A Nonparametric Multivariate Multi-Index Drought Monitoring Framework

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ABSTRACT

Accurate and reliable drought monitoring is essential to drought mitigation efforts and reduction of social vulnerability. A variety of indices, such as the standardized precipitation index (SPI), are used for drought monitoring based on different indicator variables. Because of the complexity of drought phenomena in their causation and impact, drought monitoring based on a single variable may be insufficient for detecting drought conditions in a prompt and reliable manner. This study outlines a multivariate, multi-index drought monitoring framework, namely, the multivariate standardized drought index (MSDI), for describing droughts based on the states of precipitation and soil moisture. In this study, the MSDI is evaluated against U.S. Drought Monitor (USDM) data as well as the commonly used standardized indices for drought monitoring, including detecting drought onset, persistence, and spatial extent across the continental United States. The results indicate that MSDI includes attractive properties, such as higher probability of drought detection, compared to individual precipitation and soil moisture–based drought indices. This study shows that the MSDI leads to drought information generally consistent with the USDM and provides additional information and insights into drought monitoring.

1. Introduction

Drought is one of the most damaging natural hazards and could result in devastating effects to social and ecological systems. The annual economic damage of droughts across the continental United States is estimated to be $6–8 billion on average (FEMA 1995). The 2002 widespread drought over large portions of 30 states resulted in estimated damages–costs of over $10 billion (Lott and Ross 2006). In 2010, two major droughts, which occurred in Somalia and Thailand, together affected 8.9 million people (Guha-Sapir 2011). Thus, drought monitoring and prediction is of critical importance for risk assessment and decision making, as well as for taking prompt and effective actions to avoid–reduce the effects of droughts.

The development of a comprehensive drought monitoring system capable of providing early warning of a drought's onset, severity, persistence, and spatial extent in a timely manner is a critical component in establishing a national drought policy or strategy (Hayes

et al. 2011). Different drought indices have been developed and applied for drought monitoring and prediction. The Palmer drought severity index (PDSI; Palmer 1965) is widely used for drought characterization (Dai et al. 2004; Dai 2011). The standardized precipitation index (SPI) proposed by McKee et al. (1993) is commonly used for meteorological drought monitoring and has been adopted as an important monitoring tool to detect the early emergence of drought (Shukla et al. 2011). The SPI is obtained by transforming the cumulative probability of the precipitation for a particular time period using the inverse of the standard normal distribution. In the recent Inter-Regional Workshop on Indices and Early Warning Systems for Drought, the SPI is recommended for characterizing meteorological drought for worldwide use, while no consensus is reached in the drought indices to characterize agricultural and hydrological droughts (Hayes et al. 2011). The standardization concept of the SPI can also be applied to other variables to derive drought indices such as the standardized soil moisture index (SSI; Hao and AghaKouchak 2013) and the standardized runoff index (SRI; Shukla and Wood 2008) for drought monitoring.

The performance of different variables differs in detecting the drought onset, persistence, and termination. A meteorological drought (deficit in precipitation)

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may develop quickly and end abruptly, while the onset of an agricultural drought (deficit in soil moisture) responds to a meteorological drought with some time lag (Entekhabi et al. 1996; Heim 2002). After analyzing the onset and recovery of droughts over the United States, Mo (2011) argues that the onset of meteorological droughts occurred a few months earlier than agricultural droughts for the same drought event. Meanwhile, soil moisture plays an important role in modeling and predicting the drought persistence (Oglesby and Erickson 1989; Seager et al. 2005; Cook et al. 2007). These findings imply that precipitation deficit is a suitable variable for detecting the drought onset, while the soil moisture deficit is a better choice for capturing drought persistence. The differences in the physical bases of drought-related variables make it difficult, if not impossible, to develop a successful drought monitoring and prediction tool based on one single variable (or index) such as precipitation or soil moisture. The use of a single index to indicate the diversity and complexity of drought conditions and impact is one of the major limitations to drought monitoring (Wilhite 2005).

After examining and evaluating the existing drought monitoring and prediction tools, it is recognized that no single index can represent all aspects of meteorological, agricultural, and hydrological droughts and that a multi-index approach should be utilized for operational drought monitoring and prediction (Quiring et al. 2007; Hao and AghaKouchak 2013). In fact, the lack of a system/model for integration of drought-related information, including different climate variables and drought indices and their interdependent relationships, hampers reliable and timely detection of droughts and their persistence.

The aim of this study is to introduce and evaluate a modified version of a recently proposed multivariate standardized drought index (MSDI; Hao and AghaKouchak 2013) for drought monitoring by combining drought information from precipitation and soil moisture. The MSDI, along with the commonly used standardized drought indices (i.e., SPI and SSI), are derived using the National Aeronautics and Space Administration's (NASA) land-only version of Modern-Era Retrospective Analysis for Research and Applications (MERRA-Land) data and validated with the U.S. Drought Monitor (USDM) data.

2. Method

In a recent study, Hao and AghaKouchak (2013) proposed the MSDI for characterizing overall drought conditions, taking into account precipitation deficit and soil moisture deficit. This approach is an extension of the commonly used SPI proposed by McKee et al. (1993),

extended to a bivariate model of precipitation and soil moisture. Denoting the precipitation and soil moisture at a specific time scale (e.g., 1 month or 6 months) as random variables X and Y, respectively, the joint distribution of two variables (X and Y) can be expressed as

$$P(X \leq x, Y \leq y) = p, \qquad (1)$$

where p denotes joint probability of the precipitation and soil moisture. The MSDI can then be defined based on the joint probability p as (Hao and AghaKouchak 2013):

$$\mathrm{MSDI} = \phi^{-1}(p), \qquad (2)$$

where ϕ is the standard normal distribution function. Similar to the SPI, the MSDI is derived from the (joint) probability of the variables of interest, which can be used to provide drought information over different time scales (e.g., 1, 3, 6, and 12 months).

In the methodology presented in Hao and AghaKouchak (2013), the joint distribution in Eq. (1) is constructed using multivariate parametric copulas (Nelsen 2006) and requires rigorous parameter estimation and goodness-of-fit tests. In this paper, an alternative method based on the nonparametric joint distribution concept is introduced to avoid making assumptions regarding the distribution family and to alleviate the computational burden in fitting parametric distributions.

An empirical joint probability in the bivariate case can be estimated with the Gringorten plotting position formula as (Gringorten 1963; Yue et al. 1999; Benestad and Haugen 2007)

$$P(x_k, y_k) = \frac{m_k - 0.44}{n + 0.12}, \qquad (3)$$

where n is the number of the observation and m_k is the number of occurrences of the pair (x_i, y_i) for $x_i \leq x_k$ and $y_i \leq y_k$ ($1 \leq i \leq n$). Once the joint probability is derived from Eq. (3), it will be used as input to Eq. (2) in order to obtain the MSDI.

In the SPI, the gamma distribution is commonly used to compute the cumulative probability distribution of the precipitation, which will then be transformed using the inverse of the standard normal distribution (McKee et al. 1993). The soil moisture percentile or quantile is commonly used as an agricultural drought index estimated by fitting a parametric distribution such as the beta (Sheffield et al. 2004; Sheffield and Wood 2007) or Weibull (Shukla et al. 2011) distributions. An empirical cumulative probability distribution such as the Weibull plotting position formula has also been used to estimate

the SPI or soil moisture percentiles (Edwards and McKee 1997; Andreadis et al. 2005; Wang et al. 2009). In this study, we use an empirical approach to derive the marginal probability using the univariate form of the Gringorten plotting position formula expressed as (Gringorten 1963):

$$P(x_i) = \frac{i - 0.44}{n + 0.12}, \tag{4}$$

where i is the rank of the observed values from the smallest and n is the number of the observations. In other words, the SPI and SSI are derived by standardizing the marginal probabilities as described by the Gringorten plotting position formula [Eq. (4)].

3. Data and metrics

The monthly precipitation and soil moisture data from MERRA-Land are used as input variables (Rienecker et al. 2011). MERRA-Land data are generated by rerunning a revised version of the land component of the MERRA system on a horizontal resolution of $\frac{2}{3}° \times \frac{1}{2}°$ from 1 January 1980 onward (Reichle et al. 2011; Reichle 2012). In this study, the monthly precipitation (total surface precipitation) and soil moisture (total profile soil moisture content) are used to derive the SPI, SSI, and MSDI at different time scales for drought monitoring. The SPI, SSI, and MSDI used in this study are available through the Global Integrated Drought Monitoring and Prediction System (GIDMaPS; http://drought.eng.uci.edu/).

The performances of these indices are evaluated against the USDM (http://droughtmonitor.unl.edu/), which is a composite product including climate indices, numerical models, and inputs from regional and local experts from around the United States (Svoboda et al. 2002). While the USDM data cannot be regarded as a metric of ground truth, it provides a baseline for evaluation of different drought indices and has been used in a variety of studies (Svoboda et al. 2002; Anderson et al. 2011; Anderson et al. 2013). For this reason, the USDM data are used as the reference observations in this study. The USDM data are based on five categories of drought types: D0 (abnormally dry), D1 (moderate drought), D2 (severe drought), D3 (extreme drought), and D4 (exceptional drought) (Svoboda et al. 2002). The five drought categories correspond to the following thresholds of the SPI: -0.5 to -0.7 (D0), -0.8 to -1.2 (D1), -1.3 to -1.5 (D2), -1.6 to -1.9 (D3), and -2.0 or less (D4). For the sake of cross comparison, the values of the SPI, SSI, and MSDI are converted to the D0–D4 scale based on the above thresholds.

Because the USDM drought information (reference data) is weekly, the MERRA-Land–based drought indices are compared to the USDM's output closest to the end of the month being analyzed. For example, for January 2007, the USDM data of 30 January 2007 are used for analysis, while for April 2007, the USDM data of 1 May 2007 are utilized. The performance of the MSDI in drought monitoring for the 2007 and 2012 U.S. droughts is assessed, along with the performances of the SPI and SSI for the 3- and 6-month time scales. In addition to visual comparison, the probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI) are used as metrics for quantitative comparison of the SPI, SSI, and MSDI versus USDM data (Ebert et al. 2007; Wilks 2011; Gourley et al. 2012). For validation and cross comparison, the "observed" USDM data and "computed" SPI, SSI, and MSDI are regridded onto a common $0.5° \times 0.5°$ resolution grid to compute the three metrics. Assuming a drought threshold of D0 (or -0.5), each grid can be classified as hit (H, observed drought detected), miss (M, observed drought missed), false alarm (F, drought detected but not observed), and null (no drought observed or detected). The POD gives the fraction of observed drought that is correctly detected: POD $= H/(H + M)$. The FAR describes the fraction of the detected drought that is not confirmed by the observations: FAR $= F/(H + F)$. The CSI (or threat score), which combines different aspects of the POD and FAR, describes the overall skill of detection (here, drought): CSI $= H/(H + M + F)$.

It should be noted that the climatology of the USDM is not the same as that of the MERRA-Land–based drought indices; hence, drought categories (severity levels) from the two datasets may not be identical (i.e., a record drought in a 30-yr climatology may not be a record drought in a 100-yr climatology). Furthermore, while MSDI only incorporates precipitation and soil moisture, USDM involves many other input variables (e.g., reservoir levels, groundwater levels, and snowpack). In the western United States, for example, snow is an important factor to the water cycle and snow water equivalent indicators are also blended into the USDM data. This may cause differences in drought severity levels in the MSDI and USDM. For these reasons, the consistency of the spatial patterns in the two datasets is evaluated, rather than the ability of the MSDI to reproduce the USDM drought categories.

4. Results and discussion

A 33-yr record from January 1980 to December 2012 is used to construct the SPI, SSI, and MSDI. For a grid cell in Texas (longitude 100°W and latitude 30°N), the
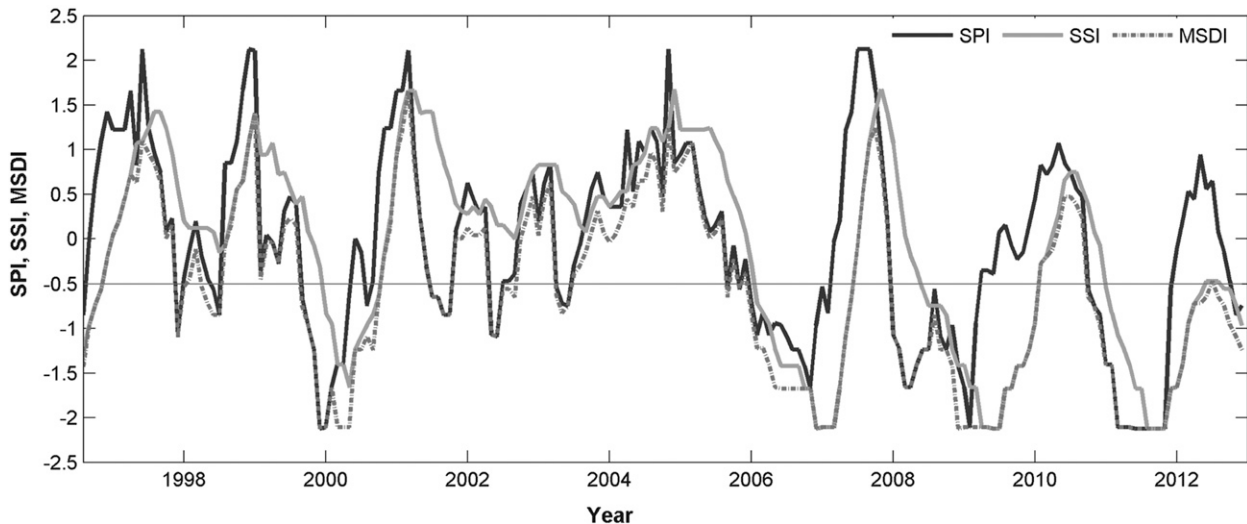
FIG. 1. Sample time series of the 6-month SPI, SSI, and MSDI for a grid cell in Texas (100°W, 30°N).

time series of the 6-month SPI, SSI, and MSDI using the monthly precipitation and soil moisture from MERRA-Land data are presented in Fig. 1. As shown, the MSDI determines the drought onset similar to the SPI and describes the drought persistence and termination similar to the SSI, which is consistent with the result from the parametric MSDI (Hao and AghaKouchak 2013). For example, for the 2005–08 drought, the onset is first detected by the 6-month SPI and MSDI, while the 6-month MSDI describes the drought persistence and termination similar to the 6-month SSI.

It is worth pointing out that the MSDI may not lead to the same drought severity as a univariate index such as SPI. The reason is that the probability corresponding to any given quantile of a joint distribution of two variables is not identical to that of the univariate distribution of each individual variable. In other words, the difference between the MSDI and a univariate index such as SPI is analogous to the difference between a bivariate distribution of two random variables relative to the univariate distributions of each individual variable. In the following, the performances of the SPI, SSI, and MSDI in drought monitoring are assessed for the 2007 and 2012 U.S. droughts with respect to USDM observations.

a. The 2007 drought

In Fig. 2, the first column displays the observed USDM drought data for the period of January–June 2007, while the second, third, and fourth columns show the 3-month SPI, SSI, and MSDI, respectively. Based on the USDM data, in January 2007 (Fig. 2), the majority of California and Arizona experienced D1 (moderate drought) to D2 (severe drought). This drought condition

expanded to larger areas and became even more severe (D2 and D3) by June 2007. As shown, the 3-month MSDI reasonably describes the USDM's drought spatial extent over the southwestern United States, while it shows drought in Washington State in May, not confirmed by the USDM. In April 2007, a large area in the western United States, including California, Nevada, Utah, and Wyoming, experienced moderate to severe drought conditions. The 3-month SPI only shows drought conditions in very limited areas. The 3-month SSI, on the other hand, indicates the drought conditions in California and parts of Nevada and Arizona. The 3-month MSDI exhibits a larger area under drought conditions than the SSI and is in better agreement with the drought condition from the USDM. In Texas, from January to June 2007, the 3-month SPI shows no drought conditions while the USDM, 3-month SSI, and 3-month MSDI indicate drought conditions in central Texas from January to March. In this particular example, the MSDI and SSI represent drought persistence more reliably. As another example, in the southeastern United States, the 3-month SPI indicates the drought onset in January 2007, while the 3-month SSI does not indicate the drought onset clearly. One can see that the 3-month MSDI captures the drought onset as early as the 3-month SPI.

To illustrate the consistency of the MSDI across different time scales, the 6-month SPI, SSI, and MSDI are presented in Fig. 3 for the period of January–June 2007. One can see that the 6-month SPI improves representation of drought persistence in the western United States (cf. Figs. 2 and 3). However, the drought conditions in Texas (January–March 2007) are still not
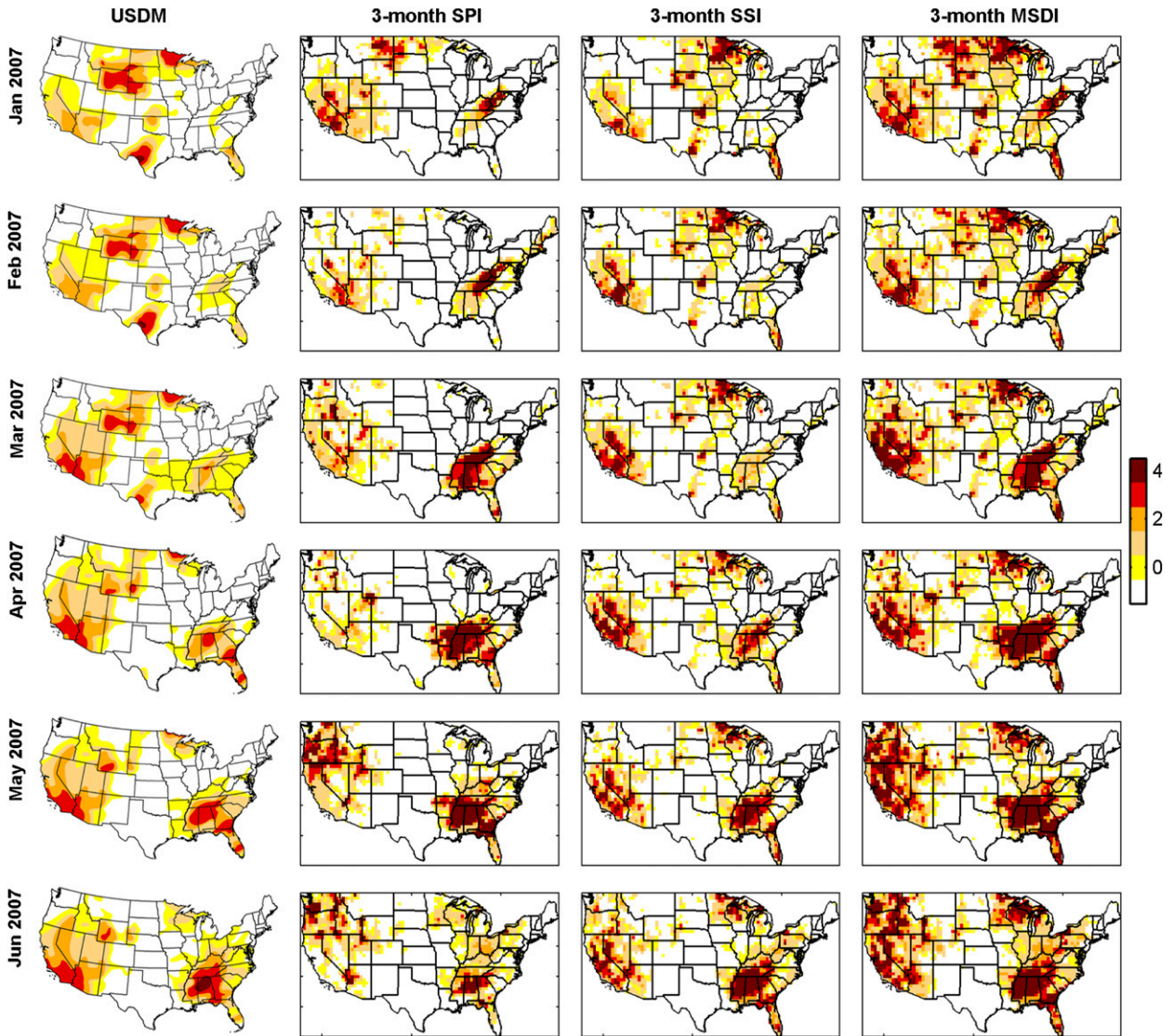
FIG. 2. (left to right) USDM and MERRA-Land–based 3-month: SPI, SSI, and MSDI. (top to bottom) January–June 2007.

represented by the 6-month SPI (see Fig. 3). Further-more, in April 2007, the 6-month SPI does not indicate drought in parts of Nevada, and the 6-month SSI does not show drought in Utah (Fig. 3). For both Nevada and Utah, the MSDI indicates drought consistent with the USDM observations (Fig. 3).

One property of the MSDI is that, if the two variables (here, precipitation and soil moisture) indicate drought (show a deficit), the MSDI would lead to a more severe drought condition than either SPI or SSI (Hao and AghaKouchak 2013). For this reason, one can see that the severity of the southwestern U.S. drought increases in the 3- and 6-month MSDI more quickly than in the 3- and 6-month SPI and SSI and may lead to more severe drought conditions than either SPI or SSI, especially

when both show a deficit. At the same time, this prop-erty of the MSDI can lead to detecting upcoming severe droughts earlier, if both input variables (precipitation and soil moisture) exhibit a departure from the clima-tology (Hao and AghaKouchak 2013). Similar to other drought indices, the MSDI may also lead to false drought signals (e.g., Washington State in May 2007). In some regions, the drought condition from MSDI (or SPI and SSI) is more severe than the USDM, which is mainly because of differences in the climatology. However, by monitoring the drought evolution during the 2007 drought at different areas, one can see that the MSDI is generally consistent with the USDM observations.

To quantitatively evaluate the SPI, SSI, and MSDI against the USDM, the drought POD, FAR, and CSI of
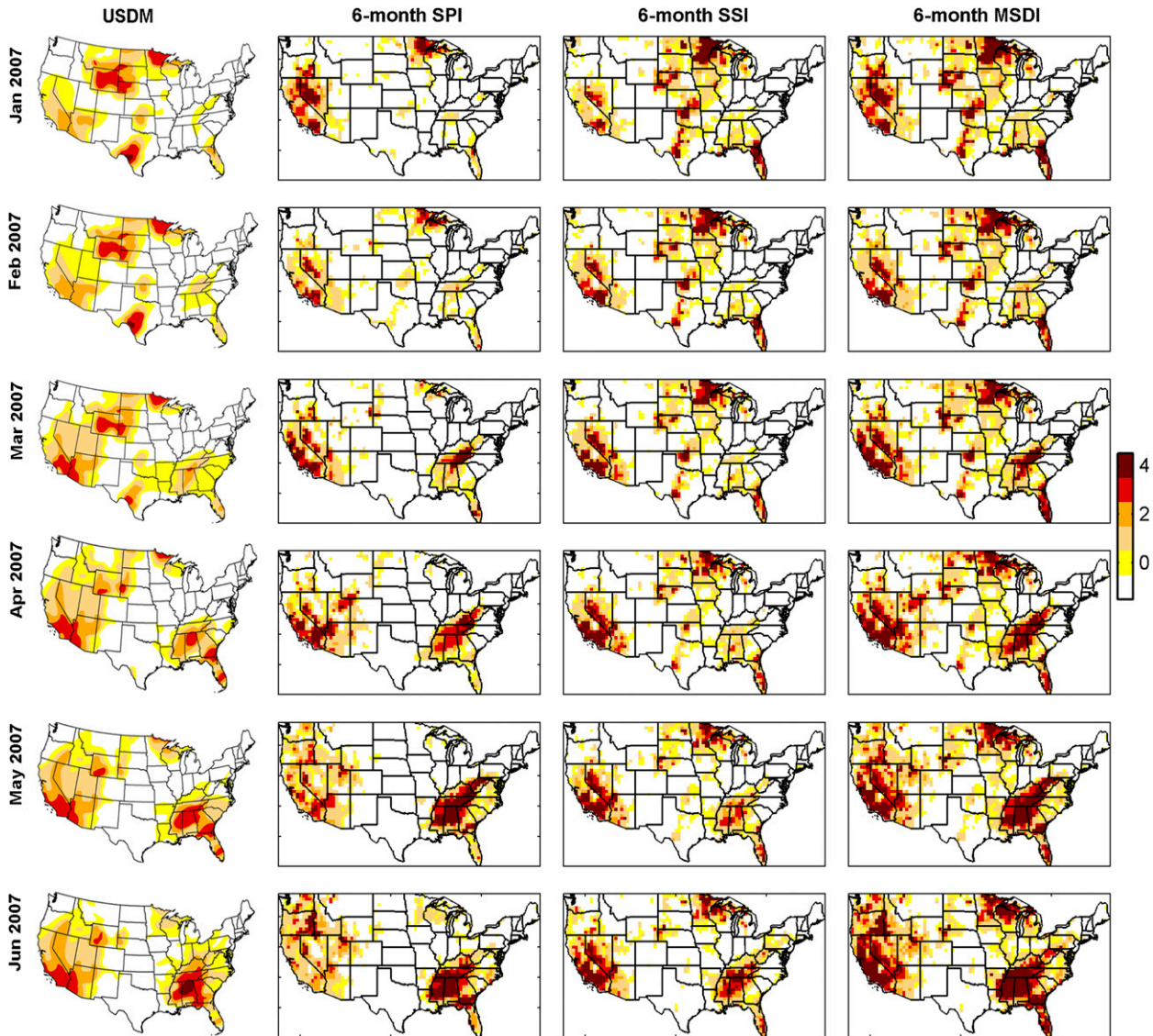
FIG. 3. As in Fig. 2, but using 6-month: SPI, SSI, and MSDI.

the 3-month (Fig. 4, left) and 6-month (Fig. 4, right) SPI, SSI, and MSDI are plotted. The presented POD, FAR, and CSI are computed for all five drought categories (D0–D4). The x axes display 12 months starting from January 2007, whereas the y axes show the unitless POD, FAR, and CSI. One can see that the POD values of the MSDI are consistently higher than those of the individual SPI and SSI for both the 3- and 6-month time scales. For March 2007, for example, the POD of the 3-month MSDI is 0.8 (80%), whereas the POD of the 3-month SPI and SSI is around 0.5. At the 6-month scale, the POD values of the SPI and SSI are quite similar, ranging from 0.4 to 0.7 (Fig. 4, right), while the POD values of the MSDI are consistently higher, ranging

from 0.6 to 0.9. As shown, at the 6-month scale, the FAR values of the MSDI are similar to those of the SSI while, at the 3-month time scale, the FAR values of the MSDI are slightly higher than those of the SPI or SSI. The CSI, which combines POD and FAR and provides an overall measure of performance, indicates that the MSDI is more consistent with the observed USDM data compared to the SPI and SSI at both 3- and 6-month time scales.

b. The 2012 drought

In this section, the performances of the three indices (SPI, SSI, and MSDI) are assessed for the 2012 drought that affected a large portion of the United States. Figures 5 and 6 present the 2012 U.S. drought as described by
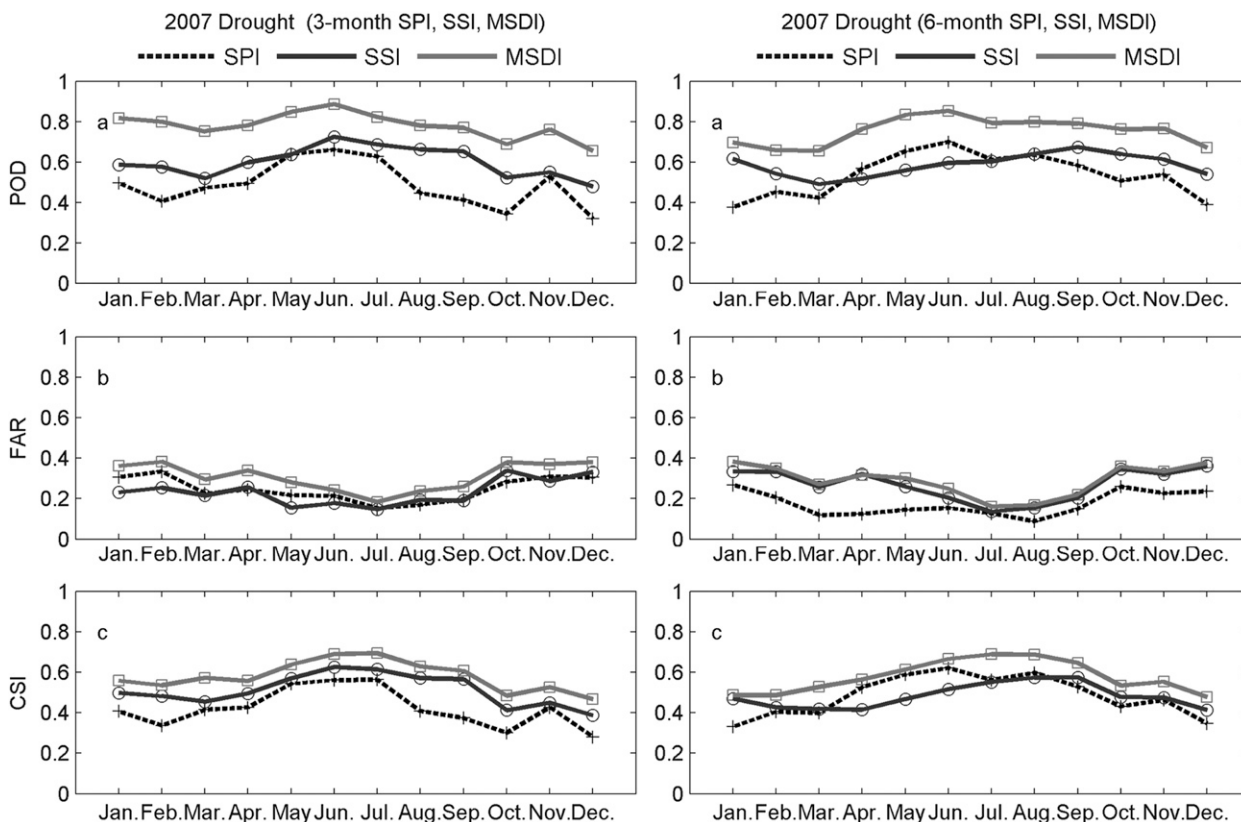
FIG. 4. (top to bottom) Drought POD, FAR, and CSI for the (left) 3-month and (right) 6-month SPI, SSI, and MSDI for January–December 2007.

the USDM and 3-month SPI, SSI, and MSDI for the periods of January–June and July–December, respectively. During January–June 2012 (Fig. 5), the USDM indicates a larger area under drought in the western United States than either the SPI or SSI, while MSDI exhibits a better agreement with the USDM with respect to the spatial extent of drought (Fig. 5).

Considering the drought persistence from January to June 2012 (Fig. 5) in the western United States, one can see that the 3-month SPI does not adequately describe the drought persistence as the drought severity from 3-month SPI lessens significantly in California by April 2012. The 3-month SSI and MSDI, however, describe the drought persistence reasonably well and similar to the USDM, although the drought condition in California in June is not consistent with the USDM. The drought condition in Arizona is first detected by the SPI in February 2012, which persists to June 2012 (Fig. 5). The 3-month SSI detects the drought onset in Arizona 1 month later (March 2012). As shown in Fig. 5, the 3-month MSDI describes the drought onset in Arizona as early as the SPI and indicates drought persistence similar to the SSI. A notable drought pattern during the

summer of 2012 is the quick onset of the drought condition in the high plains from May to June. In this period, the drought severity ramped up and reached even exceptional drought conditions. The 3-month MSDI is in better agreement with the USDM with respect to the drought severity and spatial extent in summer 2012. For example, in July 2012, the 3-month SPI does not show the USDM drought condition in Arizona, and the SSI does not indicate the drought condition in a large part of California. The 3-month MSDI, however, shows the drought condition in both California and Arizona in July 2012. Notice that the drought severity from the MSDI is more severe than that of the USDM in certain areas (e.g., high plains). Overall, the drought spatial extent from the 3-month MSDI is in better agreement with the USDM compared with the 3-month SPI and SSI in summer 2012.

The USDM and the 6-month SPI, SSI, and MSDI are plotted in Figs. 7 and 8, respectively. One can see that the persistence of the drought conditions (January–June) in southern Texas is not shown well from the 6-month SPI. The 6-month MSDI and SSI generally indicate the observed drought conditions in Texas as
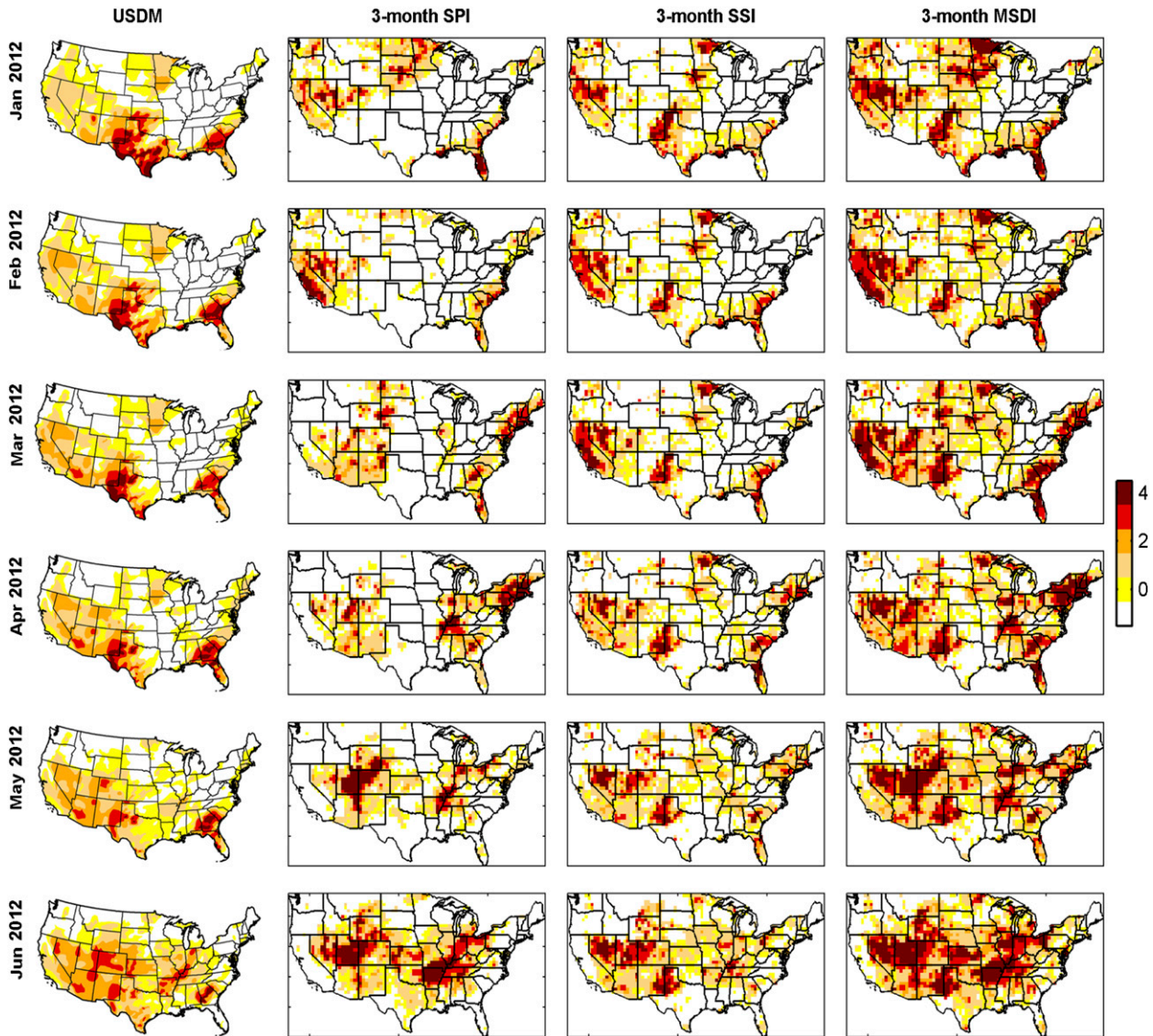
FIG. 5. As in Fig. 2, but for January–June 2012.

described by the USDM. As the drought develops in the second half of 2012 (Fig. 8), the 6-month MSDI describes the 2012 drought's spatial extent more consistently with the USDM compared to the SPI and SSI. These results confirm the previous findings for the 2007 drought that the MSDI is generally in better agreement with the USDM data with respect to the drought onset, persistence, and spatial extent.

Comparing the MSDI with the USDM observations in Figs. 5–8, one can see that, at some locations, the MSDI drought is more severe than the USDM observations. It is worth pointing out that the MSDI increases the drought severity if both the SPI and SSI show deficits. As stated previously, the drought severity from USDM and

MSDI (or SPI and SSI) may not be identical because of differences in input data climatology. For this reason, the purpose of this validation is to assess the consistency of the spatial patterns of drought from the MSDI with respect to the USDM observations. For a quantitative comparison, the drought POD, FAR, and CSI for 3-month (left) and 6-month (right) drought indices, including all drought categories (D0–D4), are presented in Fig. 9. Similar to the 3-month time scale, the POD and CSI values of the 6-month MSDI are consistently higher than those of the SPI and SSI. The FAR values of the 3-month MSDI are relatively higher than the other two indices, while the FAR values of the 6-month MSDI closely mimic those of the SSI.
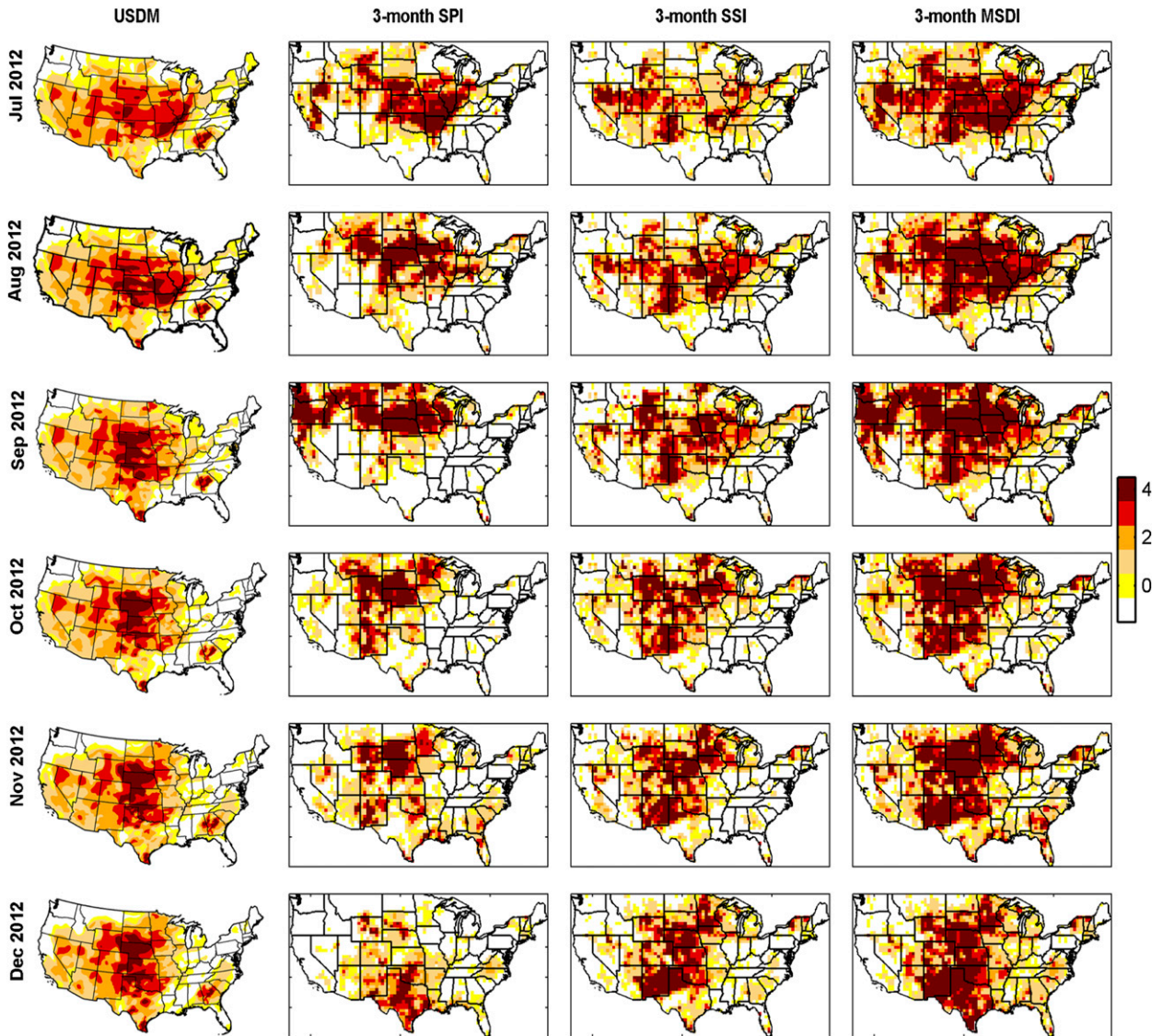
FIG. 6. As in Fig. 2, but for July–December 2012.

5. Conclusions and remarks

In the past decade, major drought events have been recorded in the United States, the Horn of Africa, Australia, Eurasia, and the Middle East, leading to much-needed attention to methods of analysis of extremes in a changing climate (AghaKouchak et al. 2013). Reliable drought monitoring is fundamental to drought mitigation efforts and water resources management. Thus far, a number of drought indices have been used for monitoring and predicting droughts. Given the complexity of drought phenomena in their onset, development, and termination, drought monitoring based on a single variable may not be sufficient for detecting drought

conditions promptly and reliably. This study outlines a multivariate, multi-index drought monitoring framework, namely, the MSDI, for describing droughts based on the states of multiple variables, such as precipitation and soil moisture. A nonparametric approach is used for describing the joint distribution of precipitation and soil moisture to derive MSDI for drought monitoring. The MSDI, along with the SPI and SSI, are used to describe two major recent droughts: the 2007 and 2012 U.S. droughts. The results are then validated with the USDM data for spatiotemporal consistency of the univariate and multivariate indices.

Based on the case studies, the MSDI generally captures the drought onset similar to the SPI and drought
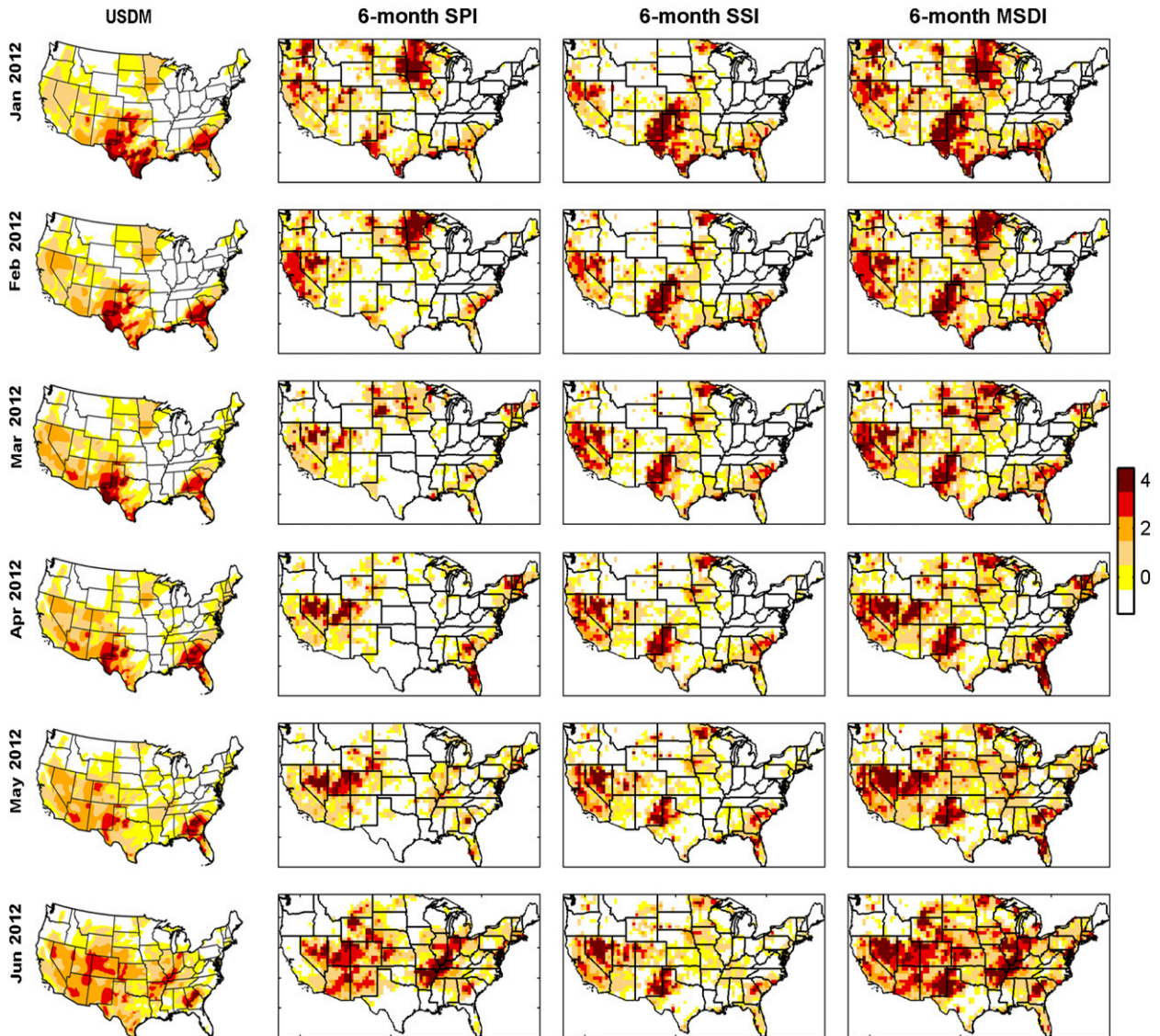
FIG. 7. As in Fig. 3, but for January–June 2012.

persistence similar to the SSI. This implies that the MSDI is capable of detecting the drought onset and persistence, which combines the properties of the SPI and SSI. The MSDI is also shown to improve the detection of the drought spatial extent in certain cases when the individual SPI or SSI does not adequately indicate the drought spatial extent. The results indicate that the MSDI exhibits higher probability of detection (POD) and critical success index (CSI) compared to the individual SPI and SSI in both 3- and 6-month time scales. However, the false alarm ratio (FAR) of droughts indicated by the MSDI is relatively higher than the SPI or SSI. The results show that, in both case studies, the spatial extents of the MSDI drought conditions are generally in

good agreement with the USDM observations. However, relative to USDM, the MSDI may exaggerate the drought severity in certain cases, especially when both precipitation and soil moisture indicate a deficit. This is primarily because 1) the climatology of the MERRA-based indices (i.e., SPI, SSI, and MSDI) is shorter than that of the USDM, which involves long-term, ground-based observations [i.e., a record drought in the MSDI (D4) derived from 33 yr of climatology may not be a record drought in the USDM, which involves a much longer record of observations], and 2) the USDM integrates numerous input variables, including subjective inputs from local climatologists, while the MSDI is based exclusively on precipitation and soil moisture conditions.
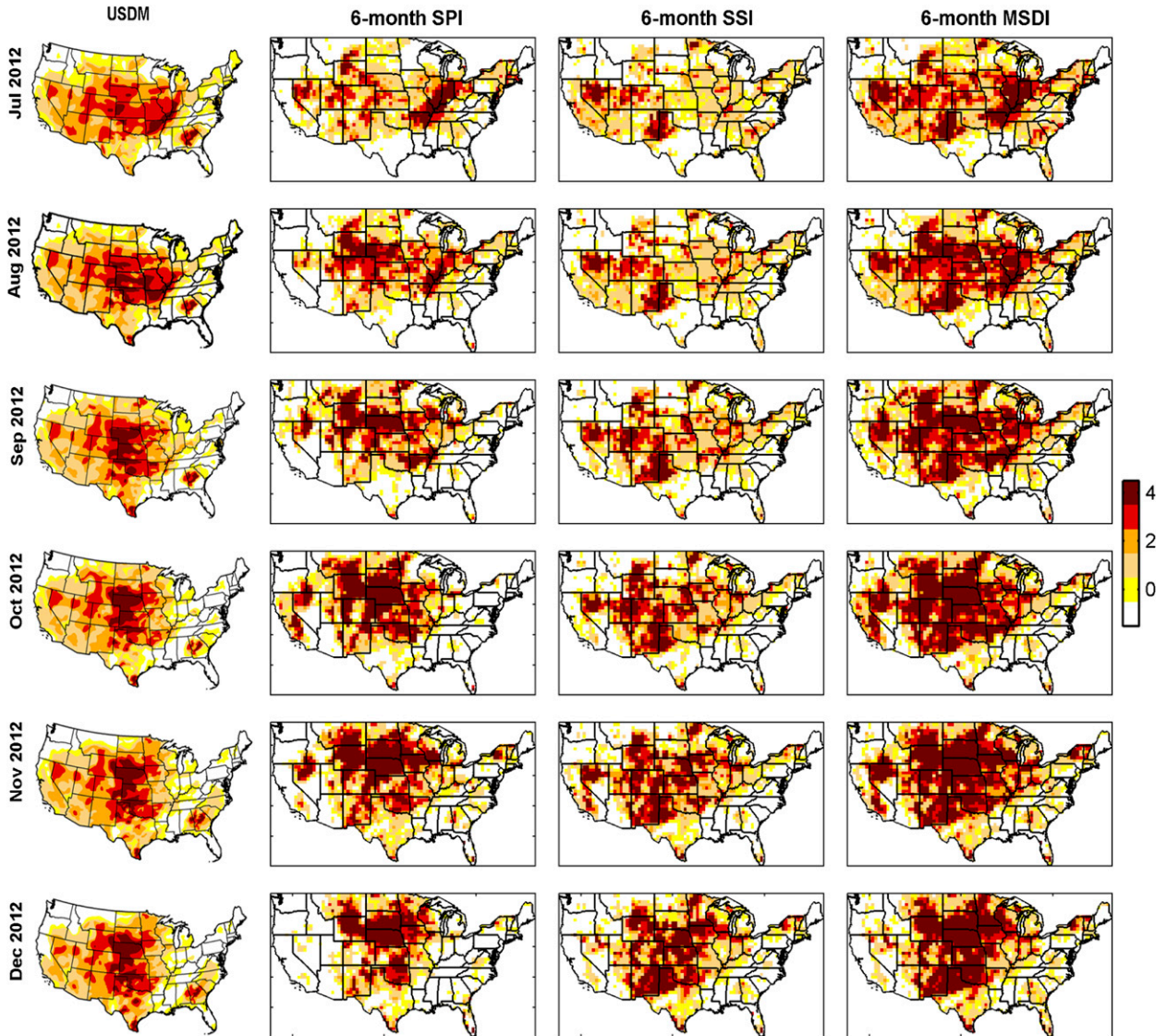
FIG. 8. As in Fig. 3, but for July–December 2012.

The objective of this study is not to show the weaknesses of the SPI or SSI, but rather, to emphasize the fact that combining information from multiple variables (here, precipitation and soil moisture) would improve drought monitoring. While precipitation and soil moisture are generally used for characterizing the meteorological and agricultural droughts, we propose the multi-index MSDI as a model that can jointly describe both drought types. In addition to precipitation and soil moisture, the proposed methodology can be applied to other drought-related variables such as runoff, temperature, and evapotranspiration. The two variables within the MSDI can be of different time scales (e.g., 6-month precipitation and 1-month soil moisture), and the drought threshold of MSDI can be different than the one used

in this paper. Efforts are underway to extend the MSDI concept by integrating more hydroclimatic variables and to use the MSDI concept for drought prediction and early warning.

The authors acknowledge that, if neither precipitation nor soil moisture (or any other combinations of variables) are reliable, the joint analysis of droughts would not lead to any improvement in drought monitoring. In fact, the MSDI can potentially improve drought monitoring if each of the selected drought-related variables can capture certain aspects of droughts. The proposed methodology requires long-term (at least 30 yr or more) observations to derive the joint distribution of precipitation and soil moisture, and a short record of observations could lead to biases in the MSDI estimates.
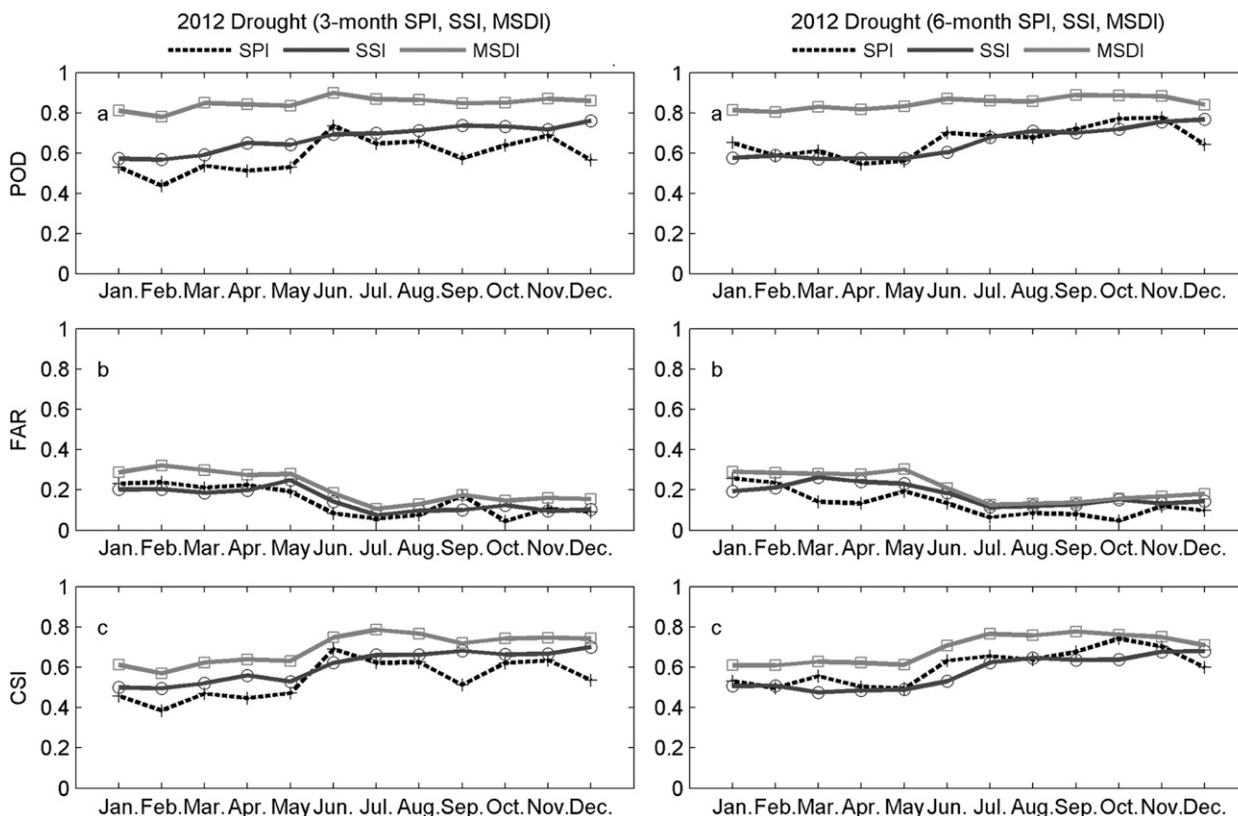
FIG. 9. As in Fig. 4, but for 2012.

We emphasize that the MSDI is not meant to replace the USDM or any other drought index. It is our view that drought monitoring and prediction should be based on multiple sources of information. Hence, we propose the MSDI to be used as an additional source of information that can potentially provide more insights into the drought monitoring.

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