A Statistical Method for Categorical Drought Prediction Based on NLDAS-2

ZENGCHAO HAO,* FANGHUA HAO,* YOULONG XIA,[+,#] VIJAY P. SINGH,[@,&] YANG HONG,[**,++,##] XINYI SHEN,[@@] AND WEI OUYANG*

* *Green Development Institute, School of Environment, Beijing Normal University, Beijing, China*
[+] *Environmental Modeling Center, National Centers for Environmental Prediction, College Park, Maryland*
[#] *I. M. Systems Group, College Park, Maryland*
[@] *Department of Biological and Agricultural Engineering, Texas A&M University, College Station, Texas*
[&] *Zachry Department of Civil Engineering, Texas A&M University, College Station, Texas*
** *Hydrometeorology and Remote Sensing Laboratory, University of Oklahoma, Norman, Oklahoma*
[++] *Advanced Radar Research Center, University of Oklahoma, Norman, Oklahoma*
[##] *School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, Oklahoma*
[@@] *Civil and Environmental Engineering Department, School of Engineering, University of Connecticut, Storrs, Connecticut*

(Manuscript received 21 July 2015, in final form 7 December 2015)

ABSTRACT

Drought is a slowly varying natural phenomenon and may have wide impacts on a range of sectors. Tremendous efforts have therefore been devoted to drought monitoring and prediction to reduce potential impacts of drought. Reliable drought prediction is critically important to provide information ahead of time for early warning to facilitate drought-preparedness plans. The U.S. Drought Monitor (USDM) is a composite drought product that depicts drought conditions in categorical forms, and it has been widely used to track drought and its impacts for operational and research purposes. The USDM is an assessment of drought condition but does not provide drought prediction information. Given the wide application of USDM, drought prediction in a categorical form similar to that of USDM would be of considerable importance, but it has not been explored thus far. This study proposes a statistical method for categorical drought prediction by integrating the USDM drought category as an initial condition with drought information from other sources such as drought indices from land surface simulation or statistical prediction. Incorporating USDM drought categories and drought indices from phase 2 of the North American Land Data Assimilation System (NLDAS-2), the proposed method is tested in Texas for 2001–14. Results show satisfactory performance of the proposed method for categorical drought prediction, which provides useful information to aid early warning for drought-preparedness plans.

1. Introduction

Drought is a creeping natural phenomenon with diverse geographical and temporal distributions that may lead to huge impacts on different sectors. For example, the 2012 U.S. drought alone caused losses of more than $35 billion (Otkin et al. 2015), and the 2010–11 drought in Africa plunged eastern Africa into a food security crisis (Dutra et al. 2013; FEWS NET 2011). With the potential increase in drought severity and frequency in the future and the vulnerability of society, it is critically important to provide accurate drought monitoring and reliable drought prediction for early warning to aid drought-preparedness plans and mitigation measures.

The complicated nature of drought and its wide impacts hinder the definition and accurate characterization of drought. Drought can be classified into meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought. Furthermore, on the basis of the availability of data, location affected, and particular application, a variety of drought indices, such as the standardized precipitation index (SPI; McKee et al. 1993), the standardized runoff index (SRI; Shukla and Wood 2008), the soil moisture percentile (SMP; Sheffield et al. 2004; Mo 2008) or its standardization [standardized soil moisture index (SSI; Hao and AghaKouchak 2013], and the Palmer drought severity index (PDSI; Palmer 1965), have been developed to

Corresponding author address: Zengchao Hao, No. 19, XinJieKouWai St., HaiDian District, Beijing 100875, China.
E-mail: haozc@bnu.edu.cn

DOI: 10.1175/JAMC-D-15-0200.1

monitor drought conditions of different types (Hao and Singh 2013; Heim 2002; Keyantash and Dracup 2002; Mishra and Singh 2010). Because an individual drought indicator is generally not satisfactory for all regions and seasons for all applications, substantial efforts have been devoted to multivariate (or integrated, composite) drought characterization by incorporating drought information from a variety of sources (Beersma and Buishand 2004; Kao and Govindaraju 2010; Keyantash and Dracup 2004; Svoboda et al. 2002; Xia et al. 2014; Rajsekhar et al. 2015), as reviewed by Hao and Singh (2015). For example, a variety of multivariate drought indices that are based on satellite remote sensing (optical, thermal, and microwave) have been developed by integrating drought-related information (e.g., vegetation, precipitation, snow, land surface temperature, soil moisture, and groundwater storage) from different sensors or bands to aid drought monitoring and assessments at the regional or global scales (Hao et al. 2016b).

Drought prediction is of critical importance to provide drought information ahead of time for early warning to aid decision makers for drought management. In recent decades, various dynamical (or physical) and statistical models have been developed for drought prediction. Dynamic models of the climate and ocean system provide seasonal climate forecasts of variables such as precipitation that can be used for meteorological drought prediction (Quan et al. 2012; Yoon et al. 2012; Mo and Lyon 2015), which in turn can be used as forcing variables to drive land surface models for agricultural and hydrological drought prediction (Luo and Wood 2007; Mo and Lettenmaier 2014; Shafiee-Jood et al. 2014; Wood et al. 2002; Yuan et al. 2013, 2015). Statistical methods are generally based on empirical relationships from historical observations, and methods such as regression, time series analysis, machine learning, and hybrid models have been used for drought prediction (Mishra and Desai 2005; Mishra and Singh 2011; Özger et al. 2012; Hao et al. 2016b). For example, Lyon et al. (2012) developed a baseline prediction method that is based on the persistence of the drought indicator SPI for meteorological drought prediction and has been shown to provide useful drought information up to several months ahead (Mo and Lyon 2015; Quan et al. 2012); it was extended recently for agricultural and integrated meteorological–agricultural drought prediction with SSI and the multivariate standardized drought index (Hao et al. 2014).

In the United States, the U.S. Drought Monitor (USDM) has been commonly used to track and display the magnitude and spatial extent of drought and its impacts for operational and research purposes (Svoboda et al. 2002). It is a composite drought product that blends multiple objective inputs and subjective adjustments on the basis of local impacts and vulnerability, in which drought conditions are classified into five drought categories on the basis of a percentile approach. The USDM has been widely applied by a diverse set of users to track drought conditions across the country and has also been used as a reference for evaluations of drought indices for drought characterization in the United States (Anderson et al. 2013; McEvoy et al. 2012; Xia et al. 2014). The USDM assesses drought conditions in categorical form but does not provide drought prediction (or forecast) information. Drought prediction in the form of categories similar to those of the USDM would be of considerable importance and would require the establishment of a relationship between USDM drought categories and other drought indicators.

Traditional linear regression to model the response variable with respect to a suite of covariates (or predictor variables) is based on the assumption that the response variable is normally distributed. When the response variable is categorical (i.e., drought category), however, the linear regression does not apply and one must resort to other methods. One method to model categorical data is the logistic regression, for which the response variable is binary. For example, Regonda et al. (2006) proposed a probabilistic forecast method for categorical streamflow forecast via a logistic regression model and use of a set of large-scale climate predictors. The logistic regression model falls short in characterizing the USDM drought category that contains multiple categories that are ordinal (or ordered). Hao et al. (2016a) introduced the cumulative-link model, which is a type of ordinal regression model, to characterize multiple USDM drought categories. By using this model, the historical USDM drought categories in Texas are reconstructed on the basis of drought indices from phase 2 of the North American Land Data Assimilation System (NLDAS-2).

In this study, a statistical method is proposed for categorical drought prediction in the form of USDM drought categories by integrating the USDM drought category as the initial condition with drought information from other sources such as drought indices from land surface simulation or statistical prediction. The proposed method is tested on the basis of USDM drought categories and drought indices from NLDAS-2 for the period from 2001 to 2014 in Texas, and results show satisfactory performance of the proposed method for categorical drought prediction. This paper is organized as follows: In section 2, the ordinal time series modeling method is introduced, along with the proposed categorical drought prediction method and parameter estimation scheme. Data and measures are discussed in section 3. Categorical drought estimation and prediction with the proposed method are presented in section 4, followed by discussion and conclusions in section 5.

2. Method

a. Ordinal time series modeling

For a response variable Y with a range of categories $(1, 2, \ldots, m)$, let the corresponding categorical time series be denoted as Y_t $(t = 1, 2, \ldots, n)$. An effective way to construct a model for the ordinal response of category j is to invoke the concept of a latent (or unobserved) response variable X in such a way that the relationship is monotonic (Agresti 2010; Fokianos and Kedem 2003):

$$Y_t = j \quad \Leftrightarrow \quad \alpha_{j-1} \le X_t \le \alpha_j \quad \text{for} \quad j = 1, \ldots, m, \tag{1}$$

where $(\alpha_0, \alpha_1, \ldots, \alpha_m)$ are a set of parameters (or cut points) that satisfy

$$-\infty = \alpha_0 < \alpha_1 < \cdots < \alpha_m = \infty. \tag{2}$$

Here the cut points α_j are envisaged as unknown points on the latent scale with similar values of the latent variable X not distinguished, resulting in the identical response Y unless the latent variable is close to the boundary.

The latent process variable X_t with respect to the covariate Z can be expressed as (Agresti 2010; Fokianos and Kedem 2003)

$$X_t = -\boldsymbol{\beta}\mathbf{Z}_{t-1} + \varepsilon_t, \tag{3}$$

where $\mathbf{Z}_{t-1}$ is the covariate (or independent variable) of the same dimension as X_t, $\boldsymbol{\beta}$ is the vector of parameters, and ε_t is a sequence of independent and identically distributed random variables with the common cumulative distribution function F.

Thus, the probability of a drought category lower than a certain category j can be expressed as

$$P(Y_t \le j) = P(X_t \le \alpha_j) = F(\alpha_j + \boldsymbol{\beta}\mathbf{Z}_{t-1}). \tag{4}$$

With different cumulative distribution functions F, there are different expressions of the model. When F is the logistic distribution function—that is, $F(x) = 1/[1 + \exp(-x)]$—the ordinal regression model can be derived as (Agresti 2010; Fokianos and Kedem 2003)

$$\log\left[\frac{P(Y_t \le j)}{P(Y_t > j)}\right] = \alpha_j + \boldsymbol{\beta}\mathbf{Z}_{t-1}. \tag{5}$$

Accordingly, the probability of Y_t falling into a certain drought category j can be expressed as

$$P(Y_t = j) = \frac{\exp(\alpha_j + \boldsymbol{\beta}Z_{t-1})}{1 + \exp(\alpha_j + \boldsymbol{\beta}Z_{t-1})} - \frac{\exp(\alpha_{j-1} + \boldsymbol{\beta}Z_{t-1})}{1 + \exp(\alpha_{j-1} + \boldsymbol{\beta}Z_{t-1})}. \tag{6}$$

From Eq. (5) or Eq. (6), the probability of response variable Y falling in each drought category at each time step can be estimated. From the estimated probabilities of each category, the drought category j with the maximum probability from among the categories can be selected.

b. Categorical drought modeling

Categorical time series modeling can now be employed to aid categorical drought prediction. We propose to predict the drought category in the target month (or period) by incorporating the previous USDM drought categories as the initial condition and drought information from other sources (e.g., drought indices from land surface simulations or statistical prediction) for the target period. The USDM drought categories, from least to most intense, include abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), and exceptional drought (D4). The condition of no drought is denoted as the ND drought category in this study. The possible outcome of drought condition at each time includes six drought categories $D = (\mathrm{ND}, \mathrm{D0}, \mathrm{D1}, \ldots, \mathrm{D4})$ that take on the values $1, 2, \ldots, 6$, respectively; that is, the first category is assigned an integer value of 1, the second category is assigned 2, and so on. Here the assignment of drought categories is for the purpose of convenience only and is not unique.

Now let $\mathbf{Y}$ be the vector of drought categories at different time periods (n in total) of dimension $n \times 1$ with categories $C_1, C_2, \ldots, C_m$, where m is the number of drought categories (in this case, $m = 6$). To incorporate information from the previous state of USDM drought categories as the initial condition to infer the drought category in the future, the Y_{t-1} of USDM drought categories for time $t - 1$ is included in the model. Here, for parsimonious purposes, only the lag-1 USDM drought category is included. To take into account drought information from other sources, such as drought indices from land surface simulations or statistical prediction, the vector $\mathbf{W}_t$ of a suite of drought indices is also included for the prediction of drought category. Accordingly, the model for the prediction of drought category Y_t with respect to the previous USDM drought category

Y_{t-1} and drought indices $\mathbf{W}_t$ can be expressed from Eq. (5) as

$$\log\left[\frac{P(Y_t \le j)}{P(Y_t > j)}\right] = \alpha_j + \boldsymbol{\beta}\mathbf{W}_t + \boldsymbol{\gamma}Y_{t-1}, \qquad (7)$$

where Y_{t-1} is the USDM drought category at time $t-1$; $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are associated parameters; and $\mathbf{W}_t$ is a suite of drought indices at time t.

c. Parameter estimation

The parameters α, β, and γ in Eq. (7) have to be estimated to implement the model. At any time t, Y_t can be expressed by the vector $(Y_{t1}, \ldots, Y_{tq})'$ of length $q = m - 1$, for which elements Y_{tj} can be expressed as (Fokianos and Kedem 2003; Guanche et al. 2014)

$$Y_{tj} = \begin{cases} 0 & \text{if} \quad j \ne Y_t \\ 1 & \text{if} \quad j = Y_t \end{cases} \quad \forall \quad j = 1, \ldots, q; \quad \forall \quad t = 1, \ldots, n. \qquad (8)$$

Accordingly, a matrix of dimension $n \times q$ is constructed for the observations and $Y_{t1} + \cdots + Y_{tm} = 1$, since only one drought category is possible at each time step.

The maximum likelihood estimation method is used for parameter estimation. For given sequences of USDM observations of m drought categories and drought indices for n time steps, the likelihood function can be obtained from Eqs. (6) and (7) as (Fokianos and Kedem 2003; Guanche et al. 2014)

$$L = \prod_{t=1}^{n}\prod_{i=1}^{m} P(Y_t = i)^{u_{ti}}, \qquad (9)$$

where $u_{ti} = 1$ for the category i in which the response falls and $u_{ti} = 0$ otherwise.

3. Data and measures

a. Data

1) USDM

The USDM is created weekly and is archived and distributed by the National Drought Mitigation Center at the University of Nebraska—Lincoln (http://droughtmonitor.unl.edu/; Svoboda et al. 2002). The USDM drought categories for the period from 2001 to 2014 are first digitized into 0.5° resolution and are regarded as the reference. The average USDM drought categories for a certain month are obtained from weekly products and are used to represent the "observed" monthly drought condition. The data for 2001–12 are used for the estimation of parameters of the model, and those for 2013–14 are used for validation.

2) NLDAS

The North American Land Data Assimilation System project has been shown to be capable of capturing the broad features of the energy flux, water flux, and state variables (Xia et al. 2012). A near-real-time NLDAS drought-monitoring system has been developed recently that is based on a range of drought indices at different time scales (Ek et al. 2011; Sheffield et al. 2012; Xia et al. 2014). In this study, monthly precipitation, soil moisture, and runoff data from the community Noah model from NLDAS-2, which is run by the National Centers for Environmental Prediction (NCEP) Environmental Modeling Center (Xia et al. 2014), were used to compute drought indices for the modeling of drought categories. Following the method of Mo (2008), three drought indices—6-month standardized precipitation index (SPI6), SMP (standardized with the normal distribution based on a 3-month running mean), and 3-month SRI (SRI3), representing meteorological, agricultural, and hydrologic drought, respectively—were used to model the drought category.

b. Measures

For probabilistic prediction (or forecasting) of multiple-category events, the rank probability score (RPS) has been commonly used for prediction evaluation (Wilks 2011). Let y_j, $j = 1, 2, \ldots, m$, denote the components of the probability forecast vector of different drought categories corresponding to an observed drought category. The observation vector has m components o_j, for which the component corresponding to the drought category that occurs is equal to 1 and the other $m - 1$ components are equal to 0. The cumulative prediction and cumulative observation vectors (denoted as $\mathbf{Y}_i$ and $\mathbf{O}_i$, respectively) are defined as

$$\mathbf{Y}_i = \sum_{j=1}^{i} y_j \quad \text{and} \qquad (10)$$

$$\mathbf{O}_i = \sum_{j=1}^{i} o_j. \qquad (11)$$

The final component Y_m and O_m are all equal to 1 by definition. The RPS is then defined to measure the sum of squared differences between components of the cumulative forecast and observations vectors, which for a single forecast–event pair is expressed as (Wilks 2011)

TABLE 1. Candidate models for categorical drought modeling as based on USDM drought category and drought indices. The associated AIC value for different models of the sample grid point (latitude 28°, longitude −98°) in this study is also shown.

Model candidate	Model expression	AIC
1	$\alpha + \beta_1\mathrm{SPI6} + \beta_2\mathrm{SMP} + \beta_3\mathrm{SRI3} + \boldsymbol{\gamma} Y_{t-1}$	225.73
2	$\alpha + \beta_1\mathrm{SPI6} + \beta_2\mathrm{SMP} + \boldsymbol{\gamma} Y_{t-1}$	230.30
3	$\alpha + \beta_1\mathrm{SPI6} + \beta_2\mathrm{SRI3} + \boldsymbol{\gamma} Y_{t-1}$	225.23
4	$\alpha + \beta_1\mathrm{SMP} + \beta_2\mathrm{SRI3} + \boldsymbol{\gamma} Y_{t-1}$	242.32

$$\mathrm{RPS} = \frac{1}{m-1}\sum_{i=1}^{m}(\mathbf{Y}_i - \mathbf{O}_i)^2. \qquad (12)$$

For a collection of n prediction pairs, the average RPS can be used. The RPS covers the range [0, 1], with a lower value indicating a better prediction.

To assess the improvement of multicategory drought prediction relative to a reference prediction, the rank probability skill score (RPSS) is used as the performance measure; it is defined as (Wilks 2011)

$$\mathrm{RPSS} = 1 - \frac{\overline{\mathrm{RPS}}}{\overline{\mathrm{RPS}}_{\mathrm{ref}}}, \qquad (13)$$

where $\overline{\mathrm{RPS}}$ and $\overline{\mathrm{RPS}}_{\mathrm{ref}}$ are the means of RPS for the prediction from the proposed method and reference prediction, respectively. The reference prediction of the drought category for a specific period is defined as the drought category of the previous period (or the persistent prediction). RPSS ranges from $-\infty$ to 1. A value of RPSS equal to 1 indicates a perfect multicategory probability prediction, and a negative RPSS implies that the model is performing worse than the reference. Positive RPSS indicates that the prediction from the proposed method has better prediction skill than the reference prediction.

4. Results

a. Model setup

With lag-1 USDM drought category and drought indices SPI6, SMP, and SRI3 representing meteorological, agricultural, and hydrological droughts, respectively, four models are chosen on the basis of different combinations of drought indices, as shown in Table 1. Model 1 is based on the combination of all three indices and models 2, 3, and 4 are chosen by combining two indices. For each model, more than one drought index is used to model drought categories to illustrate the application of the proposed method, since it has been well recognized that multiple drought indices are generally required to characterize the drought condition (Hao and Singh 2015; Svoboda et al. 2002; Xia et al. 2014).

An important step in modeling drought categories with the proposed method is the selection of different models in Table 1 for each grid point. In this study, the Akaike information criterion (AIC; Akaike 1974) is used for the selection of different models [or covariates in Eq. (7)] for the statistical inference of drought category. For each grid point, after parameter estimation, the model in Table 1 with the minimum AIC is selected and is then used to model drought categories.

b. Model estimation for 2001–12

The model parameter is first estimated with USDM drought categories and NLDAS-2 drought indices for the period of 2001–12. The sample grid point (latitude 28°, longitude −98°), which is located in southern Texas, is used to illustrate the modeling of drought categories. The AIC value for each model, as based on data from 2001 to 2012, for this grid point is shown in Table 1. As a result, model 3 with drought indices SPI6 and SRI3 as covariates in Eq. (7) is selected, because the corresponding AIC value is the smallest. In specific terms, the estimated model in Eq. (7) can be expressed as

$$\log\left[\frac{P(Y_t \le j)}{P(Y_t > j)}\right] = \alpha_j + \beta_1\mathrm{SPI6}_t + \beta_2\mathrm{SRI3}_t + \boldsymbol{\gamma} Y_{t-1}, \qquad (14)$$

where parameters are estimated as $\boldsymbol{\alpha}$ = (−11.45, −8.56, −6.21, −3.20, −0.16) corresponding to different drought categories, $\boldsymbol{\beta} = (\beta_1, \beta_2) = (1.26, 0.63)$ corresponding to different drought indices, and $\boldsymbol{\gamma}$ = (12.16, 9.21, 7.94, 6.07, 3.49) corresponding to drought categories in the previous period ($Y_{t-1,1}, \ldots, Y_{t-1,5}$) constructed from Eq. (8).

The drought category from USDM for the sample grid point from 2001 to 2014 is shown in Fig. 1a (solid line), from which it can be seen that serious drought events occur (drought categories D2–D4) during 2001–12 (e.g., drought during 2006, 2008, 2009, and 2011). For observed drought indices (SPI6 and SRI3) for this grid point from 2001 to 2012 as shown in Figs. 1b and 1c, values are generally low during 2006, 2008, 2009, and 2011, the combination of which indicates drought categories with serious drought conditions. The estimated drought category at this grid point for the period 2001–12 is also shown in Fig. 1a (dashed line). We examine the drought condition in August 2008 as an example. The drought category from USDM for this period is D2 and that for the previous month (July 2008) is D3. The values of drought indices SPI6 and SRI3 for August 2008 are 0.18 and 0.74, respectively, which do not indicate a

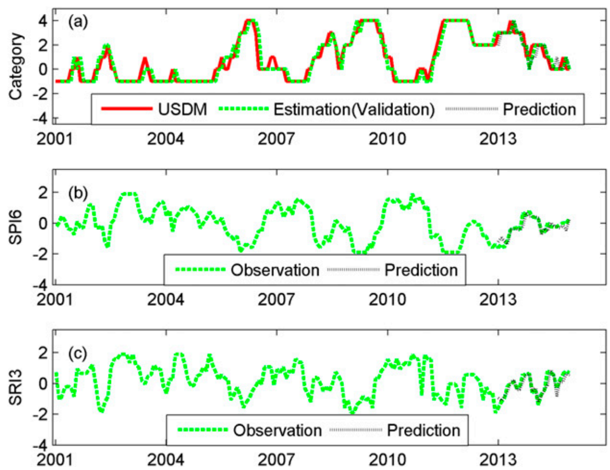

FIG. 1. (a) Comparison of the USDM category (solid line) and the estimated drought category (dashed line), along with observed (b) SPI6 and (c) SRI3 values from NLDAS-2 (green dashed line) for 2001–14 for the sample grid point (latitude 28°, longitude −98°). The 1-month-lead prediction of drought category for 2013–14 is shown in (a) (dotted line), and 1-month-lead statistical predictions of SPI6 and SRI3 for 2013–14 are shown in (b) and (c) (dotted lines).

drought condition. From Eq. (14), the estimated probabilities for six different drought categories are 0.001, 0.012, 0.10, 0.61, 0.25, and 0.018, respectively. The drought category associated with the highest probability (i.e., D2 with highest probability 0.61) is selected as the estimated drought category. Thus, for this period, the change of drought category from D3 to D2 is accurately estimated, as based on the USDM drought category of the previous period and drought indices for the current period. Overall, it can be seen from Fig. 1 that for this grid point the estimated drought category is relatively close to the observed drought category from USDM, although a certain discrepancy may exist.

To further show the performance, the observed drought category from USDM for a few periods, including June 2006, July 2008, March 2009, and August 2011, in Texas is shown in Figs. 2a–d, along with the estimated drought categories in Figs. 2e–h. The drought condition in the form of drought categories is estimated relatively well for these four months in Texas. For example, for June 2006, the D3–D4 drought condition is mainly clustered in northern and southeastern Texas (Fig. 2a), with most of the remaining regions being covered by D1–D2 drought categories. These drought patterns are generally shown well from the estimation in Fig. 2e. For July 2008 (Fig. 2b) and March 2009 (Fig. 2c), the D3–D4 drought is mainly clustered in the southern region, as is clearly seen from the estimation in Figs. 2f and 2g, respectively. The 2011 drought event in Texas is the most extreme 1-yr drought on record (Hoerling et al. 2013). For August 2011, the whole Texas region is covered by D3–D4 drought from USDM (Fig. 2d), which is also captured by the proposed method in Fig. 2h. There are certain discrepancies in limited regions in these four periods. For example, for March 2009, most of eastern

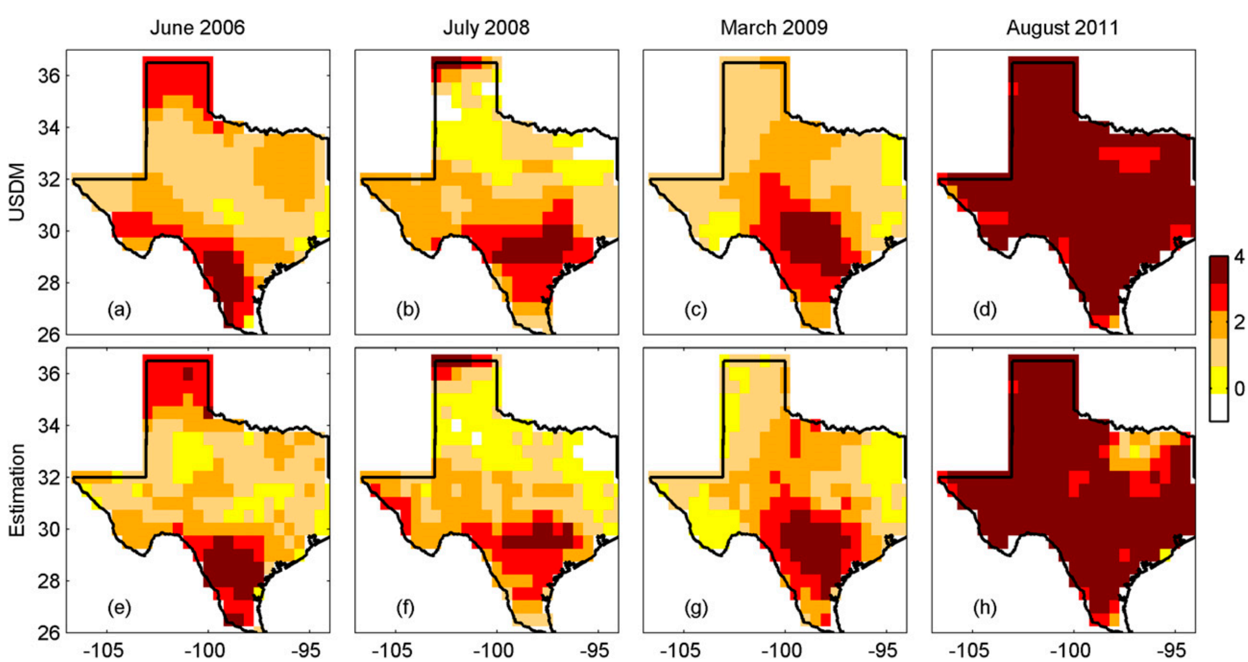

FIG. 2. Drought categories from (a)–(d) USDM and (e)–(h) estimation for four months (June 2006, July 2008, March 2009, and August 2011) during 2001–12.

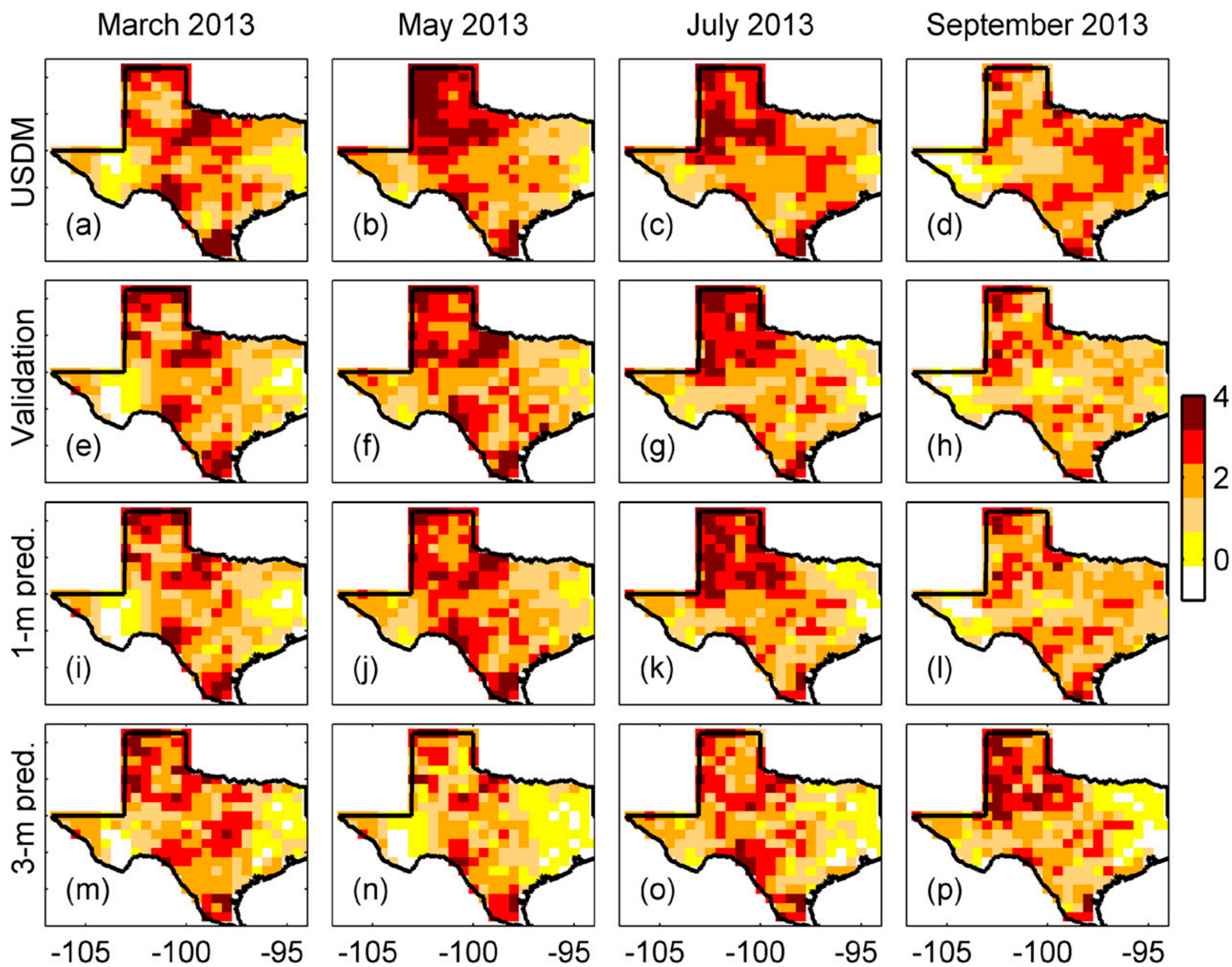

FIG. 3. Drought categories from (a)–(d) USDM, (e)–(h) validation, (i)–(l) 1-month-lead prediction, and (m)–(p) 3-month-lead prediction for four months (March, May, July, and September) in 2013.

Texas is covered by the D1 drought category from USDM while large eastern regions are shown with the D0 drought category from the estimation. Overall, the model estimates drought categories well when compared with USDM.

c. *Model validation with observed drought indices for 2013–14*

The statistical model is then applied to the USDM drought category and NLDAS-2 drought indices of the period of 2013–14, which were not used in the model estimation in section 4b, to evaluate the model predictive performance. For the sample grid point, the drought category of the period of 2013–14 is estimated with Eq. (14), with parameters estimated on the basis of the data for 2001–12. The observed USDM drought category for January 2013 is D3 (with drought category D2 for December 2012). From Eq. (14), the probabilities of D2 and D3 drought categories are 0.43 and 0.48 (probabilities of other drought categories are substantially lower, given that the summation is equal to 1), and the drought category (D3) from USDM is correctly estimated (with the highest probability 0.48). Notice that the probability of D2 is close to that of D3 and is also likely to be the estimated drought category. Thus, the change of drought category from D2 to D3 is captured, with a relatively high likelihood of drought condition persisting with D2 category (0.43).

The drought category from USDM and the estimated drought category for the validation for four months in 2013 (March, May, July, and September) is shown in Figs. 3a–h. Drought categories from the validation generally resemble the drought condition from USDM well. For example, severe-drought conditions (D2–D4) for March 2013 exist in northern Texas, are exacerbated in the summer by July 2013, and then recover by September 2013. From Figs. 3e–h, these drought patterns are revealed relatively well by the estimated drought categories (e.g., D3–D4 drought categories are estimated in July 2013 in northern Texas). Overall, the proposed method satisfactorily estimates the drought categorical form for 2013–14 with parameters that were estimated on the basis of data for 2001–12.

d. Drought prediction with predicted drought indices for 2013–14

The model in Eq. (7) can then be used for operational drought prediction in the categorical form, as based on USDM drought categories as the initial condition and drought indices from other sources, for which drought indices from statistical predictions are used in this section. To be specific, the prediction of drought indices, including SPI, SMP, and SRI, is obtained through the baseline drought prediction (Lyon et al. 2012), which is similar to the concept of ensemble streamflow prediction (ESP; Day 1985).

For an L-month-lead drought prediction, the equation for predicting a drought category Y_{t+L} can be expressed as

$$\log\left[\frac{P(Y_{t+L} \le j)}{P(Y_{t+L} > j)}\right] = \alpha_j + \boldsymbol{\beta}\mathbf{W}_{t+L} + \boldsymbol{\gamma}Y_{t+L-1}, \quad (15)$$

where $\mathbf{W}_{t+L}$ is the L-month-lead prediction of drought indices from the baseline drought prediction, and Y_{t+L-1} is the lag-1 drought category.

When $L > 1$, the lag-1 drought category Y_{t+L-1} is assumed to be the predicted drought category in the previous time step. For example, the equation for 2-month-lead prediction ($L = 2$) for the target period $t + 2$ can be expressed from Eq. (15) as

$$\log\left[\frac{P(Y_{t+2} \le j)}{P(Y_{t+2} > j)}\right] = \alpha_j + \boldsymbol{\beta}\mathbf{W}_{t+2} + \boldsymbol{\gamma}Y_{t+1}, \quad (16)$$

where $\mathbf{W}_{t+2}$ is the 2-month-lead prediction of drought indices for the target period $t + 2$ from the baseline method and Y_{t+1} is the predicted USDM for the period $t + 1$ from Eq. (15).

From the USDM drought category as the initial condition and drought indices from a statistical baseline drought prediction, drought categories can be predicted with Eq. (15) several months ahead. For the sample grid point, the 1-month-lead prediction of drought category for 2013–14 is shown in Fig. 1a (dotted line) as based on lag-1 USDM category and 1-month-lead predictions of SPI6 (Fig. 1b) and SRI3 (Fig. 1c; dotted line), which show satisfactory prediction of categorical drought when compared with that from USDM (Fig. 1a). For example, for January 2013, the predicted SPI6 and SRI3 values are −1.20 and −0.95, respectively. On the basis of the USDM drought category D2 for December 2012 and predicted SPI6 and SRI3 for January 2013, the estimated probabilities of drought falling in the D2 and D3 categories for January 2013 are 0.58 and 0.30, respectively. The predicted drought category is assigned D2, since the associated probability is the highest among all categories. Although the change of drought category from D2 to D3 is not correctly predicted in this case, the relatively high probability (0.30) of changing to the D3 drought category is estimated from the model.

Figures 3i–p show 1- and 3-month predictions of the drought category for four months in 2013 (March, May, July, and September) in Texas. The 1-month prediction generally resembles the drought condition from USDM relatively well. For example, patterns of drought development in northern Texas (including severe-drought conditions during May and July) are shown fairly well when compared with drought category from USDM in Figs. 3a–d. For 3-month drought prediction in Figs. 3m–p, the prediction generally degrades relative to that for the 1-month prediction. For example, for September 2013, the D0 drought category is predicted in the northeastern region but the drought categories from USDM are D1–D3. The prediction does show useful information in certain regions, such as northern Texas (e.g., D3–D4 drought categories for March 2013).

e. Prediction-skill assessment

The prediction skill of the proposed method is then assessed with RPSS to analyze the improvement over the reference prediction (i.e., a "persistence" forecast). The value of RPSS of the estimated drought category as based on the estimation (or the 0-month-lead prediction) for 2001–12 is shown in Fig. 4a. It is seen that RPSS is positive in the whole region, indicating satisfactory estimation of the drought category by the proposed method. In other words, the prediction with the USDM as the initial condition and drought indices from NLDAS-2 performs better than that from only the persistence of the drought category. Meanwhile, the performance of the proposed method in the categorical drought estimation with respect to that from only the individual drought index is also assessed to illustrate the improvement over the individual index (regarded as the reference prediction in this case). For simplicity, drought indices SPI (i.e., SPI6 in this study) and SMP, which are heavily used in the development of USDM, are used as references, for which the estimation of drought category follows the percentile approach recommended by USDM (Svoboda et al. 2002). The RPSS values of the estimated drought category as based on the reference SPI (Fig. 4b) and SMP (Fig. 4c) for 2001–12 in

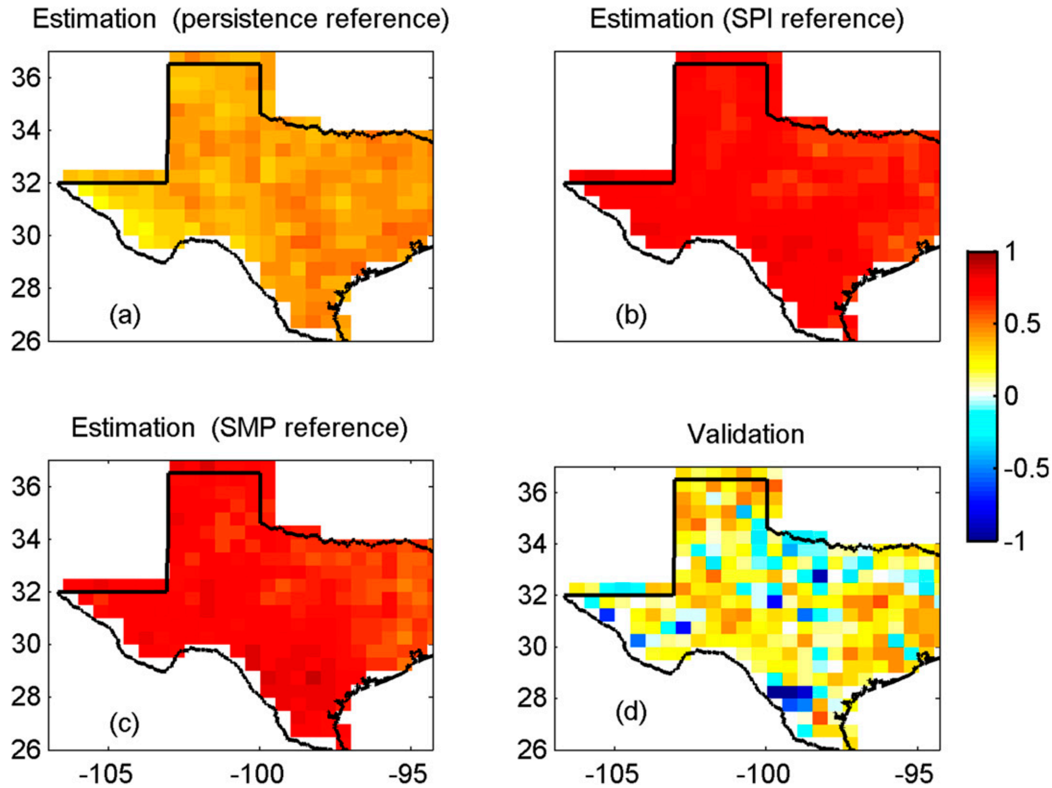

FIG. 4. RPSS for estimation as based on 2001–12 with the reference defined as (a) persistence, (b) SPI, and (c) SMP, and (d) the validation as based on 2013–14.

Texas are consistently positive and relatively high, which confirms that the proposed method performs better than the individual index in estimating the drought category. This is understandable, since a unique feature of USDM is that it takes into account multiple drought indices from a variety of sources. In the following, we will focus on the comparison using persistence as the reference prediction. RPSS of the estimated drought category on the basis of the validation for 2013–14 with the drought indices from NLDAS-2 is shown in Fig. 4d. It is seen that in most regions RPSS is positive, indicating good performance of drought category predictions, although negative RPSS is shown in limited regions.

The RPSS values for 1- and 3-month predictions with the initial condition of USDM and drought indices from the statistical prediction are shown in Figs. 5a and 5b (for 3-month prediction, the reference forecast of the period t is defined as the observed value of the period $t-3$), respectively. In large portions of the regions, the RPSS value is positive for 1- and 3-month predictions, indicating better prediction from the proposed method than the reference (or persistence prediction). For the 3-month prediction, the RPSS value is negative in certain regions (e.g., northeastern Texas), indicating that the prediction performance drops off at longer lead time and that the proposed model is not performing as well as the reference. To further show the prediction performance, the bias of the drought category (drought category from 1- and 3-month prediction minus the observed USDM category) for 2013–14 is shown in Figs. 5c and 5d. For 1- and 3-month predictions, generally the drought category is underestimated to some extent in the northeastern region and is overestimated in parts of western and southwestern regions. The lag in the performance of 1- and 3-month prediction dropping off (or the lag at which the RPSS hits zero or negative value) is shown in Fig. 5e (i.e., 0 means that the proposed model is not as good as the persistence prediction at lag 0 and 3 means that the proposed model performs better than the persistence prediction at lag 3). In certain northeastern regions and limited areas in the western and southwestern regions, the prediction drops off at 0 lag; in parts of the central and eastern regions, the proposed method outperforms the persistence prediction at lag 3.

The prediction performance of the proposed method in this regard is determined by both the initial drought

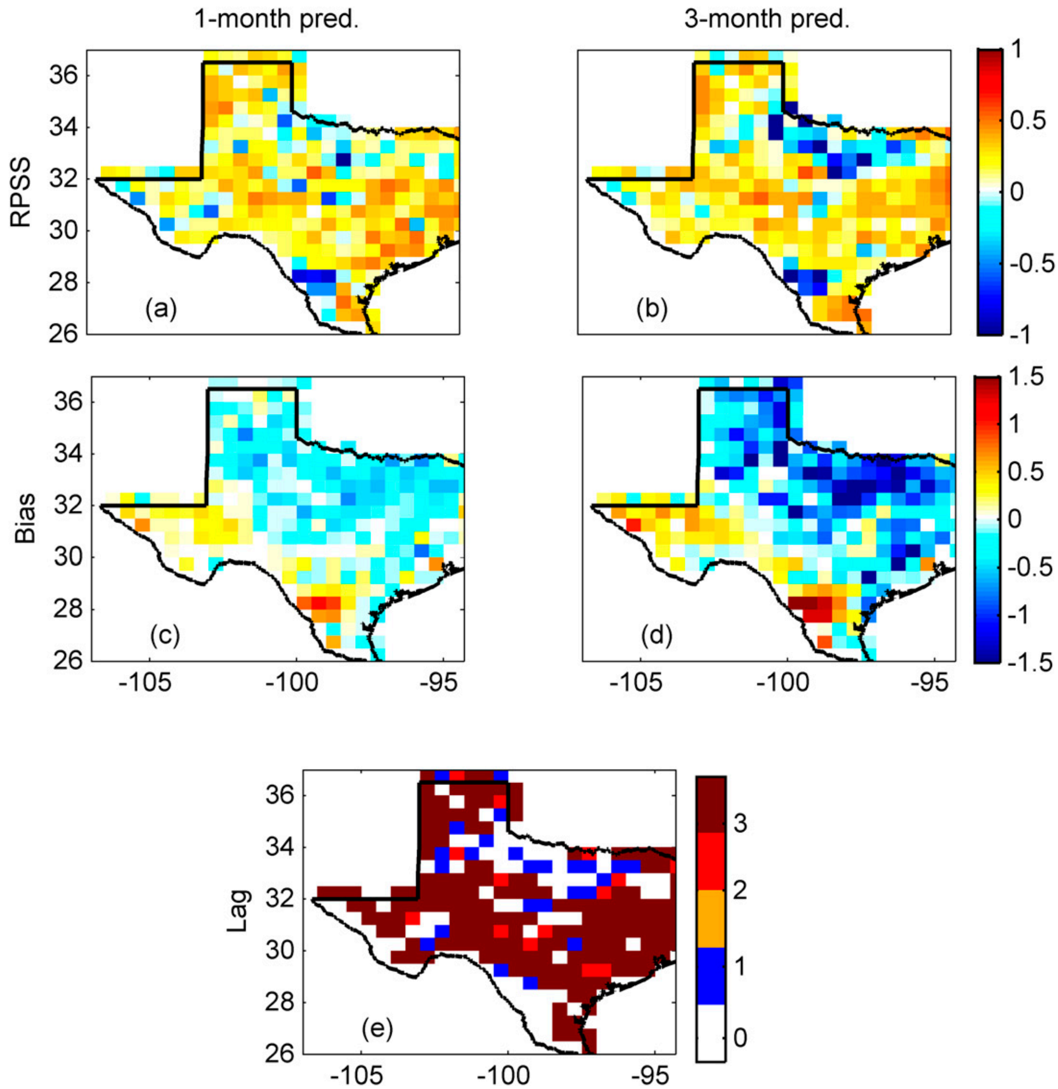

FIG. 5. RPSS for (a) 1- and (b) 3-month-lead drought prediction, along with (c), (d) the corresponding bias of the drought category for 2013–14. (e) The lag of the prediction dropping off.

condition from USDM and the prediction performance of drought indices from the baseline statistical prediction. A systematic analysis of the impact of initial condition and statistical prediction on categorical drought prediction in Texas or other regions is beyond the scope of this study and will be carried out in the future. It is also recognized that, because of the short record of USDM, the prediction performance evaluation in this section is based on observed USDM categories of two years, which may lead to some uncertainty in the assessment. Overall, the proposed method performs better than the persistence prediction of the drought category in most regions of Texas and shows good potential in operational drought prediction to aid early drought warning.

5. Discussion and conclusions

A statistical method is proposed for categorical drought prediction by integrating the USDM drought category as the initial condition with a suite of drought indices from other sources, such as land surface simulation or statistical prediction. The proposed method is tested in Texas for the period from 2001 to 2014 using USDM drought categories and drought indices from NLDAS-2, and results demonstrate its satisfactory performance in predicting drought categories. Considering the wide application of USDM, drought prediction in the same categorical form from this study shows great promise to aid drought early warning and would be useful and convenient for delivering drought information to decision makers.

Because of the complicated nature of drought, using three drought indices representing meteorological, agricultural, and hydrological drought that are based on precipitation, soil moisture, and runoff, respectively, may not be sufficient to characterize the drought condition in operational applications, and different combinations of drought indices would be needed in different regions and seasons to facilitate reliable drought prediction. In addition, only the lag-1 USDM drought category and drought indices for the target period are used as the covariate for the prediction of the drought category. In theory, USDM drought categories for different lags in the historical period and drought indices previous to the target period may also be incorporated in the model to further improve the prediction. In the model setting, a relatively large number of parameters are possibly involved to account for different drought categories and drought indices, which may be a potential limitation of this model. Considering the relatively short record of USDM, it is desirable to keep the model parsimonious in practical application. In the proposed method, when estimated probabilities of two (or more) drought categories are close it is challenging to specify the estimated drought category for decision making. In addition to selecting the drought category with the highest probability, other methods (e.g., probability-weighted average of drought categories with associated probabilities) may be used.

The statistical ESP method employed in this study to predict drought indices (SPI, SMP, and SRI) of meteorological, agricultural, and hydrologic drought in the target period can be revised or extended to improve the statistical prediction performance. Various extensions of the ESP method, which are generally based on the constructed analog or conditional relationship with climate indices, have been explored to aid the prediction of hydroclimatic variables, including precipitation, temperature, and streamflow (Delle Monache et al. 2013; Shrestha et al. 2015; Shukla et al. 2014; Wang et al. 2011; Werner et al. 2004; Yuan et al. 2013), which can also be used for drought prediction. For example, the ESP method can be revised to facilitate drought prediction on the basis of selecting or weighting historical samples either through searching historical records in past situations similar to those in progress (termed ''analogue ESP''; Yao and Georgakakos 2001) or conditioning on climate indices (termed ''conditional ESP''; Hamlet and Lettenmaier 1999; Trambauer et al. 2015). In this manner, categorical drought prediction may be improved through the refined prediction of drought indices. In addition, instead of using the statistical prediction of drought indices, the proposed method can also be extended to integrate advances in dynamical climate prediction, such as NCEP Climate Forecast System (CFSv2; Saha et al. 2014; Yuan et al. 2011) or North American Multi-Model Ensemble (NMME; Kirtman et al. 2014; Mo and Lyon 2015), to facilitate categorical drought prediction, which will be assessed in the future. Moreover, the proposed method can also be extended to incorporate information from other sources, such as large-scale atmospheric circulation patterns (e.g., ENSO), as covariates in the ordinal time series modeling to improve drought prediction in certain regions.

The proposed model essentially takes into account the previous USDM drought category, which can be regarded as the initial condition, and drought information from other sources, which can be land surface simulation and statistical prediction to provide possible drought conditions in the future, to perform a categorical drought prediction. It inherently combines multiple sources of drought information to facilitate drought prediction and thus meets the need of an integrated approach in drought characterization that has been highlighted recently. A categorical integrated drought monitoring and prediction system (CIDMAPS) is under development with the proposed method. Because the statistical prediction of drought indices employed in this study is based on the baseline drought prediction (Lyon et al. 2012), this study essentially establishes the baseline of the categorical drought prediction. The proposed method provides a flexible tool for drought prediction in categorical form in different regions in the United States and would be useful for early drought warning for operational drought management to reduce potential impacts.

Acknowledgments. The authors are grateful to the editor and anonymous reviewers for their valuable comments and suggestions. This work is supported by the program of the ''Twelfth Five-Year Plan'' for Science and Technology Research of China (2012BAD15B05) and Youth Scholars Program of Beijing Normal University (Grant 2015NT02). We thank the Environmental Modeling Center of the National Oceanic and Atmospheric Administration National Centers for Environmental Prediction for providing the NLDAS-2 datasets.

REFERENCES

Agresti, A., 2010: *Analysis of Ordinal Categorical Data*. John Wiley and Sons, 424 pp.

Akaike, H., 1974: A new look at the statistical model identification. *IEEE Trans. Autom. Control*, **19**, 716–723, doi:10.1109/TAC.1974.1100705.

Anderson, M. C., C. Hain, J. Otkin, X. Zhan, K. Mo, M. Svoboda, B. Wardlow, and A. Pimstein, 2013: An intercomparison of drought indicators based on thermal remote sensing and NLDAS-2 simulations with U.S. Drought Monitor classifications. *J. Hydrometeor.*, **14**, 1035–1056, doi:10.1175/JHM-D-12-0140.1.

Beersma, J. J., and T. A. Buishand, 2004: Joint probability of precipitation and discharge deficits in the Netherlands. *Water Resour. Res.*, **40**, W12508, doi:10.1029/2004WR003265.

Day, G. N., 1985: Extended streamflow forecasting using NWSRFS. *J. Water Resour. Plann. Manage.*, **111**, 157–170, doi:10.1061/(ASCE)0733-9496(1985)111:2(157).

Delle Monache, L., F. A. Eckel, D. L. Rife, B. Nagarajan, and K. Searight, 2013: Probabilistic weather prediction with an analog ensemble. *Mon. Wea. Rev.*, **141**, 3498–3516, doi:10.1175/MWR-D-12-00281.1.

Dutra, E., L. Magnusson, F. Wetterhall, H. L. Cloke, G. Balsamo, S. Boussetta, and F. Pappenberger, 2013: The 2010–2011 drought in the Horn of Africa in ECMWF reanalysis and seasonal forecast products. *Int. J. Climatol.*, **33**, 1720–1729, doi:10.1002/joc.3545.

Ek, M. B., and Coauthors, 2011: North American Land Data Assimilation System Phase 2 (NLDAS-2): Development and applications. *GEWEX News*, Vol. 21, No. 2, International GEWEX Project Office, Silver Spring, MD, 6–7.

FEWS NET, 2011: East Africa: Past year one of the driest on record in the eastern Horn. U.S. Agency for International Development Famine Early Warning System Network Special Rep., 1 p. [Available online at http://www.fews.net/sites/default/files/documents/reports/FEWS%20NET%20EA_Historical%20drought%20context_061411.pdf.]

Fokianos, K., and B. Kedem, 2003: Regression theory for categorical time series. *Stat. Sci.*, **18**, 357–376, doi:10.1214/ss/1076102425.

Guanche, Y., R. Mínguez, and F. J. Méndez, 2014: Autoregressive logistic regression applied to atmospheric circulation patterns. *Climate Dyn.*, **42**, 537–552, doi:10.1007/s00382-013-1690-3.

Hamlet, A. F., and D. P. Lettenmaier, 1999: Columbia River streamflow forecasting based on ENSO and PDO climate signals. *J. Water Resour. Plann. Manage.*, **125**, 333–341, doi:10.1061/(ASCE)0733-9496(1999)125:6(333).

Hao, Z., and A. AghaKouchak, 2013: Multivariate standardized drought index: A parametric multi-index model. *Adv. Water Resour.*, **57**, 12–18, doi:10.1016/j.advwatres.2013.03.009.

——, and V. P. Singh, 2013: Entropy-based method for bivariate drought analysis. *J. Hydrol. Eng.*, **18**, 780–786, doi:10.1061/(ASCE)HE.1943-5584.0000621.

——, and ——, 2015: Drought characterization from a multivariate perspective: A review. *J. Hydrol.*, **527**, 668–678, doi:10.1016/j.jhydrol.2015.05.031.

——, A. AghaKouchak, N. Nakhjiri, and A. Farahmand, 2014: Global integrated drought monitoring and prediction system. *Sci. Data*, **1**, 140001, doi:10.1038/sdata.2014.1.

——, Y. Hong, Y. Xia, V. P. Singh, F. Hao, and H. Cheng, 2016a: Modeling drought categories for probabilistic drought characterization using ordinal regression. *J. Hydrol.*, **535**, 331–339, doi:10.1016/j.jhydrol.2016.01.074.

——, and Coauthors, 2016b: Satellite remote sensing drought monitoring and predictions over the globe. *Hydrologic Remote Sensing: Capacity Building for Sustainability and Resilience*, Y. Hong, Y. Zhang, and S. I. Khan, Eds., CRC Press, 392 pp., in press.

Heim, R. R., 2002: A review of twentieth-century drought indices used in the United States. *Bull. Amer. Meteor. Soc.*, **83**, 1149–1165, doi:10.1175/1520-0477(2002)083<1149:AROTDI>2.3.CO;2.

Hoerling, M., and Coauthors, 2013: Anatomy of an extreme event. *J. Climate*, **26**, 2811–2832, doi:10.1175/JCLI-D-12-00270.1.

Kao, S. C., and R. S. Govindaraju, 2010: A copula-based joint deficit index for droughts. *J. Hydrol.*, **380**, 121–134, doi:10.1016/j.jhydrol.2009.10.029.

Keyantash, J., and J. A. Dracup, 2002: The quantification of drought: An evaluation of drought indices. *Bull. Amer. Meteor. Soc.*, **83**, 1167–1180, doi:10.1175/1520-0477(2002)083<1191:TQODAE>2.3.CO;2.

——, and ——, 2004: An aggregate drought index: Assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage. *Water Resour. Res.*, **40**, W09304, doi:10.1029/2003WR002610.

Kirtman, B., and Coauthors, 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. *Bull. Amer. Meteor. Soc.*, **95**, 585–601, doi:10.1175/BAMS-D-12-00050.1.

Luo, L., and E. F. Wood, 2007: Monitoring and predicting the 2007 U.S. drought. *Geophys. Res. Lett.*, **34**, L22702, doi:10.1029/2007GL031673.

Lyon, B., M. A. Bell, M. K. Tippett, A. Kumar, M. P. Hoerling, X.- W. Quan, and H. Wang, 2012: Baseline probabilities for the seasonal prediction of meteorological drought. *J. Appl. Meteor. Climatol.*, **51**, 1222–1237, doi:10.1175/JAMC-D-11-0132.1.

McEvoy, D. J., J. L. Huntington, J. T. Abatzoglou, and L. M. Edwards, 2012: An evaluation of multiscalar drought indices in Nevada and eastern California. *Earth Interact.*, **16**, 1–18, doi:10.1175/2012EI000447.1.

McKee, T. B., N. J. Doesken, and J. Kleist, 1993: The relationship of drought frequency and duration to time scales. Preprints, *Eighth Conf. on Applied Climatology*, Anaheim, CA, Amer. Meteor. Soc., 179–184.

Mishra, A. K., and V. R. Desai, 2005: Drought forecasting using stochastic models. *Stochastic Environ. Res. Risk Assess.*, **19**, 326–339, doi:10.1007/s00477-005-0238-4.

——, and V. P. Singh, 2010: A review of drought concepts. *J. Hydrol.*, **391**, 202–216, doi:10.1016/j.jhydrol.2010.07.012.

——, and ——, 2011: Drought modeling—A review. *J. Hydrol.*, **403**, 157–175, doi:10.1016/j.jhydrol.2011.03.049.

Mo, K. C., 2008: Model-based drought indices over the United States. *J. Hydrometeor.*, **9**, 1212–1230, doi:10.1175/2008JHM1002.1.

——, and D. P. Lettenmaier, 2014: Hydrologic prediction over the conterminous United States using the National Multi-Model Ensemble. *J. Hydrometeor.*, **15**, 1457–1472, doi:10.1175/JHM-D-13-0197.1.

——, and B. Lyon, 2015: Global meteorological drought prediction using the North American Multi-Model Ensemble. *J. Hydrometeor.*, **16**, 1409–1424, doi:10.1175/JHM-D-14-0192.1.

Otkin, J. A., M. Shafer, M. Svoboda, B. Wardlow, M. C. Anderson, C. Hain, and J. Basara, 2015: Facilitating the use of drought early warning information through interactions with agricultural stakeholders. *Bull. Amer. Meteor. Soc.*, **96**, 1073–1078, doi:10.1175/BAMS-D-14-00219.1.

Özger, M., A. K. Mishra, and V. P. Singh, 2012: Long lead time drought forecasting using a wavelet and fuzzy logic combination model: A case study in Texas. *J. Hydrometeor.*, **13**, 284–297, doi:10.1175/JHM-D-10-05007.1.

Palmer, W., 1965: Meteorological drought. Weather Bureau Research Paper 45, 65 pp. [Available online at https://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf.]

Quan, X.-W., M. P. Hoerling, B. Lyon, A. Kumar, M. A. Bell, M. K. Tippett, and H. Wang, 2012: Prospects for dynamical prediction of meteorological drought. *J. Appl. Meteor. Climatol.*, **51**, 1238–1252, doi:10.1175/JAMC-D-11-0194.1.

Rajsekhar, D., V. P. Singh, and A. K. Mishra, 2015: Multivariate drought index: An information theory based approach for integrated drought assessment. *J. Hydrol.*, **526**, 164–182, doi:10.1016/j.jhydrol.2014.11.031.

Regonda, S. K., B. Rajagopalan, and M. Clark, 2006: A new method to produce categorical streamflow forecasts. *Water Resour. Res.*, **42**, W09501, doi:10.1029/2006WR004984.

Saha, S., and Coauthors, 2014: The NCEP Climate Forecast System version 2. *J. Climate*, **27**, 2185–2208, doi:10.1175/JCLI-D-12-00823.1.

Shafiee-Jood, M., X. Cai, L. Chen, X.-Z. Liang, and P. Kumar, 2014: Assessing the value of seasonal climate forecast information through an end-to-end forecasting framework: Application to U.S. 2012 drought in central Illinois. *Water Resour. Res.*, **50**, 6592–6609, doi:10.1002/2014WR015822.

Sheffield, J., G. Goteti, F. Wen, and E. F. Wood, 2004: A simulated soil moisture based drought analysis for the United States. *J. Geophys. Res.*, **109**, D24108, doi:10.1029/2004JD005182.

——, Y. Xia, L. Luo, E. F. Wood, M. Ek, K. E. Mitchell, and N. Team, 2012: Drought monitoring with the North American Land Data Assimilation System (NLDAS): A framework for merging model and satellite data for improved drought monitoring. *Remote Sensing of Drought: Innovative Monitoring Approaches*, B. Wardlow, M. Anderson, and J. Verdin, Eds., CRC Press, 227–259.

Shrestha, R. R., M. A. Schnorbus, and A. J. Cannon, 2015: A dynamical climate model–driven hydrologic prediction system for the Fraser River, Canada. *J. Hydrometeor.*, **16**, 1273–1292, doi:10.1175/JHM-D-14-0167.1.

Shukla, S., and A. W. Wood, 2008: Use of a standardized runoff index for characterizing hydrologic drought. *Geophys. Res. Lett.*, **35**, L02405, doi:10.1029/2007GL032487.

——, C. Funk, and A. Hoell, 2014: Using constructed analogs to improve the skill of National Multi-Model Ensemble March–April–May precipitation forecasts in equatorial East Africa. *Environ. Res. Lett.*, **9**, 094009, doi:10.1088/1748-9326/9/9/094009.

Svoboda, M., and Coauthors, 2002: The Drought Monitor. *Bull. Amer. Meteor. Soc.*, **83**, 1181–1190, doi:10.1175/1520-0477(2002)083<1181:TDM>2.3.CO;2.

Trambauer, P., M. Werner, H. Winsemius, S. Maskey, E. Dutra, and S. Uhlenbrook, 2015: Hydrological drought forecasting and skill assessment for the Limpopo River basin, southern Africa. *Hydrol. Earth Syst. Sci.*, **19**, 1695–1711, doi:10.5194/hess-19-1695-2015.

Wang, E., Y. Zhang, J. Luo, F. H. S. Chiew, and Q. J. Wang, 2011: Monthly and seasonal streamflow forecasts using rainfall-runoff modeling and historical weather data. *Water Resour. Res.*, **47**, W05516, doi:10.1029/2010WR009922.

Werner, K., D. Brandon, M. Clark, and S. Gangopadhyay, 2004: Climate index weighting schemes for NWS ESP-based seasonal volume forecasts. *J. Hydrometeor.*, **5**, 1076–1090, doi:10.1175/JHM-381.1.

Wilks, D. S., 2011: *Statistical Methods in the Atmospheric Sciences*. 3rd. ed. Elsevier, 676 pp.

Wood, A. W., E. P. Maurer, A. Kumar, and D. P. Lettenmaier, 2002: Long-range experimental hydrologic forecasting for the eastern United States. *J. Geophys. Res.*, **107**, 4429, doi:10.1029/2001JD000659.

Xia, Y., and Coauthors, 2012: Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. *J. Geophys. Res.*, **117**, D03109, doi:10.1029/2011JD016048.

——, M. B. Ek, C. D. Peters-Lidard, D. Mocko, M. Svoboda, J. Sheffield, and E. F. Wood, 2014: Application of USDM Statistics in NLDAS-2: Optimal blended NLDAS drought index over the continental United States. *J. Geophys. Res. Atmos.*, **119**, 2947–2965, doi:10.1002/2013JD020994.

Yao, H., and A. Georgakakos, 2001: Assessment of Folsom Lake response to historical and potential future climate scenarios: 2. Reservoir management. *J. Hydrol.*, **249**, 176–196, doi:10.1016/S0022-1694(01)00418-8.

Yoon, J. H., K. Mo, and E. F. Wood, 2012: Dynamic-model-based seasonal prediction of meteorological drought over the contiguous United States. *J. Hydrometeor.*, **13**, 463–482, doi:10.1175/JHM-D-11-038.1.

Yuan, X., E. F. Wood, L. Luo, and M. Pan, 2011: A first look at Climate Forecast System version 2 (CFSv2) for hydrological seasonal prediction. *Geophys. Res. Lett.*, **38**, L13402, doi:10.1029/2011GL047792.

——, ——, J. K. Roundy, and M. Pan, 2013: CFSv2-based seasonal hydroclimatic forecasts over the conterminous United States. *J. Climate*, **26**, 4828–4847, doi:10.1175/JCLI-D-12-00683.1.

——, ——, and Z. Ma, 2015: A review on climate-model-based seasonal hydrologic forecasting: Physical understanding and system development. *Wiley Interdiscip. Rev.: Water*, **2**, 523–536, doi:10.1002/wat2.1088.