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On the mechanisms of two composite methods for construction of multivariate drought indices

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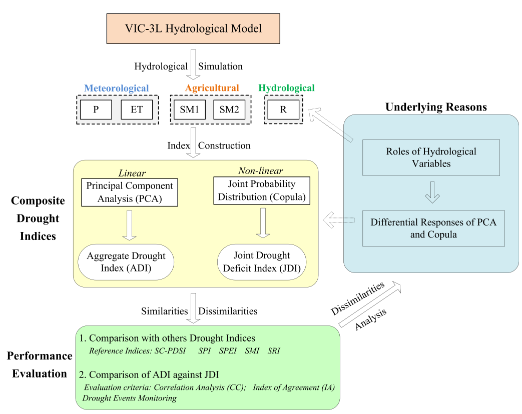
HIGHLIGHTS

- Two composite drought indices were constructed based on VIC-3L simulations.
- Performances of ADI and JDI for multivariate drought characterization were assessed.
- The degree of consistency between ADI and JDI was evaluated.
- Actual evapotranspiration was the main factor for inconsistency between ADI and JDI.

GRAPHICAL ABSTRACT



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ABSTRACT

Droughts are comprehensive and complex issues that need to be characterized from a multivariate perspective. In recent years, a number of composite indices have been proposed for drought characterization. However, rare studies have systematically compared similarities and dissimilarities of these indices, and they have provided little insights into the combination mechanisms. To address this issue, two widely used combination approaches, namely the principal component analysis (PCA) and copula based joint probability distribution were employed, with the corresponding integrated product denoted as the Aggregate Drought Index (ADI) and Joint Drought Deficit Index (JDI). Five constituents for constructing ADI and JDI were derived from the variable infiltration capacity model (VIC) monthly simulations over the Yellow River basin (YRB), China, including precipitation (P), actual evapotranspiration (ET), soil moisture of top two layers, and runoff (during 1961–2012). Results showed that the behavioral patterns of ADI and JDI may not be easily influenced by the variation of one single element, and they represented comprehensive moisture status well. A further comparison between these two composite indices suggested that ADI and JDI behaved similarly in most areas of YRB, with some dissimilarities in the source region. The particular behavior of ET was responsible for the inconsistency. Comparing to other regions, an enhanced role of potential evapotranspiration (PET) was imposed on ET in the source region, leading to a poor relationship of ET with P and other hydrological variables. Accordingly, when constructing composite drought indices, the drought information indicated by ET was more easily abandoned by ADI but reserved in JDI. This study clearly demonstrates the mechanisms of two common integrated approaches in blending different drought

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information, which has significant implications for composite drought indices construction and application, and potentially provides some valuable references for the improvement of monitoring techniques in future drought related researches.

1. Introduction

Drought is a stochastic and recurring natural hazard that has costly and devastating impacts on surface and groundwater supply, crop production, ecological water quality, electricity production (hydropower), modern industrial production, waterborne transportation, etc. (Wilhite, 2000; Van Loon, 2015; Crausbay et al., 2017). In the context of global warming and expanding water consumption, water shortages, arising from abnormally dry conditions, are further aggravated and become more severe, which highlights the significance of developing early drought warning systems and improving drought monitoring techniques (Hayes et al., 2011; Trenberth et al., 2014).

In recent years, drought indices have become a primary option for drought monitoring and characterization. Based on different variables and mathematical algorithms, more than 150 drought indices have been proposed (Niemeyer, 2008). Among these indices, the Palmer drought severity index (PDSI; Palmer, 1965) and the standardized precipitation index (SPI; McKee et al., 1993) could be regarded as two outstanding representatives, with their algorithms widely applied in other drought indices. For example, following the physical scheme that PDSI adopts, several new PDSI variants intending to solve the drawbacks of the original version (e.g., coarse hydrological modeling, inconsistent spatial behavior, and fixed time scale) have been developed (e.g., Wells et al., 2004; Xu et al., 2012; Liu et al., 2017). Following the standardization and definition of time scales in SPI, several standardized indices (SIs) such as the standardized runoff index (SRI; Shukla and Wood, 2008) and the standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al., 2010) were developed by considering different hydro-meteorological variables (e.g., runoff for SRI, precipitation and evapotranspiration for SPEI). In spite of their wide applications in regional and global drought assessment, it should be noted that the above listed indices have been mostly developed for one specific form of droughts.

Drought can be classified into four types: meteorological, agricultural, hydrological, and socio-economic (Mishra and Singh, 2010). Among these four types, the meteorological drought is recognized as the driving force, which has the potential to cause a lagged impact on soil moisture content (i.e., agricultural drought). The persistent depletion of soil moisture storage may further influence groundwater system, resulting in hydrological drought (Zargar et al., 2011; Zhu et al., 2016). In other words, the same area during one certain period may experience different types of droughts more or less simultaneously, and it may not be sufficient to use one single drought index (e.g., SPI) to depict the comprehensive water deficit conditions. This highlights the necessity of drought characterization from a multivariate perspective.

As an effective countermeasure, the proposal of composite drought indices incorporating a variety of drought information brings a new direction to depict the moisture deficiency (Hao and Singh, 2015; Huang et al., 2016). For instance, the U.S. Drought Monitor (USDM), that integrates multiple climate drought indices, land surface model outputs, and subjective modifications based on local impacts and vulnerability, can be recognized as a state-of-the-art composite product which is extensively applied for drought monitoring and assessment (Svoboda et al., 2002). Thereafter, several mathematical statistics approaches were introduced to blend information with a variety of composite drought indices proposed. These include the linear combination approach based indices like the Aggregate Drought Index (ADI; Keyantash and Dracup, 2004), Grand Mean Index (GMI; Mo and Lettenmaier, 2013), and Objective Blended North American Land Data Assimilation System (NLDAS) Drought Index (OBNDI) (Xia et al., 2014). With respect to the nonlinear method, the copula function is mostly used, such as the Joint Drought Deficit Index (JDI; Kao and Govindaraju, 2010). In spite of these developments, rare studies have comprehensively evaluated the similarity and difference among these blending methods, as well as a lack of systematic analysis on their each strengths and limitations in combining various sources.

The objective of this paper is to investigate the mechanisms of two popular blending approaches, namely the principal component analysis (PCA) and the joint probabilistic distribution (copula) methods, in constructing composite drought indices, with their products denoted as ADI and JDI, respectively. The remainder of this study is organized as follows. Information on hydro-meteorological forcings, combined with the procedures of two drought indices and the evaluation framework are described in Section 2. Section 3 presents spatiotemporal comparisons between ADI and JDI, combined with an analysis of the reasons underlying the disparate behaviors between the two blending approaches. Finally, conclusions are drawn in Section 4.

2. Materials and methods

2.1. Study area and datasets

The Yellow River basin (YRB; located between 32°N–42°N and 96°E–119°E) in China was selected as the study area. With a total length of 5456 km, the river flows through nine provinces, controlling a drainage area of 795,000 km^2. Because of its vast spatial range, this basin spans over four climate zones, i.e. arid, semi-arid, semi-humid, and humid climate zones from northwest to southeast, respectively. The elevation ranges from 0 to 6403 m above sea level with topography generally decreasing from west to east (Fig. 1). The Tibet Plateau, Loess Plateau and Huang-Huai-Hai Plain are three primary geomorphic types. Affected by the monsoon climate and diverse terrain conditions, precipitation in YRB presents a high spatial variability and intensively falls between June and September, accounting for approximately 58%–75% of the annual precipitation.

The datasets used in this study included daily hydro-meteorological observations (span from 1961 to 2012) and geographical information. As shown in Fig. 1, 101 national standard meteorological stations in and around YRB were employed, and the records including precipitation, mean temperature, maximum and minimum temperatures, and wind speed were downloaded from the China Meteorological Data Service Centre (http://data.cma.cn/). Streamflow observations of 10 hydrological stations (i.e., Tangnaihai (TNH), Lanzhou (LZ), Toudaoguai (TDG), Wubu (WB), Longmen (LM), Hejin (HJ), Xianyang (XY), Huaxian (HX), Sanmenxia (SMX) and Huayuankou (HYK)) situated at the trunk stream and main tributaries were collected from the "China Year Books of Hydrology" which were published by the Hydrological Bureau of the Ministry of Water Resources (http://www.hydroinfo.gov.cn/). The geographical information needed to drive the hydrological model included: the digital elevation data with a 3 arc-second (about 90 m) spatial resolution was retrieved from the shuttle radar topography mission digital elevation model (http://srtm.csi.cgiar.org/); the land cover image (1 km in spatial resolution) was provided by the University of Maryland's 1 km Global Land Cover Production (Hansen et al., 2000); and soil data with a 30 arc-second (about 1 km) spatial resolution was collected from the 5-min Food and Agriculture Organization dataset (Allen et al., 1998).