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Uncertainties, Correlations, and Optimal Blends of Drought Indices from the NLDAS Multiple Land Surface Model Ensemble

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ABSTRACT

This study analyzed uncertainties and correlations over the United States among four ensemble-mean North American Land Data Assimilation System (NLDAS) percentile-based drought indices derived from monthly mean evapotranspiration ET, total runoff Q, top 1-m soil moisture SM1, and total column soil moisture SMT. The results show that the uncertainty is smallest for SM1, largest for SMT, and moderate for ET and Q. The strongest correlation is between SM1 and SMT, and the weakest correlation is between ET and Q. The correlation between ET and SM1 (SMT) is strongest in arid–semiarid regions, and the correlation between Q and SM1 (SMT) is strongest in more humid regions in the Pacific Northwest and the Southeast. Drought frequency analysis shows that SM1 has the most frequent drought occurrence, followed by SMT, Q, and ET. The study compared the NLDAS drought indices (a research product) with the U.S. Drought Monitor (USDM; an operational product) in terms of drought area percentage derived from each product. It proposes an optimal blend of NLDAS drought indices by searching for weights for each index that minimizes the RMSE between NLDAS and USDM drought area percentage for a 10-yr period (2000–09) with a cross validation. It reconstructed a 30-yr (1980–2009) Objective Blended NLDAS Drought Index (OBNDI) and monthly drought percentage. Overall, the OBNDI performs the best with the smallest RMSE, followed by SM1 and SMT. It should be noted that the contribution to OBNDI from different variables varies with region. So a single formula is probably not the best representation of a blended index. The representation of a blended index using the multiple formulas will be addressed in a future study.

1. Introduction

The North American Land Data Assimilation System (NLDAS) runs four land surface models (LSMs) over the NLDAS domain covering southern Canada, the contiguous United States (CONUS), and northern Mexico in support of improved weather prediction and land data assimilation. The NLDAS was initiated in 1999 via the collaboration among the National Oceanic and Atmospheric Administration (NOAA), the National Aeronautics and Space Administration (NASA), and several universities as a tool for improving the land initial conditions for numerical weather predictions. Since then, the system has expanded its scope to include model intercomparison studies (Xia et al. 2012a,b), evaluation of NLDAS products (Peters-Lidard et al. 2011; Xia et al. 2012c), and development of a near-real-time NLDAS drought monitoring system (Ek et al. 2011; Sheffield et al. 2012; Xia et al. 2013). The drought monitoring system provides a range of drought indices, including daily, weekly, and monthly anomalies and percentiles of hydrologic fields (soil moisture, snow water equivalent, total runoff, streamflow, evaporation, and precipitation) output from the four land surface models [Noah, Mosaic, Sacramento (SAC), and Variable Infiltration Capacity (VIC)] on a common 1/8° grid using common hourly meteorological forcing (see the drought tab on the NLDAS website, www.emc.ncep.noaa.gov/mmb/nldas). The climatology of each hydrologic field

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was calculated as the average of 28 yr (1980–2007) of simulated or observed (i.e., precipitation) data. The climatology was used to generate NLDAS drought monitor (NLDASDM) products to provide to the U.S. Drought Monitor (USDM) author group. To keep the consistency of these operational products, we still use the 28-yr climatology without including recent extreme events. However, a sensitivity test shows small effects on CONUS calibration, although it may have a significant effect on a given specific region (e.g., Texas or the Great Plains). Updating the NLDAS, phase 2 (NLDAS-2), climatology (from 28 to 33 yr) is an ongoing project.

The uncertainty across models of the monthly mean total column soil moisture percentile has been assessed by Sheffield et al. (2012). The results show encouraging consistency in the depiction of large-scale drought events, although the development of drought at smaller scales appears to differ considerably across models, despite the commonality of meteorological forcings and underlying landscape parameters. Mo et al. (2011) evaluated soil moisture and water and energy fluxes from different systems, that is, the ensemble-mean of the NLDAS models (Xia et al. 2012b), the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR; Saha et al. 2010), and the North American Regional Reanalysis (NARR; Mesinger et al. 2006), using in situ observations. The results showed that the NLDAS ensemble-mean was the closest to the observations when compared with the other two systems. Mo et al. (2012) further analyzed the uncertainty of the NLDAS ensemble-mean total column soil moisture percentile using a ratio method and found that its uncertainty was small over the entire CONUS, although there were larger uncertainties in the northeast and western mountainous regions. This result is consistent with that derived from Sheffield et al. (2012).

To support U.S. operational drought monitor activity, the NCEP/Environmental Modeling Center (EMC) NLDAS team currently uses a daily archive to provide ensemble-mean total runoff, top 1-m soil moisture, and total column soil moisture percentiles at three time scales (i.e., daily, past week, and past month) to the U.S. Drought Monitor author group. These NLDAS products, particularly the top 1-m and total column soil moisture percentiles at the three time scales, are heavily used within the USDM (E. Luebuhusen 2011, personal communication). In addition, the NCEP/EMC NLDAS drought monitor also provides ensemble evapotranspiration ET percentiles to the public (see www.emc.ncep.noaa.gov/mmb/nldas/). However, except for monthly total column soil moisture percentile, the other drought indices have not been comprehensively analyzed and compared yet, although these indices have been widely used in U.S. drought monitoring and analysis (Andreadis et al. 2005; Wang et al. 2009). This study focuses on investigating uncertainties and correlations of monthly drought indices (percentiles) and using this information to establish an Objective Blended NLDAS Drought Index (OBNDI)—a unified index. The reason is that both USDM (http://droughtmonitor.unl.edu/) and NCEP Climate Prediction Center (CPC) experimental objective blends of drought indicators (www.cpc.ncep.noaa.gov/products/predictions/tools/edb/droughtblends.php) used one unified index criterion as their operational products. These two operational products have been widely used and accepted by governmental agencies and other stakeholders because of their simplicity. Therefore, one blended index can be more easily used than multiple drought indices for the public users. The blending method in this study utilizes an optimization approach called very fast simulated annealing (VFSA) as used in Xia (2007) to minimize the root-mean-square error (RMSE) between CONUS drought area percentage simulated from NLDAS blended indices and that derived from the USDM for a 10-yr period (2000–09). We first establish a link between the NLDAS drought monitor and the USDM. We use a "jackknife" method (Harnack and Lanzante 1985; Xia et al. 1999) to validate the OBNDI and reconstruct a 30-yr CONUS drought percentage area. It should be noted that a single formula is probably not the best representation of a blended index, as the contribution to OBNDI from different variables varies with region (Xia et al. 2013, 2014). The paper is organized as follows. Section 2 describes the NLDAS drought monitor and drought indices and investigates the uncertainties of these drought indices and correlations among them. Section 3 describes the optimization approach for developing the NLDAS blended drought index. Section 4 presents the reconstruction of the 30-yr OBNDI and demonstrates its capacity to capture CONUS drought areas and the spatial distribution of drought by comparing with USDM results. Section 5 gives the summary and discussion.

2. NLDAS drought monitor, drought indices, their uncertainties, and correlations

To support the National Integrated Drought Information System (NIDIS), the NLDAS team established the real-time NLDAS drought monitor (www.emc.ncep.noaa.gov/mmb/nldas/drought/). As full terrestrial water and energy cycles are represented in NLDAS, we depict drought in terms of any one or a combination of components, such as precipitation, ET, snow water equivalent SWE, streamflow, and soil moisture. The NLDAS-2 real-time monitor provides a range of drought indices, including daily, weekly, and monthly anomalies

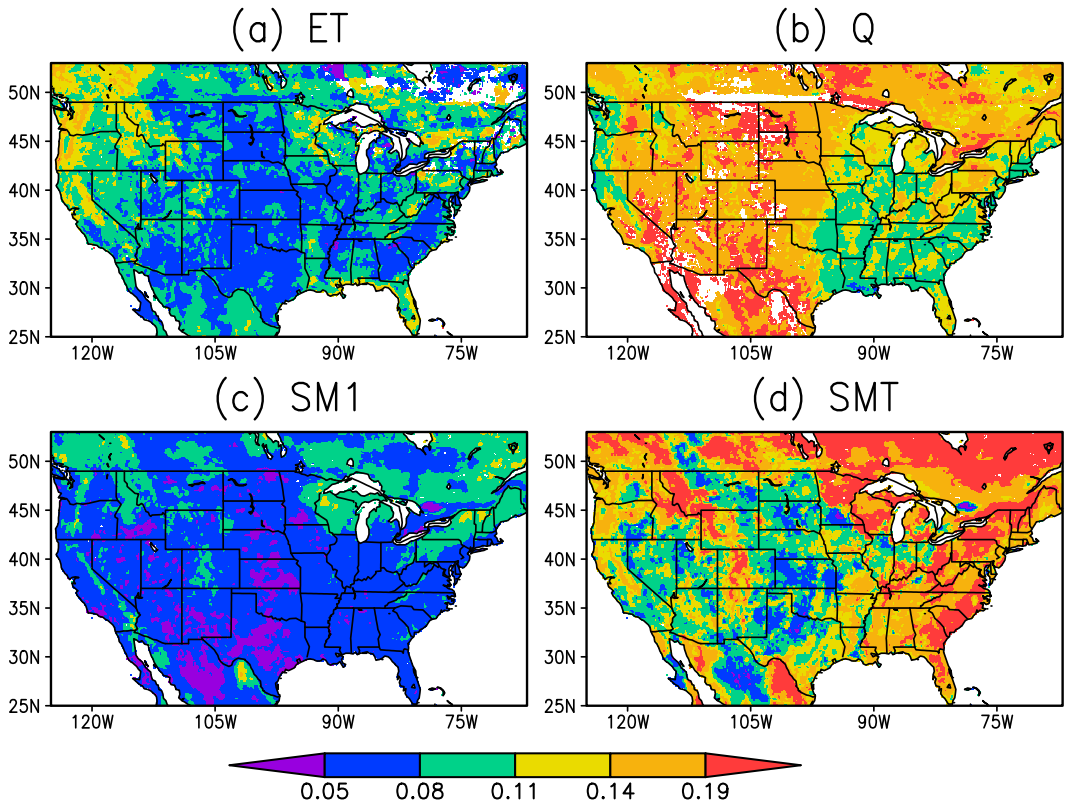

FIG. 1. Variance of ensemble-mean monthly (a) ET, (b) Q, (c) SM1, and (d) SMT percentile for a 30-yr (1980–2009) period. The variance is calculated only when the ensemble-mean percentile is <30% (when the abnormally dry case appears).

and percentiles of hydrologic fields (soil moisture, SWE, total runoff Q, streamflow, evaporation, and precipitation) output from the four LSMs on a common 1/8° grid. It therefore provides a multimodel estimate of current drought conditions across the United States. For soil moisture, the percentile climatology file contains 140 soil moisture values (five for each of the 28 yr) for each grid box. Percentiles are based upon a 5-day moving window of soil moisture values. This acts to smooth out the soil moisture record. Monthly analyses for each grid box are also computed by comparing the past 30 days to the corresponding period in the percentile climatology. Taking day 1 of the month as an example, hourly soil moisture values from this day are averaged together to form a single value. This value is then ranked against the soil moisture values from each day of the 5-day window surrounding day 1 of the corresponding month in the percentile climatology. This same process is then repeated for days 2–30 of the month, with each day of the month contributing equally to the overall ranking value. For the other variables such as SWE, Q, and ET, the same processes can be used to calculate monthly percentiles relative to their own climatologies. We used the same definition for the drought category classification as used by the USDM author group: D0 (abnormally dry, percentile ≤30%), D1 (moderate drought, percentile ≤20%), D2 (severe drought, percentile ≤10%), D3 (extreme drought, percentile ≤5%), and D4 (exceptional drought, percentile ≤2%).

A four-model ensemble mean is calculated for daily, weekly, and monthly top 1-m soil moisture SM1, total column soil moisture SMT, and total runoff and is directly provided to the USDM author group as a data source to generate the USDM. For this study, we focus on ensemble-mean drought indices at a monthly time scale. Figure 1 shows the uncertainty of four ensemble-mean drought indices: monthly percentile for ET (Fig. 1a), Q (Fig. 1b), SM1 (Fig. 1c), and SMT (Fig. 1d). The uncertainty is defined as the averaged variance:

$$\mathrm{Var}_{x,y,t} = \sqrt{\sum_{m=1}^{M} \frac{1}{M}(S_{x,y,t,m} - \overline{S}_{x,y,t})^2} \quad \text{if} \quad \overline{S}_{x,y,t} \le 30\% \tag{1a}$$

$$\mathrm{VA}_{x,y} = \frac{1}{T}\sum_{t=1}^{T} \mathrm{Var}_{x,y,t}, \tag{1b}$$

where $S_{x,y,t,m}$ is the monthly percentile of each index for yth latitude, xth longitude, tth month, and mth model. The quantity $\overline{S}_{x,y,t}$ is the four-model ensemble mean, T is the total number of months with drought severity of D0 or above (≤30%) for a 30-yr (1980–2009) period, and $\mathrm{VA}_{x,y}$ is the uncertainty.

It should be noted that this uncertainty is simply a measure of the variance across the models rather than a measure of the true uncertainty of the drought estimate. The true uncertainty in the drought estimate is much larger, since many sources of uncertainty are not accounted for here (i.e., forcing errors, etc.). The results (Fig. 1) show that there is the smallest uncertainty for SM1, the largest uncertainty for SMT and Q, and uncertainty for ET is in between. The smallest uncertainty for ET appears in arid and semiarid interior regions because of the larger evapotranspiration efficiency (evapotranspiration divided by total precipitation), and the largest uncertainty appears in the northwest of the NLDAS domain because of the smaller evapotranspiration efficiency. In contrast, small uncertainty for Q appears in wetter regions in the west and east because of the larger runoff ratio (total runoff/precipitation), and large uncertainty for Q appears in arid–semiarid interior regions because of the smaller runoff ratio. These results are consistent with previous NLDAS-2 data analyses (Xia et al. 2012b). Except for southern Canada and some parts of the northeastern and northwestern CONUS, most of the NLDAS domain has small uncertainty for SM1. Relatively large uncertainty in southern Canada northeastern and northwestern United States is snow related. The spatial distribution characteristics for SMT are similar to those for ET.

Figure 2 shows the statistically significant correlation (at the 95% confidence level) between different NLDAS indices. First, we select all available months that have a drought occurrence (D0 or above) for both indices (the contours in Fig. 2 show the number of months with simultaneous drought occurrence). The results show that there is less correlation (lower correlation) between ET and Q for all regions except for some parts of northern Mexico (Fig. 2a). There are some correlations between ET and SM1 (SMT) in arid/semiarid regions (Fig. 2b and Fig. 2c). There are stronger correlations between Q and SM1 (SMT) in wet regions (Fig. 2d and Fig. 2e). There is the strongest correlation between SM1 and SMT for most regions of the NLDAS domain, which is expected given that SMT includes SM1.

Figure 3 shows the conditional frequency of a variable being in a certain percentile range given a certain drought status (e.g., D2–D4) during a 30-yr period (1980–2009). The conditional frequency is represented as the percentage for a given pixel in a certain drought status and is calculated by counting the number of times that a variable is below a certain percentile threshold, dividing by the number of total months, and multiplying by 100%. For severe drought and above cases (from D2 to D4), ET and Q have the conditional frequencies smaller than 1% in the southwest and southeast of the NLDAS domain, respectively. SM1 has the largest conditional frequency for almost all regions of the NLDAS domain. SMT has an in-between conditional frequency. If moderate drought and abnormal drought are included, conditional frequency increases, as shown in Fig. 3. There are higher conditional frequencies of ET in arid–semiarid regions when compared to those in wet regions, and Q has higher conditional frequencies in wet regions when compared to those in arid–semiarid regions, which is consistent with the uncertainty and correlation analysis. Higher conditional frequencies also appear in arid–semiarid regions for SM1 and SMT. Overall, SM1 has the highest conditional frequencies because of the higher variability in near-surface soil moisture when compared to SMT. It should be noted that ET has small conditional frequencies (<0.1%) for D2–D4 drought status (severe drought or above) in the Great Plains, as shown in Fig. 3. Possible reasons for this depend upon the precipitation. In the no-precipitation case, available soil moisture is very limited for severe drought, and this may result in larger ET values due to high air temperature and dry air humidity until soil reaches its wilting point, when transpiration will stop and ET will become very low. In the case including precipitation, almost all precipitation is evaporated and little precipitation goes into the soil; hence, the soil is still dry, yet ET is large. Both cases may have large ET values. In addition, besides soil moisture availability, other factors such as stomatal resistance, plant coefficient related to vegetation species, and root distribution seasonal factor related to root zone soil temperature (Wei et al. 2013) may also affect ET variation (e.g., conditional frequencies for D2–D4 drought status). Therefore, dry soil moisture does not necessitate having low ET values.

3. OBNDI and its validation

In section 2, we showed that the differences between the NLDAS drought indices vary by region. Therefore, in order to combine the advantages of different indices, we propose a blended drought index for the NLDAS drought monitor:

$$\mathrm{BD} = \sum_{i=1}^{N} W_i \mathrm{PC}_i, \tag{2}$$

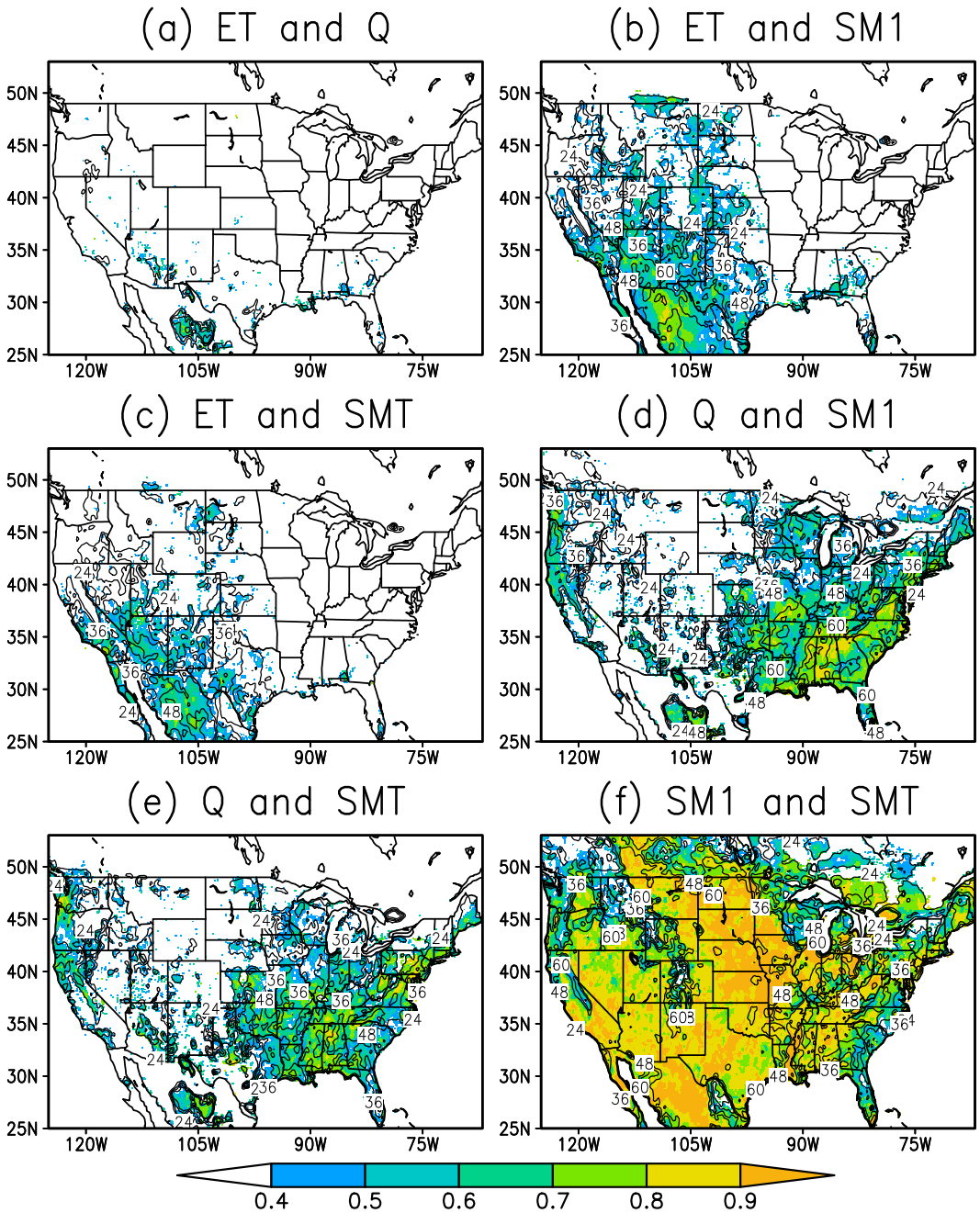

FIG. 2. Correlation between different ensemble-mean monthly percentiles: (a) ET and Q, (b) ET and SM1, (c) ET and SMT, (d) Q and SM1, (e) Q and SMT, and (f) SM1 and SMT. Contours represent the number of months when two indices simultaneously have at least D0 or above drought occurrence, and the shaded area represents the regions with significant correlation at the 95% confidence level.

where BD is a blended drought index, W_i is the weight coefficient for ith drought index PC_i, and N is the number of drought indices. Selection of these weights is a challenging issue. The CPC experimental objective blended drought monitor (CPC OBDM) (www.cpc.ncep.noaa.gov/products/predictions/tools/edb/Docs/Product_Description_Drought_Blends.html) has suggested empirical weights for a short-term blended index. However, these weights cannot be used for NLDAS drought indices as they are different from those used for CPC's blend. Therefore, we decided to use an optimization approach to select the optimal weight coefficients for the blended NLDAS drought index.

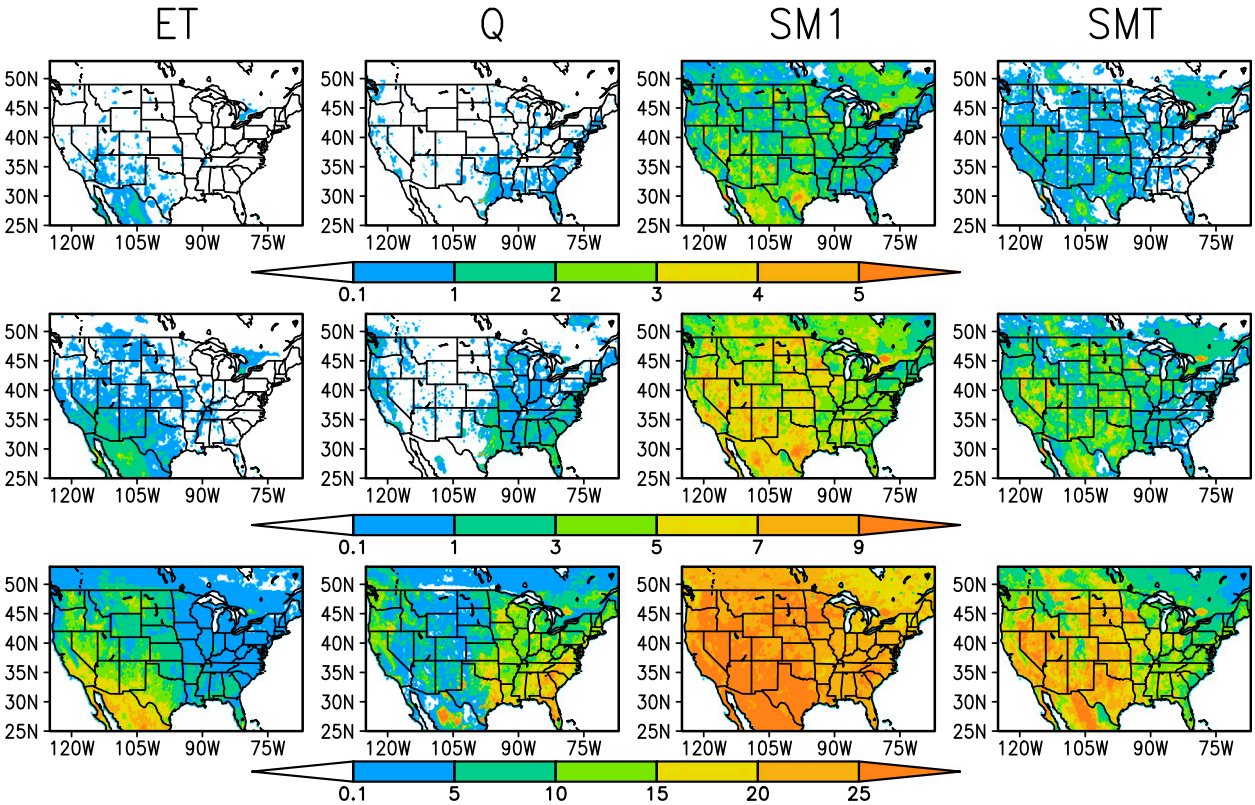

FIG. 3. The conditional frequency of a variable being in a certain percentile range given a certain drought status during a 30-yr period (1980–2009). The conditional frequency is calculated as 100 × (number of months in a given drought category)/(number of total months). (from top to bottom) D2–D4, D1–D4, and D0–D4 and (from left to right) ET, Q, SM1, and SMT.

a. Optimization approach

The optimization approach used in this study is VFSA. Details of VFSA have been described and used by many scientists (Sen and Stoffa 1996; Xia 2007). Here only a brief description is given. One may use the "temperature" parameter constructed within the Metropolis algorithm (Metropolis et al. 1953) to locate the global minimum of an error function as defined in the following section by very slowly lowering the temperature parameter within

$$P = \exp\left(\frac{-\Delta E}{T}\right), \tag{3}$$

where P is the probability of acceptance of a new parameter set with positive change of error function values, ΔE is the change in the value of error functions calculated by new and previous parameter sets (see section 3b), and T is a control parameter analogous to temperature. As used in a previous study (Xia 2007), T is set equal to 3.0. If the change is negative, this new parameter set is accepted. If the change is positive, and if and only if P is less than a randomly generated number between 0 and 1, the new parameter set is rejected. This iterative process is analogous to the annealing process within a physical system where the lowest energy state between atoms or molecules is reached by the gradual cooling of the substance within a heat bath. Because of this physical analogy, the algorithm is called "simulated annealing." To enhance the ability of simulated annealing to converge to the global minimum of the error function, Ingber (1989) introduced a new procedure for selecting parameter sets according to a temperature-dependent Cauchy distribution. This modified simulated annealing algorithm is called VFSA. This modified algorithm is described as follows.

Let us assume that model parameter m_i at kth iteration is represented by m_i^k, such that

$$m_i^{\min} \le m_i^k \le m_i^{\max}, \tag{4}$$

where $m_i^{\min}$ and $m_i^{\max}$ are the minimum and maximum values of the model parameter m_i. This model parameter value is perturbed at iteration $k + 1$ using

$$m_i^{k+1} = m_i^k + z_i(m_i^{\max} - m_i^{\min}), \quad m_i^{\min} \le m_i^{k+1} \le m_i^{\max}, \tag{5}$$

where $z_i \in [-1, 1]$. The variable z_i is generated from the distribution

$$g_T(z) = \prod_{i=1}^{\mathrm{NM}} \frac{1}{2(|z_i| + T_i)\ln\left(1 + \frac{1}{T_i}\right)} \tag{6}$$

and has a cumulative probability

$$G_{T_i} = \frac{1}{2} + \frac{\mathrm{sgn}(z_i)}{2} \frac{\ln\left(1 + \frac{|z_i|}{T_i}\right)}{\ln\left(1 + \frac{1}{T_i}\right)}, \tag{7}$$

where NM is the number of model parameter sets. Ingber (1989) showed that for such a distribution, the global minimum can be statistically obtained by using the cooling schedule

$$T_i(k) = T_{0i} \exp(-c_i k^{1/\mathrm{NM}}), \tag{8}$$

where T_{0i} is the initial temperature for model parameter i and c_i is a parameter to be used to control the temperature. The acceptance rule of the VFSA algorithm is the same as that used in the Metropolis rule. However, the VSFA is more computationally efficient when compared with the simulated annealing algorithm.

b. Experiment design

In general, the error function is defined as the RMSE between the observed and simulated data. However, observed drought data do not exist. The USDM (Svoboda et al. 2002) is a state-of-the-art drought monitoring tool in the United States that uses objective datasets as input to a subjective drought analysis. The USDM authors use six key indices [i.e., Palmer drought severity index, CPC soil moisture percentile derived from leaky bucket model, U.S. Geological Survey (USGS) daily and weekly streamflow percentile, percent of normal precipitation, standard precipitation index, and objective blends of drought indicators for long- and short-term drought] and many other indicators (approximately 30–50 in any given week) to quantify drought across the United States to manually produce a first draft of the map each week. The use of feedback from local experts, as well as information on impacts related to droughts, helps to clarify the drought severity for any particular region. These experts provide the USDM authors with their impacts, data, products, interpretations of several indicators for their local area, and comments on the current drought status and the daft map. This process ensures that USDM is close to the real U.S. drought situation for any given week. We downloaded 12 yr (2000–11) of the weekly drought percentage area over the CONUS from the USDM archives website (http://droughtmonitor.unl.edu/MapsAndData/DataTables.aspx) for five categories (D0–D4, D1–D4, D2–D4, D3–D4, and D4). We then calculated a monthly CONUS drought percentage using the number of days as weights to average the weekly values. At the same time, we calculated a monthly CONUS drought area percentage from each of the four NLDAS drought indices using the same categories and the same period as used in the USDM. We used 10-yr monthly drought area percentages to construct our error function (the last 2 yr were excluded as the USDM authors have referenced NLDAS products since 1 January 2010). The RMSE E can be defined as

$$E = \frac{1}{\mathrm{MT}} \sum_{t=1}^{\mathrm{MT}} \sqrt{\frac{1}{C} \sum_{c=1}^{C} (A_{t,c} - O_{t,c})^2}, \tag{9}$$

where MT is total number of months (120 in this study); C is the number of drought categories as described in section 3b (five in this study); and $A_{t,c}$ and $O_{t,c}$ are the CONUS drought percentage area from the OBNDI and the USDM, respectively. The ranges of all four weights are selected to be from 0 to 1. By this optimization process, VFSA automatically searches for optimal weights to minimize the error function E. The OBNDI is expressed as

$$\mathrm{OBNDI} = 0.6253\mathrm{SM1} + 0.0253\mathrm{SMT} + 0.0033\mathrm{ET} + 0.000\,01Q. \tag{10}$$

Analysis of the OBNDI shows that SM1 plays a dominant role with a 95.6% weight, SMT plays a modification role with a 3.9% weight, and ET and Q play a negligible role with a less than 0.5% weight. Therefore, SM1 is the most important NLDAS drought index and plays a dominant role in Eq. (7). In addition, we performed many sensitivity tests such as choice of error function (e.g., bias, Nash–Sutcliffe coefficient, and absolute error) and use of individual drought area percentage (e.g., D0–D4, D1–D4, D2–D4, D3–D4, D0, D1, D2, D3, D4) and use of their combinations. The results confirmed (not shown) that the RMSE used in Eq. (7) is the most appropriate error function because it generates the smallest errors and largest correlation for all five drought categories.

It should be noted that top 1-m soil moisture is used twice in the OBNDI, as total column soil moisture includes top 1-m soil moisture. The reason is that these two products have been heavily used in the USDM since January 2010. The experience from USDM authors (e.g., E. Lubuehusen 2011, personal communication)

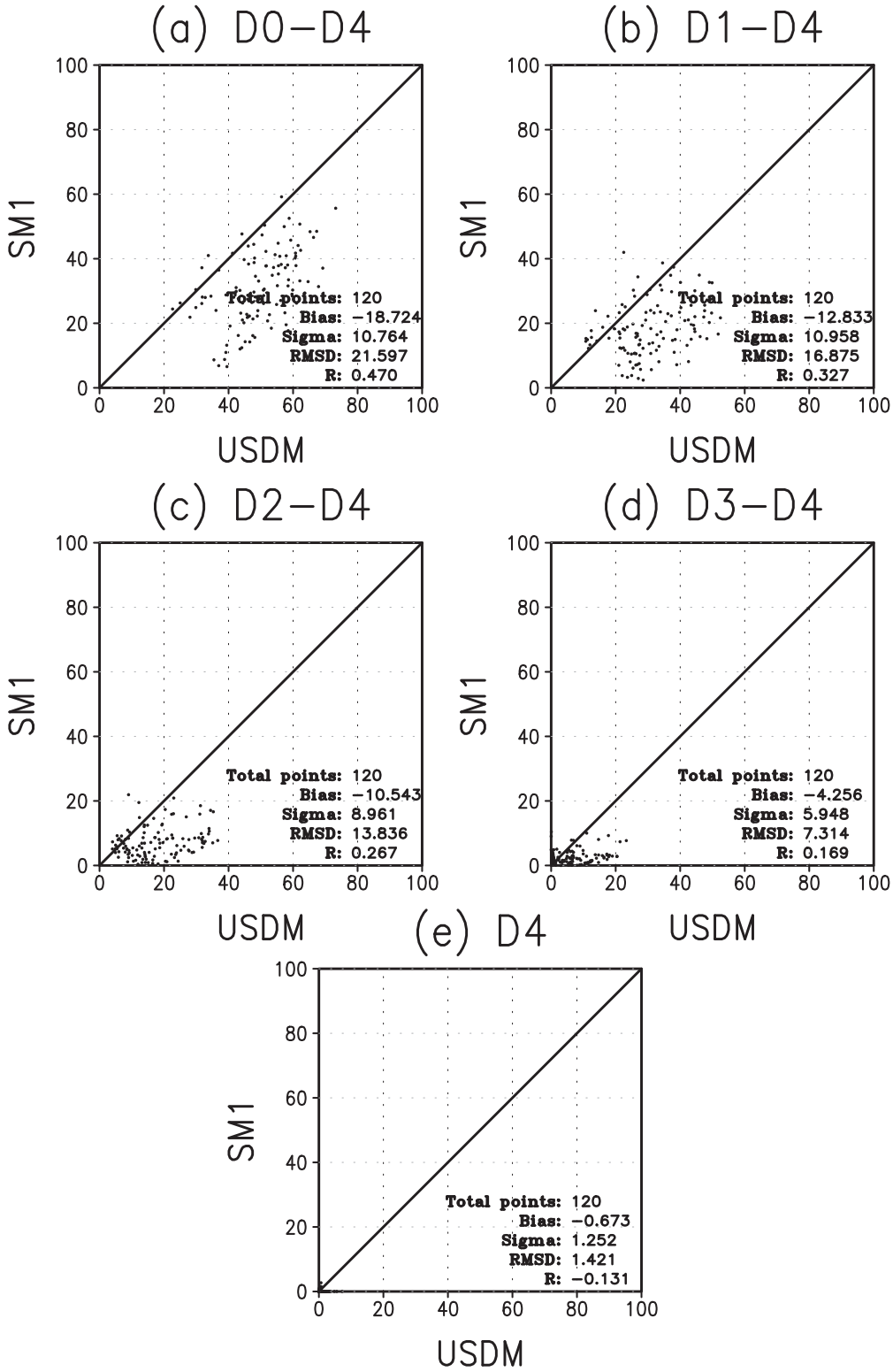

FIG. 4. Comparison of drought area percentage (%) over CONUS between NLDAS SM1 and USDM for a 10-yr period from 2000 to 2009 for drought categories: (a) D0–D4, (b) D1–D4, (c) D2–D4, (d) D3–D4, and (e) D4. The numbers are: total months, bias, standard deviation (Sigma), root-mean-square deviation (RMSD), and correlation coefficient (R). The black solid line is the 1-to-1 line.

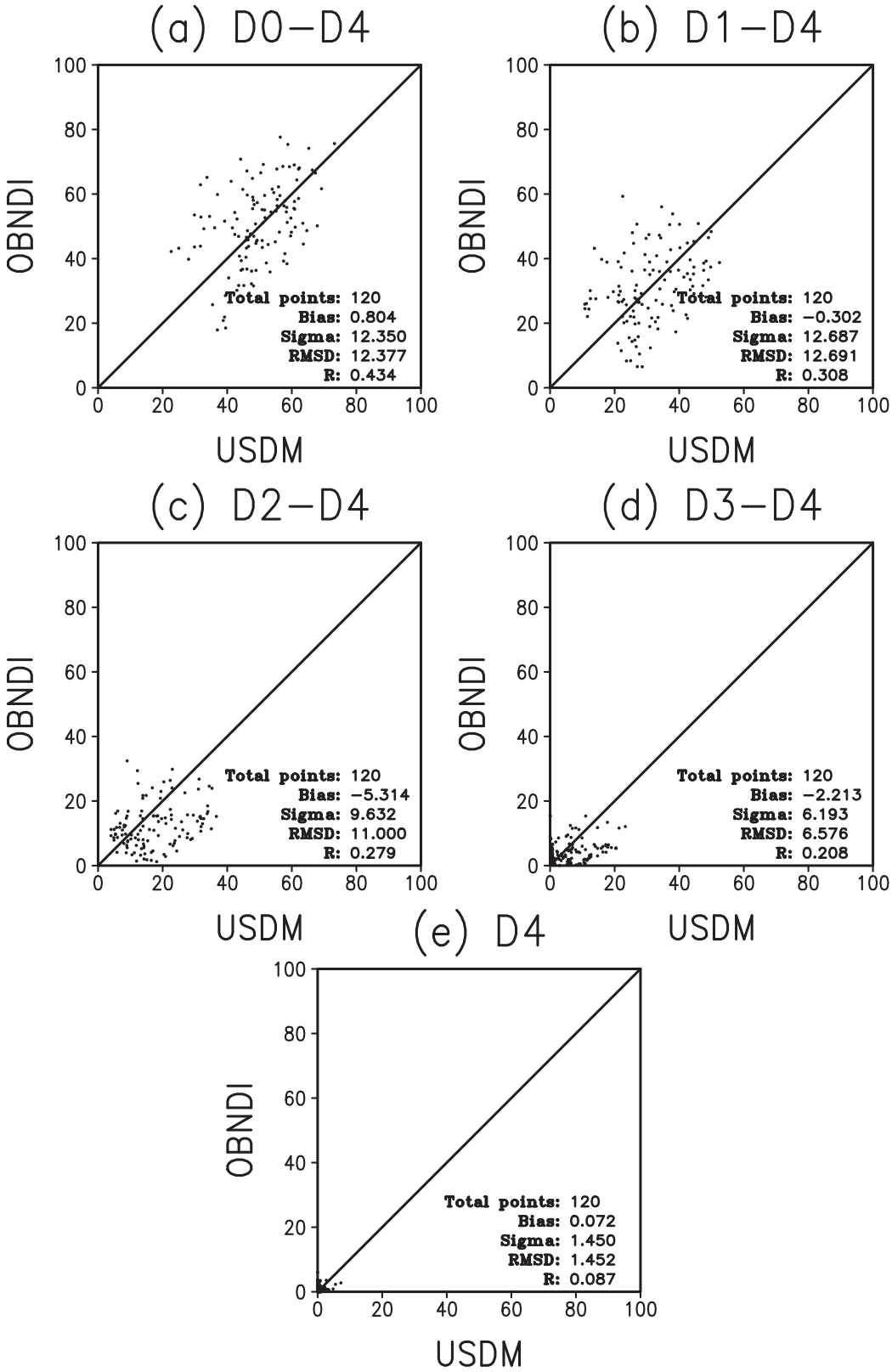

FIG. 5. As in Fig. 4, but for OBNDI and USDM.

TABLE 1. Optimal weight coefficients and error function values calculated by Eq. (9) using 9-yr data for 10 leave-one-out experiments from 2000 to 2009.

Leave one year out from 10 yr (9-yr data are used)	Error function value
2000	0.0856
2001	0.0894
2002	0.0886
2003	0.0841
2004	0.0863
2005	0.0893
2006	0.0898
2007	0.0895
2008	0.0923
2009	0.0900

TABLE 2. Optimally blended equations and their cost values when monthly percentiles for monthly SWE, SPI3, SPI6, and both SPI3 and SPI6 are incorporated into a drought blended equation (original blended equation is indicated with an asterisk).

Equation (calibration for CONUS and all months)	Cost
0.6253SM1 + 0.0253SMT + 0.0033ET + 0.00001Q	0.0882*
0.4616SM1 + 0.1682SMT +0.0001ET + 0.00003SWE	0.0891
0.2983SM1 + 0.1735SMT +0.0062ET + 0.0014SPI3	0.0945
0.0826SM1 + 0.0415SMT +0.0049ET + 0.0053SPI6	0.0879
0.1530SM1 + 0.4038SMT +0.0002SPI3 + 0.0001SPI6	0.0889
Equation [calibration for USDM West region and winter months (Dec–Mar)]	Cost
0.0956SM1 + 0.0744SMT +0.0171ET + 0.4583SWE	0.1771

demonstrated that SM1 and SMT are two important indicators for USDM. In addition, other drought monitor tools such as the U.S. Drought Monitor (http://droughtmonitor.unl.edu/) and experimental objective blends of drought indicators (www.cpc.ncep.noaa.gov/products/predictions/tools/edb/droughtblends.php) also redundantly use some key indicators such as precipitation and soil moisture in a similar way.

c. *Analysis and validation of the OBNDI*

As discussed in section 2, SM1 has the smallest uncertainty and the largest drought occurrence frequency. We first compare the CONUS drought area percentage derived from SM1 with that derived from the USDM (Fig. 4). There are significant correlations at the 5% significance level (Student's t test) for all categories except for D4. For all five categories, SM1 underestimates the USDM drought percentage area and has a large RMSE. SMT has larger bias and RMSE when compared to SM1. The bias (RMSE) is −27.0 (28.9), −19.4 (22.2), −14.1 (16.7), −5.8 (8.4), −0.7 (1.4) for D0–D4, D1–D4, D2–D4, D3–D4, and D4, respectively. The quantities ET and Q have an even much larger bias and RMSE than SMT. This means that the single NLDAS drought index alone cannot depict the USDM drought percentage area well. Figure 5 shows the comparison between drought percentage area derived from the OBNDI and USDM. The OBNDI significantly reduces biases and RMSEs for all five categories compared to SM1 (Fig. 4), although the OBNDI still underestimates the drought percentage area for D2–D4, D3–D4, and D4 categories. For D0–D4, the bias is reduced from −18.7 to 0.08 and RMSE is reduced from 21.6 to 12.4; for D1–D4, the bias is reduced from −12.8 to −0.3 and RMSE is reduced from 16.9 to 12.7; and for D2–D4, bias is reduced from −10.5 to −5.3 and RMSE is reduced from 13.8 to 11.0. For extreme drought cases, although bias and RMSE is reduced, the improvement is small (see Figs. 4, 5). Some disagreement between the OBNDI and USDM is to be expected, given that the USDM is a subjective analysis with many different inputs.

We evaluate the robustness of the results in Fig. 5 using a jackknife method (Harnack and Lanzante 1985). Nine years of data from 10-yr USDM drought area percentage are used to calibrate weight coefficients and generate cost value. This process was then repeated 10 times (each year of USDM data is left out one time) to calculate RMSE between drought area percentage of USDM and NLDAS blend for five categories (Table 1). The results show a small change when compared with the result in Fig. 5 (relative bias is smaller than 10%). This suggests that the weight coefficients calibrated from 10-yr USDM drought area percentage are robust.

d. *Impact of* SPI3, SPI6, *and* SWE *monthly percentiles*

As 3- and 6-month standard precipitation index (SPI3 and SPI6) have been widely used for meteorological drought monitoring (Heim 2002; Mo 2008; Hayes et al. 2011; Anderson et al. 2013), SPI3 and SPI6 are added to the objective blend framework and some sensitivity tests are performed. To capture impact of winter season processes on ONBDI, monthly SWE percentile derived from the NLDAS-2 VIC model is also added to the objective blend framework, as SWE has shown to have a significant impact on drought severity in western Washington State (Nijssen et al. 2013, manuscript submitted to *J. Hydrometeor.*). The VIC model is selected here as its SWE simulation is closest to the observations validated in NLDAS-1 (Pan et al. 2003; Sheffield et al. 2003) and NLDAS-2 (Xia et al. 2012b). For the other variables, such as soil moisture, ET and total runoff, ensemble-mean is used to the objective blend framework as it has the best performance when compared to any individual models (Xia et al. 2012a,b). Table 2 gives optimally blended equations and their cost values when

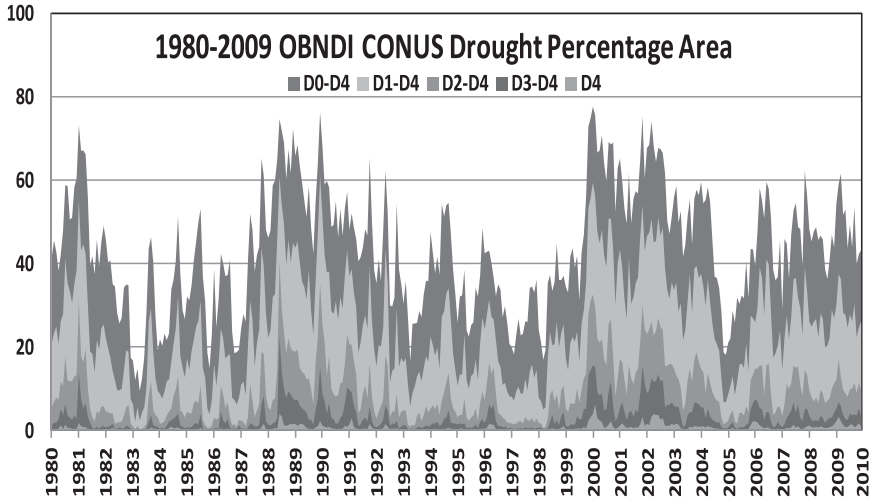

FIG. 6. Reconstructed 30-yr (January 1980 to 2010) CONUS drought area percentage for different drought categories using the OBNDI.

SPI3, SPI6, and SWE are considered. For CONUS calibration, cost value is comparable with that from ONBDI. SPI3, SPI6, and SWE have small weight (<5% total weight) when compared to soil moisture. However, for winter months (December–March) in USDM West regions (Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming; see http://droughtmonitor.unl.edu/MapsAndData/DataTables.aspx), SWE plays a dominant role (71% of total weight), soil moisture plays an important role (27% of total weight), and ET plays a small role (2% of total weight). As indicated by Anderson et al. (2013), NLDAS-2 soil moisture percentile has larger correlation with USDM than SPI3, ET, and Q, indicating the interpretation value from the land surface models. It should be noted that SPI3, SPI6, SWE, ET, and Q have small roles only when calibrating a drought area over CONUS. For a specific region or a specific season, these other variables/indices may play a dominant or an important role in an objective blend. The impact of SWE on the objective blend framework in winter months over the USDM West region has demonstrated this point. Work is ongoing to expand the spatial scale from CONUS to 6-USDM regions/48 states and to make cold and warm season tests.

4. Reconstruction and analysis of 30-yr OBNDI

Following the generation of the OBNDI using a 10-yr monthly drought area percentage dataset and its evaluation using a jackknife method, we now use the OBNDI to

TABLE 3. Billion U.S. dollar drought disasters 1980–2009 [obtained from National Climatic Data Center, Asheville, North Carolina (http://www.ncdc.noaa.gov/billions/); Texas (TX), Oklahoma (OK), Kansas (KS), California (CA), New Mexico (NM), and Arizona (AZ)].

Year	Season	Region	Damage (billion)	Deaths
1980	Jun–Sep	Central and eastern United States	$20.0	10 000
1986	Summer	Southeastern United States	$1.0	100
1988	Summer	Central and eastern United States	$40.0	7–500
1989	Aug	Northern Plains	$1.0	0
1993	Summer	Southeastern United States	$1.0	16
1996	Summer	Southern Plains	$5.0	0
1998	Summer	TX/OK	$7.5	200
1999	Summer	Eastern United States	$1.0	502
2000	Spring–summer	South-central and eastern United States	$4.0	140
2002	Spring–summer	Widespread United States	$10.0	0
2005	Spring–summer	Midwest	$1.0	0
2006	Spring–summer	Widespread United States	$6.0	0
2007	Summer–fall	Widespread United States	$5.0	16
2008	Summer	Widespread United States	$27.0	112
2009	Summer	TX, OK, KS, CA, NM, AZ	$5.0	0

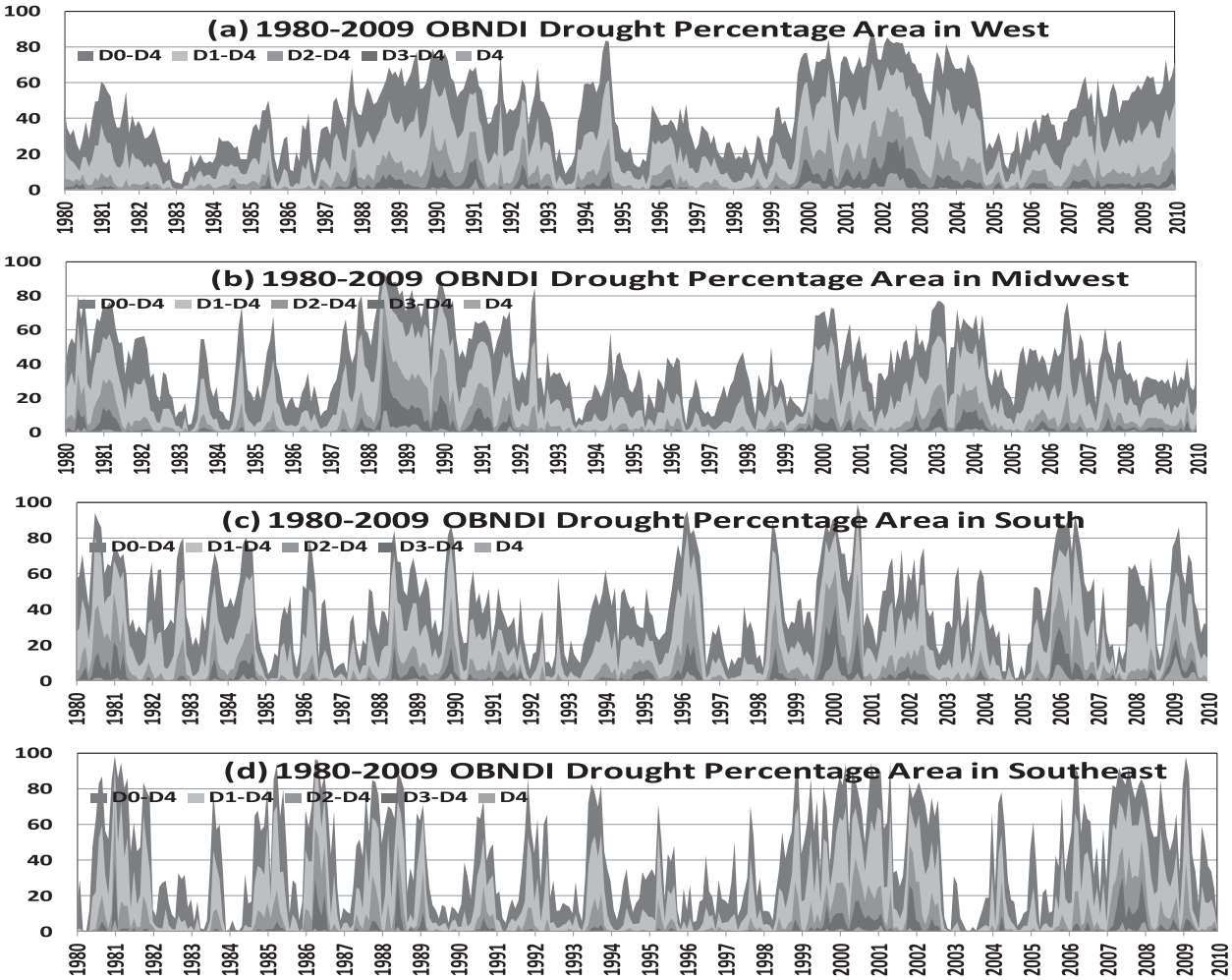

FIG. 7. Monthly variation of drought area percentage derived from OBNDI for (a) West, (b) Midwest, (c) South, and (d) Southeast region for a 30-yr period covering January–1980 to 2010.

reconstruct a 30-yr (1980–2009) monthly drought area percentage (Fig. 6) for all five categories. The results show that the OBNDI reasonably captures the droughts summarized by NCDC website for a number of notable drought years (Table 3). The strongest drought for the CONUS occurred within the 2000–04 period. Figure 7 shows the monthly variation of drought area percentage for four different regions: West, Midwest, South, and Southeast. The four regions are defined as follows: West is 25°–50°N, 125°–104°W; Midwest is 38°–50°N, 104°–81°W; South is 25°–38°N, 104°–89°W; and Southeast is 25°–38°N, 89°–67°W . The results show that the strongest drought occurred in 2002 for the West region (Fig. 7a), in 1998 for the Midwest region (Fig. 7b), in 2000 and 2006 for the South region (Fig. 7c), and in 2000 and 2007 for the Southeast region (Fig. 7d). We also analyzed the drought spatial distribution for 2000, 2002, 2006, 2007, 2009, and 2011. As one typical example, the spatial distribution of drought for the five categories for 2002 is shown in Fig. 8. From top to bottom, this represents SM1, SMT, OBNDI, and USDM, respectively. From left to right, this represents June, July, and August. For the USDM, we use the week in the middle of the month. The OBNDI outperforms SM1 and SMT relative to the USDM. As indicated by the previous analysis, SM1 has better performance than SMT. This result further suggests that SM1 is the most useful NLDAS drought index to monitor CONUS drought besides the OBNDI.

5. Summary and discussion

In this study, we investigate the uncertainty of four NLDAS drought indices (ET, Q, SM1, and SMT). The results show that the SM1 has the smallest uncertainty, SMT and Q have the largest uncertainty, and ET's uncertainty is in between in terms of intermodel variance. The correlations between ET, Q, SM1, and SMT show

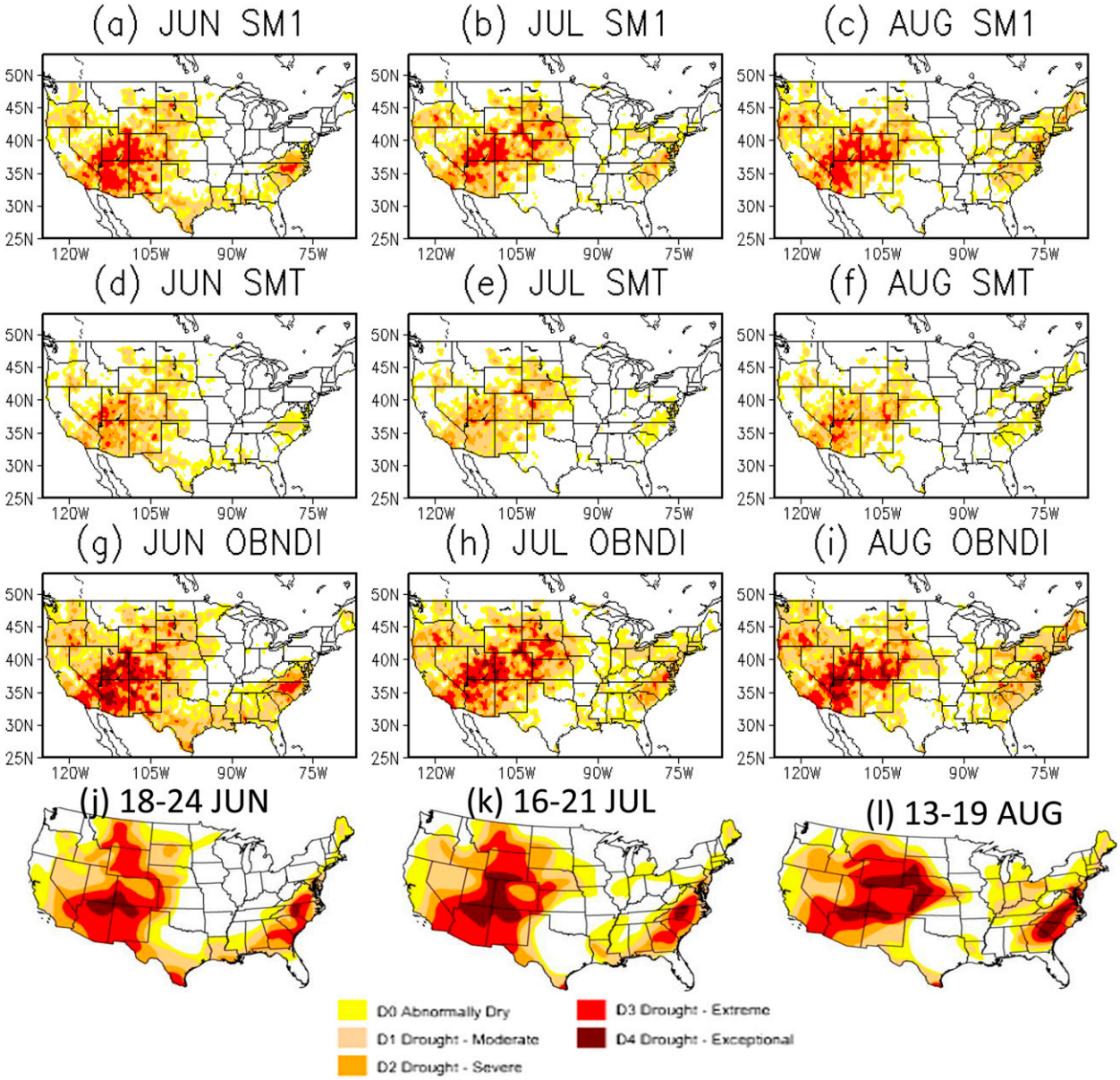

FIG. 8. Comparison of (from left to right) 2002 summer (June–August) drought conditions from (a)–(c) SM1, (d)–(f) SMT, (g)–(i) OBNDI, and (j)–(l) USDM. The first three products are on a monthly time scale and USDM is for a weekly time scale. The week in the middle of each month from USDM is used as a proxy to represent the monthly result.

that there is the strongest correlation between SM1 and SMT, the weakest correlation between ET and Q, and there is in-between correlation between ET (Q) and SM1 (SMT). For ET and SM1 (SMT), the strongest correlation mainly appears in arid–semiarid regions. For Q and SM1 (SMT), the contrary result is found. A drought frequency analysis shows that SM1 has the highest occurrence of drought and ET, Q shows the least, and the SMT result is moderate.

We used the VFSA optimization approach to establish an OBNDI by minimizing the RMSE between the CONUS drought area percentage derived from blended NLDAS drought index and the USDM. Analysis of the optimal weights shows that the weight for SM1 plays a dominant role with 95.6% of the total weight, SMT plays a small role with 3.6% of the total weight, and ET and Q play negligible roles with less than 0.5% of the total weight. The ensemble-mean SM1 and SMT underestimate the CONUS drought area percentage for all years (2000–09). This may be because 1) the USDM drought area percentage was calculated from weekly values and may be larger than ''actual'' monthly values

and 2) the simple ensemble-mean of percentiles without any adjustment diminishes the drought intensity, but we can recalculate the percentiles of the ensemble mean to reduce this problem in the future.

A jackknife method is used to do a cross-validation analysis. The results show that the OBNDI is stable and the overall performance of OBNDI is the best, followed by SM1 and SMT. We used the optimal weights to reconstruct a 30-yr (1980–2009) CONUS drought area percentage and OBNDI. The results are very encouraging when compared with those from the National Climatic Data Center (NCDC) website and USDM.

This work is novel as it establishes the linkage between the hydrometeorological products simulated from the NLDAS models (a research product) and the USDM (an operational product). However, this work still has room for improvement. One possible direction is to use this approach for each of the six regions (High Plains, Midwest, Northeast, South, Southeast, and West) as shown in the USDM archive (http://droughtmonitor.unl.edu/MapsAndData/DataTables.aspx), each state of the 48 states over CONUS (i.e., optimal weights are used as a function of state), or each division of 342 climate divisions used in the Climate Prediction Center, which is ongoing work by the NCEP/EMC NLDAS team, NASA's Hydrological Science Laboratory, and Princeton University. Furthermore, this approach can be explored for each county over the CONUS (optimal weights vary from county to county) if long-term fine-resolution (<4 km) hydrometeorological products are available, as the USDM website provides drought area percentage for each state and each county. This is possible as the EMC land-hydrology group is extending its current NLDAS system to a high-spatial-resolution (4 km) NLDAS system. This may bring some discontinuity of products between state–county boundaries, but this can be overcome using spatial smoothing. We also realize that only NLDAS products cannot totally capture variability and magnitude of USDM drought percentage area. To enhance the ability of this blend, we need to add independent drought indicators from observations (e.g., USGS streamflow percentile) and from remote sensing data [e.g., Gravity Recovery and Climate Experiment (GRACE)-based groundwater storage percentile, Vegetation Drought Response Index (VegDRI), evaporative stress index (ESI)] and operational drought indicators used in CPC objective blends [e.g., Palmer *Z* Index, Palmer Hydrologic Index, Palmer (Modified) Drought Index, and 1-month precipitation] into this blend. In addition, our NLDAS team is collaborating with CPC scientists to apply the approach developed in this study to the CPC Experimental Objective Blends of Drought Indices for short-term and long-term drought analysis and monitoring (www.cpc.ncep.noaa.gov/products/predictions/tools/edb/droughtblends.php). Some results extending the calibration region from CONUS to six USDM regions and 48 states have been addressed in our recent works (Xia et al. 2013, 2014). The results for that study will be reported in the future.

It should be noted that in its current form, OBNDI is not truly a blend, but a bias correction to SM1. However, for winter months over the USDM West region, when SWE is considered, and some cases when SPI3 and SPI6 are considered, the truly objective blend drought indices are selected by the optimization approach. Therefore, generally speaking, the objective blend framework developed in this study is feasible for the objective blend purpose of different drought indicators.

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REFERENCES

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.

Andreadis, K. M., E. A. Clark, A. W. Wood, A. F. Hamlet, and D. P. Lettenmaier, 2005: Twentieth-century drought in the conterminous United States. *J. Hydrometeor.,* **6,** 985–1001, doi:10.1175/JHM450.1.

Ek, M. B., and Coauthors, 2011: North American Land Data Assimilation System phase 2 (NLDAS-2): Its development and application to support US drought monitoring and prediction of National Integrated Drought Information System (NIDIS). *GEWEX News,* No. 21, International GEWEX Project Office, Silver Spring, MD, 7–9.

Harnack, R. P., and J. R. Lanzante, 1985: Specification of United States seasonal precipitation. *Mon. Wea. Rev.,* **113,** 319–325, doi:10.1175/1520-0493(1985)113<0319:SOUSSP>2.0.CO;2.

Hayes, M., M. Svoboda, N. Wall, and M. Widhalm, 2011: The Lincoln declaration on drought indices: Universal meteorological drought index recommended. *Bull. Amer. Meteor. Soc.,* **92,** 485–488, doi:10.1175/2010BAMS3103.1.

Heim, R. R., 2002: A review of twentieth-century drought indices used in the United States. *Bull. Amer. Meteor. Soc.,* **83,** 1149–1165.

Ingber, L., 1989: Very fast simulated re-annealing. *Math. Comput. Modell.,* **12,** 967–993, doi:10.1016/0895-7177(89)90202-1.

Mesinger, F., and Coauthors, 2006: North American Regional Reanalysis. *Bull. Amer. Meteor. Soc.,* **87,** 343–360, doi:10.1175/BAMS-87-3-343.

Metropolis, N., A. Rosenbluth, M. Rosenbluth, A. Teller, and E. Teller, 1953: Equation of state calculations by fast computing machines. *J. Chem. Phys.,* **21,** 1087–1092, doi:10.1063/1.1699114.

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

——, L. N. Long, Y. Xia, S. K. Yang, J. E. Schemm, and M. B. Ek, 2011: Drought indices based on the Climate Forecast System Reanalysis and ensemble NLDAS. *J. Hydrometeor.,* **12,** 181–205, doi:10.1175/2010JHM1310.1.

——, L.-C. Chen, S. Shukla, T. J. Bohn, and D. P. Lettenmaier, 2012: Uncertainties in North American Land Data Assimilation Systems over the contiguous United States. *J. Hydrometeor.,* **13,** 996–1009, doi:10.1175/JHM-D-11-0132.1.

Pan, M., and Coauthors, 2003: Snow process modeling in the North American Land Data Assimilation System (NLDAS): 2. Evaluation of model-simulated snow water equivalent. *J. Geophys. Res.,* **108,** 8850, doi:10.1029/2003JD003994.

Peters-Lidard, C., S. V. Kumar, D. M. Mocko, and Y. Tian, 2011: Estimating evapotranspiration with land data assimilation systems. *Hydrol. Processes,* **25,** 3979–3992, doi:10.1002/hyp.8387.

Saha, S., and Coauthors, 2010: The NCEP Climate Forecast System Reanalysis. *Bull. Amer. Meteor. Soc.,* **91,** 1015–1057, doi:10.1175/2010BAMS3001.1.

Sen, M. K., and P. L. Stoffa, 1996: Bayesian inference, Gibbs' sampler and uncertainty estimation in geophysical inversion. *Geophys. Prospect.,* **44,** 313–350, doi:10.1111/j.1365-2478.1996.tb00152.x.

Sheffield, J., and Coauthors, 2003: Snow process modeling in the North American Land Data Assimilation System (NLDAS): 1. Evaluation of model-simulated snow cover extent. *J. Geophys. Res.,* **108,** 8849, doi:10.1029/2002JD003274.

——, Y. Xia, L. Luo, E. F. Wood, M. Ek, and K. E. Mitchell, 2012: The North American Land Data Assimilation System (NLDAS). *Remote Sensing of Drought: Innovative Monitoring Approaches,* B. Wardlow, M. Anderson, and J. Verdin, Eds., CRC Press, 227–260.

Svoboda, M., and Coauthors, 2002: The Drought Monitor. *Bull. Amer. Meteor. Soc.,* **83,** 1181–1190.

Wang, A., T. J. Bohn, S. P. Mahanama, R. D. Koster, and D. P. Lettenmaier, 2009: Multimodel ensemble reconstruction of drought over the continental United States. *J. Climate,* **22,** 2694–2712, doi:10.1175/2008JCLI2586.1.

Wei, H., Y. Xia, K. E. Mitchell, and M. B. Ek, 2013: Improvement of the Noah land surface model for warm season processes: Evaluation of water and energy flux simulation. *Hydrol. Processes,* **27,** 297–303, doi:10.1002/hyp.9214.

Xia, Y., 2007: Calibration of LaD model in the northeast of the United States using observed annual streamflow. *J. Hydrometeor.,* **8,** 1098–1110, doi:10.1175/JHM618.1.

——, P. Fabian, A. Stohl, and M. Winterhalter, 1999: Forest climatology: Estimation of missing values for Bavaria, Germany. *Agric. For. Meteor.,* **96,** 131–144, doi:10.1016/S0168-1923(99)00056-8.

——, M. B. Ek, H. Wei, and J. Meng, 2012a: Comparative analysis of relationships between NLDAS-2 forcings and model outputs. *Hydrol. Processes,* **26,** 467–474, doi:10.1002/hyp.8240.

——, and Coauthors, 2012b: 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.

——, and Coauthors, 2012c: Continental-scale water and energy flux analysis and validation for North American Land Data Assimilation System project phase 2 (NLDAS-2): 2. Validation of model-simulated streamflow. *J. Geophys. Res.,* **117,** D03110, doi:10.1029/2011JD016051.

——, B. A. Cosgrove, M. B. Ek, J. Sheffield, L. Luo, E. Wood, K. Mo, and the NLDAS Team, 2013: Overview of the North American Land Data Assimilation System (NLDAS). *Land Surface Observation, Modeling and Assimilation,* S. Liang, X. Li, and X. Xie, Eds., World Scientific, 337–377.

——, 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.,* doi:10.1002/2013JD020994, in press.