A Baseline Probabilistic Drought Forecasting Framework Using Standardized Soil Moisture Index: Application to the 2012 United States Drought

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Abstract

The 2012 drought was one of the most extensive drought events in half a century, resulting in over $12 billion in economic loss in the United States, and substantial indirect impacts on global food security and commodity prices. An important feature of the 2012 drought was rapid development and intensification in late spring/early summer, a critical time for crop development and investment planning. Drought prediction remains a major challenge because dynamical precipitation forecasts are highly uncertain, and their prediction skill is low. Using a probabilistic framework for drought forecasting based on the persistence property of accumulated soil moisture, this paper shows that the U.S. drought of summer 2012 was predictable several months in advance. The presented drought forecasting framework provides the probability occurrence of drought based on climatology and near-past observations of soil moisture. The results indicate that soil moisture exhibits higher persistence than precipitation, and hence improves drought predictability.

1 Introduction

According to United States Department of Agriculture (USDA) estimates, about 80 percent of U.S. agricultural land experienced drought in 2012 which made the event more extensive than any since 1950 (USDA, 2012). A striking aspect of the 2012 drought was rapid increase in severity in early July during a critical time of crop development (USDA, 2012). The quick onset of the drought in the central plains during late spring led to a so-called “flash drought” (Hoerling et al., 2013). A drought early warning system with seasonal predictions of drought onset, severity, persistence, and spatial extent in a timely manner would provide invaluable information to decision-makers and stakeholders. There are a number of research and operational drought (or hydrologic) prediction systems (Pozzi et al., 2013; Mishra and Singh, 2010), including the Climate Prediction Center Seasonal Drought Outlook (Steinemann, 2006), the University of Washington’s Surface Water Monitor (Wood and Lettenmaier, 2006; Wood, 2008), Princeton University’s drought forecast system (Luo and Wood, 2007; Li et al., 2008; Sheffield et al., 2008), U.S. - Mexico Drought Prediction Tool (Lyon et al., 2012), and the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; Hao et al., 2014). Despite all these efforts, a community White Paper by the World Climate Research Program identified sub-seasonal to seasonal drought prediction as one of the major research gaps in hydroclimatology (WCRP, 2010).

Drought forecasting is generally based on drought indicators computed using dynamic or statistical model simulations of drought-related variables (e.g., Mishra et al., 2009; Madadgar, and Moradkhani, 2013). Droughts are classified as agricultural (soil moisture deficit), meteorological (precipitation deficit), and hydrological (streamflow/groundwater deficit), and various drought indicators based on soil moisture, precipitation and runoff have been developed to describe different aspects of droughts (Heim, 2002; Wood et al., 2002; Wood and Lettenmaier, 2006; Mo, 2008; Shukla and Lettenmaier, 2011; Hao and AghaKouchak, 2013). Most drought prediction studies are based on the Standardized Precipitation Index (SPI; McKee et al., 1993) with the input precipitation derived from dynamical weather/climate models (Yoon et al., 2012; Mwangi et al., 2013; Dutra et al., 2013, 2014a, 2014b). While dynamic models provide valuable information, precipitation forecasts are subject to high uncertainty and models exhibit very low skill in predicting precipitation with a few months lead time (Goddard et al., 2003; National Research Council, 2006; Livezey and Timofeyeva, 2008; Lavers et al., 2009). A baseline probability method is proposed for meteorological drought forecasting based on persistence of the SPI (Lyon et al., 2012), indicating that a statistical persistence-based model could lead to a good seasonal drought forecasting skill (Quan et al., 2012). Hao et al., 2014 developed a multivariate method for statistical drought prediction using a persistence-based approach.

Soil moisture is often used as an indicator of agricultural drought monitoring, and has been used in different forms (Samaniego et al., 2013) including the soil moisture percentile (Luo and Wood, 2007; Wood, 2008; Shukla et al., 2011), normalized soil moisture (Dutra et al., 2008), and soil moisture anomaly (Sheffield and Wood, 2007; Sheffield and Wood, 2008). Typically, precipitation and temperature forecasts, either from dynamic models or climatology resampling (i.e., Ensemble Streamflow Prediction, ESP method; Mo et al., 2012), are used to force land-surface/hydrologic models for predicting soil moisture conditions and drought (e.g., Luo and Wood, 2007; Luo and Wood, 2008; Trambauer et al., 2013). The uncertainty of dynamic soil moisture forecasts is even higher than the climate forcings (precipitation and temperature) because in addition to input uncertainty, model errors and uncertainty also propagate into soil moisture simulations. For this reason, different statistical methods such as conditional ESP resampling have been explored for soil moisture prediction (Wood, 2008).

Persistence is a distinctive characteristic of the soil moisture as it exhibits less variability relative to precipitation (Hao and AghaKouchak, 2014). Mo et al., (2012) emphasized the importance of the persistence of soil moisture in improving drought forecasting skill. Great strides have been made to explore soil moisture persistence properties, and results reveal that the persistence of soil moisture memory spans weeks to a couple of months (Vinnikov and Yeserkepova, 1991; Entin et al., 2000; Seneviratne et al., 2006; Koster et al., 2010). Though the persistence property of soil moisture has been well documented, the properties of accumulated soil moisture and its potential use for drought forecasting has less been investigated. In this study, a probabilistic drought prediction framework is proposed using the Standardized Soil moisture Index (SSI) as the drought indicator, which allows for the description of soil moisture across different time scales (e.g., 3-, 6-, 12 month). In other words, soil moisture is treated in a similar fashion to precipitation accumulation across different time scales relative to the corresponding long-term climatology (McKee et al., 1993). Given the temporal integration of data, SSI leads to even higher persistence compared with the commonly used soil moisture percentiles or soil moisture anomaly.

2 Data

The data sets used in this study include the monthly precipitation and soil moisture from the NASA Modern-Era Retrospective analysis for Research and Applications (MERRA-Land), available on a 2/3° × 1/2° grid from January 1, 1980 onwards (Reichle et al., 2011; Rienecker et al., 2011). MERRA data sets have been used in numerous studies in different climatic regions (Bosilovich et al., 2011; Golian et al., 2014; Wong et al., 2011). Uncertainties in MERRA data sets have been evaluated against different observations (e.g., Yi et al., 2011; Kennedy et al., 2011). The results show that MERRA provides valuable information consistent with observations especially in middle-latitudes, while uncertainties in high latitudes are often large (Yi et al., 2011; Reichle et al., 2011).

3 Methodology

The Standardized Soil Moisture Index (SSI; Hao and AghaKouchak, 2014) can be defined in a similar way to the commonly used Standardized Precipitation Index (SPI; Mckee et al., 1993) that has been used in a wide variety of studies (Dutra et al., 2013; Damberg and AghaKouchak, 2013). Here, the SSI is estimated using a nonparametric approach in which the empirical probability (*p*) of the historical soil moisture data is derived using the empirical Gringorten plotting position (Gringorten, 1963). In other words, instead of fitting a distribution function to soil moisture data, the probabilities (*p*) are obtained empirically using the empirical Gringorten approach: $(i-0.44)/(n+0.12)$ where n denotes the sample size and i refers to the rank of soil moisture data from from the smallest.

The empirical probabilities, derived from the Gringorten plotting position, are then transformed into the standard normal distribution function: $SSI = \Phi^{-1}(p)$, where Φ is the standard normal distribution function. In this approach, one can avoid making a decision about the parametric distribution function of accumulated soil moisture at different time scales. Assume that soil moisture for the month i is S_i. Then the 6-month accumulation of the soil moisture A_i for the month i can be expressed as (Hao et al., 2014):

$$A_i = S_{i-5}+S_{i-4}+S_{i-3}+S_{i-2}+S_{i-1}+S_i, \quad (1)$$

In this study, the Ensemble Streamflow Prediction (ESP) method (Twedt et al., 1977; Day, 1985) is used for resampling from historical records of soil moisture to obtain monthly moisture at the target season with the 6-month SSI as the drought indicator. Assume the l -month lead forecasting is needed based on the monthly soil moisture observations with forecast initialization at month i. Then the l month ($1 \le l \le 5$) ahead forecasting of the accumulated soil moisture A_{i+l} can be expressed:

$$A_{i+l} = S_{i+l-5} + S_{i+l-4} + S_{i+l-3} + S_{i+l-2} + S_{i+l-1} + S_{i+l} \quad (2)$$

Assume that one month lead forecasting (i.e., l=1) based on the 6-month SSI is needed. The unknown S_{i+1} is predicted by resampling the soil moisture from the historical record of the target month (i.e., i+1). As a result, an ensemble of m (i.e., the length of observation in the historical record) sequence of the monthly soil moisture in the target season can be obtained from the observed monthly soil moisture. In this manner, m sequences of accumulated 6-month soil moisture for the l month lead time can be generated by blending the observed and predicted monthly soil moisture. For example, for l=1, the blended sequences of accumulated 6-month soil moisture can be expressed as (Hao et al., 2014):

$$A_{i+1}^{(1)} = S_{i-4} + S_{i-3+} S_{i-2} + S_{i-1} + S_i + S^{(1)}_{i+1}$$

$$A_{i+1}^{(2)} = S_{i-4} + S_{i-3+} S_{i-2} + S_{i-1} + S_i + S^{(2)}_{i+1} \quad (3)$$

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$$A_{i+1}^{(m)} = S_{i-4} + S_{i-3+} S_{i-2} + S_{i-1} + S_i + S^{(m)}_{i+1}$$

where $S_{i-4}\ldots, S_i$ are the observed soil moisture prior to the target month in the 6-month window, while $S^{(1)}_{i+1},\ldots, S^{(m)}_{i+1}$ are the sequences of sampled monthly soil moisture from the observations in the historical record for the target month (here, S_{i+1}). For any time scale (sc) and lead time (l), Equation 3 can be generalized as:

$$A_{i+l}^{(1,\ldots,m)} = \sum_{j=0}^{sc-l-1} S_{i-j} + \sum_{k=1}^{l} S_{i+k}^{(1,\ldots,m)} \quad (4)$$

Note that the lead time (l) should be less than the time scale (sc) - here, 6-month. Each sequence of the blended 6-month soil moisture $A^{(j)}$, j=1,2,…m, in equation (3) can be combined with the observed 6-month accumulated soil moisture in the past years to derive the corresponding $\mathrm{SSI}^{(j)}$. Here, the probability of drought is defined as the probability that a future drought condition (SSI) is lower than an alarm threshold (e.g., SSI<-0.8 corresponding to ~20th percentile). The empirical probability is estimated by dividing the number of the forecasted values below the threshold (e.g.,-0.8) by the number of the ensemble members.

4 Results

First it is shown that the accumulated soil moisture typically exhibits much higher persistence compared to precipitation, and hence can be used for drought forecasting with up to several months lead time. Then, the 2012 summer drought conditions are predicted using the SSI with different lead times. The SSI is obtained using predicted soil moisture information using the ESP concept based on long-term climatology and near-past observations (see Section Methodology). The study focuses on the drought prediction for May to August which is an important period for agricultural decision-making.

Understanding the persistence property of soil moisture is fundamental to drought forecasting. It is hypothesized that using accumulated soil moisture would improve persistence-based drought forecasting relative to using accumulated precipitaiton. First, the persistence property of accumulated soil moisture is evaluated aginst the accumulated precipitation that has been used for meteorological drought prediction (Lyon et al., 2012; Quan et al., 2012; Hao et al., 2014; Yoon et al., 2012). The monthly precipitation and soil moisture data from MERRA-Land (Reichle et al., 2011; Rienecker et al., 2011) in California and Texas are used to examine the persistence of accumulated soil moisture relative to precipitation. Both states are among the most important producers of agricultural products, and have experienced severe/extreme drought conditions in the past decade. The autocorrelations of accumulated 6-month precipitation and soil moisture for 1- to 6-month time lags and four different initial conditions (March, April, May and June) for summer drought prediction are provided in Figure 1. In the figure, the term *initial* is defined similar to initial condition in Section Methodology. For example, March corresponds to precipitation and soil moisture form Oct. 2011 through March 2012. The boxplots present the median, 25th, 75th percentiles, and whiskers of the autocorrelations. Lyon et al., 2012 showed that variance of the accumulated precipitation can enhance or diminish the persistence of the SPI at different start times, mainly due to seasonality of precipitation. As shown, the autocorrelation of the accumulated soil moisture (or SSI) is generally higher than that of accumulated precipitation (or SPI) for the four different initial conditions. The figure shows that the autocorrelations of the accumulated 6-month soil moisture decay at a slower rate than the accumulated 6-month precipitation in both California (Figure 1a) and Texas (Figure 1b). For example, in California and for the initial condition in April, the medians of the autocorrelation coefficients are higher than 0.6 even at a 5-month lag. However, the medians of the autocorrelations of the 6-month SPI drop below 0.6 after a 4-month lag. The higher persistence of the SSI relative to SPI implies that a persistence-based model based on SSI would lead to better predications as compared to a similar model based on SPI (see also Changnon 1987).

The 6-month SSI is used as the drought indicator to monitor and predict the 2012 (May-August) U.S. drought. Figure 2a shows observed drought conditions from May to August 2012. As shown, the drought develops and intensifies quickly, affecting most of the continental U.S. including the Great Plains, the Midwest, and west and southeast. By August, a large portion of the country experienced severe, extreme, or exceptional drought conditions. In operational drought early warning, the severe drought condition is of critical concern. In this paper, the proposed methodology is tested for predicting the moderate and severe drought conditions in summer 2012. Following the U.S. Drought Monitor (USDM), D-scale, the moderate drought is defined as SSI below -0.8 (corresponding to nonexceedance probability of ~ 0.2), whereas the severe drought is defined as SSI below -1.3 (or nonexceedance probability of ~ 0.1) (Svoboda et al., 2002). The observed drought conditions below the severe level (D2) for May-August are shown in Figure 2b.

The 1-month and 2-month lead drought (SSI<-0.8) forecasts for May-August 2012 are presented in Figures 3a and 3b, respectively. The 1-month lead forecasted SSI maps for different initializations resemble the observed SSI well in terms of the spatial extent (compare Figure 3a with Figure 2a). As shown, the regions with high probability of drought (e.g., above approx. 90%) are in very good agreement with the observations. For example, the outlined methodology predicts high probability of drought over the western U.S. and high plains in August, which is consistent with observations. Furthermore, as the 2012 drought intensifies, the area with high probability of drought (Figure 3a) increases in a similar manner to the observations (Figure 2a). A visual comparison of the two month lead drought forecasts (Figure 3b) and observations (Figure 2a) reveal that the predicted drought conditions are in very good agreement with probabilities higher than 0.8 in most regions. The 1-month and 2-month lead severe drought (SSI<-1.3) forecasts for May-August 2012 are presented in Figure 4a and Figure 4b. The 1-month lead forecasts of May-August severe drought conditions are in very good agreement with observations. As shown, the severe drought condition from May-August in northern Texas, and the western U.S. are captured in the predictions. Figure 4b highlights that even at a 2-month lead, the proposed model predicts the 2012 summer drought reasonably well.

The predicted drought probability maps for July and August 2012 for 3-month and 4-month lead time are presented in Figures 5a (SSI<-0.8) and 5b (SSI<-1.3). One can see that the 3-month and 4-month lead forecasts capture the observed drought conditions with probabilities ranging from 0.1 to 0.8. The prediction skill of the model is higher in the western U.S. where drought conditions are predicted at higher probabilities relative to the Midwest. A review of Figures 3 and 4 indicate that the predicted probabilities in longer leads (i.e., 3- and 4-month) are typically lower than those of shorter (1- and 2-month) lead forecasts. Basically, in persistence-based models, as the lead month increases, one expects the forecast probabilities to decrease as well. This can be partly explained from the autocorrelations of accumulated soil moisture presented in Figure 1. As shown, in the western U.S., the 4-month lead forecasted drought probabilities for July and August 2012 are relatively high and in fairly good agreement with observations. In the Midwest and eastern U.S., the proposed model indicates relatively low probabilities of drought for 3- and 4-month lead forecasts. While the forecasted drought probabilities are lower at a 4 month lead, still they provide valuable information by showing the drought signal. While the 3- and 4- month lead forecasted probabilities of severe droughts are substantially less compared to the 2-month lead forecasts, the drought signal in the western U.S. is still strong (see Figure 5b).

It should be noted that the seasonal climate predictions based on weather/climate models initialized in April and May 2012 revealed limited drought information for May-July and June-August 2012 (Hoerling et al., 2013). This highlights that improvements in just two 2-month lead forecast could be very important for risk assessment and decision making. The presented persistence-based model with the SSI as the drought indicator provides potential capability to predict droughts that would of great value to agricultural planning.

The quality and the latency of predictions rely on the quality and availability of input data sets. Currently, limited observations of soil moisture are available across the globe, and soil moisture estimation relies on model simulations. The Soil Moisture Ocean Salinity (SMOS; Kerr et al., 2001) and the upcoming Soil Moisture Active and Passive (SMAP; Entekhabi et al., 2010) mission may provide the opportunity to integrate near real-time satellite data with long-term climate data records such as MERRA to improve drought monitoring and prediction.

5 Conclusions

Using the Standardized Soil moisture Index (SSI) as the drought indicator, a persistence-based drought prediction method is presented and used for predicting the 2012 United States drought. It is shown that because of high persistence property of soil moisture, the SSI can be used for seasonal drought forecasting. The presented statistical approach predicted the May – August drought conditions relatively well, especially for 1- and 2-month lead forecasts. The 3- and 4-month lead forecasts of the western U.S. were in good agreement with observations. However, the drought prediction signal in the eastern U.S. was not as strong at 3- and 4-month lead time. Given the persistence-based nature of the methodology, uncertainties of predictions increase with lead time. Similar behaviour has been observed in persistence-based drought recovery assessment (Pan et al., 2013). However, even 1- and 2-month lead information is valuable to some end-users including farmers and commodity investors.

It is acknowledged that, similar to other methods, both the presented modelling framework and input data sets are subject to uncertainties (e.g., see Quan et al., 2012). The presented model is based on near past soil moisture conditions and log-term climatology. Soil moisture responds to precipitation with some delay, and for this reason, the methodology may not capture rapid developments. Furthermore, this methodology relies on historical observations and because of limited samples of extreme conditions in historical records, it should not be used for predicting extreme droughts.

It is stressed that the proposed approach is not meant to replace the currently available dynamic drought forecasting models. Rather, the persistence-based predictions should be used as additional information that can potentially improve drought predictability. Finally, it should be pointed out that SSI is not suggested as an alternative to use of SPI (or other indicators) for seasonal drought prediction. The best choice of index or the best set of indicators depends on the problem in hand and the climate of the study area. It is our view that drought monitoring and prediction should be based on multiple sources of information (data and indicator) as well as models (e.g., dynamic, statistical).

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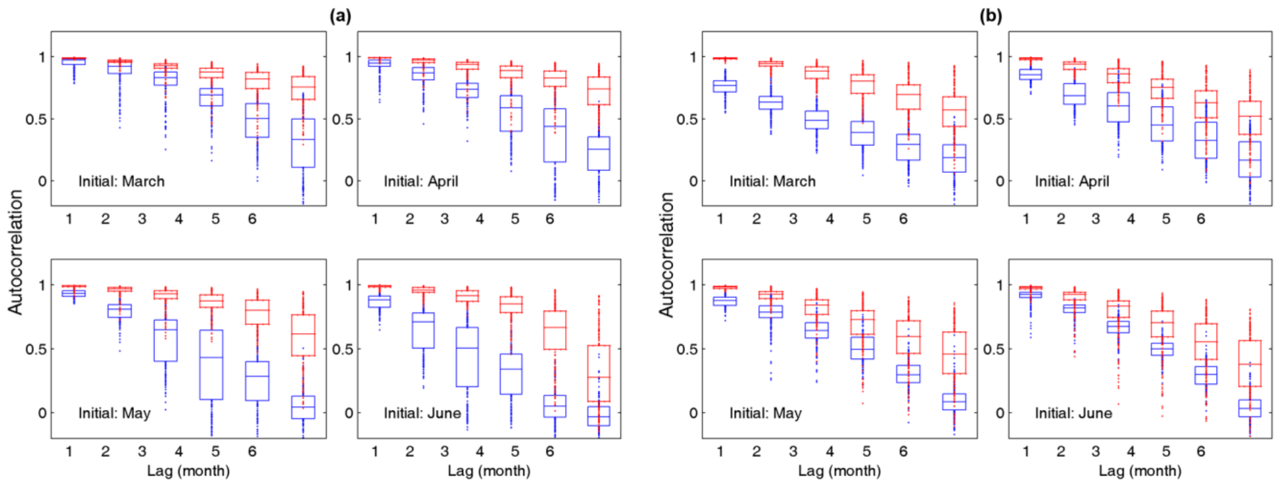

Figure 1 Boxplots of autocorrelation coefficients (up to 6 month) of accumulated 6-month precipitation (blue) and soil moisture (red) from MERRA-Land for different initial month for (a) California and (b) Texas. The boxplots show the median (center), 25th (lower) and 75th (upper) percentiles edges.

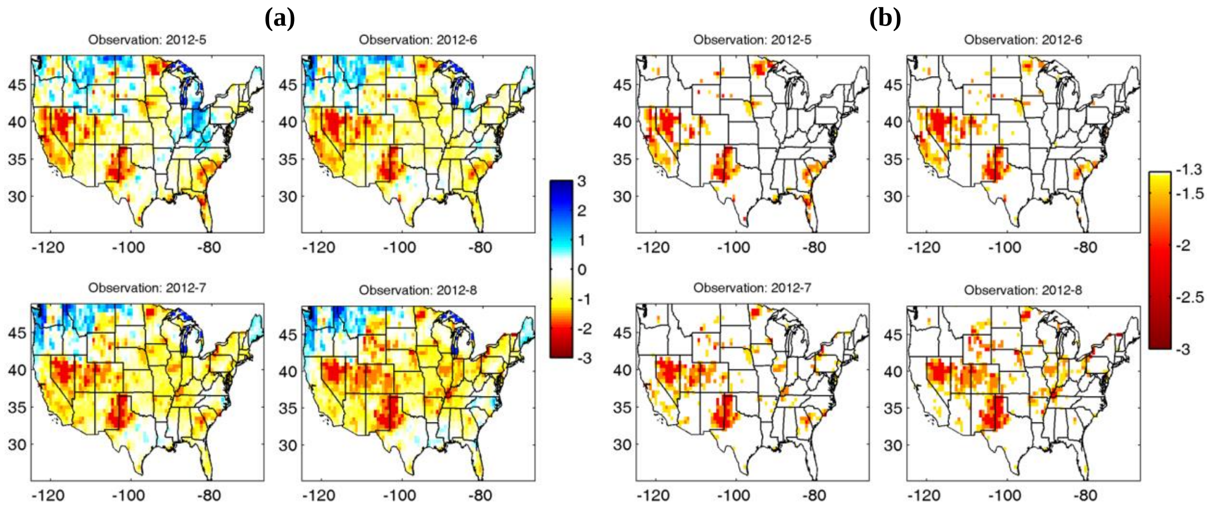

Figure 2 (a) Observed 6-month SSI for May-August 2012; (b) Observed 6-month SSI with severe drought condition (SSI<-1.3) for May-August 2012.

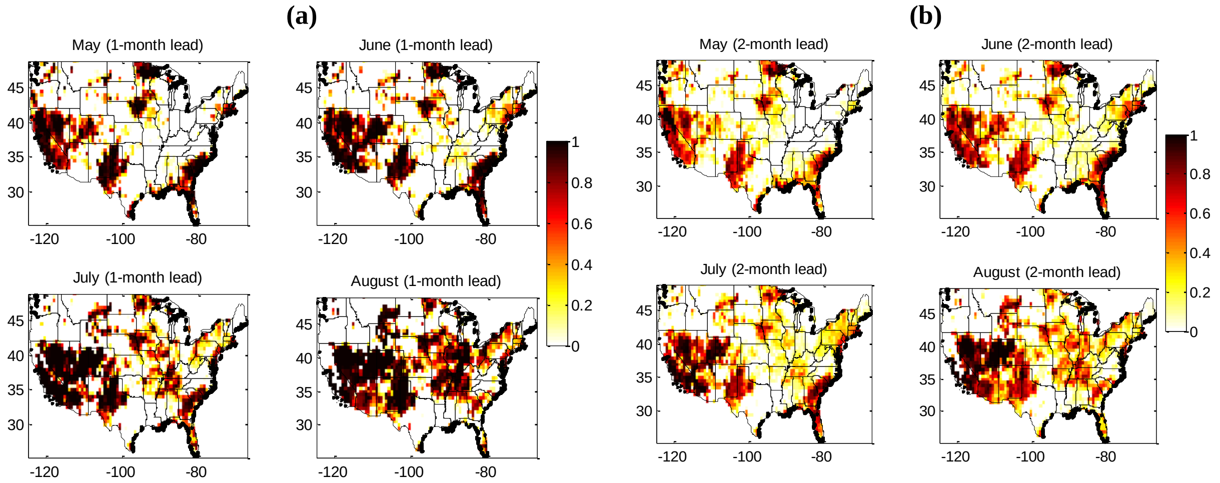

Figure 3 (a) One month and (b) two months lead drought probability predictions for May-August 2012 for SSI6<-0.8.

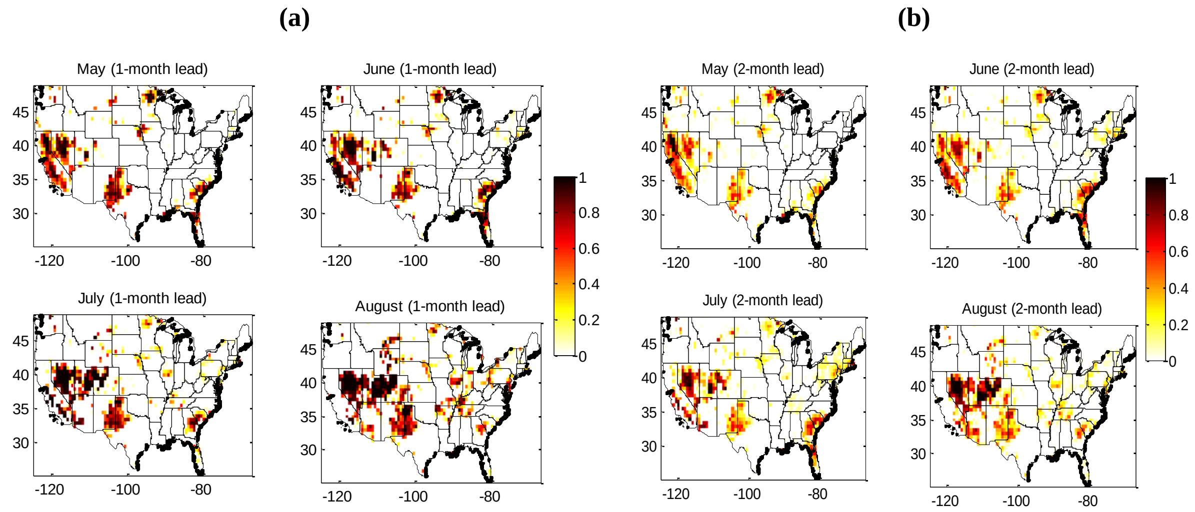

Figure 4 (a) One month and (b) two months lead drought probability predictions for May-August 2012 for SSI6<-1.3.

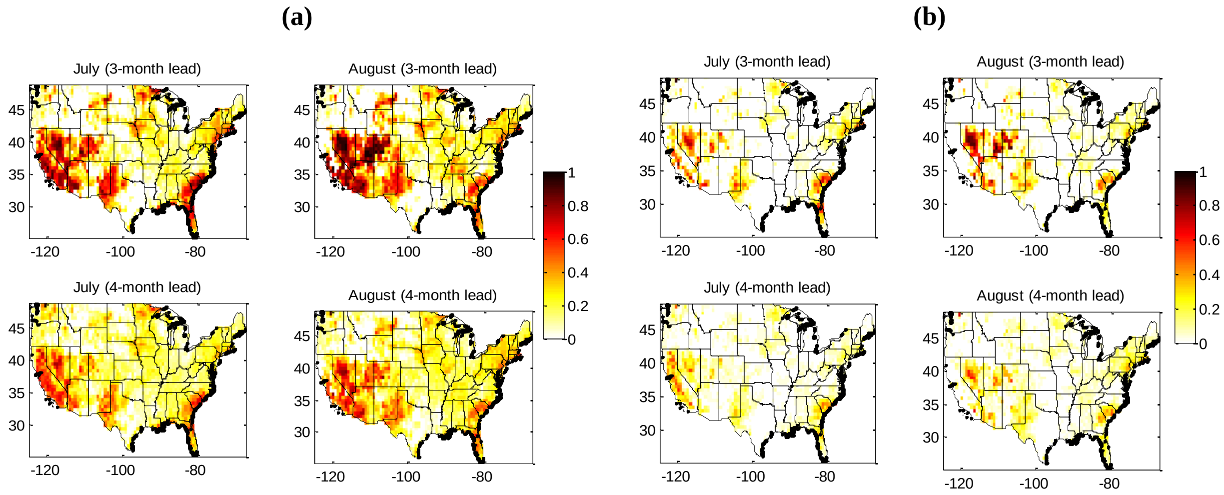

Figure 5 Three and four month lead time predictions of drought probability for July-August 2012; (a) SSI6<-0.8; (b) SSI6<-1.3