Point-by-Point Response to Review Comments

The author would like to thank the reviewers for the constructive and thoughtful comments and suggestions which led to substantial improvements in the revised version of the manuscript. In the following, the issues raised by the reviewers are addressed point-by-point in the order they are asked. Reviewer's comments are shown in black; author's reply is shown in blue text.

Anonymous Referee #1

The ESP method is applied to approximate the probability of droughts in the future with rather short lead time. Standardized Soil moisture Index (SSI) is used as agricultural drought indicator. Persistence analysis is conducted on SPI and SSI with 6-month accumulation window. The forecast method is sound; however, it is overrated by a few questionable comparisons. My major concerns are as follow:

1) Author emphasized on the higher auto-correlation in SSI time series vs SPI and concluded accordingly that SSI is a better indicator for drought forecasting (Page 1954, lines 3-5). Higher persistence is not a basis to choose among drought indicators. In fact, drought type determines the indicator; i.e. SPI for meteorological droughts and SSI or any other soil moisture-based index for agricultural droughts. Thus, this point should be cleared in the manuscript for potential future readers. According to specific attributions of SSI and SPI, they give different information about droughts. For example, flash storms as an important cause in producing flash floods (especially in wet regions with saturated/near-saturated soil) are reflected in SPI. The smooth variation in SSI cannot address sudden storms; and then, it is not appropriate in prediction of hydrological droughts where streamflow (or runoff) is used as drought variable. Flash floods can mitigate ongoing hydrological droughts to some extent. In general, persistency is not always an ideal attribution for a drought indicator. It depends on the application.

Response: The author fully agrees with the Reviewer. Please note that the SSI-based approach is not suggested as an alternative to other indicators such as SPI. Instead, it is suggested as an approach that should be considered along with other indicators. In the revised version this issue is clarified to avoid any confusion (see the last paragraph of the revised version). As the Reviewer correctly mentioned, SSI typically varies less compared to SPI (see also figures in [1]) and hence, may not be suitable for monitoring rapid storms. This issue is discussed in Conclusions Section. Also, in the revised version, it is emphasized that the choice of index depends on the application.

2) One-month lead time is very short for decision making in agricultural applications. For 6-month SSI with a lead-time of one month, the soil moisture of 5 months is available and the soil moisture of only one month is produced by ESP approach. In a 6-month window, the impact of one month is not as much to affect the total summation (and consequently SSI value). Moreover, the variable (soil moisture) itself is highly persistent as approved by Fig. 1. Hence, the agreement of observed and predicted SSI with 1 or 2 months lead-time cannot confirm the quality of forecast model. Instead, the performance of method can be illustrated in greater lead times (3 or 4 months) as shown in Fig. 5. Comparing Fig. 2 and 5, the forecast results are not encouraging. Majority of droughts are captured with low probabilities (Probability=0.1-0.5). Who might plan for droughts with low probabilities? Moreover, this analysis is conducted for July and August droughts (Fig. 5) when soil moisture is usually at its lowest amount and agricultural droughts are intense. Since the forecast model cannot capture summer droughts well, how it would perform in detecting mild droughts of other seasons. It seems that for a better picture of the performance of proposed model, it needs to be examined for a) greater lead times and b) other seasons with less severe droughts.

Response: The author's team has received funding from the National Science Foundation to interview farmers and understand user needs for drought information. Thus far, we have interviewed over 110 farmers from across the country (project still ongoing). We have learned that for some end-users even few weeks of lead time make a substantial difference (e.g., for purchasing fewer fertilizers and other related services). On the other hand, even very short lead times on drought development are important for commodity investors and investment management. We agree that longer lead predictions will be more useful. In general, longer lead predictions are subject to higher uncertainty and lower predictability (regardless of methodology). In fact, predicting droughts beyond few months is a major challenge highlighted in a recent WCRP report [2] – see also [3] [4]. It is worth highlighting that this method cannot be used for long lead predictions (e.g., 6 months and more). Theoretically, in a persistence based concept, the lead time should not exceed the time scale of the data. For this reason, this method can only be used for prediction with few months lead time (see Section Methodology).

About probabilities; for 3- and 4-month lead predictions of moderate drought threshold, the probabilities are quite high (up to 80% in some regions). However, the same methodology does not lead to high probabilities of extreme drought (see low probabilities in Figure 5b). The reason for showing Figure 5b is to objectively show strength and weaknesses of the proposed methodology. It is emphasized that this SSI-based approach may not lead to accurate prediction of very extreme conditions, mainly because we do not have long-term records of soil moisture (and sufficiently large samples of extreme soil moisture conditions).

About longer lead times and other seasons; as mentioned above, this method is not really suitable for long-lead prediction (see Figure one and a systematic decrease in autocorrelation versus time). Finally, the results are not limited to July and August. For example, the predictions for

May 2012 are shown with 1- to 4-month lead (i.e., January - April), indicating that soil moisture data from winter is used for prediction.

3) In "conclusion", there is a statement saying: "While dynamic models did not predict the 2012 summer drought well in advance, : : :". How much were the models weak in predicting 2012 droughts? According to the points in my previous comments, the proposed model could not predict those droughts well either, especially with lead times greater than 2 months. I should mention once again that model performance cannot be revealed by 1 or 2 months lead time in a 6-month accumulation window where the soil moisture of 4 or 5 months are already observed.

Response: In the revised version, Section Conclusions is updated to address the Reviewer's comment. Please note that model simulations did not predict the 2012 summer drought well. See the below quite from an Editorial by Freedman 2012:

"The three-month seasonal drought outlook, which is revised monthly, is the main drought forecasting tool produced by the federal government. It wasn't until June 21 that an outlook showed drought conditions were likely to persist and expand in the Midwest and High Plains, and by that time, the country was rapidly heating up and drying out, destined to record its hottest month on record in July."

As shown, the results indicate relatively high probabilities of drought in most regions prior to June 2012. On the other hand, and as mentioned above, even 1- and 2-month lead times are important to some drought sensitive sectors. Again, this model is not proposed as an alternative to the currently available approaches. Dynamic models are still valuable and should be used. This approach provides an alternative that can be used alongside other methods. This issue is clarified in Section Conclusions.

4) In Fig. 1, please make it clear that what time windows are used for auto-correlation analysis. The boxplots are provided for 4 initial conditions with accumulation window of 6 months. On the other hand, the lag time varies from 1 to 6 months. To my understanding, for example, for SSI with initial condition of March (i.e. accumulation window: Mar, Apr, May, Jun, Jul, Aug), the autocorrelation with 1-month lag time refers the SSI with accumulation window of Apr to Sep. Is this correct? If so, please clarify that "initial condition" refers to the start month in the accumulation window for only one variable. The other variable starts with a lag-time whose initial condition is not the same as the first variable.

Response: The definition of "initial" in Figure 1 is consistent with the one in Section Methodology. For example, initial: March indicates precipitation and soil moisture form Oct.

2011 through March 2012. This would be the initial condition for prediction from March onward. This is clarified in the manuscript (see discussion of Figure 1).

5) It is recommended that Fig. 3 and 5a be updated for SSI<-0.5 (instead of SSI<-0.8). Comparing these figures with “any” observed droughts (SSI<-0.5) is not very reliable (Fig. 2a).

Response: Throughout the paper, we have used the thresholds consistent with the so-called D-scale [5]. In this scale, -0.5 is referred to as “abnormally dry”, while -0.8 is defined as “moderate drought”. Note that both observed and simulated are compared for the same thresholds of -0.8 (we have NOT compared predicted SSI<-0.8 with observed SSI<-0.5).

6) It seems that “(Fig. 2b)” in Page 1954-line 28 should be replaced by “Fig. 2a”.

Response: Corrected; Thanks!

References

1. Hao Z., AghaKouchak A., 2013, Multivariate Standardized Drought Index: A Parametric Multi-Index Model, Advances in Water Resources, 57, 12-18, doi: 10.1016/j.advwatres.2013.03.009.

2. WCRP (2010). WCRP White Paper on ‘Drought Predictability and Prediction in a Changing Climate: Assessing Current Capabilities, User Requirements, and Research Priorities, Tech. rep., World Climate Research Programme. , Barcelona, Spain.

3. Pozzi, W.; Sheffield, J.; Stefanski, R.; Cripe, D.; Pulwarty, R.; Vogt, J. V.; Heim Jr., R. R.; Brewer, M. J.; Svoboda, M.; Westerhoff, R.; Van Dijk, A. I. J. M.; Lloyd-Hughes, B.; Pappenberger, F.; Werner, M.; Dutra, E.; Wetterhall, F.; Wagner, W.; Schubert, S.; Mo, K.; Nicholson, M. (2013). Toward global drought early warning capability. Bulletin of the American Meteorological Society, 94(6).

4. Hao Z., AghaKouchak A., Nakhjiri N., Farahmand A., (2014), Global Integrated Drought Monitoring and Prediction System, Scientific Data, 1:140001, 1-10, doi: 10.1038/sdata.2014.1.

5. Svoboda, Mark; Lecomte, Doug; Hayes, Mike; et al. (2002). The drought monitor. Bulletin of the American Meteorological Society. 83: 1181-1190.

Anonymous Referee #2

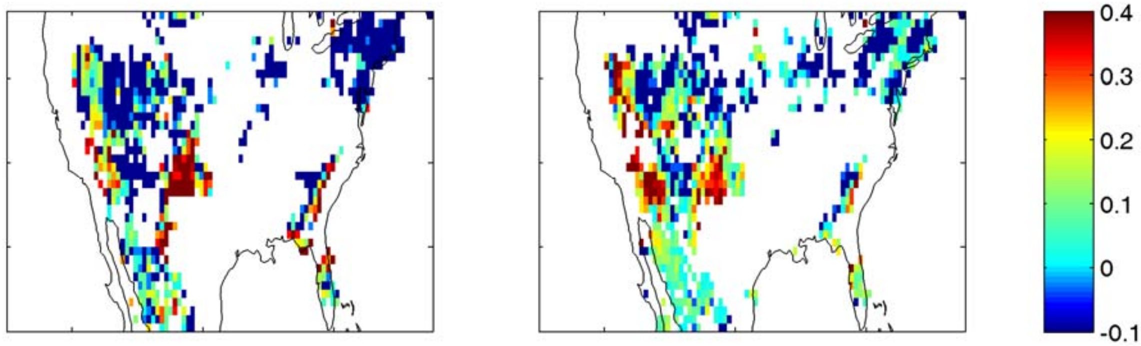
This paper presents a nonparametric statistical baseline approach for drought prediction using standardized soil moisture index. To the best of my knowledge, previous studies have primarily focused on precipitation for persistence-based statistical drought prediction. This study highlights the fact that given the higher persistence of soil moisture compared to precipitation, a baseline forecasting using soil moisture would improve drought prediction. The methodology is proposed as an additional model that can be used alongside with the currently available techniques. The framework is novel and given the importance of the topic, I believe the article is suitable for publication pending a revision. Also, the study focuses on the 2012 drought, a major recent event that has not been explored in the literature yet. I have included some comments and suggestions below:

-In Equations 1 to 3, it is not clear whether the initial conditions can obtained from one year before the target month year (for example, for predicting January, February drought). This needs more explanation.

Response: We agree with the Reviewer. In the revised version, we have addressed this issue (see Explanation of Figure 3). In summary, for the first few month of a year, the initial values will be from the previous year.

-While the difference between precipitation and soil moisture persistence is shown, it would be good to include the improvements in using soil moisture in terms of drought probabilities (either showing them side by side, or showing the differences).

Response: Technically, it is possible to provide the differences between precipitation- and soil moisture-based predictions (see the below example). The below figure shows locations where soil moisture indicates higher probability of drought for July 2-month lead (left), and August 3-month lead (right). As shown, in most regions, soil moisture leads to higher probability of drought relative to precipitation. However, soil moisture responds to precipitation with some delay and such comparison does not necessarily provide additional information. Also, this behavior may change from event to event. I believe the two methods should be evaluated as presented in Figure 1 (the overall behavior over a certain region, rather than pixel based assessment).



-While this approach probably improves drought prediction, ideally, soil moisture should be combined with other variables for a more robust statistical prediction. Can this model be extended to higher dimensions (e.g., using precipitation or runoff)? Given that both precipitation and soil moisture data are available, it is worth exploring this issue.

Response: Theoretically, this methodology can be extended to a multivariate form with more than one variable used for prediction. One can use different variables independently and then combine them for composite drought assessment. Alternatively, using the nonparametric form of the Multivariate Standardized Drought Index (MSDI; [1]), one can combine multiple data sets for multi-index drought prediction (this issue is currently under investigation by the author's team).

-Discuss uncertainties associated with the input variables. Acknowledge the limitations of the available soil moisture data sets.

Response: Per Reviewer's suggestion, a discussion is added on the uncertainty of input data sets (see Section Data). A couple of publications that evaluated input data set are cited (see Section Data). Furthermore, limitations of the input data and modeling framework are acknowledged in the manuscript.

- SSI is a relatively new index and has not been used for drought prediction before. The description of the suggested nonparametric approach needs to be discussed in more details. Why a nonparametric approach?

Response: The discussion on computation of SSI is extended and all the governing equations are provided. In a recent paper on drought monitoring, derivation of empirical SSI is discussed in detail (see [1]). For this reason, the discussion is concise and provided only to make the paper standalone.

- What is the advantage of using SSI over the other soil moisture-based indices?

Response: The main advantage of SSI over other soil moisture indices is that it can be computed for different time scales consistent with SPI. This has been discussed in the revised version.

-Is there an opportunity to integrate the upcoming satellite soil moisture data sets (e.g., SMAP) and the currently available SMOS data? It is worth to include a discussion on this topic.

Response: Yes; in fact, one of the main motivation of this study is to develop a platform for near real-time drought monitoring using satellite soil moisture data. In a recent study, an algorithm has been developed for near real-time drought monitoring by combining real-time satellite precipitation data with long-term climate data records using a Bayesian framework (see [2]). A similar algorithm can potentially be used with the upcoming SMAP satellite data combined with long-term data sets. This issue, however, requires extensive research and validation. A brief discussion is added to the revised manuscript (see last paragraph in Section Results).

-Would it be possible to condition forecasts on large scale climatic oscillations? For example, sampling from historical data with a certain condition (e.g., ENSO pattern).

Response: The ESP modeling concept can be conditioned to one or more covariates. However, the main limitation is that one needs a long record of observations. That is, for different ENSO conditions, sufficient precipitation and soil moisture observations would be necessary for probabilistic drought prediction. Unfortunately, long-term observations of soil moisture is not available and hence, conditioning the methodology on ENSO would reduce the sample size significantly.

-The fact that the drought probabilities drop at longer lead times worth a discussion.

Response: The Reviewer is right. In this model concept (and other similar probabilistic concepts), probabilities reduce as the lead time increases. This is mainly due to the nature of the persistence-based prediction (see also Figure 1 and the decreasing autocorrelations with increasing time lags). In the revised version, we have acknowledged this issue (see Section Conclusions).

-Can this model be used for drought recovery too (i.e., probability of drought recovery)? Discuss.

Response: Yes; theoretically, this methodology can be used for probabilistic assessment of drought onset as well as recovery. In a recent study, Pan et al. 2013 used a similar methodology to describe drought recovery probabilistically using precipitation data. Given that this issue is addressed in Pan et al., this study does not focus on drought recovery.

-Conclusions should be extended with a discussion on limitations of the methodology and data sets.

Response: Conclusions have been extended and a discussion on limitations of the methodology and input data sets is added to the revised manuscript.

References

1. Hao Z., AghaKouchak A., 2014, A Nonparametric Multivariate Multi-Index Drought Monitoring Framework, Journal of Hydrometeorology, 15, 89-101, doi:10.1175/JHM-D-12-0160.1.

2. AghaKouchak A., and Nakhjiri N., 2012, A Near Real-Time Satellite-Based Global Drought Climate Data Record, Environmental Research Letters, 7(4), 044037, doi:10.1088/1748-9326/7/4/044037.

Anonymous Referee #3

The article discuss about 'probabilistic drought forecasting framework using SSI and to evaluate the model for 2012 US drought'. During recent years, a large number of articles reported improved drought forecasting techniques using multiple as well as improved drought indices. Based on those previous articles, this article did not seem to be either improving drought indices or forecasting technique, whereas by applying to the continental US, it draws several shortcomings.

Drought indices: There are numerous articles highlighting the application of SPI for quantifying the drought events, which is valid as precipitation is a natural input to water resource system. However, using the concept of SPI, the standardized soil moisture index (SSI) is not useful as it should be, for example, the agricultural water sources is highly variable for USA due to precipitation pattern. The eastern USA is supplemented by rainfall, whereas western USA is irrigated by artificial means (i.e., canal and reservoir operated). Therefore by realizing this fact, the application of SSI for continental USA is a major drawback of the study. The PDSI is a more robust index based on a scientific reasoning for monitoring agricultural drought in comparison to SSI (which is based on cumulative values). Several articles developed soil moisture deficit index at a shorter temporal scale, which can be more useful for agricultural droughts monitoring and forecasting. The SSI lacks in quantifying soil moisture supply for crop growth, for example, one day extreme precipitation event within a month will provide higher soil moisture, where as it will have negative impact on crop growth.

Response: Please note that the manuscript does not suggest SSI as an alternative to SPI or PDSI (or any other indicator). This issue is highlighted in the revised version of the manuscript. I agree with the Reviewer that the agricultural water sources are highly variable over the USA, and some parts are irrigated. However, the input soil moisture data, used in this study, includes an irrigation scheme, and it is taken into account. It is acknowledged that irrigation schemes have their own limitations [1], and the author does not claim irrigation is fully represented. However, model predictions with respect to spatial pattern are consistent with observations which indicate that the observed patterns are reasonably captured.

I agree that there are "soil moisture deficit at shorter temporal scales". However, for persistence-based prediction the memory of the system plays an important role and short-term indices are not appropriate (this is due to the persistence-based nature of the modeling framework). The concept of SSI allows deriving soil moisture information using different time scales.

The Reviewer believes the " SSI lacks in quantifying soil moisture supply for crop growth". I am not sure on what basis the Reviewer believes SSI does not provide information on moisture supply. Similar to other soil moisture indices, SSI provides information on soil moisture anomalies and can be computed for different time scales. Note that monthly drought indicators are not designed to distinguish daily extreme precipitation and resolve their effects on crops. The fact that a daily extreme precipitation will lead to higher soil moisture is not unique to SSI. In fact, monthly soil moisture percentiles and other indicators will show the same signal. However, SSI offers the opportunity to derive soil moisture at longer time scales similar to SPI (e.g., 3-, 6-month). Other than that, it is similar to the other soil moisture-based indices. Having an indicator for longer time scale, the effect of one single extreme wet event may not shift the wet or dry signal. In other words, the nature of SSI allows addressing the problem raised by the Reviewer. The fact that this model is not designed to capture rapid development of extreme events is addressed in the revised version (see Section Conclusions). \\ \\

Methodology: There is a shortcoming in drought forecasting, when applying a persistence based model to a moving sum drought index (i.e., SSI based on six month accumulated values) for 1 to 2 month lead time. Similar concern was also raised by reviewer 1 (second comment). For example, taking an m period moving sum of the time-series, it will completely destroy the evidence for an m period periodicity.

Response: Please note that a persistence-based concept can only be applied to a system with a significant memory. Applying persistence-based prediction to moving sum of time series is very common and has been used in numerous other publications including streamflow and precipitation (e.g., see [2] [3] [4]).

The persistence method works well when weather variables change very little and features on the weather maps move very slowly. However, if weather conditions change significantly from month to month, the persistence method usually breaks down and is not the best forecasting method to use.

Response: We agree and this is exactly the reason, the method is applied to a moving sum. The approach has been used for drought prediction using precipitation in Lyon et al., [2]. Having a moving average of, say 6 months, soil moisture, moving one month a head, soil moisture will not change substantially (because of dominance by 5 month overlap). This is the reason that the method offers some level of drought predictability.

Therefore, the application of proposed methodology has two drawbacks: (a) application of persistence based model to a moving sum time series, (b) the constant selection of 6 month moving sum for all climatic regions of US do not seems to be true as there is a wide variation of climatic patterns across USA, for example variation of precipitation from east to west and temperature north to south, which are major drivers for soil moisture availability.

Response: We acknowledged that this method has drawbacks and discussed the limitation in the manuscript. However, applying the method to a moving sum is not a drawback. In fact, it is necessary. About the constant 6-month moving window; we do not claim that 6 month should be used for everywhere in the United States. The same modeling framework can be used for different temporal accumulations. The purpose of this study is to argue considering soil moisture accumulation alongside other variables provides additional predictive information.

The probability of drought definition (line 18, page 1952) seems to be based on number of events using a threshold level, however more damage will occur at higher severity level. The methodology section is not clearly written, a flow chart might be helpful for linking the components.

Response: Persistence-based prediction relies on historical observations and near past initial conditions. As mentioned in the manuscript, this method cannot be used for prediction of very rare and extreme events that have not been observed in the past (see Section Conclusions). In a 100 year record, a standardized value of -2 (drought severity) is expected to happen between 2-3 times. This means probabilistic analysis of extreme droughts would not be possible because of limited observations in the past. For this reason, a persistence-based method is most suitable for assessing changes in the system relative a moderate drought threshold. We have shown limitations of this method in predicting extreme conditions in Figure 5b to make sure an objective and fair assessment is provided for the readers. In fact, the purpose of showing Figure 5b is that to highlight the limitation of this method in capturing rare events.

Results: It is highlighted that 'using accumulated soil moisture would significantly improve persistence based forecasting model'. This cannot be a stressed as a major finding, as all moving sum time series will have higher persistence level. How do the box plot is created for Texas and California? Is it collection of all the gridded soil moisture ACF values? The higher ACF values of soil moisture with respect to precipitation will not hold true for across USA. This is due to the fact that higher uncertainty involved in soil moisture predictability in comparison to the precipitation as reported by several articles.

Response: It is stressed that the statement was on improvements gained by using soil moisture relative to precipitation (Fig. 1). This was not meant to be a general statement. In the revised version, the above statement has changed to make this clear. I hope that I have adequately addressed the Reviewer's concern.

About ACFs, yes; please note that a similar graph can be generated for different pixels and regions. We agree that the ACFs will be different for various regions and climate. In his classic work, Changnon [5] showed how precipitation deficiencies during a certain period translated, over time, through other components of the hydrologic cycle including soil moisture. Changnon [5] and many others assessed the temporal complexity of drought and its impacts on different variables and showed a delayed and typically smoother response in soil moisture (and groundwater) compared to the original precipitation signal - see Figure 2 in Changnon [5] which indicates higher persistence in soil moisture compared to precipitation. While the ACFs of different variables may be different over different regions, still soil moisture exhibits higher persistence relative to precipitation (e.g., see time series of SPI and SSI in [6]). For this reason, using soil moisture could improve drought prediction.

The author also highlighted similar concerns in page1950, line 5: '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: : :.(Wood, 2008). Overrated statements like line 6-10 (page 1956), should be avoided. Use of persistence based model on a moving sum time series has several limitations in comparison to the dynamic models.

Response: That is correct; the author stresses that all models and data sets have their own uncertainties and limitations. The author strongly believes in diversity of models, data and indicators for drought prediction. This is the main motivation for this work. Per Reviewer's suggestion, Page 1956 is rewritten. In the revised version, the limitations of the study are highlighted even more. I hope that I have adequately addressed the Reviewer's comment.

References

1. Sorooshian, S., Li, J., Hsu, K. L., & Gao, X. (2012). Influence of irrigation schemes used in regional climate models on evapotranspiration estimation: Results and comparative studies from California's Central Valley agricultural regions. Journal of Geophysical Research: Atmospheres (1984–2012), 117(D6).

2. Lyon, B., Bell, M.A., Tippett M.K., Kumar, A., Hoerling, M.P., Quan, X.-W, Wang, H. (2012). Baseline probabilities for the seasonal prediction of meteorological drought. Journal of Applied Meteorology and Climatology. 51(7): 1222-1237.

3. Pan, M., Yuan, X., & Wood, E. F. (2013). A probabilistic framework for assessing drought recovery. Geophysical Research Letters, 40(14), 3637-3642.

4. Hao Z., AghaKouchak A., Nakhjiri N., Farahmand A., (2014), Global Integrated Drought Monitoring and Prediction System, Scientific Data, 1:140001, 1-10, doi: 10.1038/sdata.2014.1.

5. Changnon, S. A. (1987). Detecting drought conditions in Illinois (No. 163-170). Illinois State Water Survey.

6. Hao, Z. and A. AghaKouchak (2013). Multivariate Standardized Drought Index: A multi-Index parametric approach for drought analysis. Advances in Water Resources, Volume 57: Pages 12–18

Summary
5/8/2014 9:47:29 PM

Differences exist between documents.

New Document:
2012 Drought forecasting with SSI 2014-05-06
9 pages (186 KB)
5/8/2014 9:47:19 PM
Used to display results.

Old Document:
2012 Drought forecasting with SSI 2014-01-27
8 pages (122 KB)
5/8/2014 9:47:18 PM

Get started: first change is on page 1.

No pages were deleted

How to read this report

Highlight indicates a change.
~~**Deleted**~~ indicates deleted content.
indicates pages were changed.
indicates pages were moved.

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

A. AghaKouchak[1]

[1] University of California, Irvine

Correspondence to: A. AghaKouchak (amir.a@uci.edu)

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. Our 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:

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

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 ($1 \leq l \leq 5$) 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:

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

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

$$\ldots\ldots$$

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

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}). Note for the first 5 months of the year, some of the observed soil moisture prior to the target month ($S_{i-4}\ldots, S_i$) in the past 6-month will be sampled from one year prior to the target year.

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 $SSI^{(j)}$. 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) and the upcoming Soil Moisture Active and Passive (SMAP) 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. 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).

Acknowledgements

The financial support for this study is provided by the National Science Foundation Award No. EAR-1316536 and the Hellman Foundation.