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Evaluation and modification of the Drought Severity Index (DSI) in East Asia

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ABSTRACT

The Moderate Resolution Imaging Spectroradiometer (MODIS)-derived Drought Severity Index (DSI) can be produced at a 1-km spatial resolution and can be used for a wide range of water-resource and ecological applications. This study aims to understand the robustness and sensitivity of the DSI in East Asia, and we investigate the performance of the annual DSI using different Normalized Difference Vegetation Index (NDVI) datasets. Additionally, the MODIS-based DSI is compared to other drought indices, including the DSI with Advanced Very High Resolution Radiometer (AVHRR) NDVI (DSI_{AVHRR}) and the Standardized Precipitation Evapotranspiration Index (SPEI) with the Climate Research Unit (CRU) dataset. Three different drought indices are estimated in East Asia from 2000 to 2013 and compared via a correlation analysis based on a 5° × 5° grid. Specifically, the correlation between the DSI and DSI_{AVHRR} is relatively high (0.796), which suggests the potential use of the DSI based on combined products that include parameters such as the NDVI, although the DSI originally used only MODIS-based products. Characteristics such as the frequency and spatial extent of droughts based on the DSI are compared to those based on the SPEI using the drought classification schemes that were originally proposed for the SPEI and DSI, including mild, moderate, severe and extremely dry classes. Based on the results, we suggest a revised classification according to a comparison of the DSI and SPEI. The frequency and spatial extent results of the SPEI and DSI exhibit good agreement when using this classification. Moreover, the DSI from the revised classification is used to evaluate drought events in East Asia in 2003, 2006, 2008 and 2009. Overall, this study shows the potential of using the DSI with datasets that differ from the originally suggested datasets; however, caution must be taken when classifying and identifying drought events.

1. Introduction

A drought is a type of climate phenomenon that can be extremely rare and random (Monacelli et al., 2005). A drought may last for weeks, months or even decades and may affect local regions or continents. Thus, drought events can have devastating effects on both natural and human systems by affecting crop yields, infrastructures, industry and tourism (Wilhite, 2000; Nasrollahi et al., 2015; Xu et al., 2015).

Drought indices are widely used to assess and monitor drought events. Drought indices integrate various data, such as precipitation, evapotranspiration, streamflow and snowfall, to measure how much the climate in a given period deviates from historically established normal conditions (Narasimhan and Srinivasan, 2005). Among the widely used drought indices, the Palmer Drought Severity Index (PDSI) (Palmer, 1965) was the first embracive drought index. This index uses precipitation, temperature and soil moisture data to explain agricultural droughts. Shafer and Dezman (1982) suggested the surface water supply index (SWSI), which combines hydrological and climate variables with the PDSI. The SWSI considers reservoir storage, streamflow, snowpack, and precipitation information. However, this index shows limited potential for identifying severe droughts (Mu et al., 2013) because it should be recalculated whenever new severe drought events beyond those observed occur (Wilhite, 2005).

McKee et al. (1993) implemented the standardized precipitation index (SPI) to assess meteorological droughts. This index only uses precipitation in its drought assessment; thus, the calculation processes are simple and flexible based on the time scale. Vicente-Serrano et al. (2010) applied the Standardized Precipitation Evapotranspiration Index (SPEI) to determine the drought status. The SPEI is very similar to the SPI but considers potential evapotranspiration (PET). The moisture surplus or deficit is estimated as precipitation minus PET and then used for drought assessment.

Recently, Mu et al. (2013) proposed the Drought Severity Index (DSI), which uses moderate resolution imaging spectroradiometer (MODIS)-based ET, potential evapotranspiration (PET) and the normalized difference vegetation index (NDVI). These authors calculated

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the remotely sensed DSI globally for all vegetated land areas from 2000 to 2011. The annual DSI products were evaluated compared to the growing season PDSI, and major regional droughts were effectively captured by the DSI. While DSI products are produced at a relatively fine (i.e., 1 km) spatial resolution and are useful for a wide range of water-resource and ecological applications, the DSI should be further evaluated against other drought indices and datasets in different regions.

In this study, we aim to understand the robustness and sensitivity of the DSI in East Asia and focus on how the annual DSI performs with different NDVI datasets. Additionally, we compare the DSI to another drought index, namely, the SPEI. We use the advanced very high resolution radiometer (AVHRR) NDVI and MODIS NDVI datasets, as suggested by Mu et al. (2013). Additionally, the observed monthly precipitation and temperature datasets from the climate research unit (CRU) (Harris et al., 2014) are used to estimate the SPEI.

2. Materials and methods

2.1. Drought Severity Index

The DSI for drought assessment is derived from the MODIS products of ET, PET and NDVI and provides a method to assess and monitor drought events globally at relatively fine spatial resolutions. As discussed by Mu et al. (2013), the ratio (*RT*) in a certain month *i* between ET and PET can be defined as an indicator of the terrestrial water availability and reflects the wet or dry status, as given in Eq. (1). The DSI is then estimated using the standardized ratios of RT and NDVI, as shown in Eqs. (2) and (3):

$$RT_i = ET_i/PET_i \tag{1}$$

$$Z_i = Z_{RT} + Z_{NDVI} = (RT_i - \overline{RT})/\sigma_{RT} + (NDVI_i - \overline{NDVI})/\sigma_{NDVI} \tag{2}$$

$$DSI_i = (Z_i - \overline{Z})/\sigma_Z \tag{3}$$

where $\overline{RT}$ and $\overline{NDVI}$ are the mean values of the monthly RT and NDVI, respectively; σ_{RT} and σ_{NDVI} are the standard deviations of the monthly RT and NDVI, respectively; Z denotes the summation of the monthly standardized ratios of RT and NDVI; and $\overline{Z}$ and σ_Z are the mean and standard deviation of Z, respectively.

The standardized ratio of NDVI is only used during the growing season to minimize noise during the non-growing season (Zhao and Running, 2011). Mu et al. (2013) used MODIS snow cover to define the growing season, but this approach is not convenient for defining the growing season in all regions. Consequently, we employ a rather simple approach by defining the growing season based on a monthly air temperature, and months with average temperatures above 5 °C are included in the growing season (WMO, 2009). Leaf green-up and senescence, i.e., the growing season, could be missed at a monthly time step, which would propagate to the annual DSI. However, using climate data instead of the MODIS snow cover, as was used in the original approach by Mu et al. (2013), provided a simple approach to define the growing season, although its spatial resolution was not as high as that of the MODIS snow dataset. We also note that the original global DSI proposed by Mu et al. (2013) uses a calibration dataset from 2000 to 2011, whereas this study uses a dataset from 2000 to 2013. In summary, the differences between the DSI obtained in this study and the DSI from Mu et al. (2013) include the reference period (2000–2013 vs. 2000–2011) and the definition of the growing season (based on the air temperature vs. MODIS snow cover).

2.2. Standardized Precipitation Evapotranspiration Index (SPEI)

In this study, we compare the annual DSI to a meteorological drought index, namely, the SPEI, which has a 12-month time scale. Vicente-Serrano et al. (2010) proposed the SPEI to consider the effects of both precipitation and temperature on droughts. Additionally, this approach uses the temperature to estimate potential evapotranspiration. The SPEI is estimated by combining the climatic water balance and cumulative water deficit and adjusting a log-logistic probability distribution (Naumann et al., 2014). The procedure of estimating the SPEI according to Vicente-Serrano et al. (2010) can be summarized as follows.

First, the monthly PET is calculated using the method proposed by Thornthwaite (1948), which requires the monthly temperature, latitude and month. The monthly water deficit (*D*) is then estimated based on the precipitation (*PR*) and *PET* for a given month *j* and year *i*, as shown in Eq. (4):

$$D_{i,j} = PR_{i,j} - PET_{i,j} \tag{4}$$

Second, the accumulated monthly water deficits ($X_{i,\,j}{}^{k}$) at a time scale *k* in a given month *j* and year *i* are calculated as shown in Eqs. (5) and (6):

$$\begin{aligned} X_{i,j}^{k} &= \sum_{l=13-k+j}^{12} D_{i-1,l} + \sum_{l=1}^{j} D_{i,l}, \qquad \text{if } j < k \\ &= \sum_{l=13-k+j}^{12} (PR_{i-1,l} - PET_{i-1,l}) + \sum_{l=1}^{j} (PR_{i,l} - PET_{i,l}) \end{aligned} \tag{5}$$

$$X_{i,j}^{k} = \sum_{l=j-k+1}^{j} D_{i,l} = \sum_{l=j-k+1}^{j} (PR_{i,l} - PET_{i,l}), \qquad \text{if } j \geq k \tag{6}$$

Third, the log-logistic distribution of the accumulated monthly water deficits is estimated using the L-moments method (Hosking, 1990), as shown in Eq. (7):

$$F(X) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{7}$$

where $F(X)$ is the cumulative density function of a three-parameter log-logistic distribution and α, β and γ are the scale, shape, and origin parameters, respectively. Finally, the SPEI is estimated with $F(X)$. This procedure generally uses the approximation derived by Abramowitz and Stegun (1965), as shown in Eqs. (8)–(11):

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \tag{8}$$

$$W = \sqrt{-2\ln(P)} \qquad \text{for } P \leq 0.5 \tag{9}$$

$$W = \sqrt{-2\ln(1-P)} \qquad \text{for } P > 0.5 \tag{10}$$

$$P = 1 - F(x) \tag{11}$$

where $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$ and $d_3 = 0.001308$.

We use the SPEI values at a 12-month time scale, i.e., $k = 12$ in Eqs. (5) and (6), and compare them to the DSIs as introduced in the previous section, in contrast to Mu et al. (2013), who compared the DSI to the annual growing-season PDSI. The annual PDSI (not strictly the growing-season PDSI) is often comparable to the SPEI at a 12-month time scale (e.g., Vicente-Serrano et al., 2011), which is used in this study.

2.3. Case study in East Asia

This study focuses on East Asia (Fig. 1) to evaluate the annual DSI and the annual SPEI using remotely sensed datasets and meteorological datasets from 2000 to 2013, when all the satellite products were available. In Section 3.1, we estimate the DSI with both the MODIS NDVI and AVHRR NDVI and compare them to the SPEI estimated using the CRU dataset. In Section 3.2, we suggest using a revised classification for drought severity, such as moderate drought and severe drought, because the classification that was initially suggested by Mu et al. (2013) does not consistently capture drought events compared with the SPEI. These authors' classification was based on their global evaluation