



## Research papers

# Spatial comparability of drought characteristics and related return periods in mainland China over 1961–2013



Olusola O. Ayantobo<sup>a,b</sup>, Yi Li<sup>a,\*</sup>, Songbai Song<sup>a</sup>, Ning Yao<sup>a</sup>

<sup>a</sup> College of Water Resources and Architectural Engineering, Northwest Agriculture & Forestry University, Yangling, Shaanxi 712100, China

<sup>b</sup> Department of Water Resources Management and Agricultural-Meteorology, Federal University of Agriculture, PMB 2240, Abeokuta, Nigeria

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## ABSTRACT

The proper understanding of the spatiotemporal characteristics of multi-year droughts and return periods is important for drought risk assessment. This study evaluated and compared the spatiotemporal variations of drought characteristics and return periods within mainland China between 1961 and 2013. Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) and Composite Index (CI) were calculated at multiple timescales, the run theory was used for objective identification and characterization of drought events while Kendall's  $\tau$  method was used to analyze their dependencies. Within the univariate framework, marginal distributions of duration, severity, and peak were derived by fitting Exponential, Weibull and GDP distributions respectively and the drought return periods was investigated and mapped. Comparison of drought indices showed that SPEI and CI performed better than SPI in delineating spatial patterns of drought characteristics. This might be attributed to the temperature effect on evapotranspiration and therefore on drought index. Considering the increasing trend in reference evapotranspiration in the 21st century, the importance of utilizing temperature-based drought index is imperative. Severe and extreme droughts occurred in the late 1990s in many places in China while persistent multi-year severe droughts occurred more frequently over North China, Northeast China, Northwest China and Southwest China. The spatial patterns showed that regions characterized by higher drought severity were associated with higher drought duration. The North China, Northwest China, and Southwest China had much longer drought durations during the 1990s and 2000s. As droughts normally cover large areas, regional drought return periods has been showed to be more effective in providing support for drought management than station based drought return periods. Studies on the spatial comparability of drought return periods across mainland China have therefore been undertaken for drought mitigation and effective utilization of water resources.

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## 1. Introduction

A drought is a natural hazard that results from a deficiency of precipitation, leading to low soil moisture and river flows, reduced storage in reservoirs and less groundwater recharge (Estrela and Vargas, 2012). They are generally classified into meteorological

(lack of required rainfall), agricultural (lack of soil moisture and plant growth), hydrological (lack of surface water resources), socio-economic (failure of water resource system to meet demands) and stream health drought (deficiency in stream flow causing impacts on aquatic ecosystems) (Mishra and Singh, 2010; Sheffield and Wood, 2012; Esfahanian et al., 2016). In recent years, drought has occurred frequently in many parts of the world and has to a large extent resulted into increased water demand (Montaseri and Amirataee, 2017) and severe socio-economic impacts (Mishra and Singh, 2010). As a result of increasing drought risk, a proper understanding of the spatiotemporal characteristics of droughts is of primary importance for water resources planning and management.

Drought indices are usually used for the qualitative and quantitative evaluation of drought events (Mishra and Singh, 2010) because they provide a comprehensive picture of drought

*Abbreviations:* SPI, standardized precipitation index; SPEI, standardized precipitation evapotranspiration index; CI, meteorological composite index;  $P$ , precipitation; PR, air pressure; RH, relative humidity;  $ET_o$ , potential evapotranspiration;  $U_2$ , wind speed at 2 m;  $n$ , sunshine hour;  $T_{min}$ , minimum air temperature;  $T_{max}$ , maximum air temperature;  $T_a$ , mean air temperature;  $C_v$ , variability coefficient;  $C_{v,t}$ , temporal  $C_v$ ;  $C_{v,s}$ , spatial  $C_v$ ; Dd, drought duration; Ds, drought severity; Dp, drought peak.

\* Corresponding author.

E-mail addresses: [ayantoboo@funaab.edu.ng](mailto:ayantoboo@funaab.edu.ng) (O.O. Ayantobo), [liyikitty@126.com](mailto:liyikitty@126.com) (Y. Li).

conditions necessary for decision-making (Zargar et al., 2011). Several drought indices have been developed to monitor and quantify drought duration, intensity, severity, peak, and spatial extent (Mishra and Singh, 2010; Esfahanian et al., 2016) and according to Zargar et al., 2011, any given drought index must be able to signal the beginning or end of drought (Tsakiris et al., 2007), detect a drought and monitor it in a real-time, allowing water managers to declare drought levels and plan drought response measures in a region (Tsakiris et al., 2007), and enable the communication of drought conditions among various interested parties (Zargar et al., 2011; Montaseri and Amirataee, 2017).

Generally, each drought index requires specific input parameters in order to measure drought and in most cases, the availability of relevant data drives the choice of drought indices (Mishra and Singh, 2010). For example, a combination of meteorological variables, including  $P$  and  $T$ , is used for Palmer Drought Severity Index (PDSI) (Palmer, 1965), Crop Moisture Index (Palmer, 1968), Self-Calibrating PDSI (SC-PDSI) (Wells et al., 2004) and SPEI (Vicente-Serrano et al., 2010).  $P$  and soil moisture are used for Moisture Adequacy Index (McGuire and Palmer, 1957) and Keetch-Bryam Drought Index (Keetch and Byram, 1968) while Rainfall Anomaly Index (RAI) (Van Rooy, 1965), Deciles Index (DI) (Gibbs and Maher, 1967), Nitzche Index (Nitzche et al., 1985), SPI (McKee et al., 1993), Percent of Normal Precipitation Index (PNPI) (Willeke et al., 1994), Z-Score, China Z Index (CZI) (Ju et al., 1997) and its variant, the Modified China Z Index (MCZI) (Wu et al., 2001) have been developed on the basis of  $P$ . The time lag between the beginning of water scarcity and its impacts is referred to as the timescale of a drought (Vicente-Serrano et al., 2010) and according to Zargar et al. (2011), there are three timescales for which these drought indices are usually calculated; short-term, medium-term and long-term droughts.

In order to understand better the science behind droughts, Svoboda et al. (2002) sensed a need for an improved drought monitoring methods and Zargar et al. (2011) suggested that drought monitoring techniques could be improved by combining the existing indices which will eventually improve drought preparation and management practices, and reduce drought vulnerability. Keyantash and Dracup (2004) aggregated six hydrologic variables including precipitation, streamflow, reservoir storage, evapotranspiration, soil moisture, and snow water content to derive the Aggregate Drought Index (ADI) while Brown et al. (2008) introduced Vegetation Drought Response Index (VegDRI) by combining meteorological drought indices (SPI and PDSI), satellite-based vegetation measures, and biophysical information (land cover and available soil water capacity). Further, Karamouz et al. (2009) developed the Hybrid Drought Index (HDI) by combining the SPI, PDSI, and Surface Water Supply Index (SWSI), Balint et al. (2011) introduced the Combined Drought Index (CDI) by combining the Precipitation Drought Index (PDI), Temperature Drought Index (TDI), and Vegetation Drought Index (VDI) while Ziese et al. (2014) developed the Global Precipitation Climatology Center Drought Index (GPCC-DI) with  $1^{\circ}$  grid spatial resolution with the Modified Standardized Precipitation Index (SPI-DWD) and SPEI.

Although these indices have been frequently used in drought monitoring, few stochastic assessment studies have comparatively assessed their inherent performance. Barua et al. (2011) compared the PNPI, SPI, SWSI and ADI drought indices on the basis of historical streamflow data of the Yarra River in Australia and ADI was considered the best. Using historical rainfall data in the United States, Keyantash and Dracup (2002) compared 14 drought indices and found the SPI to be the most valuable indices in estimating drought severity. Morid et al. (2006) investigated the performance of 7 drought indices, namely DI, PNPI, SPI, CZI, MCZI, Z-Score and EDI using annual rainfall in Tehran province and discovered that the SPI, CZI, and Z-Score indices had similar behavior. Other studies

have also compared drought indices and have emphasized the comparative advantages of SPI which includes: simplicity, reliability (Guttman, 1999), and better forecast of short-term events (Keyantash and Dracup, 2002; Zargar et al., 2011; Montaseri and Amirataee, 2017). Vicente-Serrano et al. (2010) evaluated the performances of SPEI, SC-PDSI and SPI using a 100-year historical data from 11 stations around the world. They found that there was a strong agreement between SC-PDSI, SPEI, and SPI under the current climatic conditions, whereas the SPEI and SC-PDSI were superior to the SPI under global warming conditions.

The novelty of our paper is that it explores climate variability and the behavior of drought indices using data from 552 weather stations located in different agro-climatic environments in China. Drought-affected areas in China have greatly increased over the past 50 years due to spatial variations in  $P$  and  $T$  (Yang et al., 2013). For example, the large-scale drought disaster that occurred in Yunnan Province during 2009–2010 in southwest China threatened 9.65 million residents with a shortage of drinking water (Lu et al., 2012). This event was as a result of a decrease in  $P$  and abnormal high  $T$ . Also, Li et al. (2012) observed a continuous increasing trend in reference evapotranspiration in the 21st century which may influence the frequency and severity of drought events. According to Vicente-Serrano et al. (2010), drought monitoring in short-time periods (1, 3, 6 and 9 months) is significantly affected by  $ET_0$  or  $T$ . Therefore, one should use the drought indices which have been developed on the basis of  $ET_0$  or  $T$  and  $P$ , such as SPEI and PDSI, to analyze and examine such short-term drought events.

Research undertaken to assess drought using the SPEI and CI have shown them to be particularly effective in detecting drought conditions (Hernandez and Uddameri, 2014). However, little research have been undertaken to study the drought return periods based on SPEI and CI across mainland China at different timescales. Drought return periods from a station cannot provide effective support for drought management at a regional/national level because droughts normally cover large areas (Michele et al., 2013; Zhang et al., 2012a). Therefore, evaluation of the return periods of droughts for large agro-climatic environments and at different timescale is required. In this paper, we performed drought analysis using SPI; a precipitation-based index, SPEI; a new and ideal index which standardizes the difference between  $P$  and  $ET_0$ , and CI; an index that takes account of water-heat balance in order to directly evaluate the influence of  $P$  and  $ET_0$  in defining drought events under global warming. Therefore, this study evaluated and compared the spatiotemporal variation of drought characteristics and return periods of these indices in order to develop methodological guidelines for drought risk analysis. The specific objectives includes: to explore the variability of climatic variables, investigate the behavior of SPI, SPEI and CI to quantify short-term, medium-term and long-term drought events, and to produce spatial maps of drought duration, severity and peak through a thorough and quantitative analysis of drought probability within a univariate framework across a broad range of agro-climatic environments.

## 2. Methodology

### 2.1. Study area and data

China has a diverse climate, including humid, semi-humid, semiarid and arid climatic zones with varying watershed size (Fig. 1). Dry climate generally dominates western and northern China, while semi-humid and humid climate conditions primarily dominate the eastern part (Wu et al., 2011). Eastern China is influenced by the East Asian Summer Monsoon. Southwest China is influenced by a combination of the East Asian Summer Monsoon and the Indian Summer Monsoon, while Northwest China remains

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