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A generalized framework for deriving nonparametric standardized drought indicators

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ABSTRACT

This paper introduces the Standardized Drought Analysis Toolbox (SDAT) that offers a generalized framework for deriving nonparametric univariate and multivariate standardized indices. Current indicators suffer from deficiencies including temporal inconsistency, and statistical incomparability. Different indicators have varying scales and ranges and their values cannot be compared with each other directly. Most drought indicators rely on a representative parametric probability distribution function that fits the data. However, a parametric distribution function may not fit the data, especially in continental/global scale studies. SDAT is based on a nonparametric framework that can be applied to different climatic variables including precipitation, soil moisture and relative humidity, without having to assume representative parametric distributions. The most attractive feature of the framework is that it leads to statistically consistent drought indicators based on different variables.

1. Introduction

Drought is an inevitable and recurring feature of the global water cycle that often leads to significant societal, economic, and ecologic impacts [6,29,32,58,61]. An essential step in analyzing a drought event is to define it based on relevant climatic variables/conditions [15]. Drought affects all elements of the hydrologic cycle, and hence can be defined with respect to different components of the water cycle. Numerous drought and dryness indices have been developed to describe the different types of droughts, including meteorological, agricultural, hydrological and socioeconomic [60].

One of the most common indices is the Standardized Precipitation Index (SPI; [33]), which describes precipitation condition relative to long-term climatology, and is known as an index of meteorological drought [26]. Many other drought indices have been developed based on one or more climate variables, including the Palmer drought severity index (PDSI, [13,40]); Standardized Precipitation Evapotranspiration Index (SPEI; [55]); Standardized Soil Moisture Index (SSI, [3,23]); Vegetation Drought Response Index (VegDRI, [12,52]); Standardized Runoff Index (SRI, [49]); soil moisture percentile [45,56]; Percent of Normal Precipitation (PNP, [59]), Multivariate Standardized Drought Index (MSDI, [24]), Crop Moisture Index (CMI, [41]); Remotely Sensed Drought Severity Index [37]; and Evaporative Stress Index (ESI, [8]). Comprehensive reviews of drought indices are provided in [34,37].

Among the drought indices, SPI is one of the most commonly used indices that has been applied to local, regional and global scale studies (e.g., [7,9,14,35,48,57]). The SPI is widely used, primarily for its simplicity, standardized nature, and flexibility of use across different time scales (e.g., 1-, 6-, 12-month) [26]. On the other hand, SPI has a potential limitation as it assumes that there exists a suitable parametric probability distribution function representative for modeling precipitation data [10].

SPI is typically derived by fitting a gamma probability distribution function to precipitation data. The accumulated gamma probability is then transformed to the Cumulative Distribution Function (CDF) of the standard normal distribution. Though frequently used, the two-parameter gamma distribution may not be the best choice of distribution [22,43]. Analyzing Texas droughts, [43] concluded that the SPI values are quite sensitive to the choice of parametric distribution function, especially in the tail of the distribution – see also [38]. Many parametric distribution functions-such as the three-parameter Pearson type III, normal, lognormal, Wakeby, gamma, and kappa distributions-and different recommendations on the best choice of parametric distribution for modeling precipitation are reported (e.g., [10,22,43]).

On the other hand, [50] argued that the currently available indicators suffer from deficiencies including temporal inconsistency

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and statistical incomparability. Different indicators have varying scales and ranges and their values cannot be compared with each other directly. For example, SPI and PDSI cannot be directly compared as they have different scales [50]. A holistic approach to drought monitoring requires an investigation of multiple indicators (precipitation, soil moisture, runoff, evapotranspiration, etc.). The attractive feature of standardized indices is that they offer the opportunity to create statistically consistent indices based on precipitation (SPI), soil moisture (SSI), runoff (SRI), relative humidity (SRHI), etc. However, a generalized framework for generating spatially and temporally consistent drought indicators is essential in order to assess droughts based on multiple climate variables that often have different distribution functions.

This paper introduces the Standardized Drought Analysis Toolbox (SDAT) that offers a generalized framework for deriving nonparametric univariate and multivariate standardized indices. The methodology can be applied to different climate and land-surface variables (precipitation, soil moisture, relative humidity, evapotranspiration, etc.) without having to assume the existence of representative parametric distributions. This is particularly useful for drought information systems that offer data based on multiple drought indicators (e.g., [25,36,39,47]). The same nonparametric framework can be used for deriving nonparametric standardized multivariate (joint) drought indices that can describe droughts based on the states of multiple variables. A multivariate drought model links individual indicators into a composite model as an overall assessment of drought. This paper explains the mathematical concept behind SDAT, and provides example applications to different data sets. The paper is organized as follows. After this introduction, the nonparametric methodology and its differences with the original parametric model are described in Section 2. Example applications and results are presented in Section 3. The last section summarizes the findings and makes concluding remarks.

2. Methodology

In the original SPI, the frequency distribution of precipitation is described using a two-parameter gamma probability density function:

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

where $\Gamma(\alpha)$ is the gamma function, and x denotes precipitation accumulation. α and β are the shape and scale parameters of the gamma distribution that can be estimated using the maximum likelihood approach [16]. The cumulative probability $G(x)$ can be simplified to the so-called incomplete cumulative gamma distribution function assuming $t = \frac{x}{\beta}$ [16]:

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha-1} e^{-t} dt \tag{2}$$

Since Eq. (2) is not valid for zero precipitation ($x = 0$), the complete cumulative probability distribution, including zeros, can be expressed as: $H(x) = q + (1-q)G(x)$, where q, and $1-q$ are the probabilities of zero ($x = 0$), and non-zero ($x \neq 0$) precipitations. The SPI is then computed by transforming $H(x)$ to the standard normal distribution with a mean of zero and variance of one [33]. A sequence of positive SPI indicates a wet period, and a sequence of negative values represents a dry period.

Instead of the gamma (or any other parametric) distribution function, the empirical probability can be used to derive a nonparametric standardized index. We propose to derive the marginal probability of precipitation (and other variables) using the empirical Gringorten plotting position [21]:

$$p(x_i) = \frac{i - 0.44}{n + 0.12} \tag{3}$$

where n is the sample size, i denotes the rank of non-zero precipitation data from the smallest, and $p(x_i)$ is the corresponding empirical probability. Using this empirical approach, one does not need Eqs. (1) and (2) to derive the parametric probabilities. The outputs of Eq. (3) can be transformed into an Standardized Index (SI) as:

$$SI = \phi^{-1}(p) \tag{4}$$

where ϕ is the standard normal distribution function, and p is probability derived from Eq. (3). One can also standardize the percentiles using the following commonly-used approximation of Eq. (4) [1,17,38]:

$$SI = \begin{cases} -\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) & \text{if } 0 < p \leqslant 0.5 \\ +\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) & \text{if } 0.5 < p \leqslant 1 \end{cases} \tag{5}$$

where $c_0 = 2.515517$; $c_1 = 0.802583$; $c_2 = 0.010328$; $d_1 = 1.432788$; $d_2 = 0.189269$; $d_3 = 0.001308$; and

$$t = \begin{cases} \sqrt{\ln \frac{1}{p^2}} \\ \sqrt{\ln \frac{1}{(1-p)^2}} \end{cases} \tag{6}$$

Several studies argue that a single drought index may not be sufficient to describe all aspects of drought onset, persistence and termination [4,15,23,30]. For example, [23] illustrated that precipitation detects the drought onset earlier, while soil moisture describes the drought persistence more reliably (see also, [18,27]). The suggested nonparametric approach can be extended to higher dimensions to derive multivariate drought indicators. Having two drought-related variables (e.g., X = precipitation and Y = soil moisture), the bivariate distribution is defined by Hao and AghaKouchak [24] as: $p_j = Pr(X \leqslant x, Y \leqslant y)$, where p_j is the joint probability of X and Y (e.g., precipitation and soil moisture).

Having the joint probability of two (or more) drought-related variables, the empirical probability can be derived using the multivariate model of the Gringorten plotting position introduced by Yue et al. [62] $p_j(x_k, y_k) = \frac{m_k - 0.44}{n + 0.12}$, where m_k is the number of occurrences of the pair (x_i, y_i) for $x_i \leqslant x_k$ and $y_i \leqslant y_k$, and n is the sample size [24]. Similar to univariate drought indices, the joint probability of X and Y can be standardized using Eq. 4 or Eq. 5 to derive a Multivariate Standardized Drought Index ($MSDI = \phi^{-1}(p_j)$). This concept has been tested and validated for precipitation and soil moisture for monitoring the 2012 United States Drought [24].

The above univariate and multivariate nonparametric standardized approach can be used with different variables, such as precipitation, soil moisture, and relative humidity. It should be noted that there are other univariate and multivariate nonparametric methods that can be used to derive nonparametric indicators (e.g., Weibull). For long-term data sets, necessary for drought assessment, typically different empirical methods lead to similar results [53]. There are also alternative methods for deriving joint empirical probabilities such as the Kendall τ [20,31,53] that can be used for deriving nonparametric multivariate indicators based on multiple variables (e.g., MSDI).

3. Results

Since the probability distribution of precipitation is different at various climate conditions, a parametric approach to SPI may lead to inconsistent results, particularly at large scales (continental to global). The reason is that in certain areas, a distribution function (e.g., gamma) may fit the data, while in another region, the choice

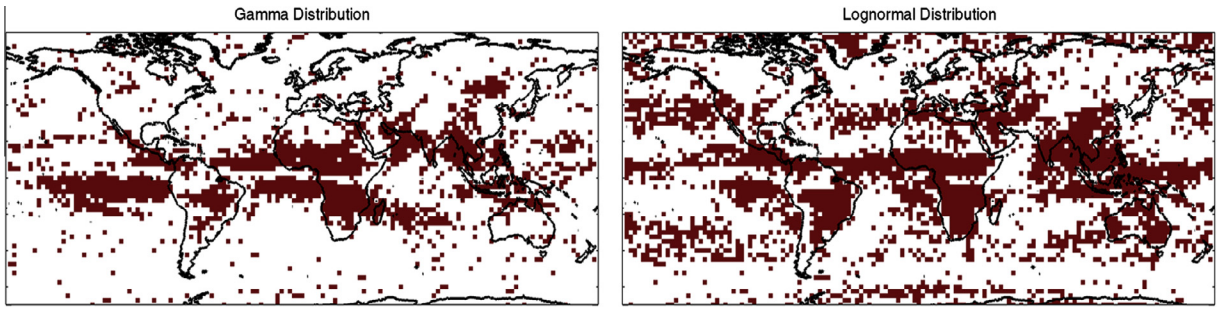

Fig. 1. Representativeness of the gamma (left) and lognormal (right) distributions for describing monthly precipitation accumulations. The dark pixels refer to locations where the Kolmogorov–Smirnov test rejects the null-hypothesis that the gamma (left) or lognormal (right) distribution fits the precipitation data.

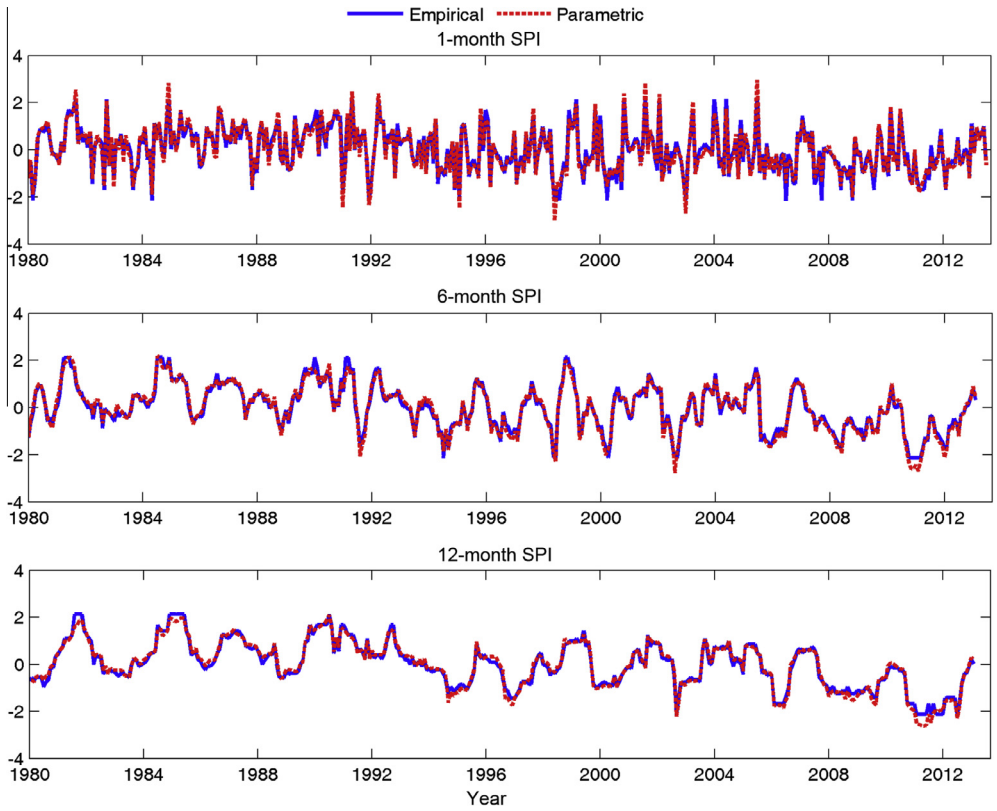

Fig. 2. Example empirical (solid blue line) and parametric (dashed red line) 1-month (top panel), 6-month (middle panel), and 12-month (bottom panel) Standardized Precipitation Index (SPI). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of the distribution function may not fit. As an example, Fig. 1 displays the fit of the Gamma (left) and lognormal (right) distributions to the Global Precipitation Climatology Project (GPCP; [2]) data from 1979 to 2012. The dark pixels refer to locations where the Kolmogorov–Smirnov test rejects the null-hypothesis that the Gamma (left) or lognormal (right) distribution fits the precipitation data.

An alternative option would be using multiple distributions and selecting one that passes a goodness of fit test such as the Kolmogorov–Smirnov (KS). However, even in a multi-distribution approach, the distribution tails [5] of SPI values would change across space, as the best fitted distribution might be different from grid to grid. Sensitivity of the SPI tails to distribution parameters [38], and hence differences at the tails of SPI across space, may lead to inconsistent or biased interpretation of extreme droughts in different regions. In a multi-distribution approach where the best choice of distribution changes across space, the characteristics of extremes change as well. For example, in two locations with different precipitation distribution functions, a SPI value may correspond to different occurrence probabilities.

To address the above limitation, and to provide statistically consistent and comparable drought indices, the Standardized Drought Analysis Toolbox (SDAT) provides tools for computing generalized univariate and multivariate standardized drought indices. Fig. 2 shows example Empirical (solid blue line) and parametric (dashed red line) 1-month (top panel), 6-month (middle panel), and 12-month (bottom panel) Standardized Precipitation Index (SPI) based on the GPCP [2] data (location Lat 17.5 N, Lon 110 W). The time series are primarily consistent, meaning the nonparametric approach can describe wet and dry conditions reliably. However, there are differences in the tails (high and low values) where a parametric distribution may not be a good fit. It should be noted that similar to parametric indices, the nonparametric standardized drought indicators can also be converted to the D-scale drought categories

[51]. The D-scale offers 5 drought categories ranging from D0 (abnormally dry) to D4 (exceptional drought). Each category corresponds to a certain probability in the standard normal distribution and hence, the transformation is straightforward (e.g., D4 corresponds to an event with approximately 2% occurrence probability).

We argue that the suggested nonparametric approach can be used to generate spatially and temporally consistent drought maps based on multiple drought-related variables. For example, in addition to the commonly used SPI and SSI, one can obtain Standardized Relative Humidity Index (SRHI) to provide additional information on wet and dry conditions. For September 2011, Fig. 3(a)–(f) display nonparametric 3-month and 6-month SPI, SSI, and SRHI. In Fig. 3, the SPI and SSI are generated using the precipitation and soil moisture from the Modern Era Retrospective-Analysis for Research and Applications-Land (MERRA-Land; [44]), whereas the SRHI is derived based on the NASA Atmospheric Infrared Sounder (AIRS; [11]) Version 6 relative humidity observations.

In 2011, the Texas-Mexico Drought [28] was a major event that let to significant economic losses. As shown, the SPI, SSI and SRHI capture the event at both 3-month and 6-month scales. The SPI and SRHI provide a meteorological perspective, while SSI offers an agricultural perspective. Depending on the application in hand, drought is described using different indicator variables such as soil moisture or precipitation [15]. The nonparametric nature of the suggested framework allows it to derive drought information from different variables (precipitation, soil moisture, relative humidity, etc.) in a consistent and comparable scale. It is worth pointing out that different drought indicators communicate different information about droughts. For instance, a meteorological drought resulting from precipitation deficit may develop rapidly, while a deficit in soil moisture (agricultural drought) in response to precipitation deficit may occur with some time lag. For this reason, the SPI often detects the drought onset earlier, while SSI describes the drought persistence more reliably [23]. The SDAT allows standardizing various climatic and land-surface variables to assess droughts based on different perspectives.

In Fig. 3, SPI and SSI are obtained using 33 years (1980–2012) of climatology, while SRHI is generated using only 10 years (2002–2012) of data. Ideally, drought assessment should be based on long-term data (30 years or more). The purpose of showing SRHI is to demonstrate that while relative humidity is not often used for drought analysis, the SDAT can be used to generate SRHI which provides valuable drought information. Also, this example shows that SDAT allows comparing multiple drought indicators based on different variables that may have different distributions.

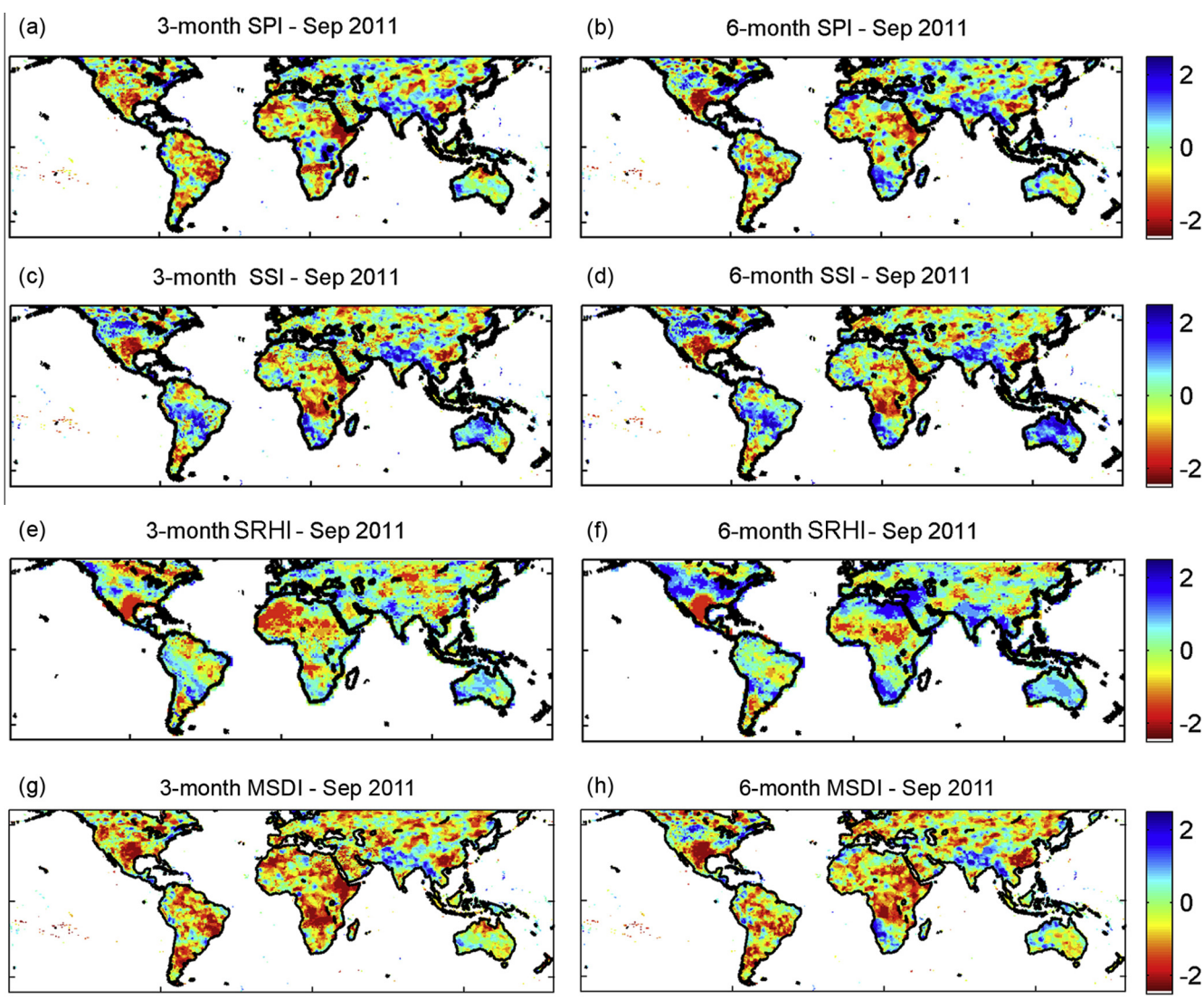

Fig. 3. Nonparametric 3-month and 6-month Standardized Precipitation Index (SPI), Standardized Soil Moisture Index (SSI), and Standardized Relative Humidity Index (SRHI) for September 2011.

As mentioned earlier, this framework allows combining multiple data sets for joint (multivariate) analysis of drought based on multiple input variables. The SDAT includes the Multivariate Standardized Drought Index (MSDI) concept that can be used with different drought related variables. The concept of MSDI has been quantitatively validated against other drought indicators and reference data for the 2007 and 2012 United States Droughts in [24]. For this reason, in this paper, only example outputs of the SDAT are presented. Fig. 3(g) and (h) shows nonparametric 3-month and 6-month MSDI for September 2011, derived from MERRA-Land precipitation and soil moisture data. The MSDI basically combines information from the first two rows in Fig. 3, and provides composite maps of overall drought conditions based on precipitation and soil moisture (composite information on meteorological and agricultural drought).

The most attractive feature of the SDAT is providing standardized indices that are statistically, spatially and temporally consistent. It is worth noting that standardized indices can be computed for different time scales (1-, 3-, 6-, 12-month). Empirical distributions are built based on the ranks of data points instead of their actual values. Given that drought analysis is typically based on relative departures from the climatology, empirical distributions are appropriate. However, the sample size should be relatively large, to avoid misleading probabilities. As shown in Fig. 2, for a 33-year monthly record (33 ×;12 values), the empirical and parametric estimates are consistent for different variables. For very short data records (e.g., less than 10 variables), which is not common in drought assessment, using an empirical distribution can lead to misleading probabilities.

4. Conclusions

Drought mitigation and response plans often rely on information based on different indicator variables and drought triggers. However, many drought indicators are not directly statistically comparable [50]. The presented nonparametric framework of the Standardized Drought Analysis Toolbox (SDAT) offers a generalized approach to develop standardized and statistically consistent drought indicators. The results show that a single distribution function may not fit the global precipitation data and hence, the original parametric SPI may not be applicable. On the other hand, using different distribution functions lead to different tail behavior and thus inconsistencies in characteristics of extremes across space.

The SDAT methodology standardizes the marginal probability of drought-related variables (e.g., precipitation, soil moisture, relative humidity) using the empirical distribution function of the data. The approach does not require an assumption on representativeness of a parametric distribution function for describing drought-related variables. It is also worth pointing out that unlike parametric indices, the suggested nonparametric framework does not require parameter estimation and goodness-of-fit evaluation. This means that the SDAT framework is computationally much more efficient than parametric indicator (e.g., original SPI), especially in large scale (continental/global) studies where parameter estimation and goodness-of-fit evaluation needs to be performed at pixel scale.

Defining drought is fundamental to both drought monitoring and prediction. Drought is a complex phenomenon that can be defined based on different climatic or land-surface variables. The suggested framework can be applied to different drought-related variables to study droughts from multiple viewpoints. We show, for example, that by standardizing relative humidity, which is not a common drought indicator, one can obtain drought information consistent with common drought indicators (e.g., SPI). Multiple viewpoints on droughts are essential for planning and management, as some indicators (e.g., SPI) detect droughts earlier while others describe drought persistence (e.g., SSI) more reliably [23]. The SDAT allows standardizing different drought-related variables for a more comprehensive assessment of droughts. There are several drought monitoring systems (e.g., [19,25,39,42,46,54]) that provides data based on one or more climatic variables. In such systems, SDAT can offer drought information based on multiple data sets in a consistent way.

The SDAT provides tools for not only univariate drought analysis, but also multivariate drought assessment. Multivariate indicators can be used to provide composite drought maps (e.g., composite meteorological-agricultural-hydrological drought conditions). Similar to the commonly used SPI, univariate and multivariate standardized indices can be obtained for different temporal scales (e.g., 1-, 3-, 6-, 12-month). This would allow assessing trends and patterns of droughts at different temporal and spatial scales.

In addition to the nonparametric indices, presented in this paper, the SDAT includes the traditional parametric ones for evaluation and cross-comparison. The source code of this MATLAB toolbox is freely available to the public, and interested readers can request a copy of the software from the authors.

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