Global and Planetary Change 155 (2017) 1–12

Contents lists available at ScienceDirect

Global and Planetary Change

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

Variations of dryness/wetness across China: Changing properties, drought risks, and causes

Qingzhong Huang[a], Qiang Zhang[b,c,d,*], Vijay P. Singh[e], Peijun Shi[b,c,d], Yongjie Zheng[a]

[a] Department of Water Resources and Environment, Sun Yat-sen University, Guangzhou 510275, China
[b] Key Laboratory of Environmental Change and Natural Disaster, Ministry of Education, Beijing Normal University, Beijing 100875, China
[c] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing 100875, China
[d] Academy of Disaster Reduction and Emergency Management, Beijing Normal University, Beijing 100875, China
[e] Department of Biological and Agricultural Engineering and Zachry Department of Civil Engineering, Texas A & M University, College Station, TX, USA.

A R T I C L E I N F O

Keywords:
Standardized Precipitation Evapotranspiration Index (SPEI)
Wetness/dryness variations
Periodicity
Water vapor flux

A B S T R A C T

Variations of wetness/dryness across China during 1949–2014 in both space and time were investigated using the grid climate data of Time-Series (TS) Version 3.23. The Standardized Precipitation Evapotranspiration Index (SPEI) was used to evaluate the wetness and dryness conditions. Results indicated that the regions that experienced a drying/wetting tendency are similar in area, and the regions dominated by a drying tendency are east of 100°E and the regions experiencing a wetting tendency are west of 100°E. A significant wetting tendency was observed in the northern parts of northwestern China, Qaidam Basin and northeastern parts of the Tibetan Plateau. Analysis of water vapor flux by air mass propagation indicated that dry regimes are attributed to continental air mass and wet regimes to oceanic air mass. Propagation of water vapor flux can thus explain the occurrence of wetness/dryness events in both space and time. The shortening of periodicity or increased frequency of wet and/or dry regimes implies intensifying and amplifying wet and dry regimes across China. The results of this study would be useful for the management of agricultural irrigation and water resources across China in a changing environment.

1. Introduction

Human-induced global warming is expected to accelerate the hydrological cycle (Allen and Ingram, 2002; Alan et al., 2003; Ziegler et al., 2003; Zhang et al., 2012). The acceleration of the cycle is altering the spatiotemporal patterns of precipitation that in turn are resulting in increased occurrences of extremes (Easterling et al., 2000; Dore, 2005) and increased occurrences of floods and droughts in many regions of the world (e.g. Easterling et al., 2000; Mirza, 2002). Arnell (1999) indicated that under the influence of global warming, the hydrological cycle will be intensified with more evaporation and more precipitation and the extra precipitation will be unequally distributed around the globe, and then would come more frequent floods and droughts. Due to catastrophic consequences of weather and hydrological extremes, such as floods, droughts, rainstorms, and heat waves and their negative effects on agricultural production, there have been a multitude of studies addressing agricultural losses as a result of agro-droughts and floods (Zhang et al., 2015). Li et al. (2012) presented a preliminary methodology and an operational approach for assessing the risk of damage due to floods impacting the population, crops, housing, and the economy at the county level in China. The acceleration in global warming and the resulting changes in precipitation have already affected global agriculture and food production systems in many ways (Godfray et al., 2011; Ye et al., 2014).

China is the largest agricultural country with the largest population in the world. Hence, food security is closely related to social stability and is therefore of global concern. Agriculture is the major source of food and fiber, especially in China. The country is being frequently hit by droughts and the frequency of their occurrence tends to be increasing. During 1990–2007, severe and extreme droughts occurred once per two years (Yuan et al., 2013). These droughts caused massive losses of agricultural production. The annual loss of grain production due to drought attacks was ~26 Mt. (million tons), amounting to about 5.2% of grain production in China. This loss of grain can feed ~75 million people and is almost equal to the total grain production of such a big grain producer as Hebei, Jilin or Hunan in China (Qin et al., 2013). However, climate change introduces a large degree of uncertainty to the projection of agricultural output, and food security will

* Corresponding author at: Key Laboratory of Environmental Changes and Natural Hazard, Ministry of Education, & Academy of Hazard Reduction and Emergency Management, Ministry of Education and Ministry of Civil Affairs, Beijing Normal University, Beijing 100875, China.
E-mail address: zhangq68@bnu.edu.cn (Q. Zhang).

http://dx.doi.org/10.1016/j.gloplacha.2017.05.010
Received 30 December 2016; Received in revised form 4 April 2017; Accepted 31 May 2017
Available online 07 June 2017
0921-8181/

be a daunting challenge for China. Therefore, it is important to evaluate the spatiotemporal properties of droughts and the underlying causes. This was the motivation for this study.

It is expected that in the next twenty years, 30%–50% more food would be required to support the growing population (Zhang et al., 2013). Xu et al. (2013) indicated that the impact of floods on grain production in China was quite serious, and high or very high risk of floods concentrated in central and eastern regions. For a majority of major grain producing provinces, the probability of 10% reduction in grain output is > 90%, given the one-hundred-year flood (Xu et al., 2013). Furthermore, future decades are expected to witness higher risks of floods. Li et al. (2015) indicated that during 2021–2050 and 2071–2100, there would be less co-occurrence of consecutive wet and dry days, and more joint extreme heavy precipitation events, implying less risk of co-occurrence of floods and droughts in the same year but higher risk of floods in China. This suggests that potential negative impacts of floods on agriculture are of considerable concern. You et al. (2011) investigated climate extremes and their linkages to atmospheric circulation and found that trends in southeastern and northwestern China is inconsistent with changes of water vapor flux, implying that anti-cyclonic circulation over the Eurasian continent have affected the changes in climate extremes in China. Zhou et al. (2008) compared summer precipitation frequency, intensity and diurnal cycle over China by using satellite data like Tropical Rainfall Measuring Mission(TRMM) and rain gauge observations, showing that satellite products are comparable to rain gauge data in reflecting spatial pattern of precipitation amount, frequency, and intensity. However, there are many drought indices such as standardized precipitation index (SPI) and palmer drought severity index (PDSI). However, when compared to individual variable of precipitation, SPEI involves precipitation and evapotranspiration and which can well reflect drought mechanisms from a viewpoint of multi-scalar.

The objective of this paper therefore is to address two questions: (1) What are the changing properties of wetness/dryness regimes defined by Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) in terms of trends and periodicity; (2) What are the causes behind SPEI-based wetness/dryness events across China. Results of this study can help clarify changing properties of wetness and dryness events across China and related causes.

2. Data

The grid meteorological data, i.e. Time-Series (TS) Version 3.23, were obtained from Climatic Research Unit (CRU) (link: http://catalogue.ceda.ac.uk). This dataset has been used in many other researches (Vicente-Serrano et al., 2010; Wu et al., 2015; Zhang et al., 2016). Besides, NCAR/NCEP reanalysis data were also collected from the Earth System Research Laboratory Physical Sciences Division [link: http://www.esrl.noaa.gov/psd/]. The dataset is from the NCAR/NCEP Reanalysis 1 Project and has been used in many studies (Lélé and Leslie, 2016; Fistikoglu et al., 2016; Fan and Yang, 2017). The meteorological variables of the CRU TS 3.23 dataset were precipitation and temperature, and meteorological variables of the NCAR/NCEP reanalysis dataset were wind speed in horizontal and vertical directions and specific humidity. The grid resolution was 0.5° × 0.5°, covering a period of 1948–2014. In this study, the study area contains 95 × 125 grid data and the grid center is located in 38.75°–54.25°N, 72.25°–134.75°E. The missing data were replaced by the regression method based on the data at the neighboring grids.

3. Methodology

In this study, droughts were monitored using Standardized Precipitation Evapotranspiration Index (SPEI) technique, and regionalization of droughts was done using Fuzzy C-Means (FCM) clustering. In addition, trends and periodicity properties of droughts were evaluated using continuous wavelet transform and also modified Mann-Kendall trend detection method. The analysis framework of this paper is showed in Fig. 1. The methods used in this study were introduced with considerable details as follows:

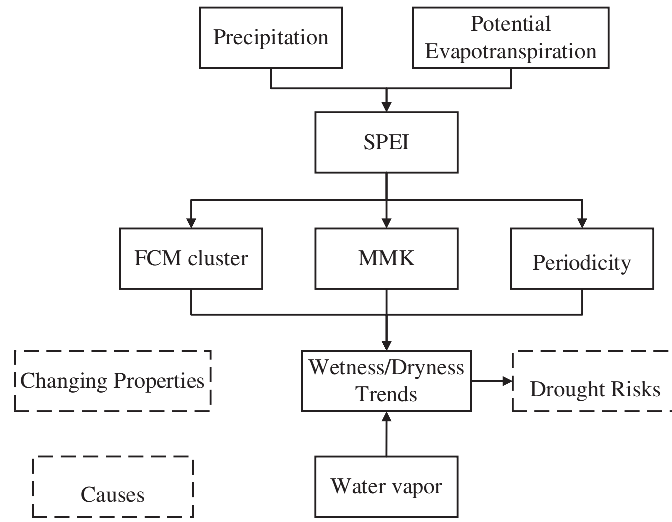

Fig. 1. Analysis framework.

3.1. Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) is a multi-scalar drought index, based on climatic data. It is used to quantify the onset, duration and magnitude of drought regimes in terms of normal conditions in a variety of natural and managed systems, such as crops, ecosystems, rivers, and water resources. Compared to the Standardized Precipitation Index (SPI), SPEI includes temperature in drought analysis which can more realistically represent the drought conditions of the study region under the influence of warming climate. The method for computation of SPEI is as follows:

The difference between monthly precipitation and evapotranspiration, D_i, is computed as:

$$D_i = P_i - PET_i \tag{1}$$

where i denotes the month and P_i the monthly precipitation with unit of mm. PET_i is the monthly potential evapotranspiration with a unit of mm, wherein the monthly potential evapotranspiration will be obtained by the Thornthwaite model (Thornthwaite, 1948).

The cumulative water difference can be formulated as, X:

$$X_i^k = \sum_{i-k+1}^{i} D_i \tag{2}$$

wherein k denotes the time scale, $k = 1, 2, \ldots, 48$.

Since D_i can be negative, the probability density function, $f(x)$, of X_i^k series can be obtained using a 3-parameter log-logistic density function as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)\left[1+\left(,\frac{x-\gamma}{\alpha}\right)\right]^{-2} \tag{3}$$

where $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and γ are, respectively, the scale, shape and location parameters. Then the 3-parameter log-logistic probability distribution, $F(x)$, can be obtained as:

$$F(\mathrm{x}) = \left[1+\left(,\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{4}$$

$\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and γ can be obtained by the L-moment method as: