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An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment

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ABSTRACT

Due to severe drought events and disastrous impacts in recent decades, substantial efforts have been devoted recently to drought monitoring, prediction and risk analysis for aiding drought preparedness plans and mitigation measures. Providing an overview of these aspects of drought research, this study presents an integrated **R** package and illustrates a wide range of its applications for drought modeling and assessment based on univariate and multivariate drought indices for both operational and research purposes. The package also includes statistical prediction of drought in a probabilistic manner based on multiple drought indicators, which serves as a baseline for drought prediction. The univariate and multivariate drought risk analysis of drought properties and indices is also presented. Finally, potential extensions of this package are also discussed. The package is provided freely to public to aid drought early warning and management.

Software availability

Name of software: drought
Developer: Zengchao Hao
Email: haozc@bnu.edu.cn
Programming language: R
License: This software is provided under the terms and conditions of the GNU GENERAL PUBLIC LICENSE Version 3
Availability: https://r-forge.r-project.org/projects/drought/
Cost: Free for non-commercial academic research

1. Introduction

Drought is among the costliest natural hazards with disastrous impacts on society and ecosystems. Severe droughts in the past decades, such as the 2012 U.S. drought and 2010–2011 East Africa drought, led to huge economic losses or even famine around the world (Dutra et al., 2013; Smith and Katz, 2013; Hoerling et al., 2014). Reliable drought monitoring and early warning play an important role in coping with drought, which requires integrated drought monitoring, prediction and risk assessment in order to track the drought status, provide prediction information, and assess the risk associated with drought impacts.

Drought can be classified mainly into four types, including meteorological, agricultural, hydrological, and socioeconomic drought (Dracup et al., 1980; Wilhite and Glantz, 1985), while other types of drought such as groundwater drought and ecological drought has also been used (Mishra and Singh, 2010). Scores of drought indices have been developed for the characterization of different drought types in past few decades (Heim, 2002; Mishra and Singh, 2010; Zargar et al., 2011; Hannaford et al., 2015; Hao and Singh, 2015; Bachmair et al., 2016), such as standardized precipitation index (SPI) (McKee et al., 1993) and the Palmer Drought Severity Index (PDSI) (Palmer, 1965), which have been widely used for drought characterizations. However, there is a lack of consistency on the universally accepted drought indicator, and the suitability of particular drought indices depends on a specific region, season and application. For example, for drought monitoring in the region where snowmelt has to be taken into account, such as western U.S., the Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) or other snow-related indices (Staudinger et al., 2014) would be the suitable choice. Meanwhile, drought conditions are generally related to multiple variables with deficit from various sources and an individual drought indicator may not suffice to characterize drought in different regions and seasons. This has resulted in a surge in the development of multivariate or composite

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drought indices to integrate different drought related variables or drought indices for efficient drought monitoring and early warning, such as the U.S. Drought Monitor (Svoboda et al., 2002), Vegetation Drought Response Index (VegDRI) (Brown et al., 2008), Optimal blended NLDAS drought index (OBNDI) (Xia et al., 2014), Reconnaissance Drought Index (RDI) (Tsakiris and Vangelis, 2005), Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), Joint Deficit Index (JDI) (Kao and Govindaraju, 2010), Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak, 2013), and Aggregated Drought Index (ADI) (Keyantash and Dracup, 2004). These univariate and multivariate drought indices provide useful tools for characterizing different aspects of drought from different perspectives for drought management.

Early drought warning is important for drought preparedness to reduce losses, which can be achieved with drought prediction through the enhanced understanding of drought causes and evolution. In past few decades, various methods have been proposed for drought prediction, based on either dynamical or statistical methods (Mishra and Singh, 2011). Statistical methods generally rely on statistical relationships of historical records, such as regression model, time series modeling, artificial intelligence methods, probability distribution method, and Ensemble Streamflow Prediction (ESP) among others (Mishra and Singh, 2011; Özger et al., 2012; Hao et al., 2016a). Dynamical drought prediction based on seasonal climate forecasts, such as NCEP Climate Forecast System Version 2 (CFSv2) (Saha et al., 2014) or North American Multi-Model Ensemble (NMME) (Kirtman et al., 2014), coupled with land surface models have been increasingly used for predicting meteorological, agricultural and hydrological drought (Wood and Lettenmaier, 2006; Luo and Wood, 2007; Yuan and Wood, 2013; Yuan et al., 2013; Nijssen et al., 2014; Shukla et al., 2014). Though great strides have been made for the understanding of drought causes and the development of prediction methods, challenges still exist, such as improvement of drought prediction skill beyond 1–2 months lead time (Pozzi et al., 2013; Hoerling et al., 2014; Wood et al., 2015; Schubert et al., 2016).

To facilitate drought risk analysis in operational drought management, the statistical inference of drought properties or indices is desired. Based on the run theory, a drought event can be characterized with certain properties (Yevjevich, 1967), such as duration, severity, intensity and spatial extent. Statistical analysis of these drought properties plays an important role in drought risk assessments and water resources planning and management. For example, the return period of a drought duration or severity can be estimated by fitting a suitable probability distribution, such as geometric or gamma, for frequency analysis (Kendall and Dracup, 1992; Mathier et al., 1992). Since drought properties are generally mutually correlated, traditional drought risk assessments with the univariate frequency analysis may not be sufficient and joint modeling of multiple properties is therefore required. For this purpose, multivariate approaches have been used for statistical analysis of drought properties (González and Valdés, 2003; Salas et al., 2005; Shiau, 2006; Nadarajah, 2009; Song and Singh, 2010; Xu et al., 2015). Moreover, different types of drought may occur simultaneously (e.g., joint deficit of precipitation, soil moisture or runoff) (Beersma and Buishand, 2004; Kao and Govindaraju, 2010; Pan et al., 2013; Ma et al., 2014) and a drought is often accompanied or aggravated by high temperature, low relative humidity or other extremes (e.g., the combination of low precipitation and high temperature or high evapotranspiration) (Lyon, 2009; Hao et al., 2013; Leonard et al., 2014; Hao and Singh, 2015; Cheng et al., 2016; Mo and Lettenmaier, 2016). Hence, to facilitate the modeling of multiple drought properties or indices for risk analysis, suitable dependence modeling techniques have to be adopted to capture various dependence structures.

Operational drought management requires accurate monitoring to track drought conditions, reliable prediction to aid early warning, and objective analysis to assess risk to reduce potential impacts of drought. The objective of this study therefore is to develop an integrated drought package to meet these needs to aid drought modeling and assessment using the R software (R Development Core Team, 2015). This paper is organized as follows. An overview of this package is provided in Section 2. Section 3 illustrates the application of different components of this package, followed by the conclusions and future development in Section 4.

2. Overview of the integrated package

2.1. Computation of drought indices

2.1.1. Univariate drought index

A univariate drought index has been commonly developed based on a single hydroclimatic variable (e.g., SPI based solely on precipitation), which is generally constructed using the percentile, anomaly, or the standardization in different ways to meet the need for drought characterization. The commonly used standardization scheme, based on the computation of SPI, can also be applied to other variables, such as soil moisture, streamflow, runoff, groundwater, and snow melt to derive different types of Standardized Drought Index (SDI), including the Standardized Soil moisture Index (SSI), Standardized Runoff Index (SRI), Standardized Groundwater Index (SGI) and Standardized Snow Melt and Rain Index (SMRI) (Shukla and Wood, 2008; Bloomfield and Marchant, 2013; Hao et al., 2014; Núñez et al., 2014; Staudinger et al., 2014; Hao and Singh, 2015). The development and application of SDI has attracted much attention, since the SDI meets certain desired properties of drought indicators, such as statistical consistency and comparability at different spatial scales (Heim, 2002; Steinemann et al., 2015; Hao et al., 2016b).

In the package, computation of the SDI of different time scales (e.g., 3-month, 6-month) is provided, which consists of SPI as a special case, and is introduced as follows. Denote the accumulated variable (e.g., precipitation, runoff, or soil moisture) of different time scales as the random variable X with the probability density function (PDF) $f(X)$. A suitable parametric distribution, such as gamma or log normal (McKee et al., 1993; Sheffield et al., 2004; Stagge et al., 2015), can be used to fit the accumulated precipitation, which can be expressed as:

$$G(x) = \int_0^x f(t)dt \tag{1}$$

When the aggregated monthly precipitation $x = 0$, the cumulative distribution function in equation (1) can be expressed as:

$$H(x) = q + (1 - q)G(x) \tag{2}$$

where q is the frequency of occurrence of $x = 0$. The standard normal distribution can be used to transfer the cumulative probability (or percentile) $P = H(x)$ to obtain the SDI:

$$SDI = N^{-1}(P) \tag{3}$$

where N is the standard normal distribution function with mean zero and standard deviation unity.

Except for the parametric distribution, the nonparametric method, including kernel density estimation or empirical plotting position formula (e.g., Weibull, Gringorten, Harris, Hazen, Beard,