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An Optimal and Flexible Approach for Drought Quantification Based on Standardised Indices

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Keywords: drought quantification | standardised drought indices | standardised evapotranspiration deficit index | standardised precipitation evapotranspiration index | standardised precipitation index

ABSTRACT

In this study we propose a novel approach to standardising drought indices that offers flexibility tailored to local conditions. This involves employing different probability distributions and the Akaike Information Criterion to identify the most appropriate distribution for each region and variable. Following this approach, our proposed methodology enhances the accuracy and comparability across different spatial and temporal scales, with improved representation of extreme drought events. Nonetheless, despite the increased computational requirements associated with this approach, the advantages are substantial. By enhancing accuracy, comparability and adaptability, it may improve drought monitoring and management practices. Moreover, the methodology provides a versatile framework for standardising a wide range of environmental variables beyond traditional drought indices, and software for calculations is provided (https://github.com/lcsc/FlexDroughtIndex). Overall, the findings of this study can advance drought assessments by providing an innovative and flexible methodology that addresses key limitations of current approaches.

1 | Introduction

Assessing drought severity is highly complex due to its multifaceted nature, which involves various physical, physiological and human mechanisms (Douville et al. 2021), its different types (Wilhite and Buchanan-Smith 2005), as well as its wide variety of impacts (Wilhite et al. 2007; Vogt et al. 2021; Conradt et al. 2023). Also, the varying degrees of vulnerability and resilience exhibited by ecosystems and societies significantly influence this assessment (Blauhut et al. 2016; Gazol et al. 2018).

However, obtaining information about the impacts caused by droughts, which is a well-established method for quantifying drought severity, is often challenging (Blauhut et al. 2015; Vicente-Serrano 2016; Cammalleri et al. 2020). On the other hand, relying on impact data for drought monitoring is complicated because real-time impact information is typically unavailable. Furthermore, the diverse and cascading environmental, agricultural and socioeconomic impacts associated with droughts are difficult to quantify (Bachmair et al. 2016; Noel et al. 2020). As a result, the quantification of drought events often relies on various climatic (e.g., precipitation, atmospheric evaporative demand [AED], actual evapotranspiration [ET]) and hydrological variables (e.g., streamflow, soil moisture, groundwater). A main assumption of these indices is that anomalies in these variables are typically associated with impacts and can accordingly provide valuable indicators of drought severity (Abatzoglou et al. 2014; Bachmair et al. 2015; Chen et al. 2016; Krueger et al. 2019).

Drought is characterised by water deficits and stress compared to long-term conditions (IPCC 2023) and it necessitates long-term data for severity assessment (Guttman 1999; WMO 2012). Due to significant spatial and seasonal variability in meteorological and hydrological variables, standardised indices are crucial for spatial and temporal comparability and drought event isolation (McKee et al. 1993). Standardisation typically involves converting real magnitudes to non-dimensional z-units, enabling comparison among regions with diverse climates and hydrological characteristics (López-Moreno et al. 2013; Barker et al. 2016; Peña-Gallardo et al. 2019). This approach facilitates comparison between different variables, such as those based on precipitation and streamflow, which have varying units and physical attributes. Additionally, standardisation aids in mapping drought severity and spatial extent across large and climatologically diverse regions (Hayes et al. 1999; Slette et al. 2020).

The transformation of hydroclimate variables into non-dimensional standardised z-units can be achieved using either empirical probabilities or a specific probability distribution. Some studies advocate for the simplicity and flexibility of the empirical approach (Mallenahalli 2020; Tijdeman et al. 2020; Raziei 2023; Raziei and Miri 2023), as it is not bound by a predetermined distribution frequency. However, these methods have specific limitations in characterising the distribution tails and, consequently, proper identification of the most extreme drought events. In addition, these methods are constrained by the upper and lower values observed during the observation period, requiring recalibration of the entire dataset with each new value, posing challenges for real-time monitoring (Noguera et al. 2022). On the contrary, employing a probability distribution tailored to the frequencies of climatic and hydrological variables offers advantages since this approach is less restricted by the maximum and minimum observed values, resulting in more precise and less uncertain calculations, particularly in the tails of the distribution (Soľáková et al. 2014; Vergni, Todisco, et al. 2017, 2021; Noguera et al. 2022). Moreover, parametric approaches enable the calculation of standardised values using a reference period, which is crucial for comparing series of different lengths and for efficient drought monitoring.

Various studies have proposed the application of specific probability distributions to calculate different drought indices. For instance, the Gamma distribution has been widely recommended to fit precipitation series obtained at different time scales for calculating the Standardised Precipitation Index (SPI) (McKee et al. 1993; WMO 2012). Likewise, the log-Logistic distribution has been suggested for computing some of the most commonly used drought indices such as the Standardised Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010; Beguería et al. 2014) and the Standardised Evapotranspiration Deficit Index (SEDI) (Kim and Rhee 2016). Conversely, alternative probability distributions have been proposed for these indices, such as the Pearson III distribution for SPI calculation (Guttman 1999) or the General Extreme Value (GEV) distribution for SPEI computation (Stagge et al. 2015; Slavková et al. 2023; Tam et al. 2023). However, other studies have highlighted limitations associated with the parametric approach based on specific distributions for calculating standardised drought indices, as the recommended probability distributions for some of these indices may not align with hydrological and climatological series across large global regions (Lloyd-Hughes and Saunders 2002; Pieper et al. 2020; Wang, Wang, Zhang, et al. 2021; Fotse et al. 2023), or they may yield suboptimal results (overestimation vs. underestimation of drought conditions) compared to alternative distributions (Moccia et al. 2022; Hinis and Geyikli 2023; Nadi and Shiukhy Soqanloo 2023; Slavková et al. 2023). Using a probability distribution that does not adequately fit the data can lead to deviations from normality in the obtained series, affecting drought quantification and spatial comparability (Zhang and Li 2020; Ghasemnezhad et al. 2022; Laimighofer and Laaha 2022; Yimer et al. 2022).

An alternative approach to solve the complexity associated with using a single probability distribution is to employ different distributions, adapting to the diverse seasonal and spatial characteristics of hydroclimate variables. This approach was proposed by Vicente-Serrano et al. (2012) in the development of the Standardised Streamflow Index (SSI), which was justified by the noticeable seasonal and spatial variations in the frequency distributions of streamflow series. Later, several studies have followed suit, standardising various meteorological variables using different statistical tests for distribution selection (Sienz et al. 2012; Blain and Meschiatti 2015; Touma et al. 2015; Hinis and Geyikli 2023; Lee et al. 2023; Slavková et al. 2023).

Considering that the primary objective of calculating standardised drought indices is to enhance spatial, temporal and variable comparability of drought conditions and to accurately represent drought severity and extreme events, it seems logical to adopt flexible approaches not bound by a single global probability distribution. While non-parametric methods have been proposed to achieve this flexibility (Farahmand and AghaKouchak 2015), there is a lack of flexible approaches that consider parametric distributions, adapt to different variables and show skill in reproducing drought conditions across different climatic regions worldwide.

In this study, we undertake a comparison of three different drought indices calculated using two distinct methodologies: (i) employing a single probability distribution at the global scale, tested across various climate conditions and endorsed by prior research and (ii) utilising diverse distributions that may vary as a function of pixel scale, variables, month of the year and drought time-scale. To achieve this objective, we applied a methodology that employs the Akaike Information Criterion (AIC) for distribution selection. We employed various statistical approaches to compare the performance of the two methods.

2 | Data and Methods

To achieve global coverage, we used precipitation and AED data from the latest version (TS v. 4.07) of the gridded database provided by the Climatic Research Unit of the University of East Anglia (Harris et al. 2020). This dataset offers global monthly information at a spatial scale of 0.5° spanning from 1901 to 2022. To mitigate uncertainties associated with data availability, our analysis focused on the period from 1950 to 2022. This dataset facilitated the computation of two out of the three drought indices examined in this study: the SPI (McKee et al. 1993), which relies solely on precipitation data, and the SPEI (Vicente-Serrano et al. 2010), which integrates precipitation and AED data. In addition to these two indices, we incorporated another index in our analysis: the SEDI (Kim and Rhee 2016), whose computation requires ET and AED data. To obtain ET data, we used the Global Land Evaporation Amsterdam Model (GLEAM) version 3.7a, covering the period from 1980 to 2022 (Martens et al. 2017). The GLEAM dataset offers global coverage at a spatial resolution of 0.25°.

The selection of these three drought indices is justified by two major reasons. Firstly, they have been extensively employed in numerous prior studies to assess drought severity from various conceptual perspectives. Each of these indices provides insights into water stress using different approaches, encompassing deficits in precipitation (SPI), the balance between precipitation and AED (SPEI) and evapotranspiration deficit (SEDI), which offers valuable information on plant water stress conditions.

Secondly, by considering these three drought indices, we encompass the entire spectrum of mathematical conditions generally inherent in drought index calculations. The variables used to compute these indices span across different ranges (Figure 1). Precipitation, utilised in calculating SPI, is constrained at 0 since precipitation cannot have negative values, while its upper limit could theoretically extend to infinity; thus, precipitation values theoretically oscillate between $[0, +\infty]$. In contrast, the difference between precipitation and AED, used for SPEI calculation, lacks theoretical upper and lower limits and can oscillate between $[-\infty, +\infty]$. Similarly, the difference between ET and AED, employed for SEDI computation, consistently yields negative values and has an upper limit at 0, given that ET cannot exceed AED; hence, it oscillates between $[-\infty, 0]$. Thus, the distinct limits collectively cover the entire spectrum of scenarios relevant for calculating other drought indices such as the Standardised Streamflow Index (SSI) (Vicente-Serrano et al. 2012) and the Standardised Soil Moisture Index (SSMI) (AghaKouchak 2014), which share a lower limit at 0 similar to SPI, and the Evaporative Demand Drought Index (EDDI) (Hobbins et al. 2016), which shares an upper limit at 0 similar to SEDI.

In our study, we used the established reference distributions to compute the different drought indices (The Gamma distribution for computing the SPI, while the log-Logistic distribution was used for calculating the SPEI and SEDI), aiming to compare the outcomes with an alternative approach that combines various probability distributions to calculate the indices, allowing for the selection of the most suitable distribution for each monthly series of each variable (such as precipitation, precipitation-AED and ET-AED). For this purpose, we consider six widely used three-parameter probability distributions for fitting hydroclimatic series (Hosking 1990; Rao and Hamed 2000): GEV, generalised Logistic (GLO) also known as log-Logistic, generalised Pareto (GPA), log-Normal (LNO), Pearson Type III (PIII) and Weibull (WEI). The parameters of the various distributions can usually be calculated by means of different approaches, usually using Maximum Likelihood or L-moment statistics. The L-moment method performs better than Maximum Likelihood for small sample

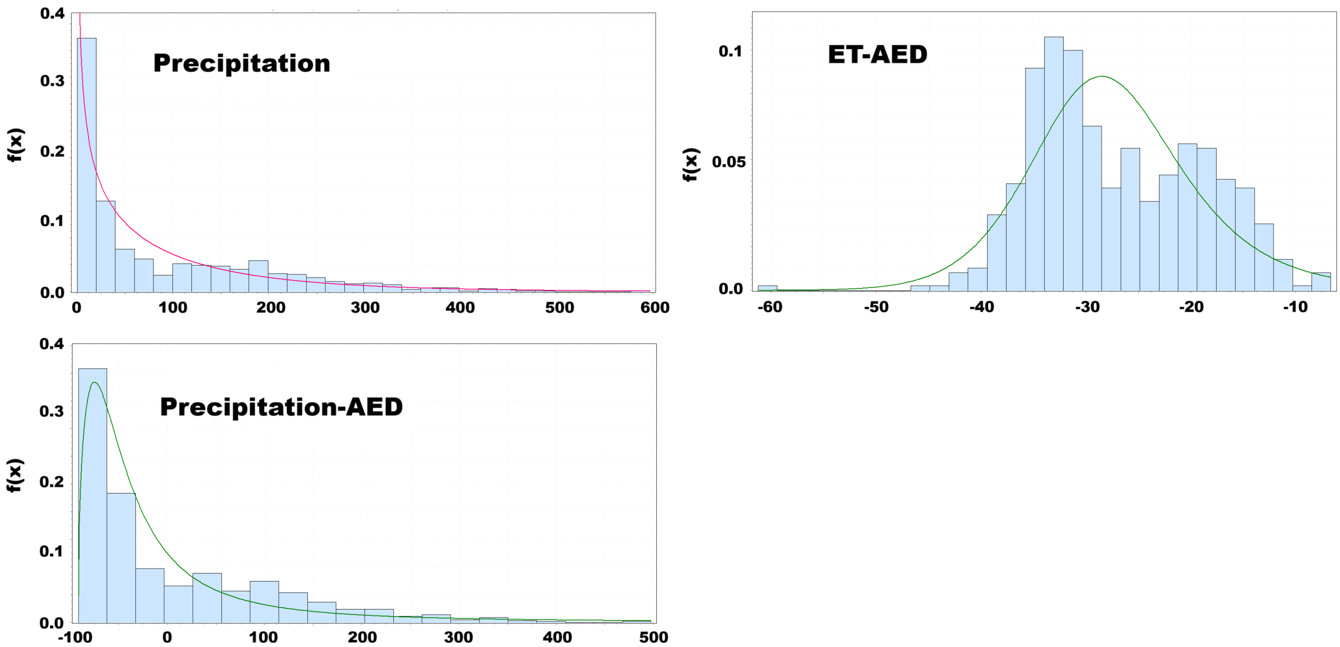

FIGURE 1 | Histograms and the commonly used probability distributions fitted to the data of precipitation (Gamma), precipitation-AED (log-Logistic) and ET-AED (log-Logistic). [Colour figure can be viewed at wileyonlinelibrary.com]

sizes (Nerantzaki and Papalexiou 2022), which are common in hydroclimate series. As one of the objectives of this study is to provide a flexible tool that users can apply to calculate drought indices across diverse hydroclimate series of varying durations, using a method like Maximum Likelihood prone to artefacts in small samples would be inadvisable.

Therefore, the parameters were computed here by means of L-moment statistics (Hosking 1990) independently for each of the 12 monthly series corresponding to each grid cell, and the variables were transformed into theoretical cumulative probabilities. These probabilities were subsequently converted into z-units using the Abramowitz and Stegun (1965) method. Additionally, considering that drought indices are typically calculated over different time scales to enhance their efficacy for drought quantification and impact assessment (McKee et al. 1993; López-Moreno et al. 2013; Vicente-Serrano et al. 2013; Barker et al. 2016), we computed the indices at time scales of 1, 3 and 12 months. Consequently, for each variable and grid cell, we derived 36 distinct sets of parameters for each distribution.

Addressing the treatment of zero values is pivotal as it can significantly influence the resulting drought indices (Wu et al. 2007; Reyes et al. 2022; Stagge and Sung 2022). For the calculation of the SPI using the Gamma distribution as a reference, we followed the standard approach to account for zero values (WMO 2012). In calculating the indices based on the most suitable probability distribution, we adopted the recommendation proposed by Stagge et al. (2015) to compute the probability of zero values using a Weibull plotting position formula, which helps mitigate biases in the final average values.

Choosing the most appropriate probability distribution from the six options mentioned is a multifaceted decision. Previous literature has proposed various methodologies, such as the utilisation of the minimum orthogonal distance between the sample of L-moments at a specific site and the theoretical curves of L-moments for different distributions (Kroll and Vogel 2002). Another approach involves employing widely used statistical tests, like the Kolmogorov–Smirnov or χ^2 tests, which compare the empirical distribution function of a variable with the cumulative distribution function (CDF) for different distributions. Subsequently, the best distribution can be selected based on criteria such as minimising the vertical difference (Blain et al. 2018; Ghasemnezhad et al. 2022; Fotse et al. 2023; Hinis and Geyikli 2023) or using information criteria like the AIC (Sienz et al. 2012; Lee et al. 2023), which is recognised as an effective statistic for selecting the most appropriate distribution for calculating the SPI (Pieper et al. 2020). In this study, we have used the AIC to determine the most suitable distribution for calculating the three different drought indices.

The challenge in calculating the AIC lies in the fact that the maximum likelihood estimates, which are necessary to compute the log-likelihoods for various models, cannot be directly obtained from the L-moment approach used for calculating the probability distributions. Instead, they are derived from the Maximum Likelihood approach. We addressed this issue by calculating the AIC based on both empirical and theoretical CDFs.

The empirical cumulative distribution function (ECDF) is a non-parametric estimator of the true CDF. Given a dataset $x = \{x_1, x_2, \dots, x_n\}$, the empirical CDF is defined as:

$$\widehat{F}(x) = \frac{1}{n} \sum_{i=1}^{n} 1\left(x_i \leq x\right)$$

where $1(\cdot)$ is an indicator function that equals 1 if $x_i \leq x$ and 0 otherwise.

For each candidate theoretical distribution $F_\theta(x)$, the estimated parameters θ (obtained using the L-moment method) allows to compute the theoretical CDF at each observation:

$$F_\theta\left(x_i\right) = P\left(X \leq x_i\right)$$

where X follows the fitted theoretical distribution.

To evaluate the goodness of fit, we compare the probability mass in each interval defined by the empirical CDF. The likelihood is approximated by comparing probabilities of data falling in successive intervals between the empirical and theoretical distributions.

Let $\widehat{F}(x)$ be the empirical CDF and $F_\theta(x)$ be the theoretical CDF. The probability of data falling within an interval $\left(x_{i-1}, x_i\right]$ is estimated as:

Empirical probability in the interval:

$$p_{empirical,i} = \widehat{F}\left(x_i\right) - \widehat{F}\left(x_{i-1}\right)$$

Theoretical probability in the interval:

$$p_{theoretical,i} = F_\theta\left(x_i\right) - F_\theta\left(x_{i-1}\right)$$

To prevent numerical errors (e.g., taking $log(0)$), a small constant ε is introduced:

$$p_{empirical,i} = \max\left[\widehat{F}\left(x_i\right) - \widehat{F}\left(x_{i-1}\right), \varepsilon\right]$$

$$p_{theoretical,i} = \max\left[F_\theta\left(x_i\right) - F_\theta\left(x_{i-1}\right), \varepsilon\right]$$

where $\varepsilon = 10^{-10}$ ensures numerical stability.

The log-likelihood function for the CDF-based approach is given by comparing the sums of the differences in segments, which approximates the derivative of the function using finite differences:

$$\log L_{CDF}(\theta) = n \sum_{i=1}^{n} p_{empirical,i} \log p_{theoretical,i}$$

Finally, we compute the AIC based on the CDF as:

$$AIC_{CDF} = 2k - 2 \log L_{CDF}(\theta)$$

k is the number of parameters in the fitted distribution (three in the case of the six distributions used in this study).

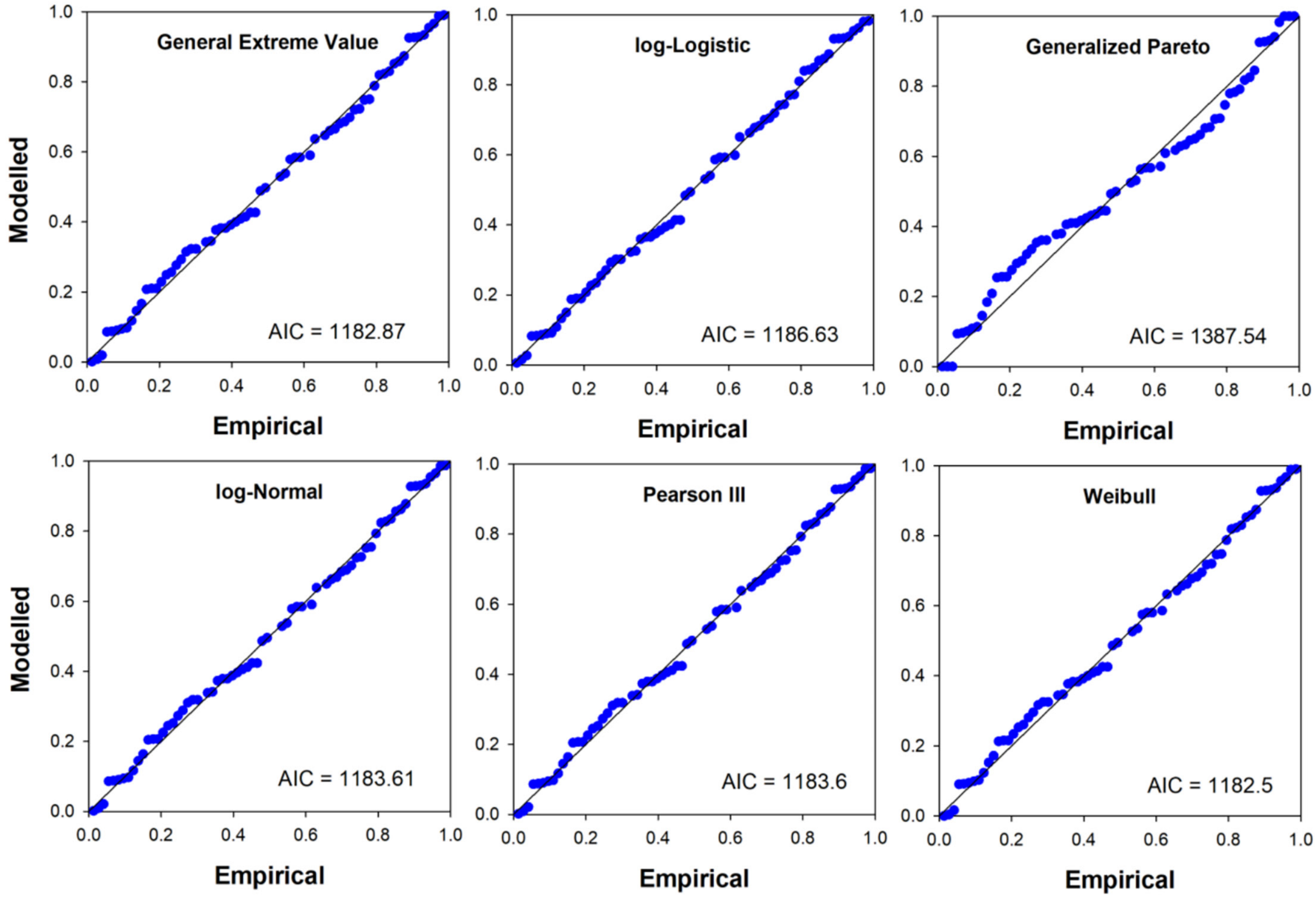

FIGURE 2 | Relationship between the empirical and the theoretical cumulative probabilities along with the Akaike Information Criterion calculated for six different probability distributions, using data from the difference between Precipitation and Atmospheric Evaporative Demand for the August (1-month) series at 105.25 W–69.75 N. [Colour figure can be viewed at wileyonlinelibrary.com]

This approach enables an objective selection of the most suitable probability distribution for standardising the series at each point, period (e.g., annual, monthly, weekly) and timescale. Figure 2 illustrates an example of the relationship between empirical and theoretical cumulative probabilities, along with the weighted distances calculated for six different probability distributions, using data from the difference between Precipitation and AED for the August (1-month) series at 105.25 W–69.75 N. The example demonstrates a generally good agreement between the empirical and theoretical cumulative probabilities. However, notable visual differences exist, with the GPA distribution showing the poorest agreement and the Weibull distribution achieving the lowest AIC among the six distributions, so this is the distribution selected to standardise the series.

This approach ensures flexibility in the selection of the probability distribution. Therefore, we obtained two versions of the four drought indices: one calculated using the single distribution recommended for each index (Gamma for the SPI and log-Logistic for the other two indices), and the second calculated by employing the six different probability distributions and selecting the best-fit one based on the weighted distance approach.

To assess the suitability of both approaches (i.e., the reference approach based on a single probability distribution and the best-fit approach), we employed various procedures: (i) the percentage of series that could not be calculated due to lack of fit, (ii) the number of values below the origin of the selected distribution, indicating no solution, (iii) the percentage of resulting standardised series in which normality was rejected according to the Shapiro–Wilks test, which has been used in similar contexts by previous studies (Naresh Kumar et al. 2009; Stagge et al. 2015). A rejection rate of $p < 0.05$ (corresponding to a 95% confidence level) is employed to differentiate standardised series adhering to a normal standard variable, (iv) the average and standard deviation of the resulting drought indices to ensure they met the requirement of having a mean of zero and a standard deviation of one, (v) the frequency of observed low and high values to the expected frequencies based on a standard normal distribution and (vi) the duration, magnitude and frequency of drought events using an arbitrary threshold of −1.28 (representing the maximum expected drought severity over a 10-year period).

3 | Results

Results indicate significant differences in the selection of the best probability distribution for the flexible multi-distribution approach depending on the drought index and temporal scale (Figure 3). As illustrated, there were minor intra-monthly

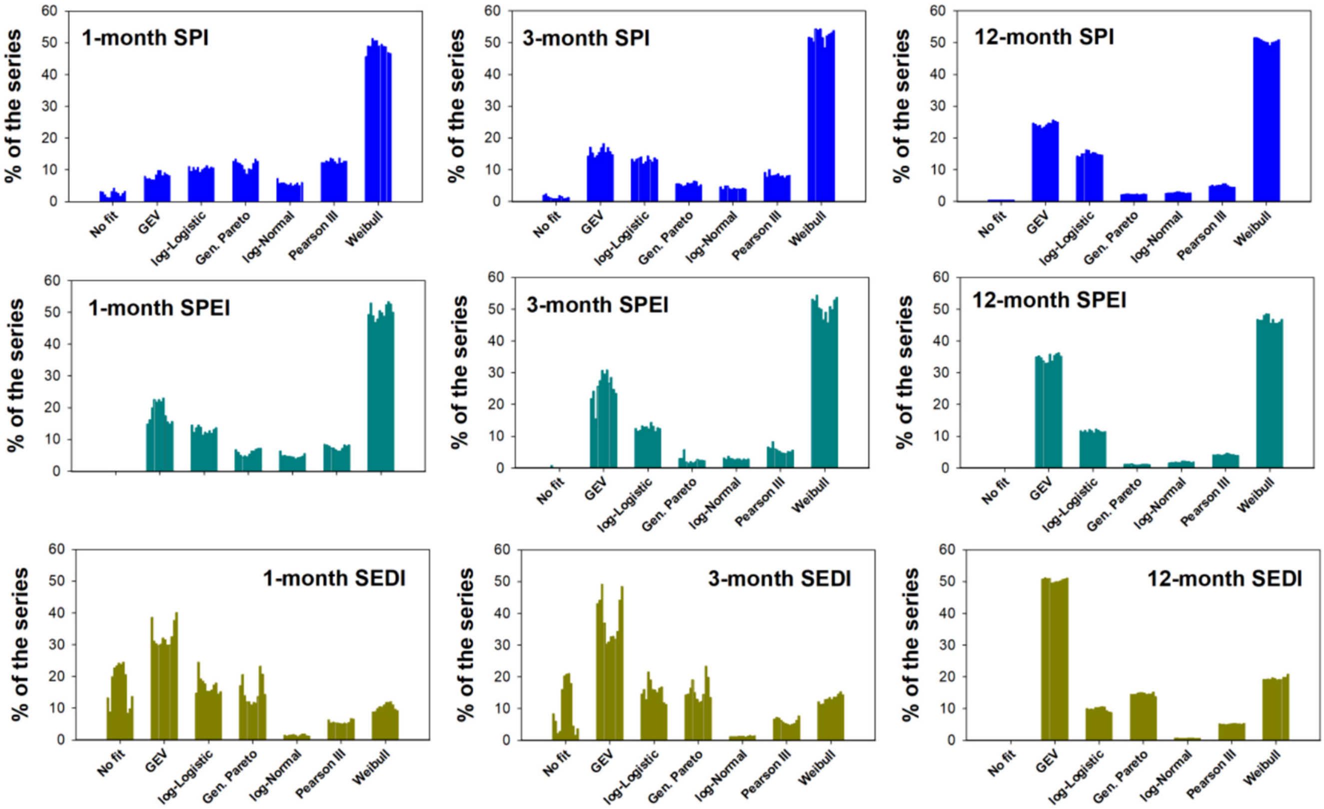

FIGURE 3 | Percentage of the global land area of the three drought indices (SPI, SPEI and SEDI) according to the selected distribution of probability for calculations. The bars represent months starting from January. [Colour figure can be viewed at wileyonlinelibrary.com]

discrepancies irrespective of the selected variable or time scale. For the SPI, despite the Gamma distribution being the reference approach, the Weibull distribution emerged as the most suitable at the global scale for 1-, 3- and 12-month time scales. Similarly, for the SPEI, the Weibull distribution was found to be the most appropriate regardless of the time scale. Nevertheless, it is important to note that while the Weibull distribution is shown to provide a better fit for a high percentage of cases (e.g., over 50% for SPI and SPEI), the combined percentages of the other distributions are also significant and often exceed those of the Weibull distribution in most cases. This underscores the need to consider multiple probability distributions for these calculations.

However, geographic patterns based on these distributions did not exhibit clear dominance (Figure S1), making it challenging to advocate for a single probability distribution that accommodates the diverse requirements of each one of the calculated indices across various regions, seasons and time scales.

To select between the two approaches, it is also necessary to consider the cases where it is impossible to fit a probability distribution to the series of different variables. Table 1 indicates the percentage of global monthly series where no fit to the probability distributions was feasible due to undefined parameters, rendering the calculation of the drought index impossible. Overall, the percentage of such series was low across the three drought indices and different temporal scales. At longer time scales (12-month), the index could be calculated for nearly all regions globally across all three indices. The differences in percentages between the two procedures were minimal, so these results were inconclusive in determining the superior approach due to the small magnitude of the percentages in most cases.

Table S1 presents the percentage of global monthly standardised series for different indices that follow a normal distribution, indicated by Shapiro–Wilks test p values greater than 0.05. Generally, both approaches resulted in the majority of standardised series at the global scale conforming to a standard normal distribution. However, the best-fit approach yielded a higher number of standardised series where the null hypothesis of normality could not be rejected, particularly for shorter time scales (1-month). This disparity was more pronounced for the SPI, with larger differences in percentages compared to longer time scales (12-months).

The spatial comparability of the resulting drought indices is crucial for ensuring that a value represents the same level of severity across different regions. Figure 4 illustrates the density curves of the mean standardised indices recorded worldwide for the different time scales. In the vast majority of cases, the dominant average values tended to be zero, irrespective of the selected approach (the single distribution vs. the best-fit approach). This alignment with a mean of zero is essential for comparability across regions. However, there are differences in the density curves of standard deviation values between the two approaches. While the standard deviations obtained from the single distribution approach tend to be closer to one, those from the best-fit approach show more variability. Nevertheless,

TABLE 1 | Percentage of global series with no fit based on a single distribution method and the Best-fit considering the three drought indices (SPI, SPEI and SEDI) at the time scales of 1-, 3- and 12-months, while also considering the 12 different monthly series.

	SPI-1		SPI-3		SPI-12	
	Gamma	**Best-fit**	**Gamma**	**Best-fit**	**Gamma**	**Best-fit**
January	1.130	1.130	0.722	0.722	0.000	0.000
February	1.058	1.058	0.835	0.835	0.000	0.000
March	0.750	0.750	0.528	0.528	0.000	0.000
April	0.506	0.506	0.361	0.361	0.000	0.000
May	0.408	0.408	0.273	0.273	0.000	0.000
June	1.115	1.115	0.284	0.284	0.000	0.000
July	1.530	1.530	0.274	0.274	0.000	0.000
August	1.041	1.041	0.629	0.629	0.000	0.000
September	0.910	0.910	0.548	0.548	0.000	0.000
October	0.620	0.620	0.309	0.309	0.000	0.000
November	0.921	0.921	0.319	0.319	0.000	0.000
December	1.156	1.156	0.426	0.426	0.000	0.000

	SPEI-1		SPEI-3		SPEI-12	
	Log-Logist.	**Best-fit**	**Log-Logist.**	**Best-fit**	**Log-Logist.**	**Best-fit**
January	0.000	0.000	0.000	0.000	0.000	0.000
February	0.000	0.000	0.000	0.000	0.000	0.000
March	0.000	0.000	0.000	0.000	0.000	0.000
April	0.000	0.000	0.000	0.000	0.000	0.000
May	0.001	0.000	0.000	0.000	0.000	0.000
June	0.003	0.000	0.000	0.000	0.000	0.000
July	0.002	0.000	0.000	0.000	0.000	0.000
August	0.001	0.000	0.000	0.000	0.000	0.000
September	0.001	0.000	0.000	0.000	0.000	0.000
October	0.000	0.000	0.000	0.000	0.000	0.000
November	0.000	0.000	0.000	0.000	0.000	0.000
December	0.000	0.000	0.000	0.000	0.000	0.000

	SEDI-1		SEDI-3		SEDI-12	
	Log-Logist.	**Best-fit**	**Log-Logist.**	**Best-fit**	**Log-Logist.**	**Best-fit**
January	9.535	8.080	6.916	5.856	0.000	0.000
February	5.748	4.957	5.391	4.572	0.000	0.000
March	1.914	1.813	1.775	1.524	0.000	0.000
April	0.896	0.865	0.829	0.725	0.000	0.000
May	0.138	0.135	0.106	0.100	0.000	0.000
June	0.039	0.038	0.000	0.000	0.000	0.000
July	0.026	0.025	0.000	0.000	0.000	0.000
August	0.394	0.386	0.000	0.000	0.000	0.000

(Continues)

TABLE 1 | (Continued)

	SEDI-1		SEDI-3		SEDI-12	
	Log-Logist.	Best-fit	Log-Logist.	Best-fit	Log-Logist.	Best-fit
September	1.401	1.335	0.006	0.006	0.000	0.000
October	3.845	3.381	0.390	0.345	0.000	0.000
November	7.496	6.360	1.372	1.178	0.000	0.000
December	10.378	8.755	3.643	3.112	0.000	0.000

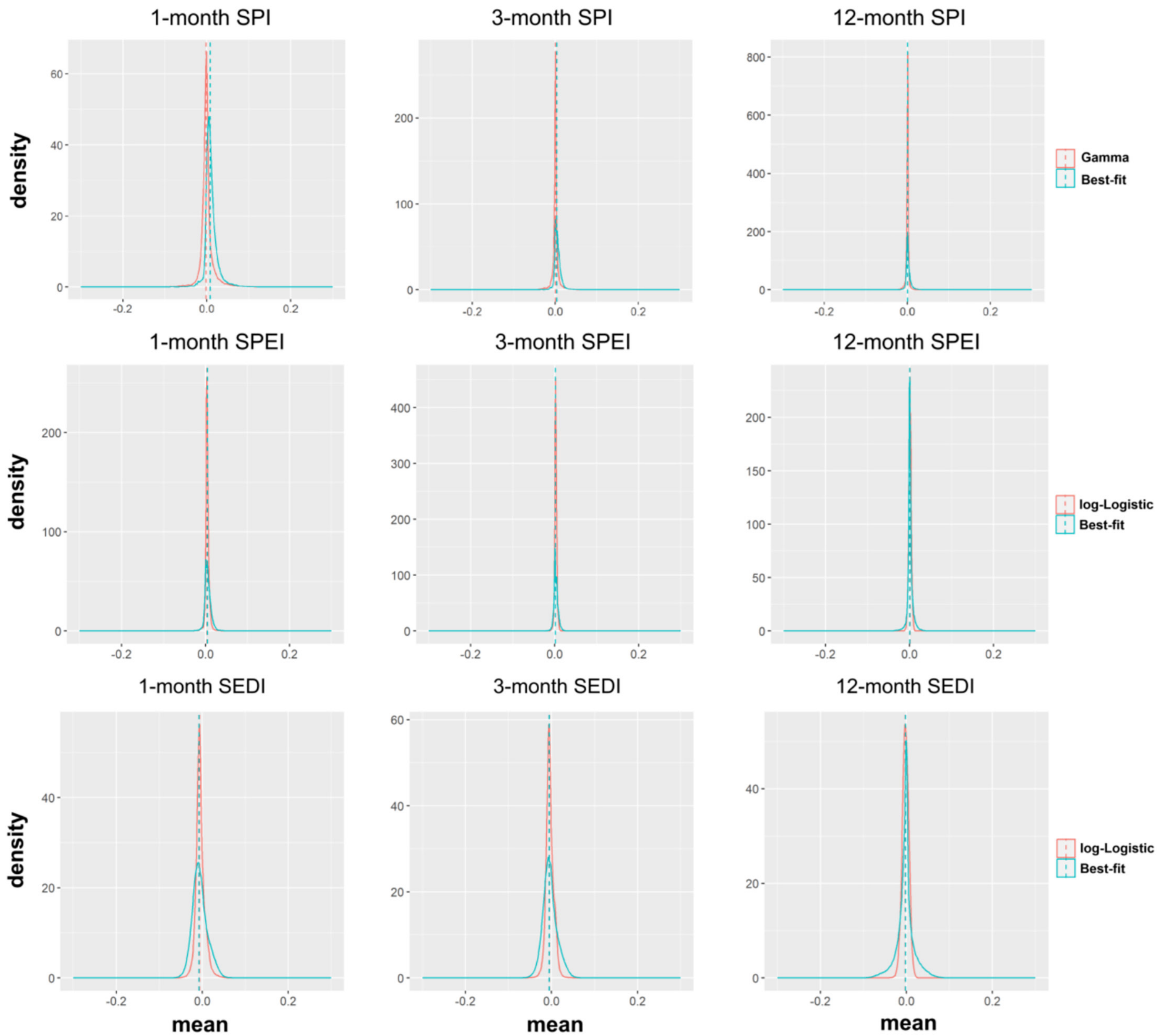

FIGURE 4 | Density curves of the mean values corresponding to different gridded series of the three tested drought indices at the three different time scales obtained by means of the single distribution and the best-fit approaches. [Colour figure can be viewed at wileyonlinelibrary.com]

since the standard deviation values are generally very close to one across most regions, the indices remain highly comparable worldwide under both approaches (Figure 5).

Further analysis confirms that there are no significant spatial patterns between the resulting standardised indices in terms of their spatial comparability following either approach

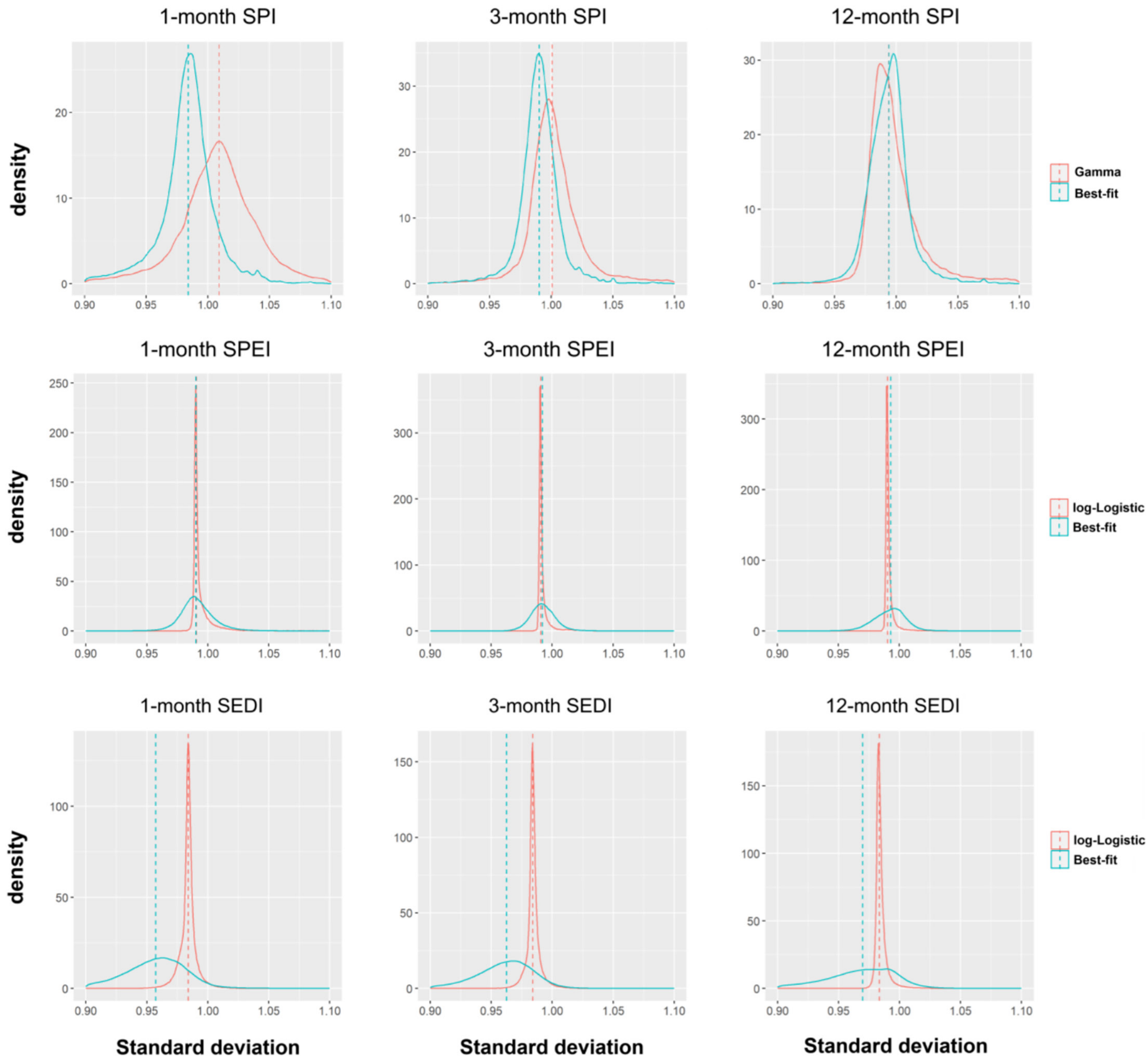

FIGURE 5 | Density curves of the standard deviation values corresponding to different gridded series of the three tested drought indices at the three different time scales obtained by means of the single distribution and the best-fit approaches. [Colour figure can be viewed at wileyonlinelibrary.com]

(Figures 6, S2 and S3). Additionally, the statistical characteristics of drought events identified at the global scale, such as average duration, magnitude and frequency, are comparable between both calculation approaches. This consistency is observed across the three drought indices and the three time scales, except for SPI at shorter time scales, where differences in the average magnitude and total number of recorded drought events were noted. These differences may be attributed to the varying treatment of zero values between the two approaches, particularly affecting arid and semiarid regions (Figures S4–S6).

A comparison between the single distribution and best-fit approaches reveals few relevant differences in various tests, except for a higher number of standardised series following a normal distribution with the best-fit approach. However, when examining the relationship between standardised values obtained from both approaches, some differences emerge, particularly affecting the lower tail of the distribution values. For instance, in the scatterplots of SPI values (Figure 7), there is generally high agreement over most of the variable range ($\approx \pm 1.8$). However, in the lower tail of the distribution, where the frequency of values is much lower, but still critical for assessing drought severity, differences are recorded. Standardised values obtained with the Gamma distribution tended to be more extreme than those obtained with the best-fit approach across all time scales. Even small changes in z-units in this lower range can significantly impact the corresponding drought return periods (Figure 8), and consequently the evaluation of extreme drought events, which pose major socioeconomic and ecological impacts. For SPEI, the best-fit approach

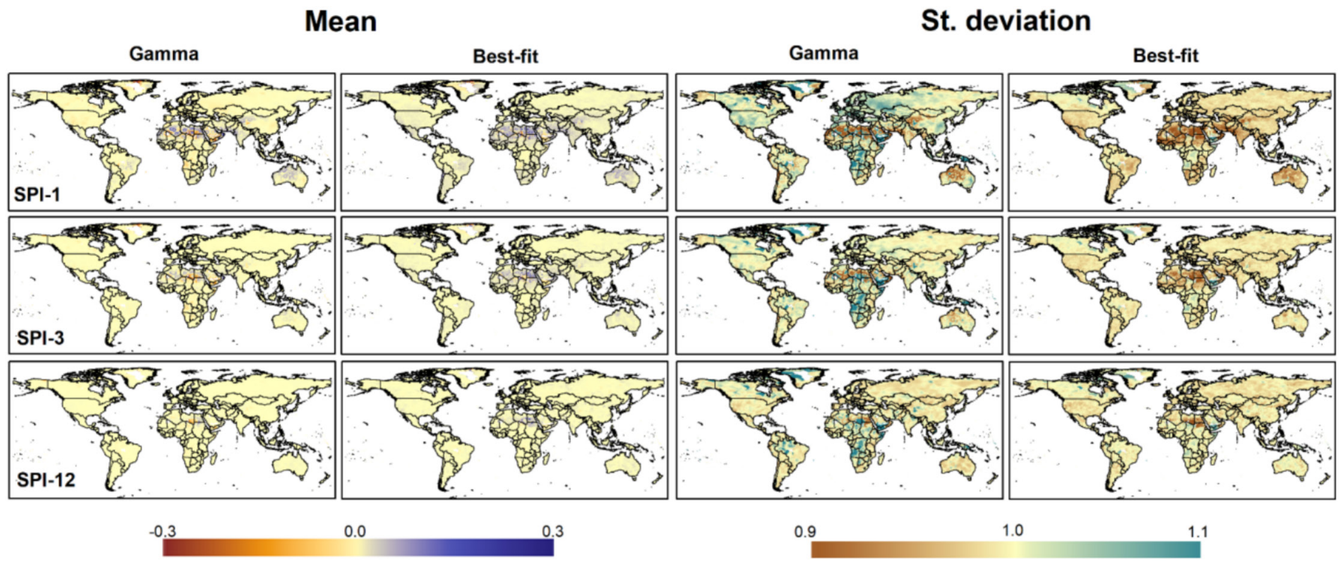

FIGURE 6 | Spatial distribution of the mean and standard deviation of the SPI values calculated at time scales of 1, 3 and 12 months obtained by means of the Gamma distribution and the Best-fit approach. [Colour figure can be viewed at wileyonlinelibrary.com]

provides the opposite behaviour to the PI, with lower values in the lower tail of the distribution and higher values in the upper part of the distribution than the single distribution approach (Figure S7). For SEDI, a similar behaviour to the SPEI is found (Figure S8).

When analysing the expected and observed frequencies of the *z*-values using different drought indices, some differences were found between the two calculation approaches (Table 2). Considering the high number of records in the gridded data at the global scale for various drought indices, one would expect observed standardised values to align closely with expected frequencies according to the normal standard distribution. However, discrepancies were observed, including both an overestimation and an underestimation of certain values.

For instance, for SPI-1, the single distribution approach tended to overestimate the expected frequencies of values below different thresholds in the lower tail of the distribution. Conversely, the best-fit approach showed frequencies more in agreement with the expected frequencies. For instance, while about 1% of values would be expected to correspond to return periods higher than 100 years, the single distribution approach provided a frequency higher than 3%, whereas the best-fit approach yields 1.19%. Similar patterns were identified for values corresponding to return periods of one in 200, 500 and 1000 years. In the upper part of the distribution, the differences between methods were smaller, and there was a higher agreement between observed and expected frequencies. However, for time scales of 3 and 12 months, there was more alignment between the *z*-values obtained from both methods, although the single distribution approach tended to overestimate more than the best-fit approach the extreme drought conditions compared to the expected frequencies.

In contrast to the findings with SPI, for the SPEI, using the single (log-Logistic) distribution approach reveals an opposite problem. The SPEI calculated by means of the log-Logistic distribution tended to underestimate the expected frequency of extreme drought events. On the contrary, although the best-fit approach slightly overestimates the frequency of extremes at high return periods, it yields values closer to the expected frequencies than the single distribution approach, particularly for return periods up to 200 years. This pattern is consistent across different time scales for the SPEI. For the SEDI, the pattern is similar to that observed for the SPEI, but even more pronounced, as the single distribution approach clearly underestimates the expected frequencies for return periods exceeding 20 years.

It is important to note that both calculation approaches encounter cases where there is no solution because the value of the variable (such as Precipitation, Precipitation-AED, AED and ET-AED) falls below the origin of the selected probability distribution, whether based on the single distribution or the best-fit approach. For example, when using the single distribution approach for 1-month SPI, approximately 1.73% of the gridded values do not yield a solution because the values of the variable are below the parameter of origin of the distribution. However, with regard to SPEI and SEDI, this issue becomes more pronounced when utilising the best-fit approach. Nonetheless, it is noteworthy that such situations account for less than 0.26% of the total cases. In light of this, we suggest addressing these non-solution values by assigning them a value of −2.88, which equates to a return period of 500 years. This decision is substantiated by the fact that these cases typically reflect extremely dry conditions.

We have developed software that calculates various indices using the best-fit approach. This software consists of a collection of routines written in the programming language R, accessible via https://github.com/lcsc/FlexDroughtIndex. With this software, users can compute several indices examined in this study, including SPI, SPEI and SEDI, across different time scales and frequencies (e.g., monthly: 12 cases per cycle). Additionally, it offers the capability to establish reference periods for calculating distribution parameters necessary for index computation over the entire analysis period.

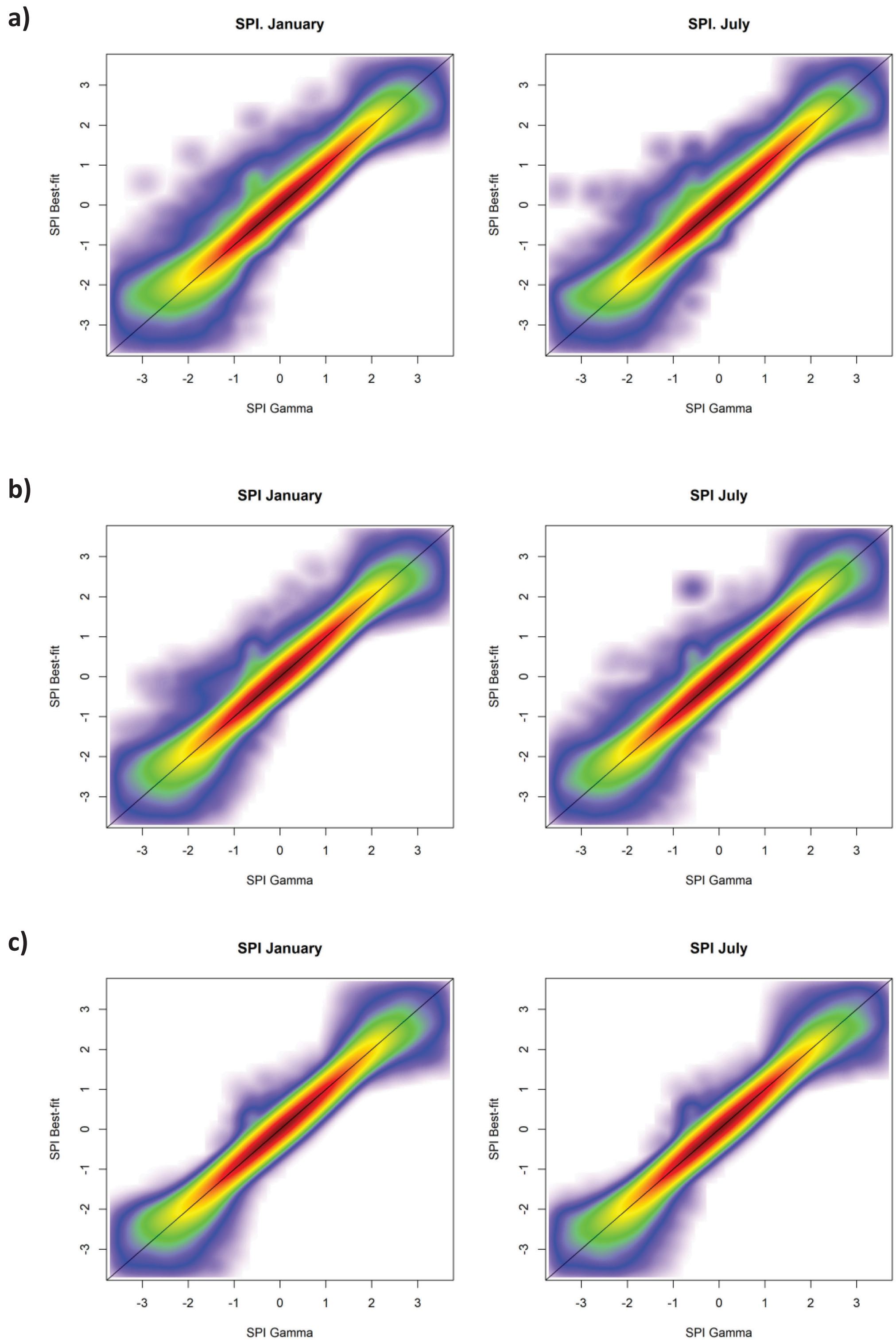

FIGURE 7 | Scatterplots showing the relationship of the SPI values at the time scales of (a) 1-month, (b) 3-month and (c) 12-month over the world calculated by means of the single (Gamma) distribution and the Best-fit approach. The values for January and July are shown in order to illustrate the most contrasted seasonal conditions. The colours represent the density of points, with the maximum density shown in red. [Colour figure can be viewed at wileyonlinelibrary.com]

Each of the three functions corresponds to one of the drought indices tested in this study. However, they are versatile and can be utilised to standardise other variables into standardised values. This flexibility accommodates various conditions within the ranges of variability, as discussed in Section 2. For instance, the SPI function, based on the best-fit approach, could standardise hydrological variables such as streamflow, soil moisture, or groundwater, as well as other meteorological variables like wind

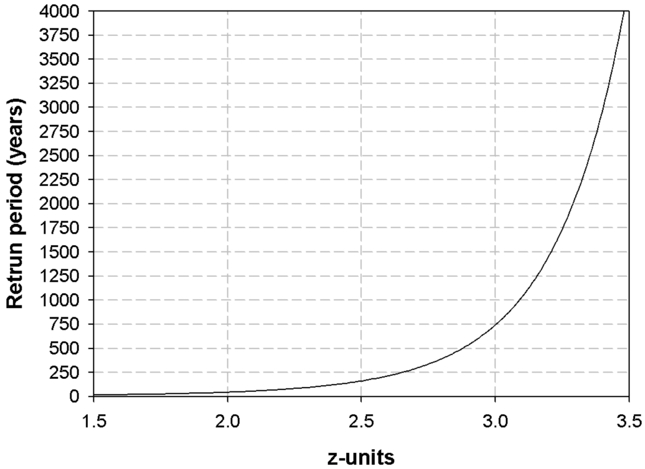

FIGURE 8 | Correspondence between the z-units and the return period in years according to the standard normal distribution.

speed. These variables typically have lower bounds at zero in their distributions, and determining the most suitable distribution for obtaining standardised series based on these variables beforehand may not be evident.

4 | Discussion and Conclusions

This study introduces a flexible approach to calculate the most common standardised drought indices. It is based on testing different probability distributions and selecting those most suitable according to the resulting normal standard series. These results are compared with the approaches based on a single probability distribution that are commonly used to calculate these drought indices. There are several sources of uncertainty in drought index calculation, with one of the main uncertainties being the length of available data (Guttman 1999; Vergni, Di Lena, et al. 2017; Carbone et al. 2018). However, the selected probability distribution used for the calculations also emerges as one of the main sources of uncertainty (Stagge et al. 2015; Laimighofer and Laaha 2022).

In agreement with recent studies (Hinis and Geyikli 2023; Lee et al. 2023; Nadi and Shiukhy Soqanloo 2023; Slavková et al. 2023; Tam et al. 2023), our findings found that the most suitable distribution to calculate standardised drought indices may change spatially, seasonally, and as a function of the calculated time scales. This suggests that the most widely recommended distributions, such as the Gamma for the SPI (WMO 2012) or the log-Logistic for the SPEI (Vicente-Serrano and Beguería 2016), may not be the best approaches to calculate these indices in large world regions, in agreement with previous studies (Pieper et al. 2020). This finding is significant because if the selection of the probability distribution strongly affects the obtained results, careful estimation is needed. Moreover, if the use of a single probability distribution does not guarantee comparability of the resulting drought indices across regions, this reinforces the need for approaches that are more flexible in the selection of distributions.

Thus, although we agree with Stagge et al. (2015), who stressed that selecting different distributions for different regions, seasons and time scales adds complexity to the calculation of drought indices, we believe that the method used in this study, based on the AIC, is robust and efficient for selecting the best distribution (Pieper et al. 2020; Laimighofer and Laaha 2022). Additionally, the use of different distributions in calculating drought indices should not affect the spatial and temporal comparability of the resulting indices, as suggested by (Stagge et al. 2015). It is essential to remember that the objective of having high-quality drought indices is not to find the probability distribution characterised by higher usability given the variability of climate conditions at regional or global scales, but to have the best standardised series possible, independent of the probability distribution used for this purpose.

Previous studies have shown that the temporal correlation between drought indices calculated by different probability distributions is usually strong (Beguería et al. 2014; Moccia et al. 2022). Additionally, the characteristics of drought events in terms of duration, magnitude and frequency can be similar when considering different probability distributions for calculation (Moccia et al. 2022). Therefore, we would not expect the proposed methodology in this study to improve characteristics of the drought indices related to the overall temporal variability. However, substantial improvements are evident in other relevant aspects.

In line with previous studies (Blain and Meschiatti 2015; Stagge et al. 2015, 2025; Wang, Wang, and Romanowicz 2021; Laimighofer and Laaha 2022), we observed that the time scale at which the drought indices are calculated significantly affects the uncertainty of the calculated drought indices. Generally, the rates of rejection of a normal distribution decrease as the drought time scale increases. Additionally, the spatial comparability of the mean and standard deviation of the z-values becomes more homogeneous and comparable spatially. This phenomenon is observed with both the single distribution and the best-fit approaches. However, we noticed that the influence of the drought time scale on the accurate representation of the expected frequencies of extreme drought conditions is also noteworthy when using the single distribution approach. With the application of the best-fit approach, this dependence on the accurate representation of the expected frequencies of extremes across drought temporal scales improves in some of the cases. It is important to bear in mind the significant uncertainties associated with standardised values at high return periods (Stagge et al. 2015), which are also not independent of the selected drought time scale (Stagge et al. 2025). Nevertheless, we would like to emphasise that, for return periods of particular relevance to drought management (e.g., 1 in 20 or 100 years), the best-fit approach yields frequencies that are closer to the theoretically expected values. This pattern holds regardless of the drought index used, reinforcing the robustness of this method for accurately calculating drought indices.

Previous studies have indicated that problems in calculating standardised drought indices due to the selection of a specific probability distribution are minimal within the main range of standardised variables (e.g., $\approx\pm1.8$) (Vergni, Di Lena, et al. 2017; Blain et al. 2018; Wang, Wang, and Romanowicz 2021). In this study, we confirm that this conclusion holds true for various variables and temporal scales at the global level, as the

TABLE 2 | The upper part of the table displays the expected frequencies (in %) corresponding to the z-values below and above certain thresholds in the lower and upper tails of the distribution. These thresholds correspond to comprehensible return periods. The observed frequencies at the global scale for the same thresholds are shown for the different drought indices at the time scales of 1-, 3- and 12-months.

Return period		1000 years	500 years	200 years	100 years	20 years	20 years	100 years	200 years	500 years	1000 years
z-index value	Below origin	Below −3.08	B. −2.88	B. −2.57	B. −2.33	B. −1.65	Above 1.65	A. 2.33	A. 2.57	A. 2.88	A. 3.08
Expected (%)	0.00	0.10	0.20	0.50	1.00	5.00	5.00	1.00	0.50	0.20	0.10
SPI-1											
Gamma	1.73	2.03	2.18	2.57	3.08	6.76	4.87	0.95	0.53	0.27	0.19
Best-fit	0.34	0.45	0.52	0.77	1.19	4.83	5.29	0.95	0.44	0.17	0.10
SPI-3											
Gamma	0.48	0.73	0.87	1.26	1.78	5.60	4.86	1.01	0.56	0.27	0.18
Best-fit	0.23	0.36	0.45	0.74	1.22	5.02	5.16	1.05	0.52	0.21	0.12
SPI-12											
Gamma	0.01	0.20	0.33	0.69	1.21	5.07	4.86	1.05	0.59	0.28	0.18
Best-fit	0.11	0.25	0.35	0.67	1.19	5.10	5.07	1.08	0.57	0.25	0.15
SPEI-1											
log-Logistic	0.01	0.05	0.07	0.18	0.40	4.30	5.14	0.43	0.14	0.04	0.02
Best-fit	0.24	0.41	0.52	0.83	1.31	5.03	5.15	1.03	0.53	0.25	0.18
SPEI-3											
log-Logistic	0.00	0.02	0.05	0.15	0.40	4.53	4.92	0.44	0.13	0.03	0.01
Best-fit	0.12	0.28	0.38	0.70	1.19	5.00	5.04	1.05	0.54	0.24	0.16
SPEI-12											
log-Logistic	0.00	0.01	0.03	0.12	0.38	4.63	4.76	0.42	0.13	0.03	0.01
Best-fit	0.07	0.20	0.30	0.61	1.11	4.96	4.94	1.06	0.56	0.25	0.16
SEDI-1											
log-Logistic	0.02	0.04	0.06	0.13	0.37	4.61	3.94	0.32	0.13	0.06	0.05
Best-fit	0.36	0.44	0.50	0.70	1.12	5.03	3.99	0.94	0.63	0.44	0.39

(Continues)

TABLE 2 | (Continued)

Return period		1000 years	500 years	200 years	100 years	20 years	20 years	100 years	200 years	500 years	1000 years
SEDI-3											
log-Logistic	0.01	0.02	0.03	0.10	0.33	4.63	4.04	0.30	0.13	0.06	0.05
Best-fit	0.35	0.42	0.47	0.68	1.10	5.06	4.22	1.01	0.68	0.48	0.41
SEDI-12											
log-Logistic	0.00	0.01	0.01	0.07	0.28	4.53	4.12	0.25	0.08	0.03	0.02
Best-fit	0.32	0.38	0.44	0.66	1.06	5.08	4.79	1.16	0.77	0.53	0.45

agreement between standardised z-values calculated using a single distribution and those obtained using the best-fit approach is closer within this range of the variable. In other words, whether employing a single distribution approach based on widely recommended distributions or the best-fit approach described in this study, there is little difference in the calculation of z-values within this range.

Therefore, the primary challenge in calculating drought indices, as highlighted in this and previous studies (Stagge et al. 2015, 2025; Pieper et al. 2020), lies in determining drought intensity in the tail of the distribution, particularly in critical drought conditions. This finding challenges the use of non-parametric approaches based on empirical probabilities of the variable under study. While recommended by some previous studies (Farahmand and AghaKouchak 2015; Tijdeman et al. 2020; Raziei and Miri 2023) for their advantages over the main range of standardised variables (Laimighofer and Laaha 2022), these approaches are highly sensitive to biases in the tails of the distribution and strongly constrained by the maximum and minimum observed values (Soľáková et al. 2014; Vergni, Todisco, et al. 2017, 2021; Noguera et al. 2022).

Given the higher uncertainty in assessing standardised drought indices in the lower tail of the distribution, some previous studies have suggested implementing bounds in the variable's range, such as between ±3.0 (Stagge et al. 2015; Yimer et al. 2022). While these values correspond to a return period of 750 years, making it sufficiently large to be considered a very extreme value, much higher values may be much more uncertain given the length of available samples, rendering the suggested increase in the expected return period irrelevant for evaluating drought severity. However, between standardised z-values of ≈ -1.8 and -3.0, there are values corresponding to return periods between ≈25 and ≈750 years. Small differences in standardised z-units, even to the second decimal place, may correspond to vastly different return periods, signifying varying severity levels of the drought event. Thus, the accurate assessment of this range of the variable is indeed the key issue in evaluating the effectiveness of methods for calculating standardised drought indices.

Given the critical evaluation of the lower tail of the distribution across various variables and the accompanying uncertainties, alternative approaches have been proposed. For instance, (Laimighofer and Laaha 2022) suggested treating the lower tail of the distribution independently and employing extreme value theory, commonly used in hydrological estimations (Rao and Hamed 2000), and in assessing the probability of extreme precipitation events (Beguería 2005; Beguería and Vicente-Serrano 2006), to utilise theoretical extreme distributions. While this approach may offer advantages in accurately determining the severity of the most extreme drought events, it could introduce comparability uncertainties in space and time with values of drought indices within the common range of variation (e.g., ≈±1.8). Additionally, it could pose technical challenges in merging estimations conducted via two different procedures to develop efficient drought quantification and operational monitoring. However, a simpler solution could lie in the use of the proposed best-fit approach outlined in this study, which provides frequencies closer to the theoretical ones.

We have demonstrated that for the majority of variables and time scales examined here, the frequency of expected extreme drought values aligns better with observed frequencies on a global scale. The enhancement in addressing this critical issue, compared to results obtained using a single distribution, may be attributed to the better adaptability of the most suitable distribution to the specific characteristics of different variables, regional conditions, seasons and time scales. Indeed, while further testing is necessary for a comprehensive assessment, such as comparing return periods estimated by theoretical extreme distributions exclusively fitting the lower tail of the distribution values with those derived using the best-fit approach, a more accurate estimation of extreme drought conditions appears achievable with the proposed approach.

The proposed method for calculating standardised drought indices is computationally efficient. Indeed, it requires more computation time than traditional single distribution approaches because various probability distributions must be fitted to the data, and the AIC needs to be calculated to make the optimal selection. However, the provided software efficiently generates global datasets, making this approach expectedly suitable for the majority of applications across different spatial scales. This includes the frequent updates necessary for real-time drought monitoring systems.

We would also like to emphasise the flexibility of the proposed methodology in obtaining standardised drought indices, which would allow for the calculation of other drought indices that have not been extensively explored, such as the groundwater drought index (Bloomfield and Marchant 2013) or the standardised soil moisture index (AghaKouchak 2014). These indices have not been thoroughly tested in terms of the most suitable probability distributions to use at a global scale. Indeed, the generated software can be utilised to standardise any environmental variables computed at time scales ranging from daily to yearly, bounded at the upper or lower tails, or oscillating over any range of magnitude. Further research is needed to test the performance of the proposed methodology on other hydroclimatic and ecological variables. Additionally, it is necessary to determine if this approach is more suitable for point-based series measured at meteorological stations, which are not subject to the smoothing of extreme events commonly seen in gridded databases.

Author Contributions

Sergio M. Vicente-Serrano: conceptualization, methodology, software, investigation, validation, formal analysis, funding acquisition, project administration, writing – original draft, writing – review and editing. **Fergus Reig:** software. **Santiago Beguería:** conceptualization, methodology. **Ahmed El-Kenawy:** investigation, writing – review and editing. **Fernando Domínguez-Castro:** conceptualization, methodology, writing – review and editing. **Magí Franquesa:** writing – review and editing, conceptualization. **Luis Gimeno-Sotelo:** writing – review and editing, methodology. **María Adell-Michavilla:** writing – review and editing. **Amar Halifa-Marín:** methodology, writing – review and editing. **Iván Noguera:** methodology, conceptualization, software, writing – review and editing, validation. **Miguel Andres-Martin:** writing – review and editing, investigation. **Cesar Azorin-Molina:** investigation, writing – review and editing. **Alex Crespillo:** methodology, writing – review and editing. **David Pérez-Pajuelo:** methodology, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available in Climatic Research Unit at https://crudata.uea.ac.uk/cru/data/hrg/ and https://www.gleam.eu/#datasets. These data were derived from the following resources available in the public domain: Climatic Research Unit, https://crudata.uea.ac.uk/cru/data/hrg/ and Ghent University, https://www.gleam.eu/#datasets.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.