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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 termed as the initial conditions for predicting $AP_{n+1,\mathrm{m}}$ and $AS_{n+1,\mathrm{m}}$ (precipitation and soil moisture in the target month). Given that the objective of this method is seasonal drought prediction, following Yoon et al. (2012), the 6-month time scale is used for drought prediction. This means that in Eq. (2), 1-month lead drought is predicted based on the past five months of initial conditions. It should be noted that for prediction in January of year $n + 1$, the initial conditions will be sampled from year n.

Based on the ESP method, the predictions of $\underline{P}_{n+1,\mathrm{m}}$ and $\underline{S}_{n+1,\mathrm{m}}$ in Eq. (2) can be obtained from the historical records (n-year climatology). Similarly, for a 2-month lead prediction for the target month m, the accumulated precipitation (AP) and soil moisture (AS) can be expressed as:

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

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

In this case, ($P_{n+1,\mathrm{m}-5}$, $P_{n+1,\mathrm{m}-4}$, $P_{n+1,\mathrm{m}-3}$, $P_{n+1,\mathrm{m}-2}$) and ($S_{n+1,\mathrm{m}-5}$, $S_{n+1,\mathrm{m}-4}$, $S_{n+1,\mathrm{m}-3}$, $S_{n+1,\mathrm{m}-2}$) are the initial conditions, while ($\underline{P}_{n+1,\mathrm{m}}$, $\underline{P}_{n+1,\mathrm{m}-1}$) and ($\underline{S}_{n+1,\mathrm{m}}$, $\underline{S}_{n+1,\mathrm{m}-1}$) are obtained from historical records (n-year climatology).

Based on Eq. (2), n traces of accumulated precipitation and soil moisture from historical records can be derived as:

$$AP^{(i)}_{n+1,\mathrm{m}} = P_{n+1,\mathrm{m}-5} + P_{n+1,\mathrm{m}-4} + P_{n+1,\mathrm{m}-3} + P_{n+1,\mathrm{m}-2} + P_{n+1,\mathrm{m}-1} + \underline{P}_{i,\mathrm{m}} \tag{4}$$

$$AS^{(i)}_{n+1,\mathrm{m}} = S_{n+1,\mathrm{m}-5} + S_{n+1,\mathrm{m}-4} + S_{n+1,\mathrm{m}-3} + S_{n+1,\mathrm{m}-2} + S_{n+1,\mathrm{m}-1} + \underline{S}_{i,\mathrm{m}}$$

where $i = 1, \ldots, n$. For each combination $AP^{(i)}{}_{n+1,\mathrm{m}}$ and $AS^{(i)}{}_{n+1,\mathrm{m}}$, $i = 1, \ldots, n$, the MSDI$^{(i)}$ can be computed based on the accumulated precipitation and soil moisture from historical records $AP = (AP_{1,\mathrm{m}}, \ldots, AP_{n,\mathrm{m}})$ and $AS = (AS_{1,\mathrm{m}}, \ldots, AS_{n,\mathrm{m}})$, respectively. For example, having the first trace of the predicted $AP^{(1)}{}_{n+1,\mathrm{m}}$ and $AS^{(1)}{}_{n+1,\mathrm{m}}$, a new series can be constructed from the climatology of the target month m, i.e., ($AP_{1,\mathrm{m}}, \ldots, AP_{n,\mathrm{m}}, AP^{(1)}{}_{n+1,\mathrm{m}}$) and ($AS_{1,\mathrm{m}}, \ldots, AS_{n,\mathrm{m}}, AP^{(1)}{}_{n+1,\mathrm{m}}$). Then, the first predicted MSDI$^{(1)}$ for the target month m can be computed based on the empirical joint probability (see Hao et al., 2014) of AP and AS:

$$\mathrm{MSDI}^{(1)} = P(AP \leqslant AP^{(1)}_{n+1,\mathrm{m}}, \quad AS \leqslant AS^{(1)}_{n+1,\mathrm{m}}) \tag{5}$$

From the observed precipitation and soil moisture in historical records (n years), the n-ensemble member of predicted MSDI (i.e., MSDI$^{(1)}$, MSDI$^{(2)}$, …, MSDI$^{(n)}$) can be obtained. The ensemble median is computed as a measure of the drought severity. Using this ensemble approach, one can estimate the probability of the MSDI below a certain threshold (e.g., −0.8, which indicates a moderate drought). Notice that the MSDI, similar to the SPI, is a standardized index in which a sequence of negative (positive) values represents a drought (wet) period. For example, the probability of the MSDI being less than −0.8 can be computed as the number of ensemble members that fall below −0.8 divided by the total number of ensemble members n. The probabilistic nature of this model allows the estimation of the risk (probability) of the predicted events. Fig. 1 summarizes the flowchart of the proposed modeling framework for drought prediction in target month $m = 8$ (August) of year $n + 1$.

3. Study area and data

Part of the 2011 East Africa drought is used as the case study for evaluating the presented drought prediction scheme. Precipitation variability in the Horn of Africa, central East Africa, is characterized by the March–May long-duration rains and October–December short-duration rains (Lyon and DeWitt, 2012; Dutra et al., 2013). The 2010–2011 East Africa drought resulted from a precipitation deficit during both rainy seasons of the region (Dutra et al., 2013). This study focuses on part of East Africa (see Fig. 6) where the 2010–2011 droughts caused significant problems. The monthly precipitation and soil moisture data from NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-Land), available from January 1, 1980 onwards on a horizontal resolution of 2/3° × 1/2°, are used as input data (Reichle et al., 2011; Reichle, 2012). MERRA-Land data sets are available at the global scale and in near real-time. The data set has been tested and used in a number of hydrology ad water cycle studies (Bosilovich et al., 2011; Kennedy et al., 2011; Rienecker et al., 2011; Yi et al., 2011; Golian et al., 2014).

4. Results

In a recent study, Hao et al., (2014) show that the MSDI leads to higher probability of drought detection and critical success index compared to the individual SPI and SSI (see also Golian et al., 2014). For this reason, this study only focuses on drought prediction using MSDI. The evolution of the 2010–2011 East Africa drought based on the MSDI is shown in Fig. 2. The results indicate the drought onset of October 2010, when a large fraction of East Africa experienced drought. The drought persisted toward the end of 2011 and continued into 2012 in certain parts of the East Africa, although the eastern Horn of Africa recovered from the drought by November 2011 (Fig. 2). Similar drought onset and persistence patterns were found in the previous studies (e.g., Dutra et al., 2013). For a better illustration of the temporal development of drought and assessing the MSDI-based predictions, time series of drought development and forecasts are presented in Fig. 3 for one pixel (42E, 1.5N); the location is marked with a circle in Fig. 2. The figure shows the observed MSDI and the ensemble median of 1-month lead predicted MSDI (Fig. 3, top) and the 1-month lead probability of drought occurrence (Fig. 3, bottom). As mentioned earlier, computing the drought probability of occurrence requires defining a drought threshold. Throughout this paper, drought is defined as the MSDI below −0.8 (moderate drought (Svoboda et al., 2002), or approximately the 20th percentile of climatology).

In Fig. 3 (top), the red line represents drought observed from MERRA-Land data, whereas the green line displays the 1-month lead predictions based on the ESP and MSDI using MERRA-Land historical observations. In this grid, the MSDI turns negative (indicating drought) in September 2010 and drops below −0.8 in November 2010. The observed MSDI remains negative (and below −0.8) until September 2011, indicating long-term drought persistence. High values of the observed MSDI after September 2011 show a wet period, which led to drought recovery over parts of the Horn of Africa by the end of 2011. Fig. 3 reveals that the 1-month lead predictions of the MSDI ensemble median follow the observations closely, indicating a reasonable prediction at 1-month lead time.

With regard to drought onset, the MSDI predictions, similar to observations, show the drought onset (negative MSDI) in September 2010, although the drought severity values from the ensemble median of the predictions are greater than observations in the first few months of drought development. As shown, the probability of drought occurrence (MSDI < 0.8) increases to 0.4 and 0.6 in October 2010 and December 2010, respectively (Fig. 3 bottom). These relatively high drought occurrence probability values are the first signals of the 2011 drought. With respect to drought persistence, the MSDI predictions show the drought persistence from October 2010 to September 2011, which is consistent with the observations (Fig. 3, top). Note that the probability of drought occurrence also remains high and nearly 1 throughout the drought, except for a few time steps, when it drops to around 0.7. With regard to drought

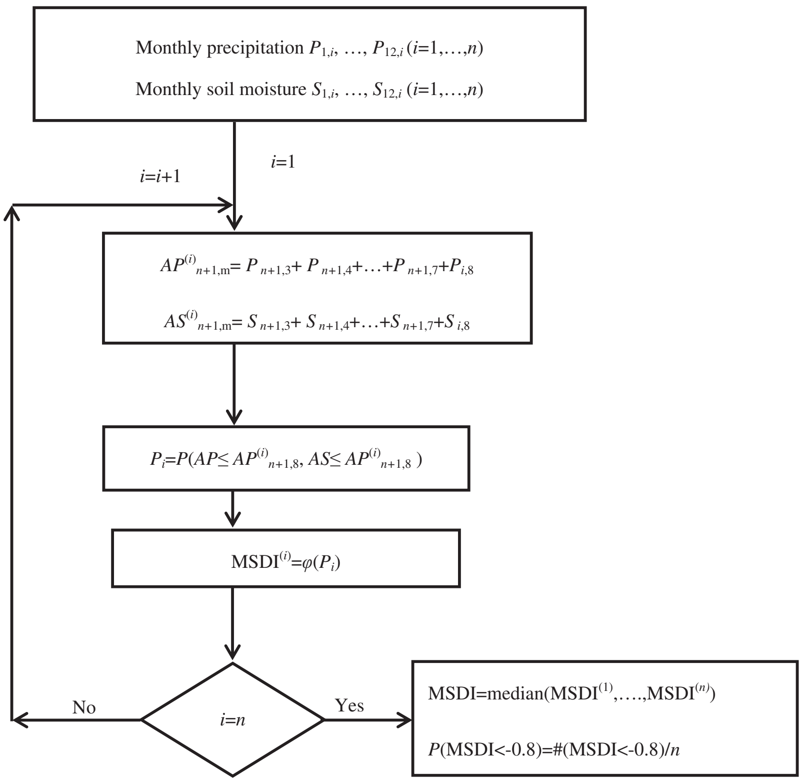

Fig. 1. Flowchart of the drought prediction algorithm for 1-month lead prediction of the MSDI at target month $m = 8$ (August) of year $n + 1$. For a 1-month lead prediction with $m = 1$ (January) of year $n + 1$, the initial conditions should be sampled from year n.

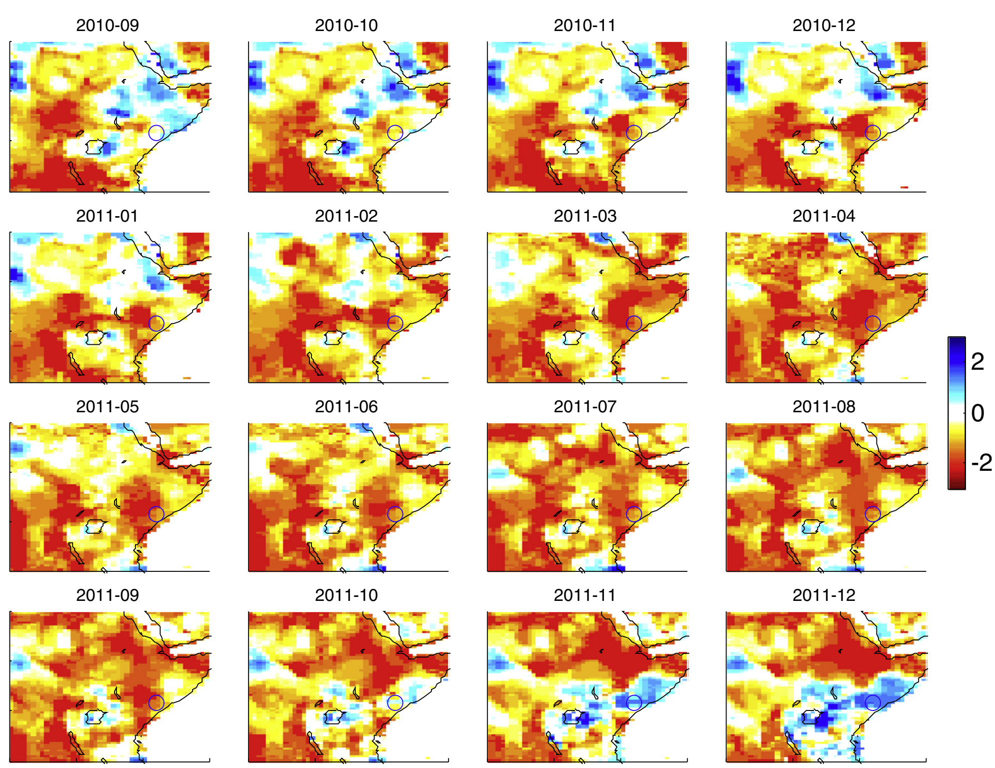

Fig. 2. Evolution of the 2010–2011 East Africa drought based on the MSDI.

termination, the predictions from the ensemble median (Fig. 3, top) and the probability values (Fig. 3, bottom) exhibit drought termination in November 2011 in the selected grid, while the observations show that the drought terminates in October 2011.

The 2-month lead predictions of the ensemble median and the probability of occurrence of drought are shown in Fig. 4. As shown, the ensemble median of the 2-month lead predictions turns negative at the same time as the observations; however, in the first

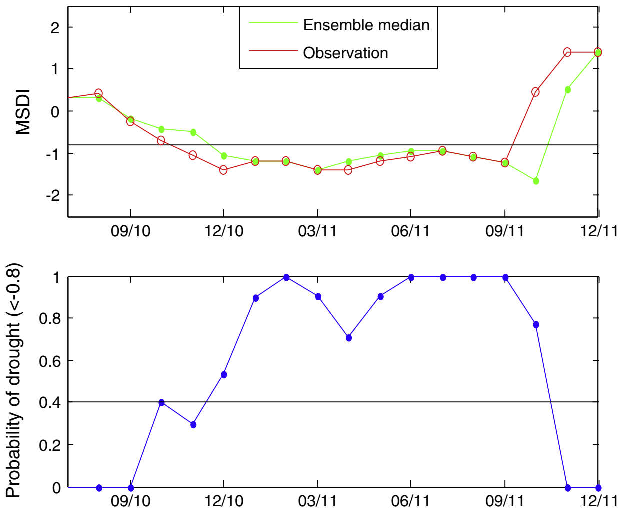

Fig. 3. 1-month lead predictions of the ensemble median and observations based on the MSDI (top), and the MSDI-based drought probability (bottom) of occurrence (MSDI < −0.8) for the grid 42E, 1.5N (marked with a circle in Fig. 2).

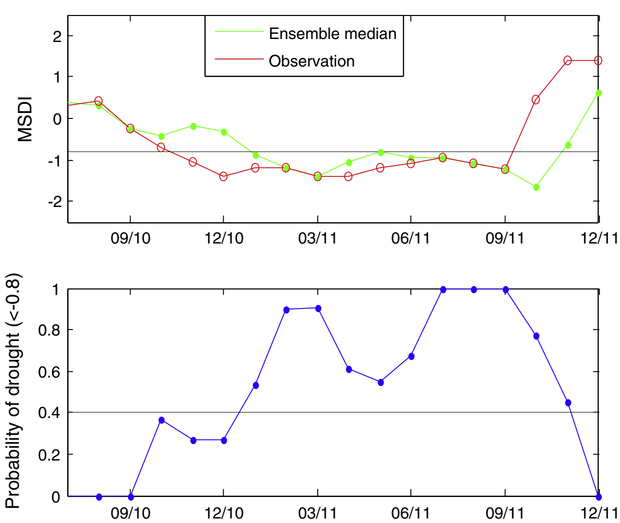

Fig. 4. 2-month ahead predictions of the ensemble median and observations (top), and the drought probability (bottom) of occurrence (MSDI < −0.8) for the grid 42E, 1.5N (marked with a circle in Fig. 2).

three months, the MSDI underestimates the severity of the event (Fig. 4, top). From January 2011 onward, the predictions are in very good agreement with the observations. The drought probability of occurrence graph (Fig. 4, bottom) shows an increase in the probability of drought as the event develops. Furthermore, Fig. 4 (bottom) confirms that the 2-month lead predictions describe the persistence of the drought very well. The predicted drought probability values are generally high throughout the event (probabilities are primarily higher than 0.6).

It should be noted that the drought prediction method presented is based on the concept of persistence, which relies on the initial conditions of the precipitation and soil moisture as well as the climatology of both variables in the target month. The importance of initial conditions and climate forcings in hydrologic prediction has been discussed in a variety of studies (Wood and Lettenmaier, 2008; Shukla and Lettenmaier, 2011). Results indicate that initial conditions play an important role in the prediction skill during the transition from a wet to a dry condition, while climate forcings are critical during the transition from a dry to a wet condition. In persistence-based drought prediction using the SPI, Lyon et al. (2012) showed that the drought prediction skill is relatively high when accumulated rainfall shows a deficit and when the target season is climatologically dry. Our findings are consistent with the previous studies (e.g., Lyon et al., 2012), and the onset of this event was predicted well using the method outlined in this paper. However, if there is extreme precipitation (soil moisture) above the climatological mean in the target season, a persistence-based model may show the predicted drought recovery with a delay of a few months. To further explain this property, we show the observed monthly precipitation and soil moisture in 2011 and their climatological means for this grid in Fig. 5. In October 2011, precipitation is much higher than the climatologic mean and is extreme enough for a drought recovery (transition from dry to wet conditions). Because of this very high (extreme) precipitation, the model that utilizes the historical record predicts the drought recovery with 1-month delay. Furthermore, much higher precipitation in late 2011 compared to the long-term climatology (Fig. 5) explains the sudden drop in the probability of drought between October–December 2011, shown in Figs. 3 and 4.

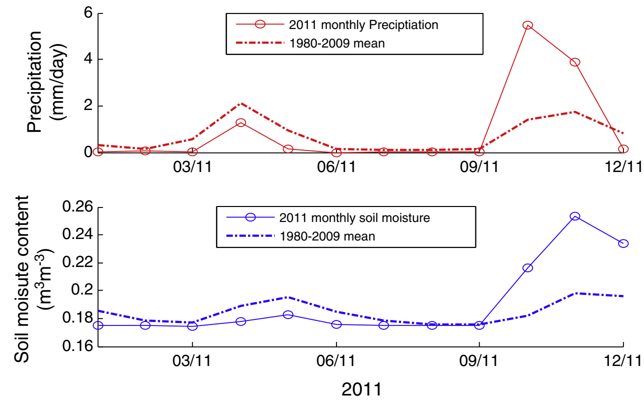

Fig. 5. Observed monthly precipitation and soil moisture for 2011 compared with the 1980–2009 climatology (monthly means).

The spatial patterns of the 1-month lead drought predictions and their corresponding probability of drought occurrence for the entire region are presented in Figs. 6 and 7, respectively. In Fig. 6, each panel shows the ensemble median of the MSDI prediction, while the panel in Fig. 7 displays the probability of the MSDI < −0.8. As shown, the spatial patterns and temporal evolution of the predicted drought (Fig. 6) are generally consistent with the observations shown in Fig. 2. In addition, the areas with high drought probability of occurrence given in Fig. 7 generally resemble the observed drought with the MSDI < −0.8.

The 3- and 4-month lead predictions of drought conditions for several months throughout the drought event are shown in Fig. 8. The presented approach captures the East Africa drought reasonably well, even for longer lead times. Even at the 4-month lead prediction, the drought onset is shown by October/November 2010 over most portions of the region, except for parts of the Horn of Africa. As shown, the 3- and 4-month lead predictions of May 2011 are in good agreement with observations (compare Fig. 5 with Fig. 2). At the 4-month lead, the drought signal is obviously weaker than the shorter lead times; however, it is still strong enough to indicate the drought conditions throughout the event over parts of the region. As mentioned in the example time series (Figs. 3 and 4) and given the fact that the model is based on the concept of persistence, the model does not detect drought termination as early as observations (see the marked area in Fig. 8). Finally, the drought probability of occurrence for the 3- and 4-month lead time is relatively high (primarily over 0.5) over portions of the region. This indicates that, even four months prior to the event,

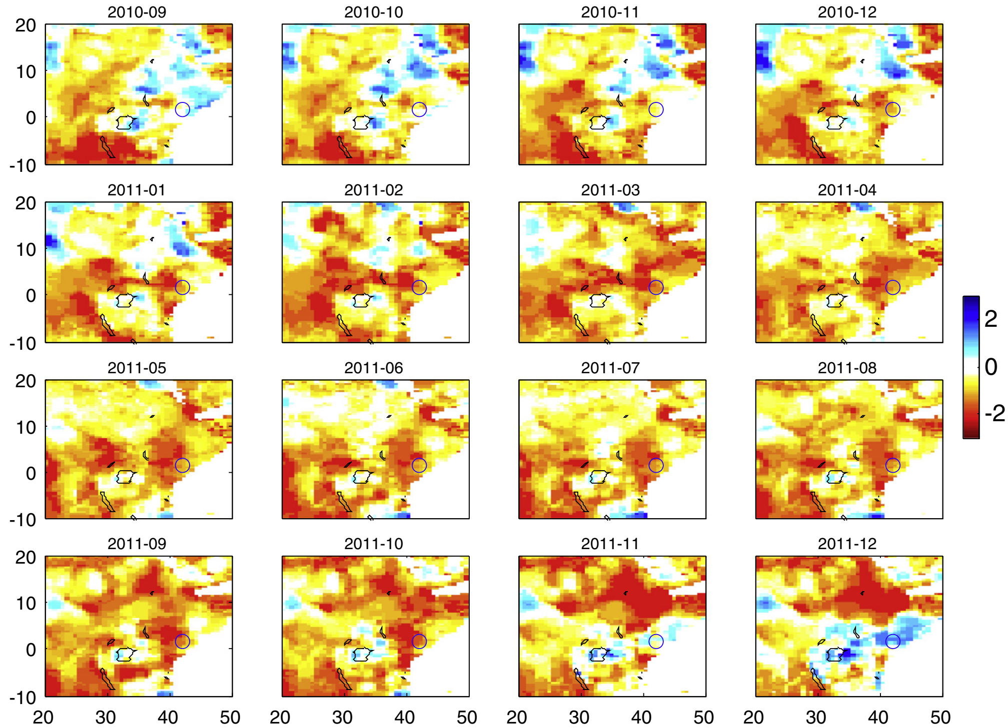

Fig. 6. Ensemble median of the 1-month lead MSDI predictions for the period September 2010 to December 2011.

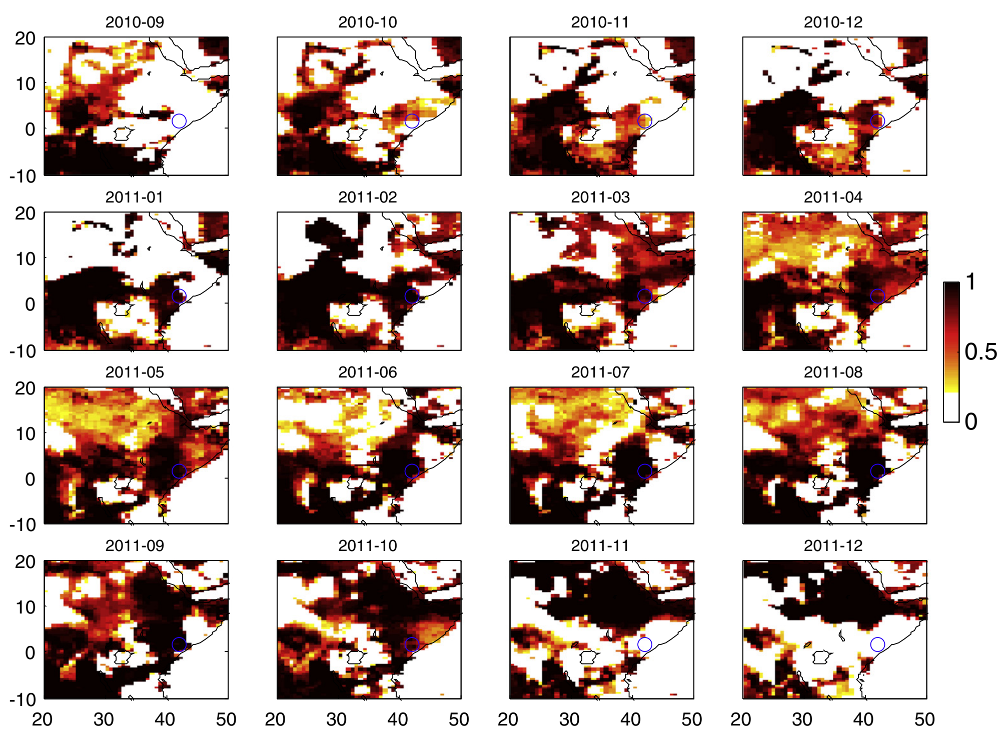

Fig. 7. Drought probability of occurrence based on the 1-month lead MSDI for the period September 2010 to December 2011.

the presented multi-index ESP method based on the MSDI would predict that a drought is likely to occur in the region.

5. Conclusion and remarks

In this study, a framework is proposed for using the Ensemble Streamflow Prediction (ESP) concept for multi-index, multivariate drought prediction. The approach uses ESP for predictions of precipitation and soil moisture and derives the Multivariate Standardized Drought Index (MSDI) from their joint distribution. The presented framework is probabilistic and, in addition to drought severity, offers the probability of drought occurrence based on the spread of the ensemble for a given drought severity threshold (here, $MSDI < -0.8$). The proposed methodology is used for

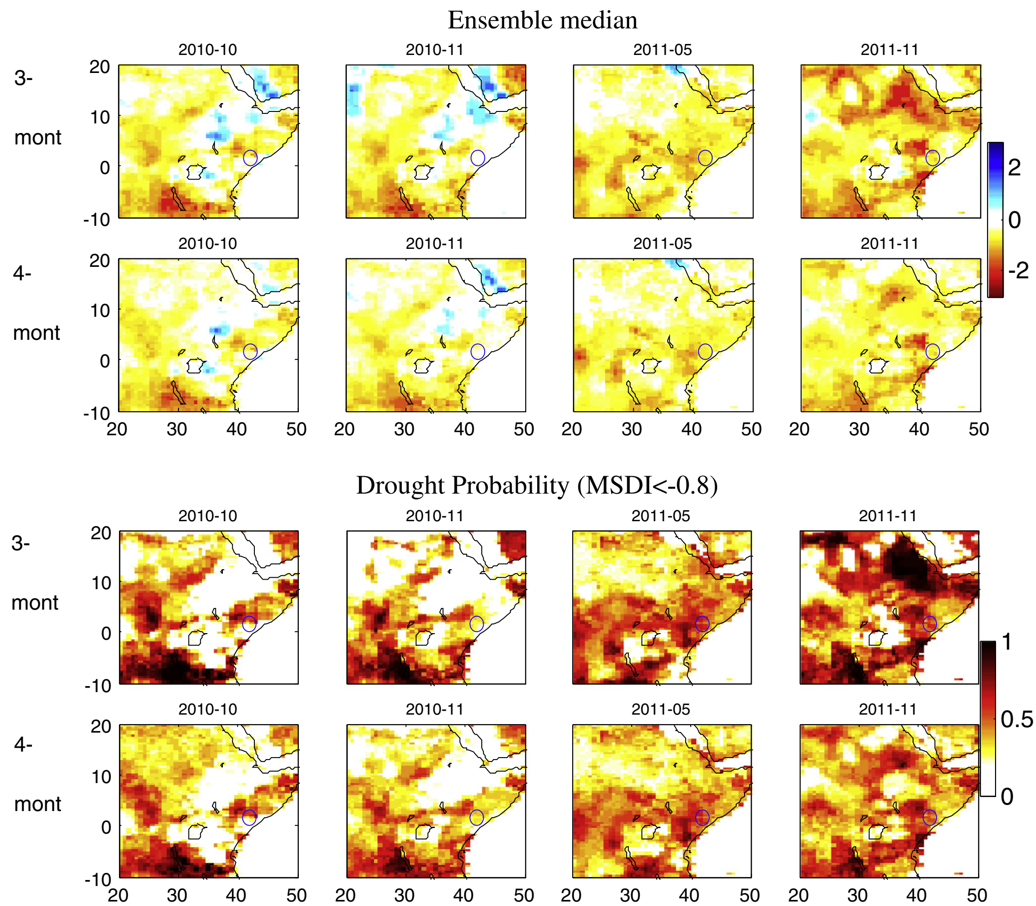

Fig. 8. 3- and 4-month lead predictions of the ensemble median (top two rows), and their corresponding drought probability (bottom two rows) for a number of time-steps throughout the event.

predicting the 2011 East Africa drought. The results show that the presented approach detects the drought onset and persistence reasonably well and is consistent with previous studies. The spatial patterns of drought evolution and their corresponding drought probability maps are in very good agreement with observations, especially with respect to the drought onset and persistence. Throughout the event, the entire region shows high probability of drought, indicating that the model is consistent over time. Overall, the results of this study indicate that the proposed multi-index ESP method based on the MSDI performs well for drought prediction and early warning over East Africa. A common deficiency of the persistence-based approaches is their limitations in predicting the drought onset. This limitation is similar to the ESP-based forecasts using precipitation and soil moisture (e.g., Lyon et al., 2012; AghaKouchak, 2014). However, this multivariate persistence-based approach is particularly useful for monitoring the drought evolution and probabilistic assessment.

This presented method is based on the persistence of accumulated variables (here, precipitation and soil moisture). By nature, the performance of a persistence-based model relies on the quality and accuracy of the initial conditions. Furthermore, the presented approach may not detect the drought termination (or transition from dry to wet conditions) as early as observations. Our results show that, if an extreme event (or at least a substantial departure from the climatology) occurs in the target month, this model may predict the drought termination with some time lag. In a recent study, Pan et al. (2013) proposed a probabilistic drought recovery method based on ensemble forecasts. Future work on combining the multivariate approach in this study and that of Pan et al. (2013) may lead to improvements in predicting drought termination.

It is pointed out that the observed precipitation deficit of October–December 2010 is related to a strong La Nina event, and the ECMWF seasonal forecasts show high prediction skill in seasonal precipitation anomalies (Dutra et al., 2013; Pozzi et al., 2013). However, the ECMWF's seasonal precipitation forecasts based on the atmosphere–ocean coupled model for March–May 2011 showed very low prediction skill (Dutra et al., 2013; Pozzi et al., 2013), primarily because of a weak relationship between precipitation and the large-scale climate indices (Camberlin and Philippon, 2002).

The presented model is available to the public in near real-time through the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; http://drought.eng.uci.edu/). More efforts are needed to integrate the model outputs into operational decision-making and drought management. Also, different types of events (e.g., moderate, extreme) should be evaluated across the globe to evaluate the robustness of the model across different climatic conditions. A topic that merits future investigation is combining the presented approach in this paper with dynamic drought prediction models. Provided that dynamic models exhibit high skills (in a season or wet/dry conditions), their simulations can be used either as the target month simulations or as members in the final ensemble. Alternatively, a hybrid persistence-based model combined with a dynamic model for drought prediction based on different choices of models over various regions/seasons may lead to improvements in drought predictability. However, these are challenging tasks and, require extensive research as the prediction skills of models vary substantially in space and time and across the choice of models.

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