Journal of Hydrology 519 (2014) 1108–1119

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

New variants of the Palmer drought scheme capable of integrated utility

Mingwei Ma [a,b,c], Liliang Ren [a,b,*], Vijay P. Singh [c,d], Xiaoli Yang [a,b], Fei Yuan [a,b], Shanhu Jiang [a,b]

[a] State Key Laboratory of Hydrology–Water Resources and Hydraulic Engineering, Hohai University, Nanjing 210098, China
[b] College of Hydrology and Water Resources, Hohai University, Nanjing 210098, China
[c] Department of Biological and Agricultural Engineering, Texas A&M University, College Station, TX 77843-2117, USA
[d] Zachry Department of Civil Engineering, Texas A&M University, College Station, TX 77843-2117, USA

ARTICLE INFO

Article history:
Received 2 June 2014
Received in revised form 19 August 2014
Accepted 21 August 2014
Available online 30 August 2014
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Sheng Yue, Associate Editor

Keywords:
Drought
Palmer drought model
Standardized indices
Variation
Joint probability
Copulas

SUMMARY

The Palmer drought model that was developed half a century ago has often been used for monitoring and decision making. It has gained wide-spread familiarity and acceptance, together with numerous complaints, criticisms and improvements. This study first introduces a recent variation of Palmer's model, i.e. the standardized Palmer drought index (SPDI) as a hybrid of a Palmer drought index (PI) and a standardized drought index (SI). Then, a more complicated methodology is employed to propose an SPDI-based joint drought index (SPDI-JDI), which is also physically based on the Palmer drought model and is a multivariate SI in nature. Using meteorological observations from twelve WMO gauges from all around the globe, empirical and parametric copula-based approaches are adopted and compared for the construction of SPDI-JDI. The findings in this study indicate that the SPDI-JDI derived from parametric copulas can provide an overall measure of the joint probability-based drought status by combining the probabilistic properties and dependence structure of multi-temporal scale marginals of SPDI. Meanwhile, the SPDI-JDI shows high coherence and correlation with individual PIs and performs well in drought detection when compared to the integration of Palmer drought severity index, Palmer modified drought index, Palmer hydrologic drought index and Palmer *Z* index as well as to the U.S. Drought Monitor observations. Taken together, new variations of the SPDI-JDI and/or SPDI are expected to bring new vigor and vitality into Palmer's drought model, making it more up-to-date for drought monitoring and prediction.

1. Introduction

Drought is a natural hazard that causes enormous damage to social and economic systems, while the consequent eco-environmental degradation is still hard to determine (Mishra and Singh, 2010). Thus, drought monitoring and prediction are of critical importance for developing measures to mitigate the impacts of droughts (Hao and Aghakouchak, 2014). To that end, a number of objective indices have been designed to evaluate and characterize droughts, of which the Palmer drought severity index (PDSI) and standardized precipitation index (SPI) are two of the most well-known indices.

The PDSI, developed by Palmer (1965), is derived from Palmer's drought model that was intended to retrospectively examine wet and dry conditions from a monthly water balance accounting scheme that involves precipitation, evapotranspiration, runoff and soil moisture (Guttman, 1998). Other variations of the Palmer drought index (PI) include Palmer modified drought index (PMDI; Heddinghaus and Sabol, 1991), Palmer hydrologic drought index (PHDI; Alley, 1985; Karl et al., 1987), and Palmer *Z* index (ZIND; Karl, 1986). The PMDI is a modification of the PDSI for real-time operational purposes, the PHDI is appropriate for presenting the hydrological aspects of drought and for monitoring long-term water supply, and the ZIND, also called monthly moisture anomaly index is a measure of wetness or dryness for an individual month.

As designed with different emphases, individual PIs are expected to be of different concerns as well. Specifically, the PDSI and PMDI are mostly labelled as being suitable for monitoring meteorological drought, the PHDI that considers more about the effects of water cycling is generally reported as a measure of hydrological drought, and the ZIND may be of more importance to agricultural interests of drought, since it mainly reflects potential moisture anomaly over short-term duration of a single month.

The PDSI and its variations have been extensively used for monitoring droughts as well as for managing different usable water resources (e.g. Cook et al., 1999; Dai et al., 2004; Choi

* Corresponding author. Address: State Key Laboratory of Hydrology–Water Resources and Hydraulic Engineering, Hohai University, No.1 Xikang Road, Nanjing 210098, China. Tel.: +86 25 8378 6001; fax: +86 25 8370 8419.

E-mail addresses: mingwei.ma86@yahoo.com (M. Ma), njRLL9999@126.com (L. Ren), vsingh@tamu.edu (V.P. Singh).

http://dx.doi.org/10.1016/j.jhydrol.2014.08.041
0022-1694/

et al., 2013). However, critical shortcomings of the PI, including the use of rather arbitrary rules in quantifying drought properties and drought classification and potential misleading spatial–temporal comparisons due to limitations in the methodology used to standardize the indices values for different locations and times, were also reported by Alley (1984) and Heddinghaus and Sabol (1991). Wells et al. (2004) adopted an auto-calculation procedure to develop the self-calibrated PDSI, which can improve the spatial comparison and probability distribution of the original PDSI. Thus in this study, all PIs including PDSI and its three variations, are computed with the proposed self-calibrating algorithm.

The SPI, introduced by McKee et al. (1993), is another landmark in the development of drought indices, which has a completely different probabilistic foundation and gives a better representation of wetness and dryness over time and space. In contrast to the PI, the SPI is designed to quantify only the precipitation deficit for different time windows and recognize the importance of time scales in revealing different aspects of drought. Moreover, the SPI is essentially a standardizing transform of the probability of observations (e.g. precipitation totals over any durations) and the procedure also applies to other variables related to drought (Guttman, 1999). For example, when applied to runoff/streamflow data it formulates the standardized runoff/streamflow index (Shukla and Wood, 2008; Vicente-Serrano et al., 2012), while soil moisture data can be processed to derive the standardized soil moisture index (Hao and AghaKouchak, 2013). Also, Vicente-Serrano et al. (2010) adopted the difference between precipitation and potential evapotranspiration to propose the standardized precipitation evapotranspiration index. All drought indices of this category can be generally termed as standardized drought index (SI), which has also been widely used for drought monitoring and determining critical water management operations (e.g. Lloyd-Hughes and Saunders, 2002; Moreira et al., 2008; Gocic and Trajkovic, 2014). Recently, a copula-based approach was presented by Kao and Govindaraju (2010) integrating the marginal SI of different temporal scales to derive a joint deficit status in precipitation and/or streamflow, as referred to the joint deficit index (JDI), which can also be regarded as a multivariate SI.

However, the PI and SI, as detailed above, are not contrary to each other or irreconcilable in nature. Directly based on the monthly water balance defined by Palmer's drought scheme, Ma et al. (2013) modified the standardization of PDSI using the mathematical framework of SI, making the PI in a new multi-temporal scale index, namely the standardized Palmer drought index (SPDI). As a hybrid of the PI and SI, the SPDI of different time scales can be further used in the design of JDI to propose an SPDI-based joint drought index (SPDI-JDI). Thus, the aim of this study is to introduce and evaluate the SPDI-JDI as another variation of the Palmer drought model for drought monitoring by combining drought information from the SPDI over various temporal scales. Following this brief introduction, Section 2 describes the data sources and methodology for formulating the SPDI-JDI on the basis of SPDI. The main results are presented in Section 3 with relevant discussion and corresponding conclusions are summarized in Section 4.

2. Data and methodology

2.1. Data description

Monthly precipitation and temperature data of twelve WMO observational stations from all around the globe (Fig. 1) are used for the construction and validation of the new integrated drought indicator. We select these meteorological stations because all of them have fairly long and reliable observations and their diversities in drought climatology provide a broad scope of surveying a drought model for general use. Specifically, time series of monthly total precipitation and monthly average temperature are downloaded from the Global Historical Climatology Network-Monthly (GHCN-M) database (available on line at http://www.ncdc.noaa.gov/ghcnm/). The data on precipitation from GHCN-M V2 and temperature from GHCN-M V3 are all continuous and are checked by means of a quality control process adjusted anomalous records. Datasets used for drought analysis span from 1900 to 2012 for most of the selected stations, though relatively limited data series of precipitation and temperature starting from 1931 are available for Xi'an station in China. Furthermore, available water capacity (AWC) of soil needed to derive the site-dependent climatically appropriate for existing conditions (CAFEC) precipitation and corresponding soil water anomaly is available from a globally-gridded $1^\circ \times 1^\circ$ digital format dataset of AWC provided by Webb et al. (2000). Besides, relevant U.S. Drought Monitor (USDM, http://droughtmonitor.unl.edu/) data closest to the end of a month are also collected to evaluate the performance of SPDI-JDI for two meteorological stations.

2.2. Standardized Palmer drought index (SPDI)

The Palmer drought model was conducted using a simple soil water balance equation, i.e.

$$D = P - \tilde{P} \tag{1}$$

where P and $\tilde{P}$ are the observed and CAFEC precipitation, respectively, and for the computation of $\tilde{P}$ the reader is referred to Palmer (1965); the water difference D between P and $\tilde{P}$ is called moisture departure. According to Ma et al. (2013), a standardized Palmer drought index (SPDI) can readily be derived through a probabilistic approach upon this moisture departure, similar to the derivation of SPI using precipitation observations. A brief description for obtaining the SPDI index is worth mentioning below.

(1) The monthly moisture departure D is aggregated over a k-month temporal window in a sliding manner, i.e. $X_k = \sum D$.
(2) The aggregation of X_k is subdivided into 12 separate series by its ending month to form the subsets X_k^m, where $m = 1$ (*Jan*), 2 (*Feb*), ..., 12 (*Dec*) indicates the ending month of X_k^m, in order to reduce the autocorrelation and to appropriately account for the seasonal variation that may exist in the samples.
(3) Each X_k^m series with different ending month is fitted by a generalized extreme value (GEV) distribution to obtain the corresponding cumulative probabilities, i.e.

$$F_{X_k^m}(x_k^m) = \exp\left\{-\left[1 - \kappa\left(\frac{x_k^m - \mu}{\alpha}\right)\right]^{\frac{1}{\kappa}}\right\} \tag{2}$$

where μ, α and κ are the location, scale and shape parameters, respectively, and are recommended to be estimated by the L-moments approach described by Hosking (1990).
(4) The SPDI_k^m can readily be computed as standardized values of $F_{X_k^m}(x_k^m)$ by taking the inverse normal distribution function Φ^{-1}, i.e.

$$\mathrm{SPDI}_k^m = \Phi^{-1}(F_{X_k^m}(x_k^m)) \tag{3}$$

Since SPDI_k^m are separately calculated for each ending month (*Jan*, *Feb*, ..., *Dec*) and are not in a time sequence, the 12 subsets of SPDI_k^m should be combined and reordered as calendar month values to form the corresponding SPDI_k time series. Details on the derivation and validation of the SPDI index can also be found in Ma et al. (2013). And this standardization algorithm makes the SPDI approximately follow a standardized normal distribution with zero mean and unit variance and share the same probabilities/quantiles