intrinsic complexities across different climatic conditions (Shamshirband *et al.* 2020). The rainfall variability and PET are affected by several factors; Adnan *et al.* (2017) reported that PET is sensitive and positively correlated with temperature, solar radiation, and wind speed and negatively correlated with vapor pressure. The developed DSDF curves determined the spatial variability of drought characteristics, however, the exact reasons for spatial variability can be investigated only after analyzing above-mentioned factors linked with precipitation and PET, which needs further investigation.

Based on best-fit distribution, the return periods of occurrence of mild, moderate, and severe droughts as well as extreme droughts were estimated for various districts (Figure 3). For taking proper measures against the drought and to overcome or minimize its negative effect on different sectors as well as ecology and society, it is important to know what precipitation deficit corresponds to what drought class (such as mild, moderate, severe, extreme) (Cavus & Aksoy 2020). It can be observed from Figure 3 that droughts of a shorter duration of 1 month have a low return period, i.e. more frequent than droughts of longer durations of 4 months. It was observed that mild drought was expected to occur once in 3 years for the 1-month duration and once in 4 years for 4 months duration for all districts. A moderate drought for a 1-month duration is expected to occur once in 9–11 years for various districts.

The weaker drought category of mild drought occurred more frequently than the stronger drought category of moderate, severe, and extreme droughts which is also comparable with the previous findings (Kebede *et al.* 2019). While considering a 4-month duration, the return period of moderate drought ranges between 26 and 42 years for various districts. Kebede *et al.* (2019) also found that compared to the 1-month time scale, drought severity was increasing but the frequency was decreasing for longer time scales of 3, 6, and 12 months. Cavus & Aksoy (2020) reported that the likelihood of drought is reduced when the drought duration increases; it is less probable to observe longer droughts. Moderate droughts for 4 months duration are expected to occur more frequently in districts Amreli, Porbandar, Botad, and Gir Somnath with return periods ranging from 26 to 28 years, but less frequently for districts Bhavnagar, Dwarka, and Junagadh with return periods ranging from 39 to 42 years. The severe drought for 1-month duration with a return period of 29–44 years for various districts with Amreli, Botad, Gir Somnath, and Porbandar is likely to observe more frequent severe droughts with a return period ranging from 29 to 32 years. The districts Bhavnagar, Dwarka, and Morbi are less likely to observe highly frequent severe droughts as compared to the rest of the districts with a return period ranging between 37 and 44 years. The extreme drought is expected to occur once in 98–174 years for various districts of Saurashtra with comparatively lower return periods for Botad and Gir Somnath as 98 and 103 years, respectively, while Bhavnagar and Dwarka are the districts that are less likely to suffer from extreme droughts for 1-month duration.

The ranges of return periods for various drought categories also conveyed that all districts had an almost identical frequency of low-severity categories of mild and moderate droughts, while a higher difference in return period was observed for severe droughts among various districts. Low-severity droughts had lesser spatial variability as compared to high-severity droughts.

Figure 3 | Return periods of mild, moderate, severe, and extreme droughts for districts of Saurashtra based on SPEI.

The developed DSDF curves can be used to calculate drought severity for a specific duration and return period. Instead of planning drought resilience for agriculture, water storage, irrigation networks, and urban water supply systems according to the average annual rainfall pattern or value of drought severity alone, the DSDF curves could serve as better preliminary data to deal with future droughts. Important decisions regarding water resource management can be made based on the drought severity and return period obtained from the DSDF curves. Drought events may be rare for certain regions and therefore, it may not be required to immediately invest in alternate irrigation or the development of drought-resistant varieties for those regions. It should be noted that the historic evaporation and rainfall data have been utilized to estimate the recurrence intervals of droughts and owing to climate change patterns of the future, there is a possibility that drought frequency may increase although it may not be indicated by drought indices and DSDF curves. The findings of the study can be used as a management tool for transferring drought information to end-users for practical purposes to overcome the challenges presented by droughts.

The regions prone to droughts can be identified using the district ranking based on the spatial comparison of the DSDF curves. The regions with lower rankings require immediate mitigation measures against the ill effects of drought (Sahana *et al.* 2020). The dependence of the farmers on rainfed farming should be reduced by adopting drought-resistant or early-maturing crops and implementing suitable water harvesting and irrigation methods (Pandya *et al.* 2020). It is advisable to invest in alternate irrigation as a priority measure for the districts faced with recurring droughts of high severity and duration. The frequency of droughts as observed from the DSDF curve serves as a critical driver in making important management decisions (Halwatura *et al.* 2015). Even short-term droughts could negatively impact agriculture. For example, short-term droughts are not favorable for the establishment of seedlings even if heavy rainfall is encountered between droughts. It is recommended to adopt the plant species based on the type of drought. It should also be ensured that the plants should not face water stress during their critical stages such as the germination stage or pod development stage (Blum 1996). The decision as to when to irrigate coupled with the use of an efficient irrigation system can ensure the plants survive in areas subjected to short-duration high severity of droughts.

The evaporation rate is expected to increase due to global warming which results in drier conditions on the ground and an increase of water vapor in the atmosphere over time (Kumar *et al.* 2021). Hence, our study recommends employing the indices like SPEI for future drought modeling and operation instead of only rainfall-based indices like SPI. The increase in the population increased the standard of living, and climate change has increased the stress on land, water, and energy supplies for countries like India. These facts enforce better interventions, risk assessment, monitoring, policies, and prediction of natural hazards like droughts. The developed DSDF curves and ranking of districts based on drought proneness are expected to guide the choice of design severity for a given duration and return period for water resources management and can provide comprehensive information for agricultural water management policies and drought mitigation planning of the Saurashtra region. The replication of the developed methodology with suitable region-specific modifications may help to reproduce such valuable information for other regions.

CONCLUSION

The study demonstrated the methodology for developing DSDF curves to identify drought proneness in terms of drought severity and duration. The most promising drought index of the semi-arid region, i.e. SPEI, was used to construct the drought severity time series of 1–4 months duration and severities for 2–100 years return periods were estimated by testing various probability distributions. The key findings of the study are presented below.

- The drought severities decreased with an increase in drought duration. The drought severities ranged from 0.10 to 0.11 for return periods of 2–10 years and duration of 1 and 4 months whereas, for a return period of 20–50 years and the same durations, the drought severities ranged from 0.42 to 0.63.
- Amreli, Bhavnagar, Dwarka, Rajkot, and Surendranagar districts are prone to be hit by frequent severe droughts. Morbi, Bhavnagar, and Junagadh are less prone to consecutive severe droughts with expected severities of 1.08, 1.05, 1.05, and 1.03 for a 50-year return period and 1.20, 1.20, 1.20, and 1.13 for a 100-year return period, respectively.
- Mild droughts are expected to occur once in 3 years for a 1-month duration and once in 4 years for a 4-month duration while severe droughts are expected to occur once in 29–44 years for various districts of Saurashtra. Considering the spatial variation of drought frequency of the region, the difference in drought frequency was less for mild and moderate drought while it was high for severe drought and very high for extreme droughts across various districts.

- The study demonstrated the importance of the development of district-specific DSDF curves to deal with future droughts and to make appropriate decisions for reducing the drought impacts on agriculture and water security.
- The main limitation of the study is DSDF curves are developed based on historic data and will remain valid if past patterns are continued. However, the use of appropriate GCM-RCM models along with techniques like bivariate or multivariate copulas and linking the drought severities with the vulnerability of agricultural, hydrological, and socioeconomic factors may be attempted in the future to enhance the applicability of the current method.

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AUTHORS CONTRIBUTION

The authors confirm their contribution to the paper as follows. P.A.P. conceptualized the whole article, collected the data, developed the methodology, analyzed the data, wrote the original draft, reviewed and edited the article, visualized the data. N.K.G. conceptualized the whole article, supervised the article and administered the project, supervised the data, and edited the draft.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Adarsh, S., Karthik, S., Shyma, M., Prem, G. D., Shirin Parveen, A. T. & Sruthi, N. 2018 Developing short term drought severity-duration-frequency curves for Kerala meteorological subdivision, India using bivariate copulas. *KSCE Journal of Civil Engineering* **22**, 962–973.

Adnan, S., Ullah, K., Khan, A. & Gao, S. 2017 Meteorological impacts on evapotranspiration in different climatic zones of Pakistan. *Journal of Arid Land.* **9**, 938–952.

Ahmad, M. I., Sinclair, C. D. & Werritty, A. 1988 Log-logistic flood frequency analysis. *Journal of Hydrology* **98**, 205–224.

Aksoy, H., Onoz, B., Cetin, M., Yuce, M. I., Eris, E., Selek, B., Aksu, H., Burgan, H. I., Esit, M., Orta, S. & Cavus, Y. 2018 SPI-based drought severity-duration-frequency analysis. In: *Proc. of 13th International Congress on Advances in Civil Engineering*, Izmir/Turkey.

Aksoy, H., Cetin, M., Eris, E., Burgan, H. I., Cavus, Y., Yildirim, I. & Sivapalan, M. 2021 Critical drought intensity-duration-frequency curves based on total probability theorem-coupled frequency analysis. *Hydrological Sciences Journal* **66**, 1337–1358.

Anonymous. 2020 *Provisional District Wise Land Utilization, Area Under Crops and Area Irrigated by Source of Gujarat State for 2018–19*. Department of Agriculture and Farmers' Welfare, Government of Gujarat, Gandhinagar, India.

Band, S. S., Karami, H., Jeong, Y., Moslemzadeh, M., Farzin, S., Chau, K., Bateni, S. M. & Mosavi, A. 2022 Evaluation of time series models in simulating different monthly scales of drought index for improving Their forecast accuracy. *Frontiers in Earth Science.* **10**, 839527.

Bandyopadhyay, N., Bhuiyan, C. & Saha, A. K. 2020 Drought mitigation: critical analysis and proposal for a new drought policy with special reference to Gujarat (India). *Progress in Disaster Science* **5**, 100049.

Bazrafshan, O., Zamani, H., Shekari, M. & Singh, V. P. 2020 Regional risk analysis and derivation of copula-based drought for severity-duration curve in arid and semi-arid regions. *Theoretical and Applied Climatology* **141**, 889–905.

Bhalme, H. N. & Mooley, D. A. 1980 Large-scale droughts/floods and monsoon circulation. *Monthly Weather Review* **108**, 1197–1211.

Blum, A. 1996 Crop responses to drought and the interpretation of adaptation. In: *Drought Tolerance in Higher Plants: Genetical, Physiological and Molecular Biological Analysis* (E. Belhassen, ed.). Springer, Dordrecht, pp. 57–70.

Cavus, Y. & Aksoy, H. 2020 Critical drought severity/intensity-duration-frequency curves based on precipitation deficit. *Journal of Hydrology* **584**, 124312.

Dalezios, N. R., Loukas, A., Vasiliades, L. & Liakopoulos, E. 2000 Severity-duration-frequency analysis of droughts and wet periods in Greece. *Hydrological Sciences Journal* **45**, 751–769.

Dupont, B. S. & Allen, D. L. 1999 *Revision of the Rainfall Intensity Duration Curves for the Commonwealth of Kentucky*. Kentucky Transportation Center Research Report, pp. 292.

Gibbs, W. J. & Maher, J. V. 1967 *Rainfall Deciles as Drought Indicators*. Bureau of Meteorology Bulletin, Commonwealth of Australia, Melbourne, Australia, p. 48.

Gupta, V., Kumar Jain, M. & Singh, V. P. 2020 Multivariate modeling of projected drought frequency and hazard over India. *Journal of Hydrologic Engineering* **25**, 1–19.

Halwatura, D., Lechner, A. M. & Arnold, S. 2015 Drought severity–duration–frequency curves: a foundation for risk assessment and planning tool for ecosystem establishment in post-mining landscapes. *Hydrology and Earth System Sciences* **19**, 1069–1091.

IPCC 2022 Summary for policymakers [H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.)]. In: *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. & Rama, B., eds.). Cambridge University Press, Cambridge, UK.

Jang, D. 2018 Assessment of meteorological drought indices in Korea using RCP 8.5 scenario. *Water* **10**, 283.

Jin, J., Song, Z., Cui, Y., Zhou, Y., Jiang, S. & He, J. 2016 Research progress on the key technologies of drought risk assessment and control. *Journal of Hydraulic Engineering* **47**, 398–412.

Ju, X. S., Yang, X. W., Chen, L. J. & Wang, Y. M. 1997 Research on determination of indices and division of regional flood/drought grades in China. *Journal of Applied Meteorological Science* **8**, 26–33.

Kebede, A., Raju, J. P., Korecha, D., Takele, S. & Nigussie, M. 2019 Drought sensitivity characteristics and relationships between drought indices over Upper Blue Nile basin. *Journal of Water and Land Development* **43**, 64–75.

Koyel, S. & Lunagaria, M. M. 2020 Association between drought and agricultural productivity using remote sensing data: a case study of Gujarat state of India. *Journal of Water Climate Change* **11**, 189–202.

Kumar, K. N., Rajeevan, M., Pai, D. S., Srivastava, A. K. & Preethi, B. 2013 On the observed variability of monsoon droughts over India. *Weather and Climate Extremes* **1**, 42–50.

Kumar, S. K., Anand Raj, P., Sreelatha, K. & Sridhar, V. 2021 Regional analysis of drought severity-duration-frequency and severity-area-frequency curves in the Godavari River Basin, India. *International Journal of Climatology* **41**, 5481–5501.

Loukas, A. & Vasiliades, L. 2004 Probabilistic analysis of drought spatiotemporal characteristics in Thessaly region, Greece. *Natural Hazards and Earth System Sciences* **4**, 719–731.

Malakiya, A. D. & Suryanarayana, T. M. 2016 Assessment of drought using standardized precipitation index (SPI) and reconnaissance drought index (RDI): a case study of Amreli district. *International Journal of Science and Research* **5**, 1995–2002.

Mallya, G., Mishra, V., Niyogi, D., Tripathi, S. & Govindaraju, R. S. 2016 Trends and variability of droughts over the Indian monsoon region. *Weather and Climate Extremes* **12**, 43–68.

Manual for Drought Management 2020 Department of Agriculture, Cooperation & Farmers Welfare, Ministry of Agriculture & Farmers Welfare Government of India, New Delhi.

McKee, T. B., Doesken, N. J. & Kliest, J. 1993 The relationship of drought frequency and duration to time scales. In: *8th Conference on Applied Climatology Proceedings*, Anaheim, pp. 179–184.

Mishra, A. K. & Singh, V. P. 2010 A review of drought concepts. *Journal of Hydrology* **391**, 202–216.

Olofintoye, O. O., Sule, B. F. & Salami, A. W. 2009 Best-fit probability distribution model for peak daily rainfall of selected cities in Nigeria. *New York Science Journal* **2**, 1–12.

Palchaudhuri, M. & Biswas, S. 2013 Analysis of meteorological drought using standardized precipitation index – a case study of Puruliya district, West Bengal, India. *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering* **7**, 119–126.

Pandya, P., Kumarkhaniya, R., Parmar, R. & Ajani, P. 2020 Meteorological drought analysis using standardized precipitation index. *Current World Environment* **15**, 477–486.

Pandya, P., Gontia, N. K. & Parmar, H. V. 2022 Development of PCA-based composite drought index for agricultural drought assessment using remote-sensing. *Journal of Agrometeorology* **24**, 384–392.

Pandya, P. A. 2023 Development of drought forecasting indices and crop yield modeling using remote sensing and GIS. PhD thesis, Junagadh Agricultural University, Junagadh, Gujarat, India.

Patel, P. M., Saha, D. & Shah, T. 2020 Sustainability of groundwater through community-driven distributed recharge: an analysis of arguments for water scarce regions of semi-arid India. *Journal of Hydrology: Regional Studies* **29**, 100680.

Pathak, A. R., Mathukia, R. K., Chopada, M. C., 2016 Saurashtra, the drought prone region of Gujarat. In: *Droughts and the Way Forward* (Varshneya, M. C., Javalekar, A., Shah, R. G. & Patil, D. B., eds.). Kamdhenu University, Gandhinagar, pp. 86–104.

Quiring, S. M. 2009 Monitoring drought: an evaluation of meteorological drought indices. *Geography Compass* **3**, 64–88.

Rajasivaranjan, T., Patel, N. R., Ponraj, A., Kumar, V. & Surendran, U. 2019 Development and application of SPI generator using open source for analyzing drought at a varying time scale. *Journal of Agrometeorology* **21**, 420–426.

Reddy, M. J. & Ganguli, P. 2012 Bivariate flood frequency analysis of upper Godavari River flows using Archimedean copulas. *Water Resources Management* **26**, 3995–4018.

Rhee, J. & Im, J. 2017 Meteorological drought forecasting for ungauged areas based on machine learning: using long-range climate forecast and remote sensing data. *Agricultural and Forest Meteorology* **237–238**, 105–122.

Sahana, V., Sreekumar, P., Mondal, A. & Rajsekhar, D. 2020 On the rarity of the 2015 drought in India: a country-wide drought atlas using the multivariate standardized drought index and copula-based severity-duration-frequency curves. *Journal of Hydrology: Regional Studies* **31**, 100727.

Sahana, V., Mondal, A. & Sreekumar, P. 2021 Drought vulnerability and risk assessment in India: sensitivity analysis and comparison of aggregation techniques. *Journal of Environmental Management* **299**, 113689.

Samantaray, A. K., Singh, G., Ramadas, M. & Panda, R. K. 2019 Drought hotspot analysis and risk assessment using probabilistic drought monitoring and severity–duration–frequency analysis. *Hydrological Processes* **33**, 432–449.

Sergio, M., Vicente-Serrano, S., Gerard, V. S., Santiago, B. & Cesar, A. M. 2015 Contribution of precipitation and reference evapotranspiration to drought indices under different climates. *Journal of Hydrology* **526**, 42–54.

Shamshirband, S., Hashemi, S., Salimi, H., Samadianfard, S., Asadi, E., Shadkani, S., Kargar, K., Mosavi, A., Nabipour, N. & Chau, K. W. 2020 Predicting standardized streamflow index for hydrological drought using machine learning models. *Engineering Applications of Computational Fluid Mechanics* **14**, 339–350.

Singh, V. & Mondal, M. 2020 Assessment of the water crisis in a drought prone area through experimentation. *Journal of Critical Reviews* **07**, 10874–10885.

Thornthwaite, C. W. 1948 An approach toward a rational classification of climate. *Geographical Review* **38**, 55–94.

Tiwari, K. N., Paul, D. K. & Gontia, N. K. 2007 Characterization of meteorological drought. *Hydrology Journal* **30**, 15–27.

Todmal, R. 2022 *Intensity, Frequency and Coverage of Hydro-Meteorological Droughts and Agriculture in the Semi-Arid Region of Maharashtra (India)*.

Tsakiris, G. & Vangelis, H. 2005 Establishing a drought index incorporating evapotranspiration. *European Water* **9–10**, 3–11.

Van Rooy, M. P. 1965 A rainfall anomaly index independent of time and space. *Notos* **14**, 43–48.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. 2010 A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of Climate* **23**, 1696–1718.

Willeke, G., Hosking, J. R., Wallis, J. R. & Guttman, N. B. 1994 *The National Drought Atlas*. Institute for Water Resources Report 94-NDs-4, Army Corps of Engineers, Washington, D.C.

Won, J. & Kim, S. 2020 Future drought analysis using SPI and EDDI to consider climate change in South Korea. *Water Supply* **20**, 3266–3280.

Won, J., Choi, J., Lee, O., Park, M. J. & Kim, S. 2020 Two ways to quantify Korean drought frequency: partial duration series and bivariate exponential distribution, and application to climate change. *Atmosphere* **11**, 476.

Xu, W., Tang, M. & Li, Y. 2022 A new method for assessment of regional drought risk: information diffusion and interval mapping adjustment based on k-means cluster points. *Journal of Water and Climate Change* **13**, 4302–4316.

Yang, X., Shao, X. H., Mao, X. Y., Li, M. H., Li, X. N. & Li, R. Q. 2019 An analysis of drought evolution characteristics based on standardized precipitation index: a case study in Southwest Guizhou Autonomous Prefecture, China. *Journal of Agrometeorology* **21**, 31–35.

Yaseen, K. A. & Osamah, A. O. 2016 Comparative study of four meteorological drought indices in Iraq. *IOSR J. Applied Physics* **8**, 76–84.

Yevjevich, V. 1967 *Objective Approach to Definitions and Investigations of Continental Hydrologic Droughts*. Hydrology Papers 23, Colorado State University, Rangely, CO.

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