



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.

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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 socio-economic [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 non-parametric 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:

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

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]:

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

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 non-parametric standardized index. We propose to derive the marginal probability of precipitation (and other variables) using the empirical Gringorten plotting position [21]:

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

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:

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

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]:

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

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

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

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: $p_j = \Pr(X \leq x, Y \leq y)$, 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 $x_i \leq x_k$ and $y_i \leq y_k$, 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

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