An Evaluation of the North American Regional Reanalysis Simulated Soil Moisture Conditions during the 2011–13 Drought Period

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ABSTRACT

Accurate and timely information on soil moisture conditions is an important component to effectively prepare for the damaging aspects of hydrological extremes. The combination of sparsely dense in situ networks and shallow observation depths of remotely sensed soil moisture conditions often force local and regional decision-makers to rely on numerical methods when assessing the current soil state. In this study, soil moisture from a commonly used, high-resolution reanalysis dataset is compared to observations from the U.S. Climate Reference Network (USCRN). The purpose of this study is to evaluate how well the North American Regional Reanalysis (NARR) captured the evolution, intensity, and spatial extent of the 2012 drought using both raw volumetric values and standardized anomalies of soil moisture. Comparisons revealed that despite a dry precipitation bias of 22% nationally, NARR had predominantly wetter 5-cm volumetric soil conditions over the growing season (April–September) than observed at USCRN sites across the contiguous United States, with differences more pronounced in drier regions. These biases were partially attributed to differences between the dominant soil characteristics assigned to the modeled grid cells and localized soil characteristics at the USCRN stations. However, NARR was able to successfully capture many aspects of the 2012 drought, including the timing, intensity, and spatial extent when using standardized soil moisture anomalies. Standardizing soil moisture conditions reduced the magnitude of systematic biases between NARR and USCRN in many regions and provided a more robust basis for utilizing modeled soil conditions in assessments of hydrological extremes.

1. Introduction

Soil conditions are a critical component of the moisture and energy transfers that impact weather and climate systems through local, regional, and global feedbacks (Legates et al. 2011; Seneviratne et al. 2010). The influence of this feedback is particularly evident during extreme hydrological dry events, such as droughts. While atmospheric circulations and interannual variability (i.e., El Niño and La Niña) have been found to influence the onset and prolong drought conditions (Trenberth and Guillemot 1996), once drought has been established the availability of soil moisture for evapotranspiration will reduce over time, resulting in surface warming as the soil dries (Seneviratne et al. 2010). The increased warming leads to further drying, creating a positive feedback that reinforces and often intensifies drought conditions (AghaKouchak et al. 2014; Trenberth et al. 2013). Karl et al. (2012) attributed the severity of the 2012 drought, which resulted in an estimated $31.5 billion in damages and 123 related deaths (Smith et al. 2016), in part to this temperature-reinforcing feedback. In addition, the impacts of hydrological extreme events are still

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felt following the recovery, with lingering effects on commodity prices and elevated societal risks (e.g., forest fires, poor water quality, health impacts, and temperature extremes) in the years and months that follow. To mitigate agricultural and societal impacts to future events, timely and accurate data on soil conditions are necessary for forecasters, local decision-makers, and others assessing the severity of and managing societal risks to hydrological extremes (Sheffield et al. 2004).

Despite the importance of soil moisture data, high-quality in situ observations and remotely sensed soil conditions are often limited spatially or have short observational records (Seneviratne et al. 2010; Sheffield et al. 2004). For in situ measurements, this is further complicated by a lack of consistent instrumentation type (e.g., gravimetric, neutron probes, heat dissipation sensors, time, and frequency domain reflectometry), reporting depths, and calibration methods used among the available in situ networks. These differences make it challenging to combine observations from multiple networks (Ford et al. 2015; Robock et al. 2000); however, attempts to merge multiple soil monitoring networks are underway for weather and climate modeling purposes both in the United States (Quiring et al. 2016) and globally (Dorigo et al. 2011).

Methods to monitor soil conditions directly through satellite remote sensing are generally limited to the first few centimeters of the soil column, and the utility of these observations is impacted by vegetation density, atmospheric transparency, and processing algorithms (Seneviratne et al. 2010). Some general purpose satellite instruments have been used to estimate soil moisture, including passive microwave systems such as the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) and active microwave systems such as the Advanced Scatterometer (ASCAT; Ochsner et al. 2013). The first dedicated satellite for measuring soil moisture using the more moisture-sensitive L-band of microwave emissions was the ESA Soil Moisture Ocean Salinity (SMOS) mission, which achieved good results in test watersheds (Jackson et al. 2012) but tended to have difficulties with radio frequency interference and a dry bias in some regions (Ochsner et al. 2013). The NASA Soil Moisture Active Passive (SMAP) mission satellite has proven to be quite successful in recent comparisons with in situ calibration sites, achieving a $0.038\,m^3\,m^{-3}$ unbiased root-mean-square difference in estimating volumetric soil moisture over 36-km^2 cells (Chan et al. 2016). However, these results are strongly impacted by vegetation density since vegetation also emits L-band radiation from water in the plants, which impact soil moisture estimates. While microwave remote sensing can provide surface state inputs for modeling deeper layers of soil moisture, only the critical information captured by in situ networks can be used to verify these models or estimate vegetation health and its feedbacks on the atmosphere (i.e., evapotranspiration rates, roughness length, and albedo; Legates et al. 2011; McPherson 2007). Furthermore, it is challenging to estimate deeper soil conditions from the top layer, as soil moisture conditions at deeper depths do not always temporally align well with the upper layers (Bell et al. 2015; Ford et al. 2014). Given the lack of spatially dense soil monitoring networks and limitation of remotely sensed products, current evaluations of soil conditions used in many applications often rely upon numerical modeling methods to provide temporally and spatially continuous soil moisture estimates (Sheffield et al. 2004).

Model simulations of soil conditions by necessity use simplified representations of complex hydrological processes such as lateral flow over topography, infiltration, gravity percolation, evapotranspiration, and interactions with the water table, among others, potentially introducing biases and/or range limits in simulated soil moisture results. These factors are further compounded by the spatially heterogeneous vegetation type, canopy density, and soil characteristics over the model grid, which must be represented as one or several dominant soil and vegetation types (Xia et al. 2015a) within the land surface model (LSM). LSMs simulate these hydrological processes in addition to radiative, heat, and moisture transfers between the land and atmosphere. There are a number of LSMs, each developed with its own purpose and set of governing equations (Koster et al. 2009), which can result in a range of estimated soil conditions with the same atmospheric forcing. Moreover, the choice of the LSM and how it interacts (coupled or offline) with the atmospheric model may also result in some additional model uncertainty (Fan et al. 2011; Koster et al. 2009). Despite the variety of potential error sources for simulated soil conditions, many of these biases should remain consistent throughout a model run. Therefore, a stable model may produce relative soil moisture changes over time that parallel the seasonal evolution of observed soil moisture conditions (Koster et al. 2009) and possibly capture the evolution of hydrological extremes (drought and saturation; Mesinger et al. 2006).

In this study, simulated soil conditions from the North American Regional Reanalysis (NARR) will be compared with in situ measurements from the U.S. Climate Reference Network (USCRN) over the 2012 drought, which is one of the most widespread droughts in recent American history (Hoerling et al. 2014). The purpose of this study is to investigate the ability of a widely used and available reanalysis model to simulate soil moisture extremes during drought. The performance of NARR will be evaluated from both absolute and relative perspectives, focusing on its ability to simulate soil moisture trends, intensity, and the spatial extent of the 2012 drought. It is anticipated that the NARR may not model absolute quantities of volumetric soil moisture well in some circumstances, as noted by Xia et al. (2015a,b), but may resolve the time evolution, intensity, and spatial extent of soil moisture changes during the 2012 drought, making it a useful tool for local and regional decision-makers to monitor ongoing and future hydrological extremes with a historical context.

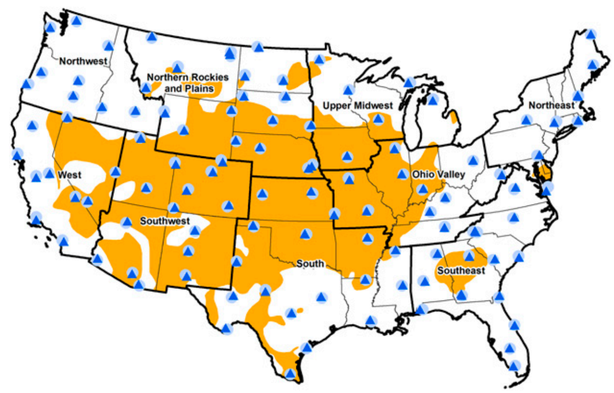

FIG. 1. Map of USCRN stations (blue triangles) and selected nearest NARR grids (light blue circles) used in the comparison study overlaid on the National Drought Monitor's areas experiencing severe to exceptional drought conditions (orange) for 21 Aug 2012 and the National Centers for Environmental Information (NCEI) climate regions (bold outlines).

2. Data description

a. NARR

NARR is a model product from the National Centers for Environmental Prediction (NCEP) that simulates historical (1979) to present atmospheric and soil conditions (Mesinger et al. 2006). The model assimilates a variety of available observational datasets to improve model performance, including ground-based, dropsonde, rawinsonde, aircraft, satellite, and ship data, but does not assimilate in situ soil data. NARR does assimilate gauge precipitation data; this is accomplished indirectly by altering the latent energy profile, which has been found to improve the simulation of precipitation over other reanalyses (Mesinger et al. 2006; Nigam and Ruiz-Barradas 2006). However, Nigam and Ruiz-Barradas (2006) and Dominguez and Kumar (2008) note that the assimilation process for precipitation can create imbalances between the atmosphere and land surface model, impacting modeled evaporation and soil moisture. The impacts of the assimilation process should be taken into consideration when evaluating the performance of NARR with respect to in situ data. NARR products are available at a 3-h frequency over a 32-km resolution grid that covers North America with 45 levels in the vertical. Soil conditions (temperature and moisture) are simulated using a coupled Noah[1] LSM, which simulates land–atmosphere interactions (surface evaporation, energy) and soil conditions. The Noah LSM uses the Penman approach to approximate potential evaporation from a single canopy model and at the midpoint of four layers within the soil columns at depths of 5, 25, 70, and 150 cm (Chen and Dudhia 2001; Mitchell 2005).

b. USCRN

The USCRN is a climate monitoring network providing observations of surface (temperature, precipitation, wind speed, relative humidity, solar radiation, and surface inferred temperature) and subsurface (soil moisture and temperature) conditions from 114 stations in the contiguous United States (CONUS) at hourly to subhourly temporal resolution (Diamond et al. 2013). The network began monitoring soil conditions during the summer of 2009 with full deployment across the CONUS completed in 2011 (Bell et al. 2013). Soil moisture and temperature are observed nominally at five depths: 5, 10, 20, 50, and 100 cm. Three redundant sets of probes are installed at three plots surrounding the station's instrument tower (within 2.0 m), using the Stevens HydraProbe. This probe is a coaxial impedance dielectric reflectometry sensor that detects the real dielectric of the soil, which is converted to volumetric soil moisture using the general loam equation of Seyfried et al. (2005). For the deeper soil layers (20, 50, and 100 cm), the exact depth of each sensor may vary with soil conditions. The lower-layer depths were installed only where the soil was deep enough and had few rocks; 25 of the 114 stations do not have any soil probes below 10 cm depth. The monitoring depths for each station are available in the USCRN metadata system (https://www.ncdc.noaa.gov/isis/stationlist?networkid=1). Sensor redundancy provides quality-control (QC) processes with multiple observations from which to identify failing–drifting sensors and reducing the number and length of data gaps (backup sensors), which enhances the quality and continuity of the soil climate record. In addition to automated QC, soil observations are manually reviewed at a monthly frequency to monitor sensor health and identify suspicious observations missed by automated QC. Soil data are stored as an hourly average of redundant sensors for each layer, with 5-min values available

[1] The Noah LSM is a community model developed in collaboration with the National Centers for Environmental Prediction, Oregon State University, Air Force, and Hydrologic Research Laboratory (Noah).

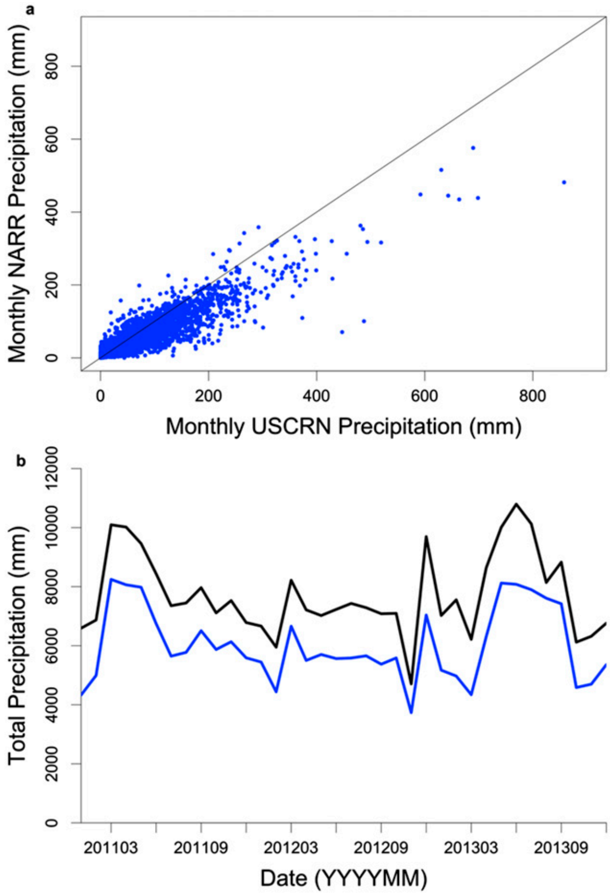

FIG. 2. USCRN and NARR (a) scatter plot of nationally averaged monthly precipitation and (b) time series of USCRN (black) and NARR (blue) accumulated national total precipitation.

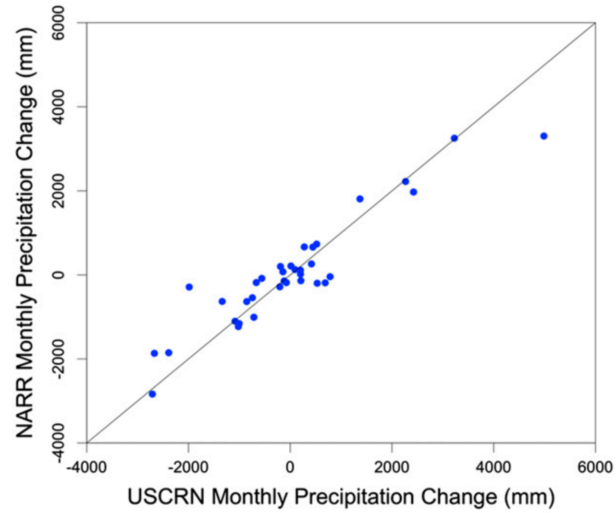

FIG. 3. Scatterplot of USCRN and NARR first-order differences of monthly national total precipitation.

for the top 5-cm soil layer. For a more complete description of this dataset, see Bell et al. (2013).

3. Methodology

NARR and USCRN precipitation and soil moisture conditions at the 5-cm depth were compared over the 2012 drought. The 5-cm depth was chosen to maximize the number of locations available for comparison since NARR lacked a 10-cm equivalent depth and only 89 of the 114 USCRN stations reported at depths deeper than 10 cm. To resolve temporal differences between USCRN (hourly) and NARR (3 hourly), station observations were resampled to the lower temporal resolution by taking the hourly observation that corresponded to NARR output times (0000, 0300, 0600, 0900, 1200, 1500, 1800, and 2100 UTC). For precipitation, USCRN hourly data were summed over the 3-h periods that matched NARR precipitation aggregates. If any of the precipitation or soil moisture observations from NARR or USCRN were missing, the variables from both NARR and USCRN for this time period were omitted.

The NARR variables used for precipitation and 5-cm soil moisture were the total precipitation (the sum of microphysical and convective-based precipitation; A_PCP_221_SFC_acc3h) and the top layer of the nonfrozen soil moisture variable (SOILL_221_DBLY). The NARR data used for the comparison with USCRN were taken from the model grid nearest to the corresponding station based on the distance from the grid centroid (Fig. 1). Only NARR grids where soil conditions were modeled (i.e., over land surfaces) were considered in the selection process, which resulted in an average grid-centroid to USCRN station distance of 11.8 km. NARR comparisons with USCRN were evaluated as NARR minus USCRN and included the coefficient of determination r^2 and index of agreement D metrics to assess goodness of fit described by Legates and McCabe (1999). The D was developed by Willmott (1981) to overcome limitations of r^2 that can result in high correlations despite sizable differences and as described in Eq. (1), where O is observation, $\overline{O}$ is the observation mean, P is the prediction, $\overline{P}$ is the prediction mean, and i is the ith iteration over the total observations N:

$$D = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2}. \quad (1)$$

The comparison evaluated the evolution, intensity, and spatial extent of the 2012 drought at the national,

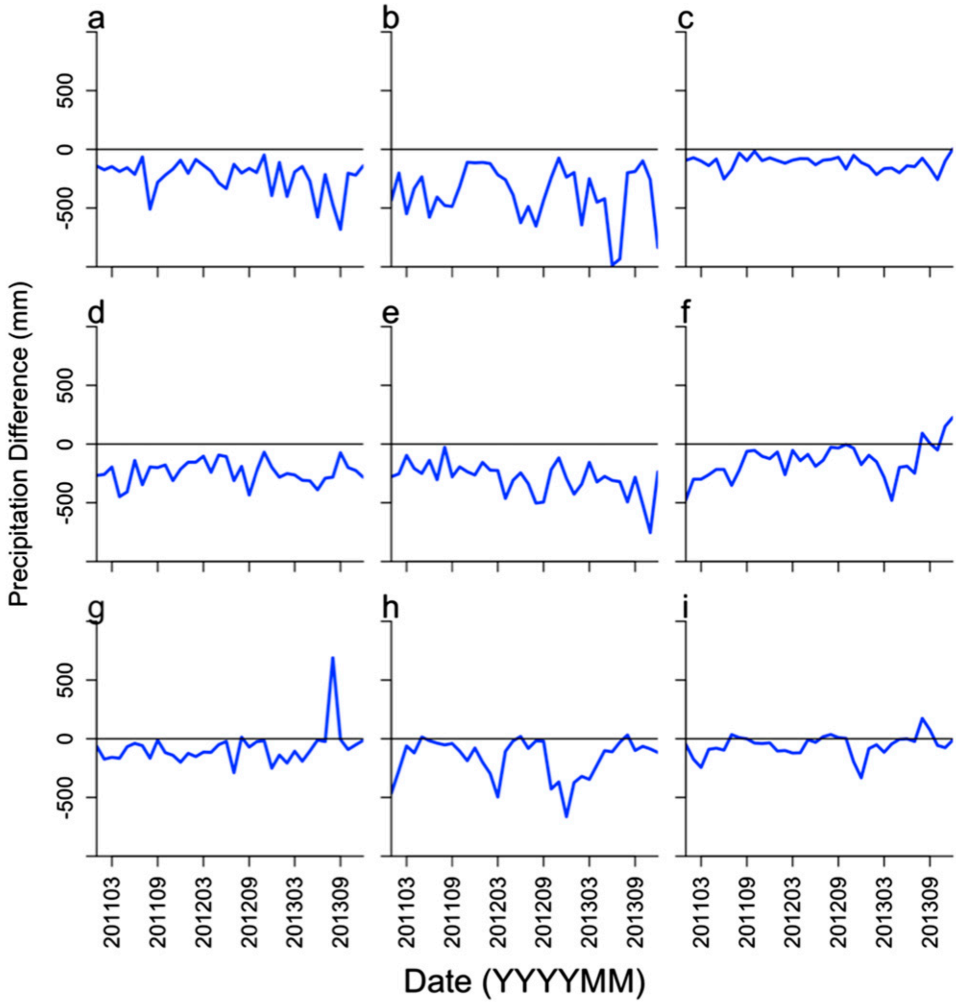

FIG. 4. Regional NARR minus USCRN monthly precipitation from 2011 to 2013 for the (a) Northeast, (b) Southeast, (c) upper Midwest, (d) Ohio Valley, (e) South, (f) northern Rockies and Great Plains, (g) Southwest, (h) Northwest, and (i) West.

regional [climate regions defined by Karl and Koss (1984)], and station levels.

NARR and USCRN were compared at each CONUS station for the period from January 2011 (predrought) to December 2013 (post drought) to cover the evolution of the 2012 drought similar to Bell et al. (2015). In addition to comparing volumetric soil moisture measurements, standardized anomalies of USCRN and NARR soil data were evaluated to monitor soil moisture tendencies from the mean. Soil moisture anomalies for NARR and USCRN were computed based upon the station's period of record (POR), 5–6 yr for most stations, to September 2014, which is the last date available from NARR at the time. This was done to ensure NARR and USCRN anomalies were computed over the same period for each station. While national and regional variations in station PORs may impact the spatial congruity of anomalies among some neighboring stations, this will have little impact on the analysis of NARR's performance over the 2012 drought, which is the intent of this study. The temporally aligned observations from USCRN and NARR were smoothed using a 7-day moving window with the mean computed at the center to lessen the impact of brief spikes in sensor observations associated with rain events. NARR and USCRN interannual means and standard deviations were calculated over each station's POR and then smoothed with a 15-day running mean in order to remove seasonal cycles. Anomalies were then calculated by taking the original 7-day smoothed soil moisture values and subtracting the 15-day smoothed POR mean time series; standardized anomalies were then generated by dividing the anomalies by the POR standard deviation. Standardization of soil conditions lessens the impacts of location and peak-to-trough spread in the dataset as described by Steinemann (2003).

While anomalies are traditionally computed using base periods over a decade or longer, Quiring et al. (2015) found that soil moisture measurements from a small number of years (3–6 yr) provided a stable cumulative distribution function similar to the 15-yr dataset from which subsets were drawn. These results suggest that shorter PORs are not necessarily an impediment to evaluating soil moisture anomalies. In addition, the intent of the use of anomalies in this study was to compare relative shifts in modeled and observed soil conditions from the mean rather than assessments of hydroclimatic changes over time.

4. Results

a. Precipitation comparison

NARR simulated less gridcell precipitation than observed at USCRN locations (Figs. 2a,b). This was particularly evident for wetter months (>300 mm), resulting in a U.S. monthly average dry bias for all station locations of 14.9 mm or −22%. The dry bias may be attributed to the inability of the model's convective scheme to simulate heavier intragridcell precipitation rates. The model dry bias was nearly systematic and persistent from 2011 to 2013 (Fig. 2b), but NARR and USCRN did have similar month-to-month precipitation first-order differences (Fig. 3). The similar temporal patterns of monthly precipitation between USCRN and NARR indicate NARR was able to capture both reductions in monthly total precipitation leading into drought and a recovery in 2013 similar to USCRN, including a lack of precipitation in the spring of 2012.

The NARR precipitation bias was also evident across U.S. climate divisions (Figs. 4a–i). Mean precipitation biases ranged between −5.5 and −25.8 mm (−16.7% and −29.0%), with some of the larger biases observed in the eastern half of the United States, where conditions are generally wetter (Table 1). The coefficient of determination and the index of agreement, which ranged between 0.59 and 0.90 and 0.83 and 0.96, respectively, also showed generally higher levels of agreement for western regions. The better agreement may be attributed to a strong positive NARR precipitation bias that occurred between August and December 2013, which eased the prior year's (2011 and 2012) negative precipitation biases, shown in Figs. 4f–i. The larger contrasts in precipitation between NARR and USCRN impacts these regions' soil moisture comparisons during the 2013 recovery year, as will be discussed below.

TABLE 1. NARR monthly averaged precipitation regional mean difference, percent difference, coefficient of determination, and index of agreement.

Region	Mean difference (mm)	Percent difference (%)	r^2	D
National	−14.9	−22.0	0.81	0.91
Northeast	−25.8	−25.3	0.65	0.83
Southeast	−22.2	−21.2	0.72	0.87
Upper Midwest	−19.2	−29.0	0.76	0.87
Ohio Valley	−21.8	−21.9	0.76	0.88
South	−15.5	−25.4	0.83	0.90
Northern Rockies and Great Plains	−7.5	−17.5	0.70	0.90
Southwest	−5.6	−19.8	0.59	0.86
Northwest	−18.3	−19.6	0.84	0.92
West	−5.5	−16.7	0.90	0.96

b. Soil moisture comparison

The soil moisture comparison was conducted using only the warm season months from April to September, so as to avoid frozen soil conditions. Despite a dry precipitation bias, NARR simulated wetter mean volumetric soil moisture conditions than observed at USCRN locations by 0.05 $m^3 m^{-3}$ nationally (Table 2). Standardized anomalous soil moisture conditions would produce a mean of exactly zero if averaged over the base period, but in this case, only a subset of months were averaged, so the results deviate from zero. However, NARR and USCRN mean standardized differences were still very close to zero (Table 3), much more so than in the case of their absolute soil moisture values. A scatterplot of 5-cm volumetric soil moisture (Fig. 5a) revealed that NARR tended to overestimate soil moisture in dry conditions and underestimate soil moisture in wet conditions compared to USCRN, resulting in relatively low r^2 and D values of 0.27 and 0.66, respectively (Table 2). The scatterplot shows NARR had lower (~0.05 $m^3 m^{-3}$) and upper bounds (around 0.4 $m^3 m^{-3}$) when simulating volumetric soil moisture conditions (Fig. 5a), which may have been caused by contrasts between modeled and actual field capacity and wilting point at USCRN stations. It may be that the NARR grids and USCRN point locations have dissimilar capabilities of soil moisture storage that limited the range of simulated moisture conditions. Standardized anomalous soil conditions between NARR and USCRN were somewhat better correlated with an r^2 of 0.32 and D of 0.77 (Table 3), with no obvious threshold limitations from the scatterplot despite some spread (Fig. 5b). While NARR-modeled volumetric and standardized anomalous soil conditions were driest in 2012, standardized anomalous soil moisture conditions between NARR and USCRN were much more similar than volumetric (Figs. 6a,b).

TABLE 2. NARR monthly averaged 5-cm volumetric soil moisture regional mean difference, coefficient of determination, and index of agreement.

Region	Mean difference ($m^3 m^{-3}$)	r^2	D
National	0.05	0.27	0.66
Northeast	0.00	0.04	0.47
Southeast	0.06	0.30	0.67
Upper Midwest	−0.01	0.02	0.46
Ohio Valley	0.00	0.53	0.83
South	0.03	0.32	0.68
Northern Rockies and Great Plains	0.04	0.21	0.65
Southwest	0.09	0.37	0.57
Northwest	0.11	0.42	0.63
West	0.12	0.26	0.44

TABLE 3. As in Table 2, but for standardized soil moisture anomaly.

Region	Mean difference (std dev)	r^2	D
National	0.00	0.37	0.78
Northeast	0.08	0.16	0.65
Southeast	0.03	0.49	0.83
Upper Midwest	0.05	0.19	0.68
Ohio Valley	0.15	0.55	0.85
South	0.06	0.40	0.79
Northern Rockies and Great Plains	−0.07	0.51	0.85
Southwest	−0.19	0.21	0.69
Northwest	−0.11	0.45	0.82
West	0.07	0.19	0.68

For six of the nine regions, NARR had a wet volumetric soil moisture bias, with the other three having biases near 0, from −0.01 to 0.12 $m^3 m^{-3}$ (Table 2). Volumetric biases were generally larger in the driest portions of the country (i.e., West, Southwest, and Northwest regions; Table 2) and when soil moisture conditions were drier over the three years (Figs. 7a–i). The larger volumetric biases for the drier locations/periods are thought to be associated with the model's higher limit on minimal soil moisture conditions, as shown in Fig. 5a, which results in a persistent wet bias relative to USCRN as stations observe drier conditions (Figs. 7h,i). However, standardized anomalous soil moisture conditions, which evaluate how soil conditions differ from the interannual mean, revealed NARR simulated drier than observed conditions in these western regions with the exception of the West (Table 3). In fact, six of the nine regions had negligible standardized anomaly differences of less than 0.1 standard deviation.

Despite the wet bias, NARR was able to simulate drier volumetric soil moisture in regions experiencing drought (Fig. 7a); however, the volumetric values during drought conditions differed considerably between USCRN and NARR. In the South and Southeast, which experienced drought during 2011, NARR and USCRN volumetric soil conditions were driest in 2011 before recovering in 2012 and 2013 (Figs. 7b,d). For regions hardest hit with the 2012 drought (the Ohio Valley, the upper Midwest, and the northern Rockies and Great Plains), NARR was able to capture 2012 as the driest of the three years with differing rates of recovery in 2013 (Figs. 7c,e,f). NARR standardized anomalous soil moisture also captured the evolution of drought over these regions, but with considerably smaller offsets from observed, which indicate the model was able to capture relative changes from the POR mean during drought intensity over the regions. However, NARR anomalous soil conditions diverged from USCRN with a strong wet bias in the West and Southwest regions, likely due to stronger monsoonal activity, as noted previously in Figs. 4g and 4i.

A station analysis of mean soil moisture over the summer months (June–August) from 2011 to 2013 was performed to identify spatial patterns of drought intensity. Apart from an obvious wet to dry gradient across the United States (east to west), which was persistent from year to year, the spatial extent of the 2012 drought was difficult if not impossible to detect using volumetric data, even from USCRN observations (Figs. 8a–c). However, a drought signal over U.S. interior regions was discernible from USCRN volumetric station data when comparing individual station summer means from year to year (Figs. 8a–c). This was less clear for NARR (Figs. 8d–f). However, standardized soil moisture anomalies clearly showed the spatial extent and intensity of the 2012 drought across central regions of the United States (Figs. 9a–f). In 2011, USCRN and NARR standardized soil moisture anomalies showed drier soil conditions (<-0.5 standard deviation) over Texas and the Southeast, although NARR had more continuous and drier (<-1.0 standard deviation) soil anomalies in western Texas and southern New Mexico. Despite similar overall spatial patterns in 2012, USCRN had a larger area of negative standardized soil moisture anomalies (<-1.0 standard deviation) over Indiana, Ohio, and parts of the upper Midwest than NARR, indicating NARR simulated drought conditions were not as severe in some locations. During the recovery in 2013, USCRN and NARR both had standardized anomalies greater than 1.0 standard deviation over much of the Southeast and Northeast regions. However, USCRN had a much wider band of positive standardized soil moisture anomalies (>0.5 standard

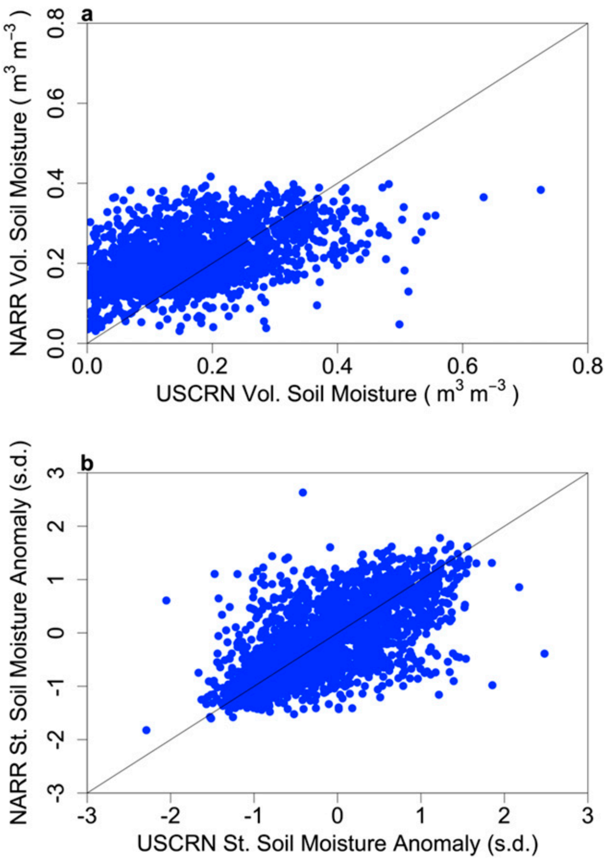

FIG. 5. USCRN vs NARR monthly average (a) volumetric soil moisture and (b) standardized soil moisture anomalies.

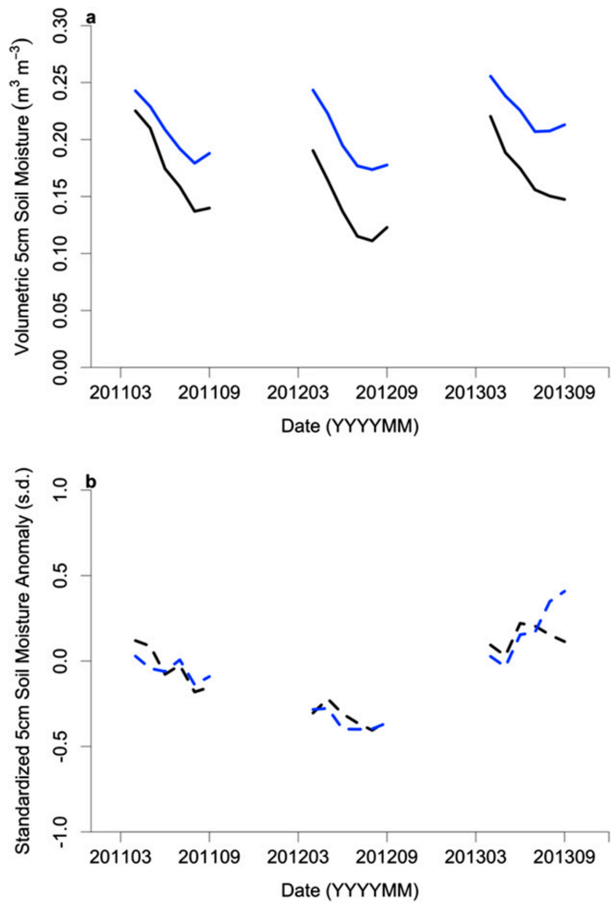

FIG. 6. Time series of USCRN (black) and NARR (blue) national monthly 5-cm averaged (a) volumetric soil moisture and (b) standardized soil moisture anomaly.

deviation) that extended into the southern Ohio Valley and Northeast regions (Figs. 9c,f). These results show that NARR was able to capture similar spatial patterns of standardized departures during the 2012 drought as observed, but slightly underreported the severity of the extreme conditions at some stations. In the South and Southwest, NARR modeled drier than observed conditions over the 2011 drought area in contrast to underreporting extremes in the 2012 drought.

5. Discussion and conclusions

NARR modeled precipitation was consistently less than observed at USCRN stations. The NARR bias was detected both nationally and regionally, which may be partially explained by different spatial scales between the model grid (representing an area) and USCRN stations (representing a point). However, spatial inhomogeneity in the distribution of precipitation across a model grid will diminish over monthly time scales (Gutowski et al. 2003). In addition, the NARR bias was more systematic in time than would be expected if spatial inhomogeneity was the primary factor for NARR and USCRN differences. Further research that included a denser network of stations monitoring precipitation also had a similar dry bias with respect to NARR (not shown here). These results suggest that precipitation biases found in this study are likely more attributed to biases associated with the model, which could include limitations in the convective parameterization scheme, dampened vertical motions within the model as noted by Jones et al. (1995), or the assimilation dataset or processes. Further inquiries into NARR precipitation biases using multiple networks or the assimilation dataset used in NARR may be warranted to isolate these biases further. However, NARR precipitation for most regions had similar temporal trends with respect to USCRN and was able to capture a drought signal with less precipitation in 2012 than was observed despite the systematic biases.

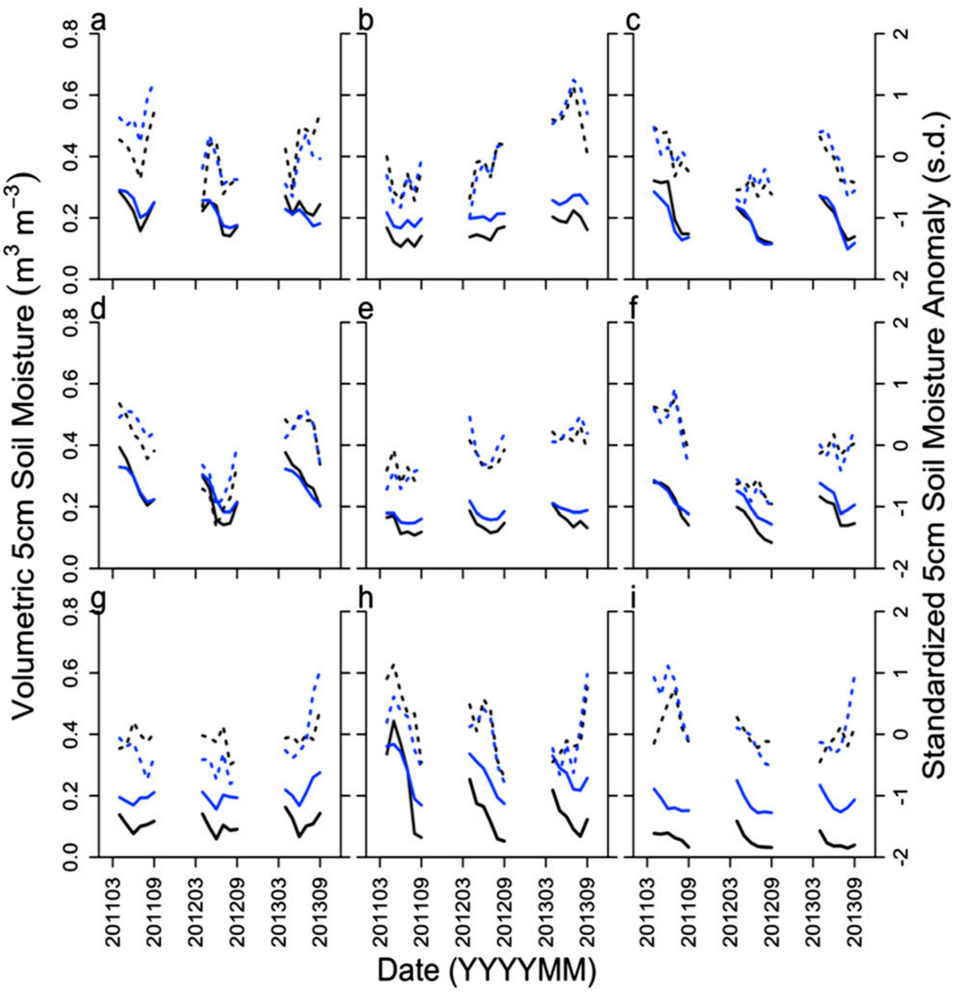

FIG. 7. USCRN (black) and NARR (blue) monthly 5-cm averaged volumetric soil moisture (solid lines) and standardized anomaly (dashed lines) for the (a) Northeast, (b) Southeast, (c) upper Midwest, (d) Ohio Valley, (e) South, (f) northern Rockies and Great Plains, (g) Southwest, (h) Northwest, and (i) West.

For soil moisture conditions, NARR overestimated (underestimated) moisture at the 5-cm depth for drier (wetter) soils conditions, which was in line with earlier comparisons studies using the Noah LSM (Fan et al. 2011; Koster et al. 2009; Xia et al. 2015a). The soil moisture biases were likely related to a combination of multiple issues such as the assimilation process for precipitation, which can negatively impact surface evaporation (Dominguez and Kumar 2008), the choice of dominant soil characteristics over the model grid, and or grid scale versus point measurements. Given that the direction of soil moisture biases varied with soil moisture condition (dry bias during wet conditions and vice versa) and that other studies (Xia et al. 2015a) using denser state mesonets found similar-sized wet soil moisture bias from the Noah LSM used in this study, the choice of soil characteristics in the model likely had a larger role in the NARR bias as described by Xia et al. (2015a,b). Further comparisons of NARR and USCRN soil moisture minima and maxima from 2011 to 2013 show that soil moisture extremes from NARR were not as severe as observed (Figs. 10a,b), which supports the assertion that the model has a wilting point and field capacities that did not match well with USCRN stations. If similar results are found in other soil monitoring networks, these results suggest NARR may not be capable of simulating extreme volumetric soil moisture conditions and that the direction of the modeling bias will change with extreme type (flooding vs drought), warranting further research.

Despite the challenges of NARR to simulate soil moisture extremes, standardized soil moisture anomalies were

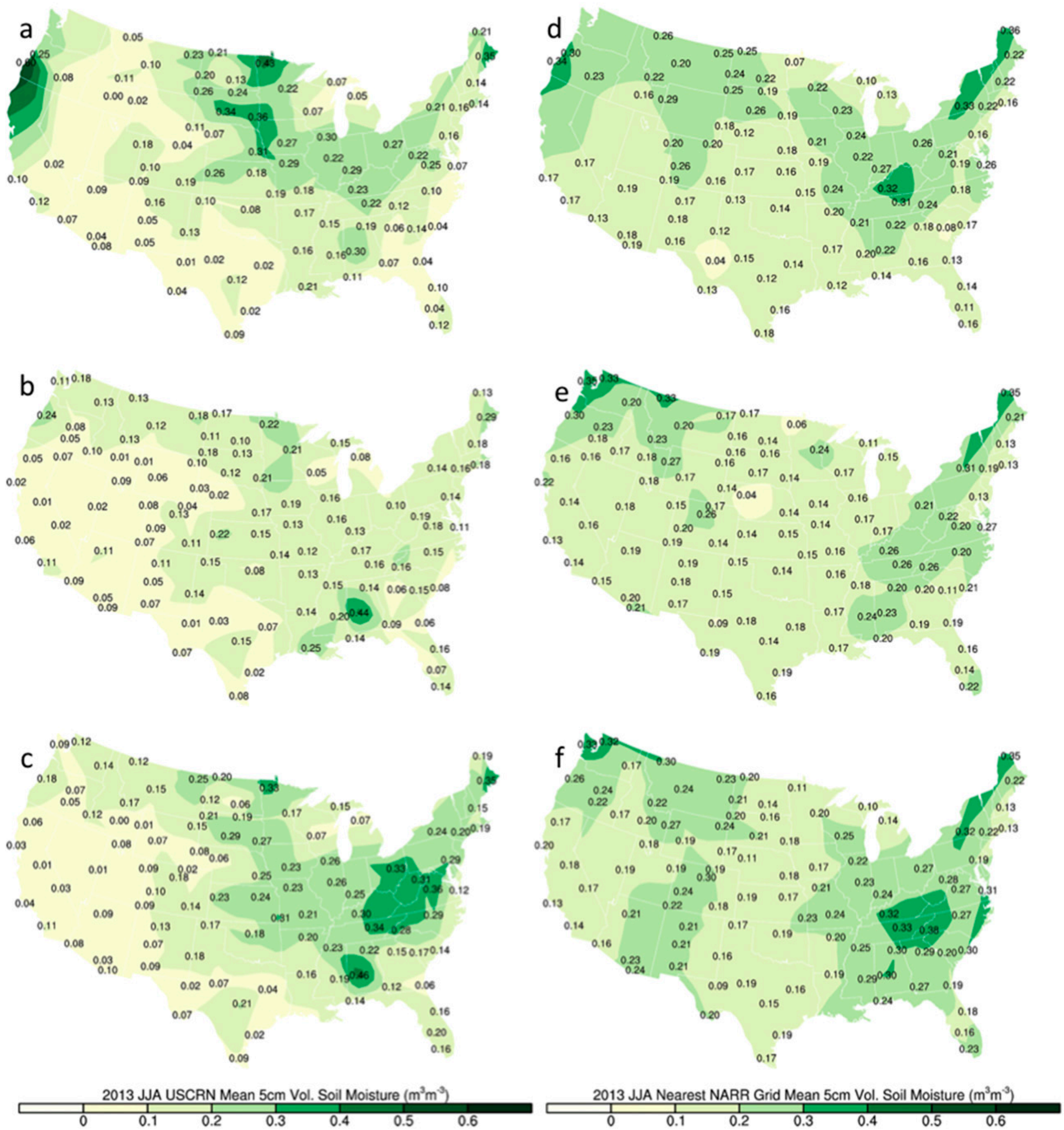

FIG. 8. Annual June–August (left) USCRN and (right) NARR 5-cm volumetric soil moisture average for (a),(d) 2011; (b),(e) 2012; and (c),(f) 2013.

well matched to USCRN, with little or no systematic biases. This was particularly true for western or other regions where the model's minimum soil moisture value was greater than observed. This is not to say that there were no disparities, but that standardized anomalies allowed for further inquiry beyond such systematic offsets in volumetric conditions. For instance, it would have been difficult to identify that simulated soil conditions were slightly drier than observed in the western half of the United States in 2011 based solely on volumetric soil moisture output from NARR. Likewise, detecting the reverse of these results in the latter months of the 2013 growing season when NARR simulated more precipitation than observed in western regions would have been challenging to detect. Moreover,

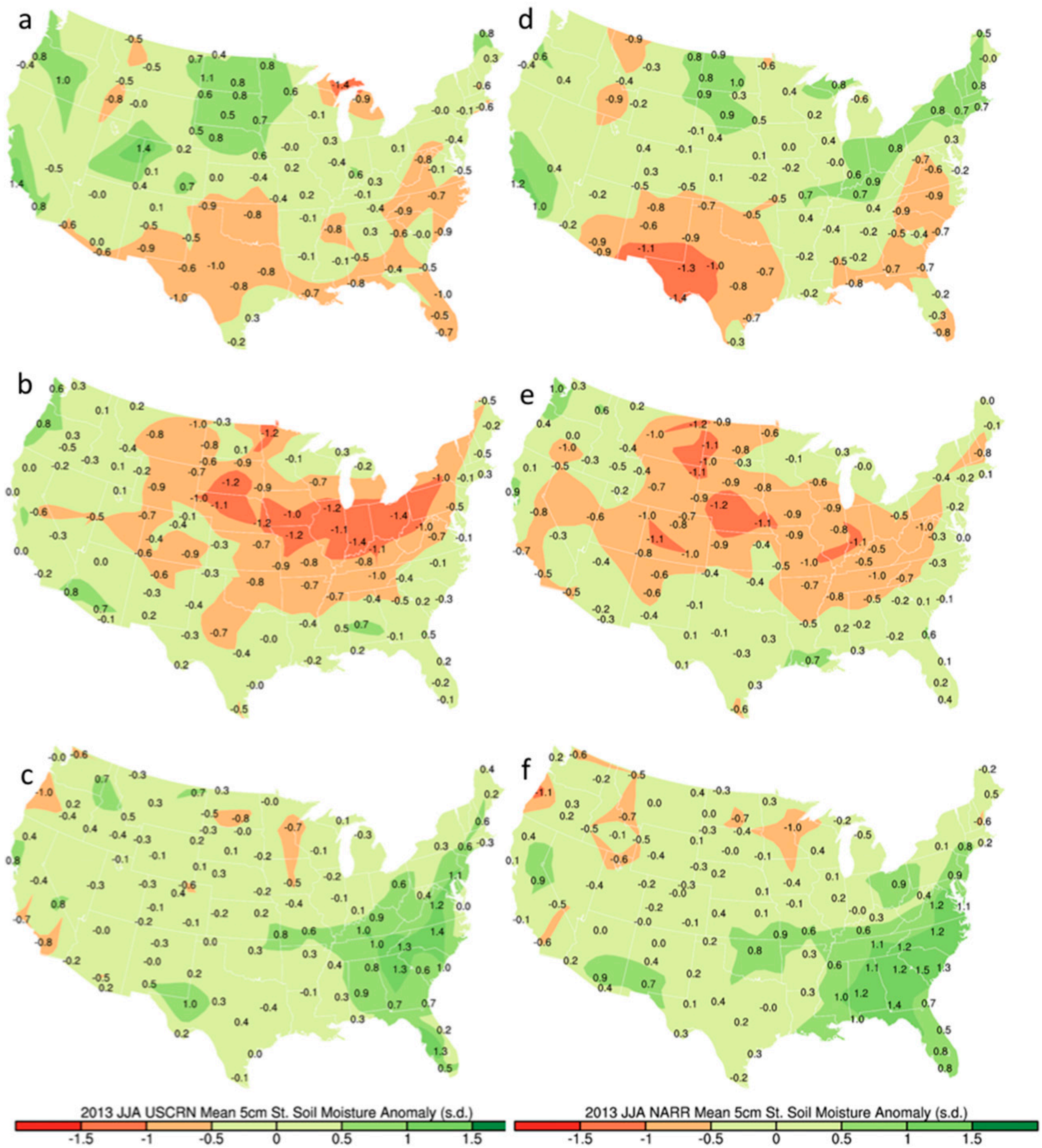

FIG. 9. As in Fig. 8, but for standardized soil moisture anomaly average.

the use of standardized soil anomalies allowed for a more holistic evaluation of modeled and observed biases, which may be greatly beneficial to identifying and diagnosing model limitations in addition to better assessments of modeled soil moisture conditions.

While NARR was not able to capture soil moisture extremes in some regions, the model was able to detect the timing of transitions from drought to recovery in the South and Southeast regions from 2011 to 2012 and the interior United States from 2012 to 2013 as detected at USCRN (Bell et al. 2015). This was likely due to assimilation of observational datasets where the Noah LSM was forced with drying (wetting) atmospheric conditions. In addition, the spatial structure of the 2012

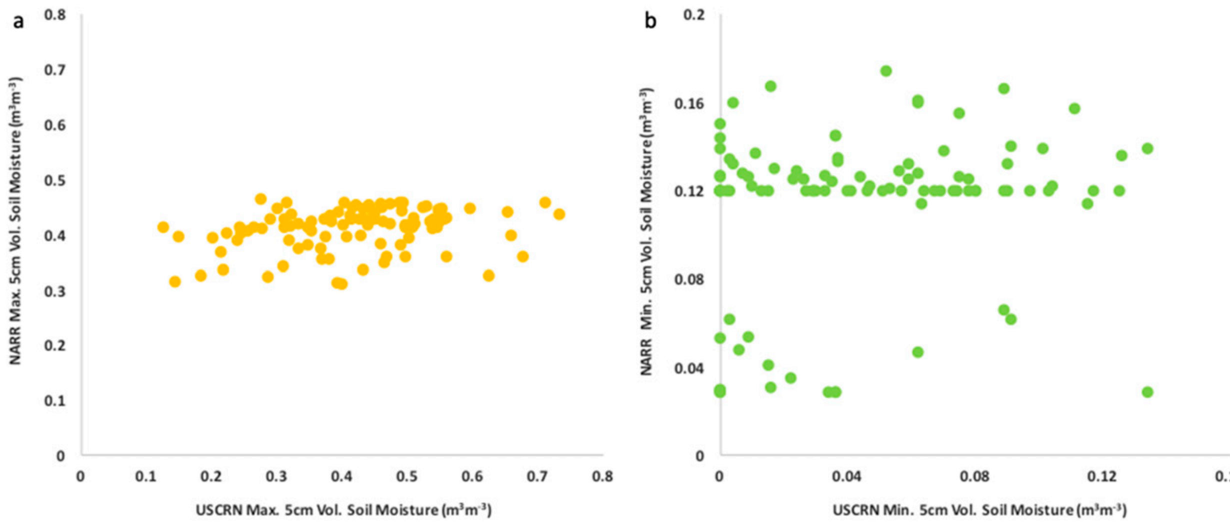

FIG. 10. USCRN station vs collocated NARR gridcell 2011–13 (a) maximum and (b) minimum volumetric soil moisture value.

drought was easily discernible once soil conditions were standardized, which was true not only for modeled data, but also for station observations. When soil conditions are evaluated based on standardized deviations from the mean (both modeled and observed), it was possible to assess relative soil moisture conditions (wet or dry) with respect to the mean or normal conditions regardless without knowledge of local climatology, soil characteristics, vegetation cover, and other persistent impacts on volumetric soil moisture. These results indicate that standardizing soil moisture anomalies allow information from both modeled and observed soil moisture conditions in monitoring–assessing hydrological extremes. In addition, this approach may be helpful when merging soil moisture observations from multiple networks into a single dataset of standardized anomalies as well as improved assessments of model performance.

In conclusion, NARR volumetric soil moisture conditions were biased with respect to USCRN observations of volumetric soil moisture. These biases were largely mitigated when soil conditions were compared using standardized anomalies. Despite these biases in absolute soil moisture values, NARR was able to reasonably capture drought patterns and intensity in both 2011 (South and Southeast regions) and 2012 (central U.S. region). This was evident at both national and regional scales. These results indicate that while modeled soil conditions have notable biases similar to Fan et al. (2011) and Koster et al. (2009), NARR was able to capture the evolution of soil moisture conditions over the 2012 drought, which is useful to decision-makers and others monitoring hydrological extremes by allowing users to assess if soil conditions are wetter or drier than normal with a degree of confidence, provided the modeled data have been standardized. In addition, standardized soil moisture anomalies can be a more useful metric in evaluating model strengths and weakness with respect to station observations than volumetric soil moisture. However, further research is necessary to determine how extensible these results are to other numerical models (i.e., with and without data assimilation) and at deeper soil moisture layers that encompass the root zone for multiple types of hydrologic extremes (i.e., floods, flash floods, and droughts).

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