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A multivariate approach for persistence-based drought prediction: Application to the 2010–2011 East Africa drought

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SUMMARY

The 2011 East Africa drought caused dire situations across several countries and led to a widespread and costly famine in the region. Numerous dynamic and statistical drought prediction models have been used for providing drought information and/or early warning. The concept of Ensemble Streamflow Prediction (ESP) has been successfully applied to univariate drought indicators (e.g., the Standardized Precipitation Index) for seasonal drought prediction. In this study, we outline a framework for using the ESP concept for multivariate, multi-index drought prediction. We employ the recently developed Multivariate Standardized Drought Index (MSDI), which integrates precipitation and soil moisture for describing drought. In this approach, the ESP concept is first used to predict the seasonal changes to precipitation and soil moisture. Then, the MSDI is estimated based on the joint probability of the predicted accumulated precipitation and soil moisture as composite (multi-index) drought information. Given its probabilistic nature, the presented model offers both a measure of drought severity and probability of drought occurrence. The suggested model is tested for part of the 2011 East Africa drought using monthly precipitation and soil moisture data obtained from the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA-Land). The results indicate that the suggested multi-index predictions are consistent with the observation. Furthermore, the results emphasize the potential application of the model for probabilistic drought early warning in East Africa.

1. Introduction

Drought is among the most costly natural hazards, and reliable drought prediction would provide invaluable information for preparedness and mitigation. The 2011 East Africa drought was one of the most recent extreme events that led to famine and severe food crises in several countries, affecting over 9 million people (Funk, 2011; OCHA, 2011; USAID/FEWSN, 2011; ACTED, 2011). There is a consensus that a proactive plan through drought mitigation and vulnerability reduction is more efficient than a plan for crisis management (reactive approach), especially if drought involves food crises (WMO-GWP, 2011). Early warning systems and probabilistic drought forecasts are fundamental for developing and implementing a proactive drought mitigation plan (WMO, 2006). Furthermore, probabilistic and risk-based drought monitoring and prediction information is not only useful for early warning systems, but is also vital for successful drought relief management throughout an extreme event.

There are several research and operational models that provide drought monitoring and/or prediction information over East Africa (Heim, Jr. and Brewer, 2012; Hao et al., 2014). The U.S. Agency for International Development (USAID) Famine Early Warning System Network uses satellite data and rainfall forecasts for drought early warning (Funk, 2009). Operated by the Land Surface Hydrology Group at Princeton University, the experimental African Flood and Drought Monitor (Sheffield et al., 2014) offers near real-time monitoring of land surface hydrological conditions using the Variable Infiltration Capacity (VIC) (Sheffield et al., 2008; Yuan et al., 2013). Also, the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; Hao et al., 2014; Momtaz et al., 2014) provides drought information based on multiple drought indicators and input data sets.

Anderson et al. (2012) developed a drought monitoring product based on merged soil moisture estimates from three remote monitoring techniques and examined the temporal and spatial evolution of the Horn of Africa drought. AghaKouchak and Nakhjiri (2012) developed a near real-time Bayesian-based drought monitoring algorithm using long-term Global Precipitation Climatology Project (Adler et al., 2003) and high resolution near real-time satellite observations. This data set shows a statistically significant drying trend in East Africa over the past three decades (Damberg and AghaKouchak, 2014).

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Different indicators have been proposed to characterize drought (Heim, 2002; Mishra and Singh, 2010), such as the Standardized Precipitation Index (SPI) (McKee et al., 1993) and the Palmer Drought Severity Index (PDSI) (Palmer, 1965). The SPI has been widely used for drought monitoring and is recommended by the World Meteorological Organization (WMO) for monitoring meteorological drought (Hayes et al., 2011). The concept of the SPI can be applied to other variables such as soil moisture (SSI: Hao and AghaKouchak, 2013) and runoff (SRI: Shukla and Wood, 2008) for agricultural and hydrological drought monitoring, respectively. Drought is a complex phenomenon, and one single indicator (e.g., precipitation) may be insufficient for describing all drought features, although droughts primarily originate from sustained precipitation deficits. It is argued that the integration of precipitation with other drought-related variables, such as soil moisture and streamflow, is essential for efficient drought monitoring and early warning systems (Wilhite, 2005). For this reason, and in recent years, a variety of integrated drought indicators that combine different variables have been proposed, such as the Aggregate Drought Index (ADI) (Keyantash and Dracup, 2004), the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), the Joint Deficit Index (JDI) (Kao and Govindaraju, 2010), the Combined Drought Indicator (CDI) (Sepulcre-Canto et al., 2012), and the Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak, 2014).

Drought is typically predicted by using monthly to seasonal forecasts of climatic variables as inputs to drought indicators. There are generally two types of methods for drought prediction: (a) dynamic methods based on weather/climate model simulations, and (b) stochastic methods. The dynamic method for drought prediction relies on the prediction of relevant climate variables (e.g., precipitation) and then computing the corresponding drought indicator (e.g., SPI) (Yoon et al., 2012). Furthermore, dynamically predicted precipitation (and temperature) can be used as forcing to drive land surface models for predicting soil moisture and runoff for agricultural and hydrological drought monitoring (Luo and Wood, 2007; Mo et al., 2012). Dynamic models offer valuable information, especially for short-term forecasting (Yoon et al., 2012). However, their seasonal forecasts (especially, precipitation) exhibit high uncertainty and low seasonal prediction skill (National Research Council, 2006; Livezey and Timofeyeva, 2008; Lavers et al., 2009; Yoon et al., 2012).

Several stochastic models have been developed/used for prediction of hydrometeorological variables based on the autoregressive moving-average (ARMA) approach (Kendall and Dracup, 1992; Mishra and Singh, 2011), independent component analysis (ICA) method (Westra et al., 2007, 2008), Canonical Correlation Analysis (Barnston, 1994; Ntale et al., 2003; Shabbar and Barnston, 1996), resampling techniques (Rajagopalan et al., 1997), partial mutual information (PMI) criterion (Sharma, 2000; Sharma et al., 2000), and the Ensemble Streamflow Prediction (ESP) method (Twedt et al., 1977; Day, 1985; Wood and Lettenmaier, 2006; Wood, 2008; Lyon et al., 2012; AghaKouchak, 2014; Souza Filho and Lall, 2003; Shukla and Lettenmaier, 2011; Mo et al., 2012). The latter is based on the concept of persistence (or autocorrelation) of the SPI resulting from the accumulation of precipitation over time (e.g., 3-, 6-month). In a recent study, Yuan and Wood (2013) compared the ESP forecasts with those from multiple climate forecast models for meteorological drought onset prediction, and showed that dynamical models have higher deterministic forecast skill than ESP, although the probabilistic forecast skill is not necessarily better than ESP without additional statistical analysis (e.g., Bayesian conditional ensemble calibration). This highlights that importance of improving the current statistical drought prediction techniques.

In previous studies, the ESP approach has been applied to univariate drought indicators for seasonal drought prediction (e.g., Lyon et al., 2012). Limitations of univariate drought assessment have been discussed in numerous publications (Hao and AghaKouchak, 2013). In this study, we outline a framework for applying the ESP concept for multivariate, multi-index drought prediction. In this approach, the ESP concept is first used to predict the seasonal changes to precipitation and soil moisture. Then, the recently developed Multivariate Standardized Drought Index (MSDI) is used to derive composite multi-index drought information based on precipitation and soil moisture. The modeling framework is probabilistic and provides not only a measure of drought severity, but also probability of drought occurrence. This framework is used for prediction of the 2011 East Africa drought using monthly precipitation and soil moisture data.

The paper is organized as follows. Following this introduction, the methodology and modeling framework is introduced in detail in Section 2. Section 3 discusses the data and study area. The results are provided in Section 4, followed by the summary of the findings and remarks in Section 5.

2. Method

The Multivariate Standardized Drought Index (MSDI) integrates drought information from precipitation and soil moisture and provides a composite of meteorological and agricultural drought conditions (Hao and AghaKouchak, 2013). In essence, the MSDI is the multivariate version of the commonly used SPI (McKee et al., 1993). Denoting the accumulated precipitation and soil moisture for a certain time scale (e.g., 1-, 3-, 6-month) as random variables X and Y, their joint probability distribution (p) can be expressed as:

$$\Pr(X \leqslant x, Y \leqslant y) = p \tag{1}$$

The MSDI can then be computed as: MSDI = $\varphi^{-1}(p)$, where φ is the standard normal distribution function. The joint probability of precipitation and soil moisture in Eq. (1) can be estimated with either a parametric or an empirical method (Hao and AghaKouchak, 2013, 2014). Similar to the SPI, the MSDI can be estimated at different time scales (e.g., 1-, 3-, 6-month) to characterize drought.

In the ESP method, the historical observations are assumed to be equally likely scenarios of the future. In previous studies, univariate indices such as precipitation (Lyon et al., 2012) and soil moisture (AghaKouchak, 2014) percentile are used with the ESP concept for drought prediction. In this study, a multivariate framework is proposed for applying the ESP to multiple variables (here, precipitation and soil moisture). The MSDI is then used for multi-index characterization of drought based on ESP-based predictions of precipitation and soil moisture.

Assume that monthly precipitation and soil moisture data are available up to year $n+1$ (an n-year climatology is available for the study area). We define the target month m as the month for which drought conditions are to be predicted. In the following, the step-by-step process to derive 1-month lead drought prediction for the month m of year $n+1$ using the ESP and the 6-month MSDI is discussed. Denote the 6-month accumulated precipitation (AP) and soil moisture (AS) for target month m of year $n+1$ as $AP_{n+1,\mathrm{m}}$ and $AS_{n+1,\mathrm{m}}$, which can be expressed as (Hao et al., 2014):

$$AP_{n+1,\mathrm{m}} = P_{n+1,\mathrm{m}-5} + P_{n+1,\mathrm{m}-4} + P_{n+1,\mathrm{m}-3} + P_{n+1,\mathrm{m}-2} + P_{n+1,\mathrm{m}-1} + \underline{P}_{n+1,\mathrm{m}} \tag{2}$$

$$AS_{n+1,\mathrm{m}} = S_{n+1,\mathrm{m}-5} + S_{n+1,\mathrm{m}-4} + S_{n+1,\mathrm{m}-3} + S_{n+1,\mathrm{m}-2} + S_{n+1,\mathrm{m}-1} + \underline{S}_{n+1,\mathrm{m}}$$

where $\underline{P}_{n+1,\mathrm{m}}$ and $\underline{S}_{n+1,\mathrm{m}}$ are precipitation and soil moisture to be predicted for the target month m, respectively. In the above equation, the accumulations ($P_{n+1,\mathrm{m}-1}$, $P_{n+1,\mathrm{m}-2}$, $P_{n+1,\mathrm{m}-3}$, $P_{n+1,\mathrm{m}-4}$, $P_{n+1,\mathrm{m}-5}$) and ($S_{n+1,\mathrm{m}-1}$, $S_{n+1,\mathrm{m}-2}$, $S_{n+1,\mathrm{m}-3}$, $S_{n+1,\mathrm{m}-4}$, $S_{n+1,\mathrm{m}-5}$) are