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Research article

Development and evaluation of a comprehensive drought index

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ABSTRACT

Droughts are known as the world's costliest natural disasters impacting a variety of sectors. Despite their wide range of impacts, no universal drought definition has been defined. The goal of this study is to define a universal drought index that considers drought impacts on meteorological, agricultural, hydrological, and stream health categories. Additionally, predictive drought models are developed to capture both categorical (meteorological, hydrological, and agricultural) and overall impacts of drought. In order to achieve these goals, thirteen commonly used drought indices were aggregated to develop a universal drought index named MASH. The thirteen drought indices consist of four drought indices from each meteorological, hydrological, and agricultural categories, and one from the stream health category. Cluster analysis was performed to find the three closest indices in each category. Then the closest drought indices were averaged in each category to create the categorical drought score. Finally, the categorical drought scores were simply averaged to develop the MASH drought index. In order to develop predictive drought models for each category and MASH, the ReliefF algorithm was used to rank 90 variables and select the best variable set. Using the best variable set, the adaptive neuro-fuzzy inference system (ANFIS) was used to develop drought predictive models and their accuracy was examined using the 10-fold cross validation technique. The models' predictabilities ranged from $R^2 = 0.75$ for MASH to $R^2 = 0.98$ for the hydrological drought model. The results of this study can help managers to better position resources to cope with drought by reducing drought impacts on different sectors.

1. Introduction

Droughts are common and recurring phenomena affecting many sectors such as agriculture, water supply, economic, social, and ecosystems (Heim, 2002). Droughts' impacts on these sectors make it difficult to develop a universal/all-embracing definition of drought, since each sector measures drought differently (Whitmore, 2000; Heim, 2002). Drought definitions are generally categorized into meteorological, agricultural, hydrological, socio-economic, and stream health (AMS, 1997; Heim, 2002; Esfahanian et al., 2016). Meteorological drought is generally defined as a period of precipitation deficiency (several months or years) compared to a long term average (Whitmore, 2000; Heim, 2002; Mishra and Singh, 2010; Sheffield and Wood, 2012). The impacts of meteorological drought are a reduction in infiltration, runoff, deep percolation, and ground water recharge (NDMC, 2016). Agricultural drought is defined as a period of soil moisture deficiency resulting from precipitation shortage for a short period of time (few weeks duration) (Heim, 2002; Sheffield and Wood, 2012). The impacts of agricultural drought are a reduction in crop biomass and yield, and plant growth (Heim, 2002; NDMC, 2016). Hydrological drought is defined as a period of deficiency in water supply due to prolong precipitation shortage (Heim, 2002). The impacts of hydrological drought are a significant reduction in streamflow, groundwater, reservoir, and lake levels (Whitmore, 2000; Heim, 2002; NDMC, 2016). The concept of socioeconomic drought, which is not the subject of this study, is based on the impacts of meteorological, agricultural, and hydrological droughts on the supply and demand of some economic goods (Heim, 2002; NDMC, 2016). Finally, stream health drought is defined as a period of deficiency in streamflow causing irreversible impacts on aquatic ecosystems (Esfahanian et al., 2016).

Several drought indices have been developed to monitor and quantify drought. Drought indices are primarily tools to investigate

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drought duration, intensity, severity, and spatial extent (Mishra and Singh, 2010). Each drought index requires specific input parameters in order to measure drought. Precipitation is usually used alone or in combination with other parameters for this matter (Heim, 2002; Mishra and Singh, 2010; Sheffield and Wood, 2012). Usually for meteorological drought, precipitation is the primarily parameter (Dai, 2011). For agricultural drought, soil moisture content is commonly used with the secondary parameters of precipitation and/or evapotranspiration (Dai, 2011). For hydrological drought, streamflow is often used beside precipitation (Dai, 2011). Finally, for stream health drought, index flow, stream size, and stream temperature are used to capture fish vulnerability to drought. The index flow is defined as the median of the summer month with the lowest daily flowrate for the given period (Hamilton and Seelbach, 2011; Esfahanian et al., 2016).

However, one of the biggest challenges for using these indices is that for each drought category (e.g. meteorological, agricultural, and hydrological), dozens of indices exist. Meanwhile, each drought index requires different input parameters and uses a unique method to measure drought severity. Measuring the drought severity level (e.g. metrological) while using different methods has resulted in a wide range of responses or even contradictory conclusions. Therefore, there is need to introduce a collective understanding of categorical drought conditions, since no single index was universally accepted as the best practice in each category.

Despite the current progress in understanding the science behind droughts, there is still a need to improve drought monitoring methods, which will ultimately improve drought preparation and management practices, and reduce drought vulnerability on different sectors (Svoboda et al., 2002). This can only be achieved if one considers both categorical and overall impacts of drought, since focusing on one aspect can have unintended consequences on other aspects of drought. For example, a goal of a commodity stakeholder group is to develop a mitigation strategy to address drought impacts on agriculture. One solution is to use additional water from surface and ground water resources; however, this solution unintentionally worsens the impacts of drought on stream health. Therefore, a comprehensive approach to address drought problems can only be achieved if categorical and overall impacts of drought are well understood. Under this circumstance, resources can be allocated in a way that solves a categorical impact of drought while minimizing the negative impacts to other drought categories or improve the overall drought condition. Therefore, it was suggested that drought monitoring techniques can be improved by combining the existing indices to better capture the overall impacts of drought (Zargar et al., 2011). In general, the methods used for combining drought indices can be classified as: 1) decision matrix analysis (Svoboda et al., 2002; Balint et al., 2011; Ziese et al., 2014); 2) classification and regression tree (CART) analysis (Tadesse and Wardlow, 2007; Brown et al., 2008); and 3) regression technique (Keyantash and Dracup, 2004; Karamouz et al., 2009).

In the decision matrix analysis, multiple criteria are first identified to guide the final outcome. This technique was used by Svoboda et al. (2002) to create the Drought Monitor, which is a composite of meteorological drought indices (such as Palmer Drought Severity Index and Standardized Precipitation Index), and hydrologic and remote sensing information. The relationship between the Drought Monitor components and drought severity were defined using the decision matrix analysis (Svoboda et al., 2002). Additionally, the Combined Drought Index (CDI) was introduced by Balint et al. (2011), which is the combination of the Precipitation Drought Index (PDI), Temperature Drought Index (TDI), and Vegetation Drought Index (VDI). The weighted average of the PDI, TDI, and VDI indices were used to compute the CDI. The assigned weight for the PDI was 50% and 25% weight was assigned for each TDI and VDI indices (Balint et al., 2011). Ziese et al. (2014) developed the Global Precipitation Climatology Center Drought Index (GPCC-DI) with 1° grid spatial resolution, which is a combination of the Modified Standardized Precipitation Index (SPI-DWD) and Standardized Precipitation Evapotranspiration Index (SPEI). The GPCC-DI is calculated by taking the average of SPI-DWD and SPEI indices for each grid cell (Ziese et al., 2014).

The CART analysis is a tree-building technique, which constructs a set of decision rules to build predictive models. This technique was used by Tadesse and Wardlow (2007) to develop the Vegetation Outlook (VegOut) to predict future vegetation conditions. In this tool meteorological drought indices (Standardized Precipitation Index and Palmer Drought Severity Index), oceanic indices (such as Southern Oscillation Index, and Multivariate El Niño and Southern Oscillation Index), and satellite and biophysical data were combined using a rule-based regression tree method. A year later, Brown et al. (2008) introduced a new index named Vegetation Drought Response Index (VegDRI) based on the CART concept. In this index, meteorological drought indices (Standardized Precipitation Index and Palmer Drought Severity Index), satellite-based vegetation measures, and biophysical information (such as land cover and available soil water capacity) were combined using CART analysis in order to develop the VegDRI empirical models for different seasons.

The regression technique estimates the linear and nonlinear behavior between the dependent and independent variables. This technique was used by Keyantash and Dracup (2004) to develop an Aggregate Drought Index (ADI) that considers meteorological, hydrological, and agricultural categories of drought. In this index, six hydrologic variables including precipitation, streamflow, reservoir storage, evapotranspiration, soil moisture, and snow water content were aggregated using principle component analysis (Keyantash and Dracup, 2004). In addition, the Hybrid Drought Index (HDI) was developed by Karamouz et al. (2009) using this technique. This index is a combination of the Standardized Precipitation Index, the Palmer Drought Severity Index, and the Surface Water Supply Index (Karamouz et al., 2009). An artificial neural network technique was used to predict the HDI based on the three drought indices (Karamouz et al., 2009).

Given the lack of a universal drought definition in monitoring drought, the goal of this study is to introduce a universal drought definition that considers several aspects of drought including meteorological, agricultural, hydrological, and stream health. This universal definition can improve drought monitoring, which can help decision makers to better allocate the resources to reduce drought impacts on different sectors. The objectives of this study are to: (1) define categorical drought indices (meteorological, agricultural, and hydrological) based on commonly used drought indices; (2) define a universal definition of drought by combining the categorical scores; (3) select the best variable sets to construct predictive drought models; (4) develop predictive drought models for each drought category and the universal drought index.

2. Materials and methodology

2.1. Study area

The Saginaw River Watershed is the largest watershed in Michigan, and is located in the eastern part of central Michigan (Fig. 1). The watershed has a total area of 16,122 km^2 and drains into Lake Huron. There are 145 subbasins in the Saginaw River Watershed, with the majority of them being warmwater streams. From the meteorological standpoint, Saginaw River Watershed has an average annual precipitation of 816 mm (Fig. S1), and an average