Journal of Hydrology 527 (2015) 608–618

Contents lists available at ScienceDirect

Journal of Hydrology

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

Integrated index for drought assessment based on variable fuzzy set theory: A case study in the Yellow River basin, China

Shengzhi Huang [a], Jianxia Chang [a], Guoyong Leng [b,*], Qiang Huang [a]

[a] State Key Laboratory Base of Eco-Hydraulic Engineering in Arid Area, Xi'an University of Technology, Xi'an 710048, China
[b] Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

ARTICLE INFO

Article history:
Received 20 March 2015
Received in revised form 6 May 2015
Accepted 14 May 2015
Available online 21 May 2015
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Alon Rimmer, Associate Editor

Keywords:
Integrated drought index
Variable fuzzy set theory
Entropy weight method
Qualitative change point
The Yellow River basin

SUMMARY

It is of great importance to construct an integrated drought indicator, which is of great importance to drought risk assessment and decision-making. Given the fuzzy nature of drought, the variable fuzzy set theory was applied to develop an Integrated Drought Index (IDI) combining meteorological, hydrological, and agricultural factors across the Yellow River basin in North China. The runoff and soil moisture were derived by driving the calibrated Variable Infiltration Capacity (VIC) model with observed atmospheric forcing. Furthermore, the law of mutual change of quality and quantity was adopted to identify qualitative change points of annual IDI series in the Yellow River basin. The results indicate that: (1) the Integrated Drought Index (IDI) has a better performance compared with Standardized Precipitation Index (SPI) and Standardized streamflow Index (SSFI), and it is more sensitive and effective to capture drought onset and persistence, largely owing to its combination with the information of different drought-related variables; (2) spatially, the middle reaches has a higher drought risk than the rest portions of the Yellow River basin; seasonally, drought risk in spring and winter is larger than other seasons; overall, the IDI of the basin is dominated by an insignificantly downward trend; (3) some qualitative change points of drought were identified in the Yellow River basin, and those are primarily induced by ENSO events and the construction of dams and reservoirs. This study proposed an alternative drought indicator coupled with multivariate drought-related variables by objectively determining their weights based on the entropy weight method, which has a great value in characterizing drought.

1. Introduction

Drought is a kind of natural recurring hazards, which is insidious and slow-onset, and it is usually well formed before it is realized as a threat (Pongracz et al., 1999). Drought can exert enormous impacts on economy, society, and environment (WGA (1996)). According to the Federal Emergency Management Agency, annual drought losses in the US were estimated to be US$ 6–8 billion (FEMA, 1995). Droughts are perceived as one of the most cost and least understood natural hazards and impact more people than any other types of natural hazards (Wilhite, 2000). Therefore, it is of great importance to investigate drought evolution and its possible risk (Huang et al., 2014a,b).

Drought indices are critically important to assess and to monitor drought due to their abilities to simplify complex interaction among many climate and climate-related parameters. Indicators allow researchers to quantitatively assess climate anomalies in terms of their frequency, severity, duration as well as spatial extent (Wilhite, 2000). Standardized Precipitation Index (SPI) is widely used as an effective drought indicator for drought assessment (Moreira et al., 2008; Mishra and Singh, 2010; Huang et al., 2014b). It was proposed by McKee et al. (1993) and was based on a specific window size, and monthly precipitation data are transformed into their corresponding cumulative probabilities which are then mapped into the standard normal distribution. The probabilistic nature of SPI makes it be comparable between different locations and variables (McKee et al., 1993). Although SPI has an extensive application in drought characterization, it can result in some confusions because of its inconsistent results caused by different window sizes (Vicente-Serrano and López-Moreno, 2005). Additionally, SPI fails to explain seasonal variability characteristic, for instance, a specific amount of precipitation should have different meaning in wet and dry seasons (Ma et al., 2015).

In addition to SPI, Palmer Drought Severity Index (PDSI) based on water budget accounting and relying on precipitation and temperature data was developed by Palmer (1965). Since PDSI

* Corresponding author.
E-mail address: guoyong.leng@gmail.com (G. Leng).

http://dx.doi.org/10.1016/j.jhydrol.2015.05.032
0022-1694/

provides an opportunity to characterize droughts based on multiple sources of data (precipitation and temperature), it soon became a popular selection in drought characterization and is widely utilized even today (Dalezios et al., 2000; Kim et al., 2003; Dai et al., 2004). However, it has several drawbacks (Alley, 1984; Guttman et al., 1992; Guttman, 1998). For example, its temporal scale is not obvious, the proposed water balance model is not solid, and its values lack a statistical (e.g. recurrence probability) and physical meaning (e.g. required rainfall depth) (Ma et al., 2015).

Droughts can be classified into three physical types: meteorological, agricultural, and hydrological droughts with respect to the shortages of precipitation, runoff, and soil moisture, respectively (Wilhite and Glantz, 1985; American Meteorological Society, 2004). A large number of drought indicators (e.g. the aforementioned drought indices (SPI and PDSI)) only reflect one aspect of the deficits in water resources. The current consensus among considerable researches is that developing drought index only based on an individual variable/index (e.g., precipitation, runoff, or soil moisture) is probably not sufficient for reliable risk assessment and reasonable decision-making (Hao and AghaKouchak, 2013). The drought conditions based on one drought-related variable may be different from those based on other different variables due to the complex physical linkages among evapotranspiration, infiltration, base flow, direct runoff, and groundwater motion. Moreover, droughts are impacted by cumulative effects of water shortages over different periods of time. Therefore, information derived from various drought-related sources is very necessary for successful and reasonable drought assessment. Some researchers adopted copula function to construct a new integrated drought index (Kao and Govindaraju, 2010; Hao and AghaKouchak, 2013). For instance, Kao and Govindaraju (2010) used copula function to capture the joint behavior of precipitation and streamflow to assess droughts; Hao and AghaKouchak (2013) developed a Multivariate Standardized Drought Index (MSDI) combining SPI and the Standardized Soil Moisture Index (SSI) to monitor drought based on copula function.

Nevertheless, copulas highly rely on an assumption that samples follow a given probability density function (PDF) (Huang et al., 2014b). In practice, many problems will come up caused by the assumption. As the complicated interactions among surface water, vegetation, atmosphere, soil and groundwater affect drought evolution processes, any of known distribution fails to capture drought quantiles (Sadri and Burn, 2012). Hence, the global assumption of copula functions tends to result in a big deviation for the low or high quantiles (Sharma, 2000). Although constructing a joint index based on copula for drought assessment provides new ideas for developing drought index, it also leads to some deviations. It is a helpful attempt to develop an integrated drought index through determining reasonable weights of hydrological, meteorological, and agricultural factors. Safavi et al. (2014) proposed an integrated indicator for drought assessment using multiple factors including meteorological, hydrological, land use and other factors. The integrated indicator contains a lot of information and can comprehensively reflect drought characteristics. However, the determination of the weights is a little subjective, thereby leading to some deviations in drought monitoring. Therefore, the entropy weight method that is an objective approach for determining weights and is widely utilized in water resources assessment (Zou et al., 2006) was applied to construct an integrated index for drought assessment combining meteorological, hydrological, and agricultural factors in this study, which is the major motivation of this study.

In nature, many phenomena, concepts, and events are fuzzy. For instance, drought and flood and flood season and non-flood season, these concepts and phenomena are fuzzy (Li et al., 2014). Droughts are extremely difficult to assess mainly because of the lack of a universally accepted drought definition. As mentioned above, droughts can be defined from a meteorological, agricultural, or hydrological viewpoint. Obviously, it is useful to categorize and integrate the different types of drought. However, the boundaries which are separating these categories are normally fuzzy (Wilhite and Glantz, 1985). Therefore, the variable fuzzy set theory that can be used to describe vague phenomena and capture their dynamic development processes was utilized in this study to develop an integrated drought indicator. Additionally, according to the law of mutual change of quality and quantity from materialist dialectics, the change in constantly altering things always start with gradual accumulation of small variation (variation of quantity), and it makes natural phenomena transform from one property to another (variation of quality) when the accumulation reaches to a certain degree (Li et al., 2014). Likewise, the development of droughts should also obey this law. Thus, the law of mutual change of quality and quantity based on variable fuzzy set theory also applied to investigate drought evolution and to detect its possible qualitative change point in the Yellow River basin.

The Yellow River is a very famous river in the world. It ranks the second largest river in China and the sixth largest river in the world in terms of its length (Shiau et al., 2007). Generally, approximately 12.6×10^6 ha cultivated land and 110 million residents are in the Yellow River basin (Shiau et al., 2007). However, the Yellow River is frequently suffered from droughts from ancient times to present (She and Xia, 2013). Historically, one of continuous droughts had attacked this region in 1637–1643, and the strikingly severe drought even directly triggered the demise of the Ming Dynasty (Xie and Fu, 2004). Another drought occurring between late 1920s and early 1930s had impacted approximately 20 million people, and was claimed that over 3 million lives died because of drought-related diseases and famine (Xie and Fu, 2004). Since the 1970s, the zero-flow phenomena occurring in the downstream of the Yellow River have become common and obtained wide attention. The high frequent flow interruptions during the past 30 years have caused widespread adverse impacts in agriculture, industry, and ecology. However, to date, although some scholars have researched drought evolution across the whole Yellow River basin (Xie and Fu, 2004; Shiau et al., 2007; Peng et al., 2011; She and Xia, 2013), as far as we know, all of them have assessed drought risk based on a single drought-related variable and none has adopted an integrated drought index to thoroughly investigate drought evolution characteristics in the Yellow River basin. Therefore, it is of great metric to scientifically and reasonably assess droughts based on an aggregative indicator in the Yellow River basin.

The rest of the paper is organized as follows. The second section introduces the study area and data. The methodology is provided in section three, followed by results and discussions in the fourth section. The fifth section shows the conclusions drawn from the study.

2. Study area and data

2.1. The Yellow River basin

Originating from the Qinghai-Tibet Plateau in the West China, the Yellow River flows northward, turns south and then flows eastward, and finally discharges into the Bohai Sea. It has a length of 5464 km and a drainage area of 752,443 km^2 (Shao et al., 2006). The Yellow River basin is located between 95°E–119°E and 32°N–41°N (Fig. 1). As Chinese ancestors have lived in this area since prehistoric times, the Yellow River has been called as the 'Mother River of China' for a long time (Fu et al., 2004). The annual precipitation in the Yellow River basin ranges from 123 to 1021 mm, and