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Estimating root zone soil moisture using near-surface observations from SMOS

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Abstract

Satellite-derived soil moisture provides more spatially and temporally extensive data than in situ observations. However, satellites can only measure water in the top few centimeters of the soil. Therefore estimates of root zone soil moisture must be inferred from near-surface soil moisture retrievals. The accuracy of this inference is contingent on the relationship between soil moisture in the near-surface and at greater depths. This study uses cross correlation analysis to quantify the association between near-surface and root zone soil moisture using in situ data from the United States Great Plains. Our analysis demonstrates that there is generally a strong relationship between near-surface (5 to 10 cm) and root zone (25 to 60 cm) soil moisture. An exponential decay filter is applied to estimate root zone soil moisture from near-surface observations. Reasonably skillful predictions of root zone soil moisture can be made using near-surface observations. The same method is then applied to evaluate whether soil moisture derived from the Soil Moisture and Ocean Salinity (SMOS) satellite can be used to accurately estimate root zone soil moisture. We conclude that the exponential filter method is a useful approach for accurately predicting root zone soil moisture from SMOS surface retrievals.

1 Introduction

Root zone soil moisture in vegetated regions has a significant influence on evapotranspiration rates (McPherson, 2007; Alfieri et al., 2008). Soil moisture is vital to land-atmosphere interactions, and has been shown to modulate drought conditions, especially in semi-arid environments such as the North American Great Plains (Koster et al., 2004). Several studies show that soil moisture can influence land atmosphere interactions through modification of energy and moisture fluxes in the boundary layer (Pal and Eltahir, 2001; Basara and Crawford, 2002; Taylor et al., 2007). Frye and Mote (2010) found that soil moisture and soil moisture gradients in the Southern Great Plains significantly influence convective initiation under synoptic conditions not otherwise conducive to convection. Taylor et al. (2012) found that afternoon convective precipitation in the Sahel region of Africa preferentially falls over dry soil, most likely due to enhanced sensible heat flux by anomalously low soil moisture. Despite the important role that soil moisture plays in the climate system (Legates et al., 2011), there are relatively few stations that measure soil moisture as compared to stations that measure temperature and precipitation. This impedes observation-based analyses of soil moisture-climate interactions.

Soil moisture in the North American Great Plains exhibits high variability both annually and interannually (Illston et al., 2004; Wang et al., 2013). Soil moisture not only varies over space and time, but also with depth in the soil column (Mahmood and Hubbard, 2004). Georgakakos and Bae (1994) evaluated soil moisture variability in the Midwest United States using a conceptual model and found that the persistence of soil moisture in the deeper soil was much greater than the persistence of near-surface soil moisture. Wu and Dickinson (2004) examined soil moisture variability using the National Center for Atmospheric Research Community Climate Model, version 3 (NCAR CCM3). They found that correlations between the near-surface and root zone soil moisture vary seasonally. Wu et al. (2002) studied the variability of soil moisture observations in Illinois and found that soil wetness influences how quickly soil wetting/drying move through the soil column.

Mahmood and Hubbard (2007) used a realistic soil-water energy balance process model to examine the relationship between near-surface and root zone soil moisture in Nebraska. Their results showed that cross-correlations between near-surface and root zone soil moisture datasets exhibited high variability from location to location due to differences in soil, land use and hydroclimatic conditions. They concluded that it may be possible to accurately estimate root zone soil moisture based on near-surface soil moisture. Mahmood et al. (2012) examined the predictability of soil moisture at various depths in Nebraska. They found that, in general, root zone soil moisture can be accurately estimated using 10 cm observations. However, estimation accuracy depends on the prevailing hydroclimatological conditions. In general, predictions of root zone soil moisture are more accurate when the soil is relatively wetter (Mahmood and Hubbard, 2007; Mahmood et al., 2012). Overall, previous studies have suggested that soil moisture in the root zone is correlated with near surface soil moisture. If so, satellite soil moisture retrievals may provide an accurate means of estimating water content in the root zone.

In situ measurements of soil moisture are limited in their spatial and temporal extent (Prigent et al., 2005; Reichle and Koster, 2005). Satellites provide a higher spatial resolution and a reasonable temporal resolution ranging from 1–35 + day(s). There are many different satellite missions that collect soil moisture data. Table 1 summarizes information about these satellite missions. Each of these platforms estimates soil moisture using either the C-Band (4–8 GHz) or the L-Band (1–2 GHz). The first satellite mission focused primarily on the collection of soil moisture data was the Soil Moisture Ocean Salinity (SMOS) satellite (Rudiger et al., 2009). The European Space Agency (ESA) launched the SMOS satellite in October 2010. SMOS uses microwave radiometry for estimating soil moisture (Kerr et al., 2001). L-band radiometry is achieved through 69 small antennas, resulting in a ground resolution of 50 km (Kerr et al., 2001).

Several studies have compared SMOS estimates to in situ soil moisture data. Jackson et al. (2012) used a set of relatively dense in situ soil moisture observation sites to validate SMOS retrievals over USDA Agricultural Research Service experimental watersheds. Their results showed that SMOS soil moisture estimates are in relatively good agreement with soil moisture observations. Al Bitar et al. (2012) compared SMOS soil moisture estimates with in situ soil moisture observations from Soil Climate Network (SCAN) and SNOwpack TELemetry (SNOTEL) observation networks stations throughout several regions of the United States. Their node-to-node validation performance results suggested that the accuracy of SMOS soil moisture estimates varied significantly from site to site. Collow et al. (2012) compared SMOS-derived soil moisture to in situ measurements in the US Great Plains to evaluate the accuracy of the

HESSD
10, 8325–8364, 2013

satellite measurements. They concluded that evaluating SMOS is difficult due to the lack of uniform soil moisture measurements.

SMOS measures soil water content in the top few centimeters and thus cannot explicitly represent root zone soil moisture conditions. Therefore, it is important to evaluate the degree of association between near-surface and root zone soil moisture when attempting to estimate root zone soil moisture using satellite retrievals because soil moisture is highly variable on a variety of scales. This study characterizes and quantifies the strength of the relationship between soil moisture in the near-surface layer and that in deeper layers and how the strength of the relationship varies over time and space. In situ soil moisture observations are used to calibrate an exponential filter model that uses near-surface soil moisture to predict root zone soil moisture. After calibration, this method is evaluated using SMOS retrievals to determine the accuracy of satellite-derived estimates of root zone soil moisture.

2 Data and methods

2.1 Study region

The North American Great Plains have a significant west–east precipitation gradient and north-south temperature gradient (Meng and Quiring, 2010). Vegetation and soil conditions exhibit great spatial variability across the region. Koster et al. (2004) characterize the Southern Great Plains as a “hotspot” of land-atmosphere interactions, particularly between soil moisture and antecedent precipitation. The Southern Great Plains contains one of several SMAP test bed sites which are used to validate satellite soil moisture retrievals using in situ observations (Cosh et al., 2010). The Great Plains region was selected for this study because of the relatively high density of soil moisture observations.

Daily volumetric soil water content estimates are from the Oklahoma Mesonet, www.mesonet.org, and Nebraska Automated Weather Data Network (AWDN, http:

//www.hprcc.unl.edu/awdn/). The Oklahoma Mesonet operates more than 100 stations that measure meteorological variables on daily and sub-daily resolutions across Oklahoma (Illston et al., 2008). Volumetric soil water content is estimated at Oklahoma Mesonet sites from the matrix potential using Campbell Scientific 229-L sensors at 5, 25, 60 and 75 cm. The AWDN similarly operates meteorological stations across the Northern Great Plains (You et al., 2010). AWDN estimates volumetric soil water content using Steven's Hydra Probes placed at 10, 25, 50 and 100 cm in the soil column. Oklahoma Mesonet soil moisture data are analyzed from 2000–2012, while AWDN data are available from 2006–2010. Volumetric water content data from 33 Oklahoma Mesonet sites and 22 AWDN sites are used in this study (Fig. 1). The sites were selected based on the length of record and completeness of the soil moisture data. All soil moisture data were quality controlled and distributed by the North American Soil Moisture Database at Texas A&M University (http://soilmoisture.tamu.edu).

2.2 Soil moisture data

Table 2 provides descriptive statistics of soil moisture in the near-surface (5 cm) and root zone (25 and 60 cm) averaged over all sites in Oklahoma. In general soil moisture content in the near-surface is comparable to that in the deeper layers. Average soil moisture content at Oklahoma sites is higher overall than at Nebraska sites, while daily variability, as measured by the coefficient of variation (CV) is higher at Nebraska sites than the Oklahoma sites. Soil moisture from both networks exhibits strong seasonal variability. Figure 2 displays mean monthly soil moisture and CV for each network. Mean monthly soil moisture in Oklahoma peaks in early spring followed by drying throughout spring and summer. Soil moisture recharge occurs during the winter months. These patterns are similar to those reported by Illston et al. (2004). There is relatively little intra-annual variation in mean monthly CV, although soil moisture at 5 cm is consistently more variable than at 25 and 60 cm. Mean monthly soil moisture from Nebraska shows similar patterns to Oklahoma. However, the timing of the maximum

HESSD
10, 8325–8364, 2013

and minimum soil moisture is several weeks later in Nebraska. The period between March and May corresponds with lowest soil moisture variability in Nebraska.

Soil moisture in Oklahoma and Nebraska also exhibits significant spatial variability. To characterize the longitudinal gradient in Great Plains soil moisture, driven by strong west–east gradients in precipitation, we binned each Oklahoma and Nebraska station by its longitude. Figure 3 shows the mean volumetric soil water content for (a) Oklahoma and (b) Nebraska. Stations in the eastern portion of both states generally exhibit higher average volumetric soil water content than those in the west. Mahmood et al. (2012) found that coupling between root zone and near-surface soil moisture in Nebraska was stronger wetter locations. Thus we should expect to see stronger coupling between surface and root zone soil moisture in eastern Nebraska and Oklahoma.

2.3 Methods

Two methods used in previously published studies were employed to characterize the relationship and coupling strength between near-surface and root zone layer soil moisture in Oklahoma and Nebraska (Albergel et al., 2008; Mahmood et al., 2012). The first method calculates lagged cross correlation coefficients between 5 (10) cm soil moisture observations and those at 25 and 60 (50) cm depths. Daily root zone soil moisture data is lagged −100 days to +100 days with respect to the near-surface soil moisture data. Negative lags represent root zone soil moisture leading near-surface layer soil moisture; while positive lags represent root zone soil moisture lagging near-surface layer soil moisture. Maximum lagged cross correlation coefficients between the two layers are evaluated as well as the lag time (in days) at which the maximum cross correlation was attained. Mahmood et al. (2012) used a similar methodology when examining the relationship between soil moisture observations throughout the root zone in Nebraska. Cross correlation coefficients characterize the association between soil moisture in the near-surface and root zone layers. Weak or insignificant cross correlation coefficients would indicate that soil moisture content between soil layers are not well associated

HESSD
10, 8325–8364, 2013

and that near-surface observations would have limited usefulness in predicting root zone soil moisture.

After the relationship between soil moisture data are characterized, we evaluate a method for inferring root zone soil moisture from near-surface observations. Previous studies have evaluated various forms of ensemble or extended Kalman filtering (Crow and Wood, 2003; Sabater et al., 2007; Draper et al., 2009; Hain et al., 2012) for estimating root zone soil moisture. For instance, Draper et al. (2009) found that the extended Kalman filter was useful for assimilating AMSR-E data into a land surface scheme. Li et al. (2012) employed a Kalman smoothing method to assimilate GRACE terrestrial water storage into the NASA catchment land surface model. In contrast, Hsu et al. (2012) found success employing a sequential Monte Carlo-Particle Filter technique to assimilate AMSR-E data into the Noah land surface model. All of these methods have been shown to estimate or assimilate root zone soil moisture with some skill. However, these approaches are computational intensive and can be difficult to implement.

In this study we evaluate the utility of the exponential filter method described by Albergel et al. (2008) for estimating root zone soil moisture from near-surface observations. The filter uses near-surface soil moisture observations and applies an exponential decay function to estimate root zone soil moisture. Previous studies have successfully employed similar methods to estimate root zone layer soil moisture (Wagner, 1999; Stroud, 1999). Our study is novel in that we are evaluating the utility of this method for generating root zone soil moisture based on SMOS-dervied surface soil moisture. The advantages of the exponential filter method are that it is easy to implement and it is computationally efficient. However, the exponential filter also has limitations and therefore it is likely not an appropriate method for assimilating satellite soil moisture into land surface models.

This study investigates three questions: (1) are surface and root zone soil moisture strongly related? (2) Can the exponential filter be used to predict root zone soil moisture? (3) How accurate are SMOS-based predictions of root zone soil moisture derived

HESSD
10, 8325–8364, 2013

using the exponential filter? The results section of this paper is organized around answering these three questions.

3 Results

3.1 Cross correlation results

The 5–25 cm cross correlation in Durant and Miami, Oklahoma, have pronounced peaks in strength within 5 days (Fig. 4a and b). As expected, all of the lags are positive which indicates that the surface soil moisture leads the root zone soil moisture. Similar patterns are shown in 10–25 cm cross correlation plots for Alliance North and Holdrege, Nebraska (Fig. 5a and b). The cross correlations in the 5–60 cm (Fig. 4c and d) and 10–50 cm (Fig. 5c and d) are weaker and have lag times approximately 5–10 days longer.

The maximum cross correlation and the lag at which this occurs are reported in Tables 3 and 4. Greater than 30 % of Oklahoma Mesonet soil moisture data at the 75 cm depth was missing, therefore we did not evaluate cross correlations at this depth. The maximum 5–25 cm cross correlation at Oklahoma Mesonet sites ranged from 0.95 at Miami to 0.62 at Apache, with an overall average of 0.78. The lag times for 5–25 cm ranged from 0 days at Bristow to 4 days at Acme, with an overall average of 2 days. Not surprisingly, maximum 5–60 cm cross correlations were generally weaker than the 5–25 cm. This supports that coupling strength between soil layers decreases as depth increases (Wu et al., 2002). Maximum 5–60 cm cross correlations in Oklahoma ranged from 0.86 at Lane to 0.43 at Woodward, with an overall average of 0.61. The lag times for the 5–60 cm correlations were generally longer than the 5–25 cm and they ranged from 2 days at Breckinridge to 26 days at Red Rock, Oklahoma. The decreases in cross correlation strength with depth agree with the findings of Mahmood et al. (2012).

Similar results were attained for stations in Nebraska as shown in Table 4. The maximum cross correlation for 10–25 cm ranged from 0.88 at Alliance North to 0.66 at

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

HESSD

10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

Beatrice, with an overall average of 0.79. Lag times for the 10–25 cm cross correlations ranged from 0 days at McCook to 5 days at Beatrice, with an overall mean of 2 days. Maximum cross correlations for 10–50 cm ranged from 0.71 at Central City to 0.35 at Beatrice, with an overall mean of 0.57. Lag times for the 10–50 cm cross correlations ranged from 1 day at four sites to 26 days at Scotts Bluff, with an overall mean of 8 days. Finally, cross correlations between 10–100 cm ranged from 0.55 at Merritt and Minden to 0.26 at Barta and Nebraska City, with an overall mean of 0.41. Lag times for the 10–100 cm cross correlations ranged from 1 day at Beatrice to 87 days at Cedar Point with an overall average of 33 days. Similar to the results from Oklahoma, cross correlations tend to decrease and lag times tend to increase as the depth increases.

3.2 Cross correlation strength – precipitation relationship

To assess the influence of precipitation on the strength of soil layer coupling, we created scatter plots of the average annual precipitation, attained by the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (http://www.prism.oregonstate.edu/), with the peak cross correlation coefficient at each site. The relationship between precipitation and the strength of the cross correlations between the near-surface (5 or 10 cm) and 25 cm soil moisture are shown in Figs. 6 and 7. In Oklahoma, there is a moderately strong positive relationship between the mean annual precipitation and 5–25 cm cross correlation coefficients ($R^2 = 0.33$). This suggests that wetter locations (eastern Oklahoma) tend to exhibit a stronger inter-layer soil moisture relationship. This is in agreement with the results of previous research (Mahmood and Hubbard, 2007; Mahmood et al., 2012). However, Fig. 7 shows that the relationship between mean annual precipitation and 10–25 cm cross correlations in Nebraska are negative ($R^2 = 0.27$). Mahmood et al. (2012) found that cross correlations between the 10 and 50 cm depth soil moisture in Nebraska were stronger in wetter locations. This is corroborated by our results in Oklahoma and directly contrasts with our results in Nebraska. The differences in the sign of the relationship between Nebraska and Oklahoma may be due to site-specific factors such as the near-surface depth of measurement (5 cm

HESSD
10, 8325–8364, 2013

versus 10 cm) or soil texture. However, we examined additional variables (soil texture, land cover, temperature) and were unable to determine why the relationship in Nebraska between cross correlation strength and mean annual precipitation is opposite of Oklahoma.

The cross correlation results suggest that associations between near-surface and root zone soil moisture are strong at the majority of observation sites in Oklahoma and Nebraska. Our results and those of Mahmood et al. (2012) suggest that it is possible to use surface soil moisture estimates (either from satellites or in situ measurements) to make skillful predictions of root zone soil moisture. Therefore, in the next section we evaluate the accuracy of predicting root zone soil moisture from near-surface soil moisture observations using a method which assumes strong associations between near-surface and root zone layer soil moisture.

3.3 Exponential filter results

Albergel et al. (2008) adopt a recursive exponential filter to predict root zone soil moisture from near-surface observations over multiple networks in France. The recursive formulation predicts soil wetness index, a metric of soil moisture which standardizes volumetric soil water content by the minimum and maximum values attained over the entire period of record at each location. The recursive equation adopted from Albergel et al. (2008) for predicting soil moisture at time t_n, can be written as:

$$\mathrm{SWI}_{\mathrm{m}n} = \mathrm{SWI}_{\mathrm{m}(n-1)} + K_n(\mathrm{ms}(t_n) - \mathrm{SWI}_{\mathrm{m}(n-1)}) \quad (1)$$

where $\mathrm{SWI}_{\mathrm{m}(n-1)}$ is the predicted root zone soil moisture estimate at t_{n-1}, $\mathrm{ms}(t_n)$ is the surface soil moisture estimate at t_n, and the gain K at time t_n is given by:

$$K_n = \frac{K_{t-1}}{K_{n-1} + e^{-\frac{t_n - t_{n-1}}{T}}} \quad (2)$$

where T represents the time scale of soil moisture variation, in day units. The filter is initialized with $\mathrm{SWI}_{\mathrm{m}(1)} = \mathrm{ms}(t_1)$ and $K_1 = 1$. Albergel et al. (2008) found that accuracy

HESSD
10, 8325–8364, 2013

varied as a function of T value varied. In fact, their analysis showed that each study site had an optimal T value or T_{opt} which was characterized by the highest prediction accuracy as assessed by the Nash–Sutcliffe score. We applied the filter to soil moisture in Oklahoma and Nebraska and assessed the accuracy of the root zone soil moisture estimates using several metrics including root mean square error (RMSE), mean absolute error (MAE), mean bias, the Nash–Sutcliffe score (NS) and the coefficient of determination (R^2). The T parameter corresponding to the highest NS was considered the T_{opt} for that station.

3.3.1 General filter results

Albergel et al. (2008) used 5 cm soil moisture to predict 30 cm SWI values. Therefore, we applied this approach in Oklahoma by using 5 cm SWI to predict 25 cm SWI. In Nebraska we used 10 cm SWI to predict 25 cm SWI. Results from Oklahoma show good correspondence between the predicted SWI and observed SWI values (Table 5). NS values ranged from 0.84 at Wister to 0.07 at Bixby, with an overall average of 0.63. T_{opt} parameter values ranged from 2 days at Bristow to 22 days at Woodward, with an overall average of 8 days. Results from Nebraska were similar (Table 6). NS values ranged from 0.83 at Merritt and Scotts Bluff to 0.08 at Barta, with an overall average of 0.64. T_{opt} parameter values for sites in Nebraska ranged from 3 days at Barta to 20 days at Beatrice, with an overall average of 9 days.

Root zone soil moisture predictions were generally accurate and, based on the NS, all were more accurate than simply using the observed root zone soil moisture mean as the prediction. Figures 8 and 9 show plots of monthly average error metrics for Oklahoma and Nebraska. Root zone soil moisture estimates were, for the most part, higher than the soil moisture observations. In Oklahoma (Fig. 8), mean bias is mostly negative, except for a brief period between July and September. This period coincides with increased error which is probably due to the relatively low soil moisture values in the root zone during the late summer period. Figure 8 also shows a marked drop in NS between February and April, with an NS < 0.3 in March. Illston et al. (2004) observed

HESSD
10, 8325–8364, 2013

four distinct seasonal soil moisture regimes in Oklahoma. The transition between the first regime and second regime (February–April) is characterized by the initiation of 5 cm soil moisture drying beginning in mid-March, while 25 cm soil moisture drying does not initiate until early-to-mid April. This could be one factor influencing the relatively low accuracy when predicting 25 cm soil moisture from 5 cm soil moisture during this period.

Figure 9 shows monthly average error metrics from root zone soil moisture predictions in Nebraska. Mean bias, RMSE, MAE and % MAE are all relatively consistent across months; however, R^2 and NS values increase notably between April and May. Mahmood et al. (2012) found that this period in Nebraska was characterized by soil moisture recharge at all depths. Their results also showed that coupling between 10 cm soil moisture and deeper (25, 50, 100 cm) soil moisture was strongest under the wettest conditions. Predictions of root zone soil moisture from near-surface soil moisture should be most accurate during periods of recharge at all depths.

3.3.2 Optimum T parameter

We found the station-specific T_{opt} parameter for each Oklahoma and Nebraska site, based on maximum NS value (Tables 5 and 6). Similar to the results from Albergel et al. (2008) we found that T_{opt} varies considerably between stations. However, the monthly variability in NS shown in Figs. 8 and 9 suggests that T_{opt} could be a function of both space and time. Thus we wanted to quantify the influence of the overall soil moisture conditions on the variability of T_{opt}. To do this, we binned all of the near-surface SWI values from Oklahoma and Nebraska into 10 bins of equal range (0.0–0.1, 0.1–0.2, etc.). Each near-surface SWI observation was associated with a root zone soil moisture prediction and a corresponding NS value, measuring the accuracy of the prediction. We calculated the average NS value for each near-surface SWI bin. Figures 10 and 11 show variability of the NS score and T_{opt} parameter as a function of the near-surface SWI bin for sites in Oklahoma and Nebraska, respectively.

HESSD
10, 8325–8364, 2013

The highest NS scores at Oklahoma sites (Fig. 10) are all attained at T_{opt} between 3 and 10 days. When SWI is between 0.2 and 0.7, NS scores stay positive with T_{opt} values up to 40 days. However, when SWI is less than 0.2 or greater than 0.7, NS scores quickly become negative when T_{opt} is greater than 15–20 days. Like Oklahoma sites, the highest NS at Nebraska sites occur at T_{opt} between 2 and 7 days. Nebraska NS scores also become negative when SWI is extremely dry (< 0.1) or wet (> 0.8) at T_{opt} greater than 10 days. The soil moisture estimate accuracy is very sensitive to the T_{opt} parameter when overlying near-surface soil moisture conditions are extremely dry or wet. Under more normal conditions though, the estimate accuracy seems to be nearly independent of the T_{opt} parameter.

Albergel et al. (2008) found that although T_{opt} varied strongly between stations in their study, using the overall average T_{opt} for all stations did not result in a significant decrease in model accuracy. To test this for our sites, we initialized the exponential filter model using three different T_{opt} parameters: (1) the overall average T_{opt}, which was 8 days for Oklahoma sites and 9 days for Nebraska sites, (2) site-specific T_{opt} parameters, and (3) T_{opt} based on the near-surface SWI, ms(t_n), conditions. Figures 12 and 13 show boxplots of the six error metrics calculated from the 3 different T_{opt} parameters for Oklahoma and Nebraska sites, respectively. A paired student's t test was run for each error metric at both states to see if differences between model soil moisture estimates using the three unique T_{opt} parameters were statistically significant. Figure 12 shows that using one overall average T_{opt} value when predicting root zone soil moisture values in Oklahoma does not result in significantly higher prediction error than using site-specific or ms(t_n)-specific T_{opt} parameters. Similar results are observed in Nebraska (Fig. 13), the overall average T_{opt} parameter does not result in significantly higher error than the more dynamic T_{opt} values. These results corroborate those from Albergel et al. (2008) in that a network-average T_{opt} parameter can be used with the exponential filter for regional applications to accurately predict root zone soil moisture from near-surface observations. Our results also show that this method can accurately

HESSD
10, 8325–8364, 2013

estimate root zone soil moisture in a different climatic regime (Great Plains) than the one in which it was developed and initially tested (Southern France).

4 Estimating root zone soil moisture using SMOS

The results of this study show that near-surface soil moisture is moderately to strongly coupled with soil moisture in the root zone (Sect. 3.2), and that near-surface anomalies can be used with decent skill in predicting root zone soil moisture anomalies (Sect. 3.3). Here we evaluate the utility of the exponential decay filter for inferring root zone soil moisture from SMOS-derived surface soil moisture in Oklahoma. Daily SMOS data from the year 2011 over 23 Oklahoma Mesonet sites are employed. The exponential decay filter detailed in Sect. 3.3 is used to estimate root zone soil moisture from the SMOS surface estimates. The T parameter was set to 8 days for all estimates, consistent with the results from Sect. 3.3.2 showing this value optimal for the study area.

SMOS root zone estimates are compared to 25 cm soil moisture observations from the underlying Oklahoma sites. Differences in magnitude and variability are expected between SMOS and Oklahoma Mesonet soil moisture data, due to the different spatial resolutions. Therefore differences between SMOS surface retrievals and Oklahoma Mesonet 5 cm soil moisture were used as the baseline by which to evaluate the SMOS root zone predictions. Differences between the SMOS root zone predictions and Oklahoma Mesonet 25 cm soil moisture supplemental to the baseline differences were used to evaluate the method's efficacy.

Mean bias error and NS score were used to assess the similarity between SMOS and the Oklahoma observations for the near-surface and root zone layers. The near-surface mean bias error (SMOS–Observations) was negative at each site (Fig. 14a), meaning that SMOS SWI values were consistently higher than Oklahoma Mesonet SWI values. The NS score (Fig. 14b) at every station was positive, showing good agreement between the two near-surface data. The (SMOS-Observations) root zone mean bias error (Fig. 14a) was also negative at each site and the NS score (Fig. 14b) at every station

HESSD
10, 8325–8364, 2013

but one was positive between the two root zone data. Figure 14 shows some added error between the root zone data, attributable to the exponential filter method. However, root zone soil moisture NS scores were positive at all but 2 sites. This suggests that the exponential filter method is useful for predicting root zone soil moisture. Overall root zone soil moisture estimated from SMOS near-surface retrievals using the exponential decay filter were well related to Oklahoma Mesonet observations at the 25 cm depth. The exponential filter method has applicability for estimating root zone soil moisture from satellite surface retrievals.

5 Summary and conclusions

Satellite soil moisture retrievals provide more spatially-extensive data than in situ soil moisture observations. However, satellites can only capture soil wetness in the top few centimeters of the soil. This severely limits satellite use for land-atmosphere studies which necessitate root zone soil moisture data. Several methods have previously been used to infer root zone soil moisture from near-surface observations. However, the utility of these methods are constrained by the strength of the association between near-surface layer and root zone layer soil moisture. In this study, cross correlation analysis was used to examine the relationship strength between near-surface and root zone soil moisture at 33 Oklahoma Mesonet and 22 AWDN observation stations. The results revealed generally strong relationships between soil moisture data in the near-surface and root zone layers at sites in Oklahoma and Nebraska. The lag time at which the two layers correlated the strongest varied depending on the station's hydroclimatic conditions.

After the strong association between near-surface and root zone soil moisture was established, an exponential filter method was adopted from Albergel et al. (2008) to assess the ability of predicting root zone soil moisture from near-surface observations. The filter predictions were consistently more accurate than using the near-surface soil moisture mean when predicting root zone soil moisture anomalies. However, predic-

HESSD
10, 8325–8364, 2013

tion accuracy was diminished during times of transition between recharge (wet) and utilization (dry) phases. This was attributed to the different time periods at which the near-surface and root zone soil layers respond to drying conditions. The primary function coefficient of the exponential filter (T_{opt}) varied considerably due to relative soil wetness.

The exponential filter method was applied to estimate root zone soil moisture from SMOS near-surface retrievals. The root zone estimates were compared to 25 cm soil moisture observations from 23 Oklahoma Mesonet stations. The two soil moisture datasets agreed reasonably well, although the variability of the SMOS data was far larger than that of the Oklahoma Mesonet data. The exponential filter method did introduce 14 % additional error, on average; however, the model, as assessed by the NS score, performed well at 21 of the 23 sites.

The main conclusions of this study are (1) soil moisture in near-surface and root zone layers in Oklahoma and Nebraska are strongly associated, (2) the exponential filter method performed well when predicting root zone soil moisture near-surface observations and (3) SMOS surface soil moisture retrievals can be used with the exponential filter method to estimate root zone soil moisture over Oklahoma with reasonable skill.

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HESSD
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T. W. Ford et al.

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HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

Table 1. Summary of recent satellite soil moisture missions.

Mission	Temporal resolution	Spatial resolution (km)	Type	EMR-Band	Mission website
SSM/I	Daily	25	Passive	C	http://podaac.jpl.nasa.gov/SSMI
TRMM TM	Daily	50–56	Passive	C	http://trmm.gsfc.nasa.gov/
Aqua AMSR-E	Daily	56	Passive	C	http://aqua.nasa.gov/
ERS 1-2 SCAT	35 days	25–50	Active	C	http://www.ipf.tuwien.ac.at
SMOS	3 days	50	Passive	L	http://ilrs.gsfc.nasa.gov/missions/
SMAP	2–3 days	9	Both	L	http://smap.jpl.nasa.gov/
MetOp ASCAT	29 days	50	Active	C	http://www.ipf.tuwien.ac.at/

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

Table 2. Descriptive statistics for Oklahoma and Nebraska soil moisture. Table shows the mean, maximum, minimum, range and coefficient of variation (CV) averaged over all sites. All values are volumetric soil water content ($cm^3\,cm^{-3}$) units.

Oklahoma				Nebraska			
	Average	Maximum	Minimum		Average	Maximum	Minimum
Mean 5 cm	0.27	0.39	0.19	Mean 10 cm	0.19	0.32	0.07
Mean 25 cm	0.28	0.35	0.21	Mean 20 cm	0.19	0.35	0.07
Mean 60 cm	0.29	0.38	0.19	Mean 50 cm	0.20	0.35	0.07
Max 5 cm	0.32	0.48	0.21	Max 10 cm	0.30	0.43	0.13
Max 25 cm	0.33	0.42	0.24	Max 20 cm	0.29	0.43	0.10
Max 60 cm	0.33	0.42	0.22	Max 50 cm	0.29	0.42	0.11
Min 5 cm	0.20	0.28	0.16	Min 10 cm	0.07	0.17	0.02
Min 25 cm	0.21	0.28	0.16	Min 20 cm	0.08	0.25	0.00
Min 60 cm	0.23	0.30	0.17	Min 50 cm	0.10	0.24	0.02
Range 5 cm	0.13	0.26	0.05	Range 10 cm	0.22	0.32	0.10
Range 25 cm	0.12	0.23	0.05	Range 20 cm	0.21	0.31	0.09
Range 60 cm	0.10	0.18	0.05	Range 50 cm	0.19	0.28	0.09
CV 5 cm	0.14	0.25	0.05	CV 10 cm	0.32	0.47	0.17
CV 25 cm	0.13	0.22	0.07	CV 20 cm	0.29	0.43	0.09
CV 60 cm	0.12	0.20	0.06	CV 50 cm	0.28	0.48	0.08

HESSD
10, 8325–8364, 2013

Table 3. Maximum cross correlation coefficient and the lag time (in days) at which the maximum cross correlation occurs for all sites in Oklahoma.

Site	Max 5–25 cm Cross correlation	Max 5–25 cm Lag (days)	Max 5–60 cm Cross correlation	Max 5–60 cm Lag (days)
Acme	0.77	4	0.58	25
Apache	0.62	3	0.48	14
Bixby	0.83	1	0.68	9
Breckinridge	0.79	1	0.61	2
Bristow	0.82	0	0.56	11
Butler	0.80	2	0.57	19
Centrahoma	0.91	1	0.54	19
Cheyenne	0.74	1	0.48	18
Durant	0.79	4	0.65	14
El Reno	0.76	3	0.62	12
Eufaula	0.87	1	0.71	11
Foraker	0.73	3	0.56	15
Ketchum Ranch	0.82	1	0.71	4
Lahoma	0.77	2	0.63	14
Lane	0.72	1	0.86	5
Marena	0.78	3	0.58	22
Miami	0.95	1	0.85	7
Newkirk	0.72	3	0.55	10
Nowata	0.81	2	0.62	11
Oilton	0.75	3	0.55	12
Pauls Valley	0.84	2	0.69	14
Perkins	0.81	2	0.43	27
Porter	0.80	1	0.52	11
Putnam	0.74	1	0.67	3
Red Rock	0.83	1	0.64	26
Shawnee	0.83	1	0.67	8
Stillwater	0.70	1	0.55	7
Stuart	0.82	1	0.67	9
Washington	0.75	2	0.61	7
Watonga	0.72	2	0.47	10
Waurika	0.76	3	0.56	18
Wister	0.86	1	0.73	8
Woodward	0.62	4	0.43	17
Average	0.78	2	0.61	13

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

HESSD
10, 8325–8364, 2013

Table 4. Same as Table 1, only for Nebraska sites.

Site	10–20 cm Cross correlation	10–20 cm Lag (days)	10–50 cm Cross correlation	10–50 cm Lag (days)	10–100 cm Cross correlation	10–100 cm Lag (days)
Alliance North	0.88	2	0.65	10	0.49	56
Arthur	0.84	1	0.69	2	0.47	23
Barta	0.76	1	0.69	4	0.26	7
Beatrice	0.66	5	0.35	6	0.42	1
Brunswick	0.80	1	0.51	13	0.30	34
Cedar Point	0.86	2	0.60	8	0.43	87
Central City	0.86	1	0.71	1	0.54	12
Champion	0.81	1	0.48	18	0.43	40
Cozad	0.83	2	0.73	10	0.47	50
Curtis	0.74	1	0.55	11	0.45	47
Gothenburg	0.71	1	0.50	5	0.40	45
Grand Island	0.70	4	0.50	16	0.15	41
Halsey	0.81	1	0.53	7	0.31	14
Higgens Ranch	0.82	1	0.64	1	0.46	3
Hodrege	0.76	1	0.43	15	0.42	14
McCook	0.70	0	0.53	1	0.27	59
Merna	0.82	2	0.50	12	0.47	25
Merritt	0.88	1	0.70	2	0.55	24
Minden	0.81	1	0.69	1	0.55	16
Nebraska City	0.71	1	0.46	4	0.26	29
Scotts Bluff	0.86	4	0.62	26	0.54	85
West Point	0.80	3	0.56	7	0.30	19
Average	0.79	2	0.57	8	0.41	33

HESSD
10, 8325–8364, 2013

Table 5. Summary of the accuracy of the exponential filter-based predictions of soil moisture at sites in Oklahoma. Accuracy metrics were calculated by comparing predicted 25 cm soil moisture with observations.

Site	RMSE	MAE	% MAE	Bias	*N*	R^2	Optimum *T* (T_{opt}) parameter
Acme	0.23	0.17	0.32	0.07	0.68	0.74	9
Bixby	0.23	0.20	0.26	−0.19	0.07	0.72	4
Breckinridge	0.23	0.17	0.33	0.03	0.68	0.70	4
Bristow	0.18	0.13	0.22	−0.05	0.67	0.69	2
Butler	0.16	0.12	0.24	0.03	0.78	0.79	7
Centrahoma	0.14	0.12	0.16	−0.10	0.80	0.91	5
Cheyenne	0.20	0.15	0.47	0.06	0.64	0.68	8
Durant	0.22	0.19	0.31	−0.13	0.62	0.79	9
El Reno	0.25	0.21	0.30	−0.19	0.36	0.73	10
Eufaula	0.16	0.12	0.25	−0.02	0.80	0.81	4
Foraker	0.19	0.13	0.19	−0.06	0.58	0.62	10
Ketchum Ranch	0.18	0.12	0.20	0.06	0.73	0.77	7
Lahoma	0.24	0.17	0.31	0.10	0.62	0.70	7
Lane	0.23	0.13	0.23	0.05	0.49	0.52	4
Marena	0.16	0.11	0.20	0.03	0.78	0.79	13
Miami	0.12	0.10	0.14	−0.09	0.83	0.92	4
Newkirk	0.21	0.17	0.24	−0.08	0.60	0.66	10
Nowata	0.15	0.11	0.18	0.01	0.78	0.79	8
Oilton	0.21	0.17	0.24	−0.14	0.51	0.72	10
Pauls Valley	0.15	0.11	0.19	−0.03	0.82	0.84	8
Perkins	0.17	0.14	0.23	−0.09	0.70	0.78	6
Porter	0.17	0.15	0.25	−0.08	0.65	0.75	5
Putnam	0.32	0.25	0.38	−0.24	0.12	0.63	11
Red Rock	0.16	0.10	0.15	−0.01	0.74	0.74	6
Shawnee	0.19	0.14	0.27	−0.08	0.72	0.76	6
Stillwater	0.24	0.17	0.27	−0.06	0.48	0.54	5
Stuart	0.20	0.17	0.27	−0.13	0.57	0.78	5
Washington	0.21	0.16	0.29	0.01	0.66	0.67	6
Watonga	0.20	0.15	0.34	−0.03	0.64	0.65	10
Waurika	0.20	0.15	0.26	−0.03	0.72	0.73	8
Wister	0.15	0.11	0.18	−0.05	0.84	0.87	7
Woodward	0.17	0.13	0.52	0.09	0.39	0.57	22
Average	0.19	0.15	0.26	−0.04	0.63	0.73	8

HESSD
10, 8325–8364, 2013

Table 6. Summary of the accuracy of the exponential filter-based predictions of soil moisture at sites in Nebraska. Accuracy metrics were calculated by comparing predicted 25 cm soil moisture with observations.

Site	RMSE	MAE	% MAE	Bias	N	R^2	Optimum T (T_{opt}) parameter
Aliance North	0.12	0.08	0.22	0.06	0.80	0.84	6
Arthur	0.13	0.09	0.19	−0.02	0.74	0.75	4
Barta	0.19	0.15	0.25	−0.12	0.08	0.58	3
Beatrice	0.21	0.18	0.30	−0.10	0.46	0.60	20
Brunswick	0.14	0.10	0.21	−0.02	0.75	0.75	7
Cedar Point	0.13	0.09	0.23	0.06	0.76	0.82	8
Central City	0.11	0.09	0.15	0.00	0.77	0.77	6
Champion	0.14	0.10	0.19	−0.05	0.69	0.72	13
Cozad	0.13	0.10	0.24	0.02	0.79	0.79	11
Curtis	0.18	0.13	0.30	0.03	0.63	0.65	15
Gothenburg	0.17	0.12	0.24	−0.01	0.59	0.59	8
Grand Island	0.13	0.09	0.13	−0.04	0.48	0.57	13
Halsey	0.14	0.10	0.20	−0.03	0.71	0.73	4
Higgens Ranch	0.13	0.09	0.17	−0.07	0.65	0.76	4
Hodrege	0.17	0.12	0.19	−0.04	0.61	0.64	6
McCook	0.14	0.11	0.17	−0.02	0.47	0.49	16
Merna	0.16	0.13	0.24	−0.10	0.62	0.78	6
Merritt	0.10	0.07	0.15	−0.02	0.83	0.84	5
Minden	0.14	0.09	0.17	0.02	0.71	0.72	9
Nebraska City	0.15	0.11	0.20	−0.02	0.40	0.51	8
Scotts Bluff	0.10	0.07	0.20	0.03	0.83	0.84	12
West Point	0.13	0.10	0.17	−0.01	0.75	0.75	8
Average	0.14	0.11	0.21	−0.02	0.64	0.71	9

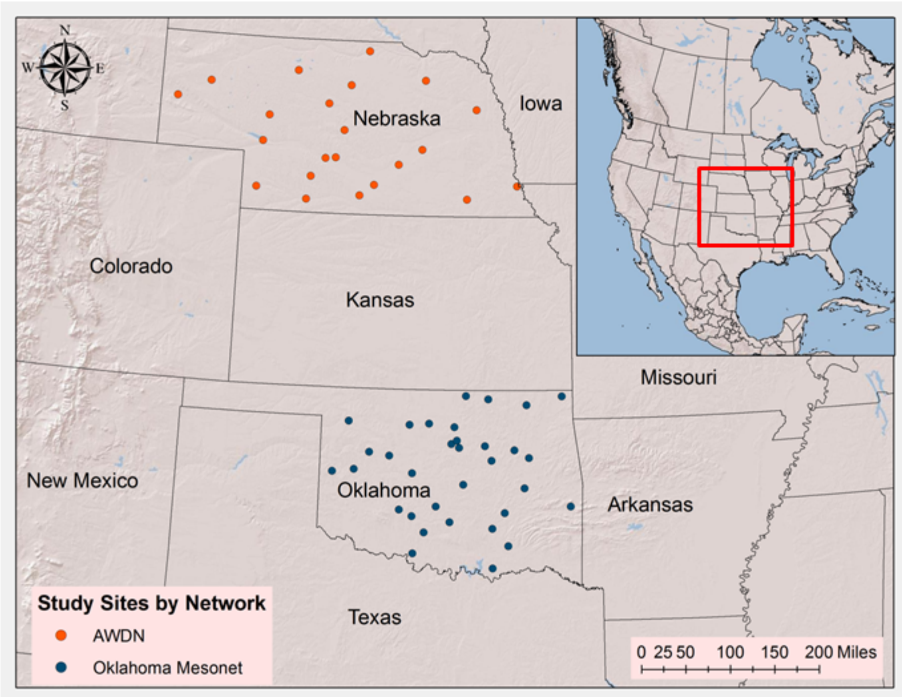

Fig. 1. Soil moisture stations in the Nebraska Automated Weather Data Network and Oklahoma Mesonet that are used in this study. Automated Weather Data Network sites shown in red and Oklahoma Mesonet sites in dark blue.

HESSD
10, 8325–8364, 2013

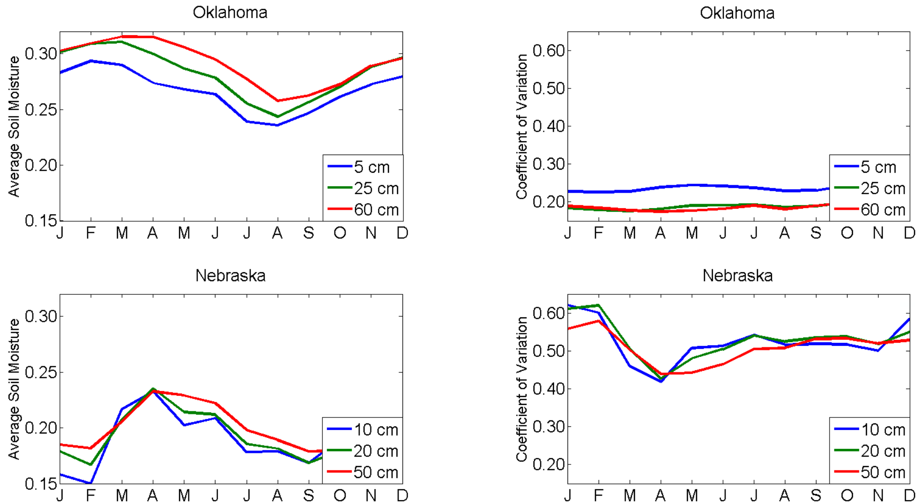

Fig. 2. Mean monthly soil moisture ($cm^3\,cm^{-3}$) in Oklahoma (top left) and Nebraska (bottom left) and mean monthly coefficient of variation in Oklahoma (top right) and Nebraska (bottom right). Blue lines represent the near-surface soil (5 or 10 cm) while the green and red lines represent soil moisture at 20 or 25 cm and 50 or 60 cm, respectively.

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

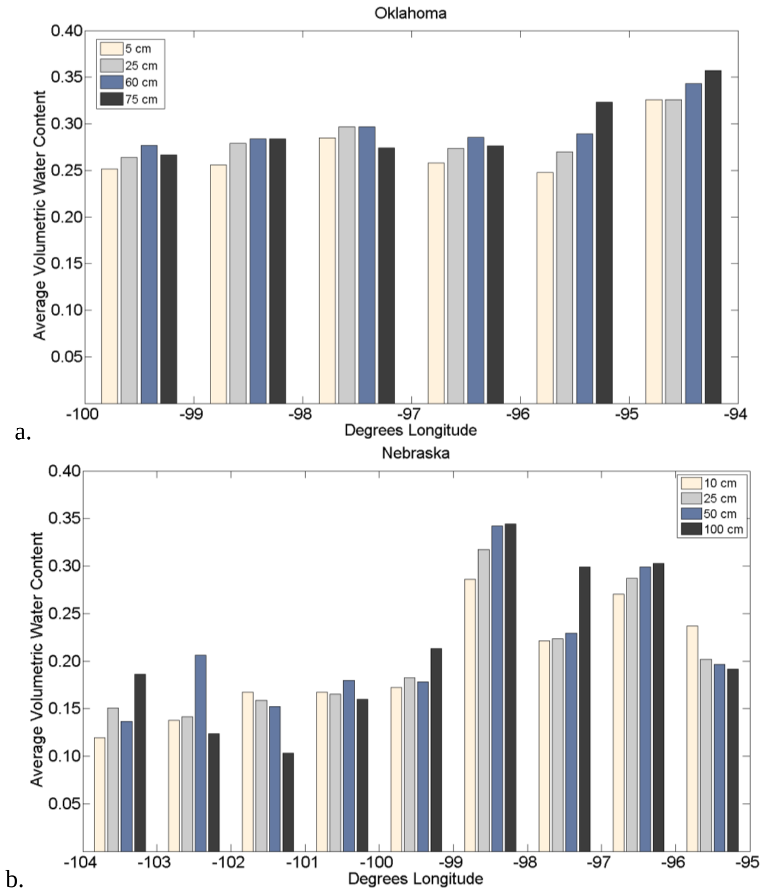

Fig. 3. Oklahoma Mesonet **(a)** and AWDN **(b)** stations are binned by the station's longitude. Bar graphs show the average volumetric soil water content for each bin at each measurement depth.

HESSD
10, 8325–8364, 2013

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

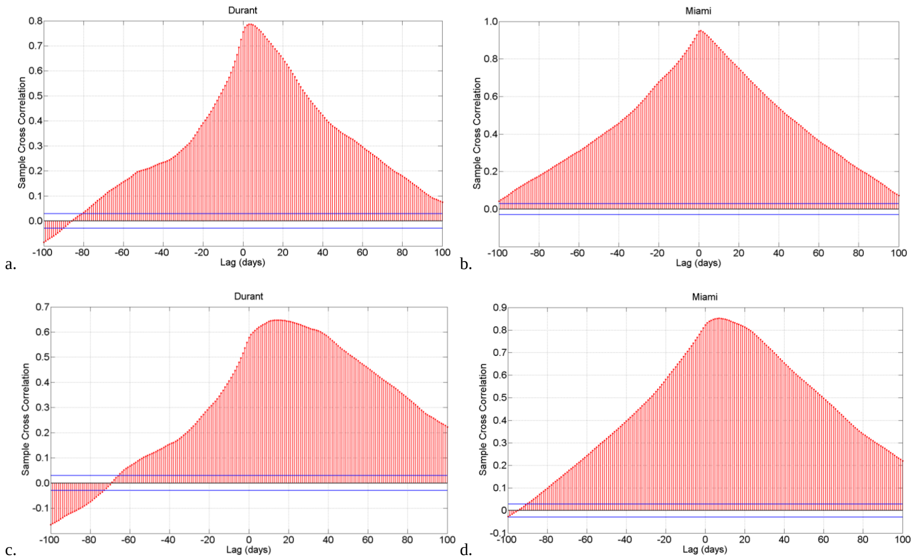

Fig. 4. Sample cross correlations at two Oklahoma stations: (**a** and **c**) show 5–25 and 5–60 cm cross correlations at Durant, Oklahoma and (**b** and **d**) show 5–25 and 5–60 cm cross correlations at Miami, Oklahoma.

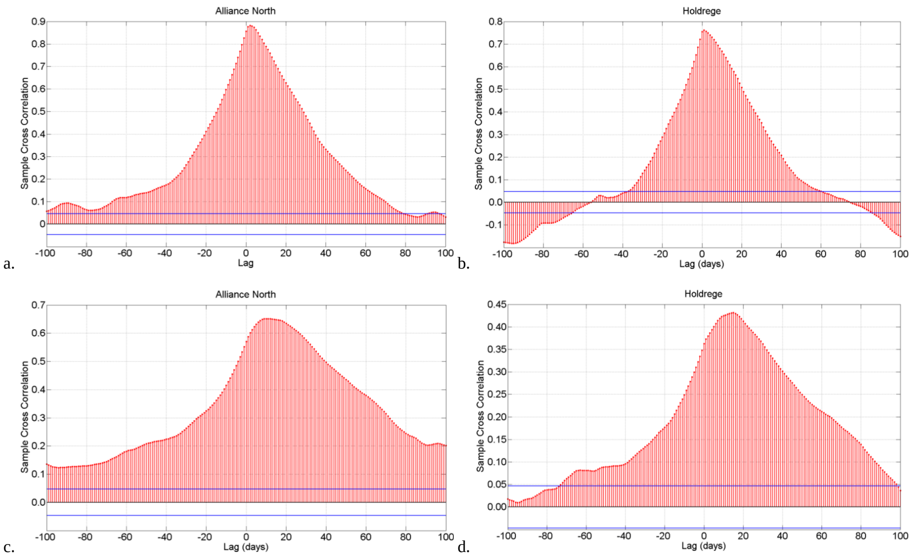

Fig. 5. Sample cross correlations at two Nebraska stations: (**a** and **c**) show 10–25 and 10–50 cm cross correlations at Alliance North, Nebraska and (**b** and **d**) show 10–25 and 10–50 cm cross correlations at Holdrege, Nebraska.

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

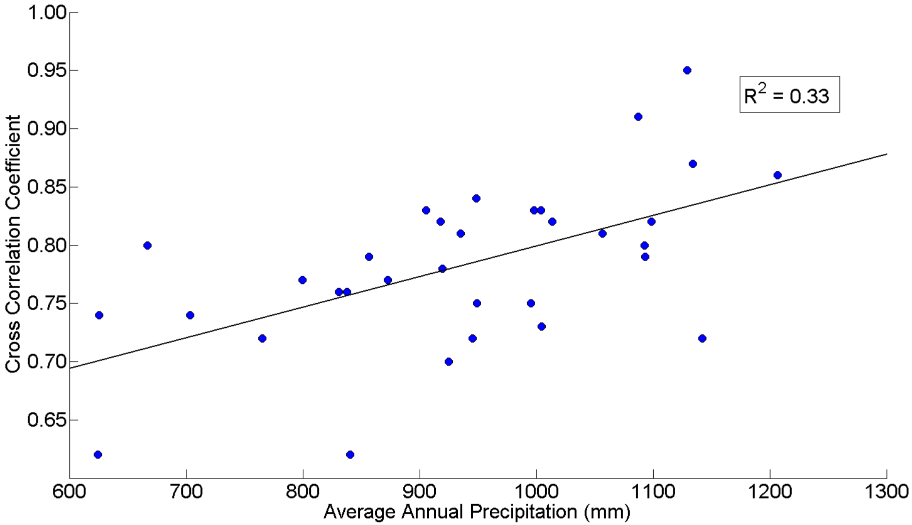

Fig. 6. Peak cross correlation between the 5 and 25 cm layers for all Oklahoma sites versus the average annual precipitation. Each point represents one site.

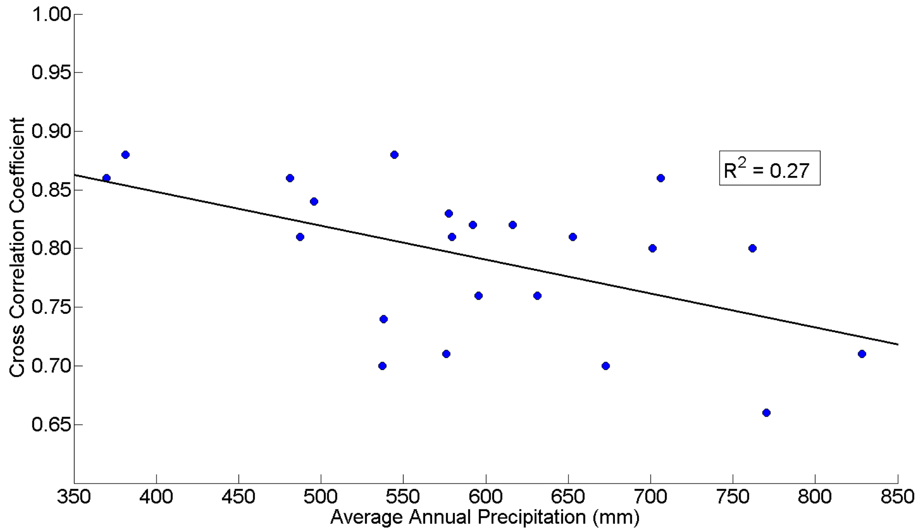

Fig. 7. Peak cross correlation between the 10 and 25 cm layers for all Nebraska sites versus the average annual precipitation. Each point represents one site.

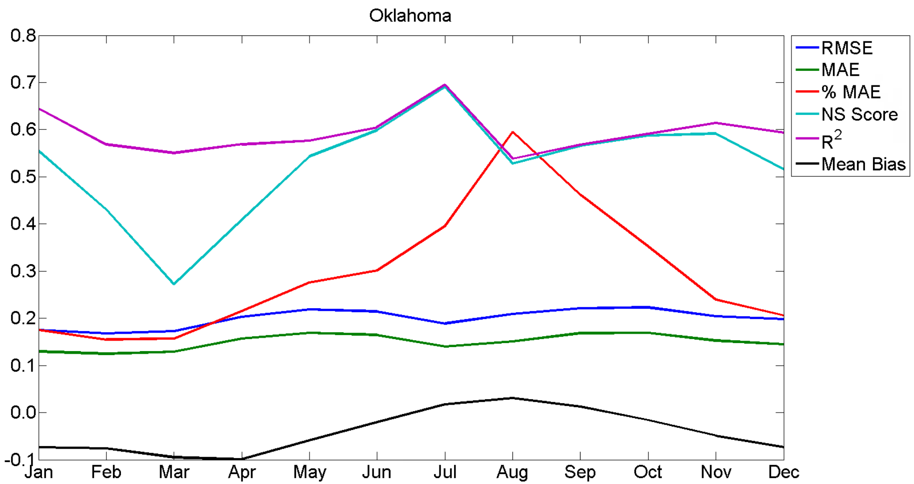

Fig. 8. Monthly average error metrics calculated from 5–25 cm soil moisture predictions. Results are averaged across all Oklahoma stations.

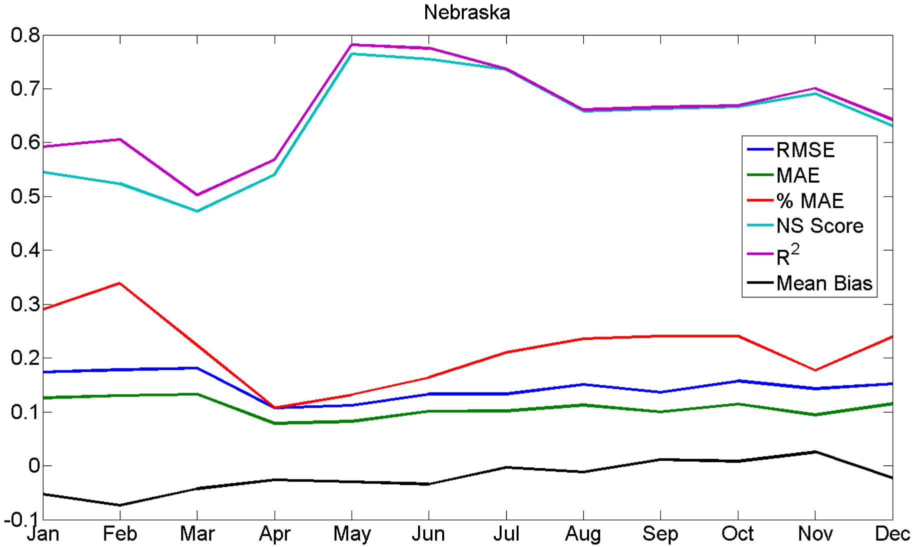

Fig. 9. Monthly average error metrics calculated from 5–25 cm soil moisture predictions. Results are averaged across all Nebraska stations.

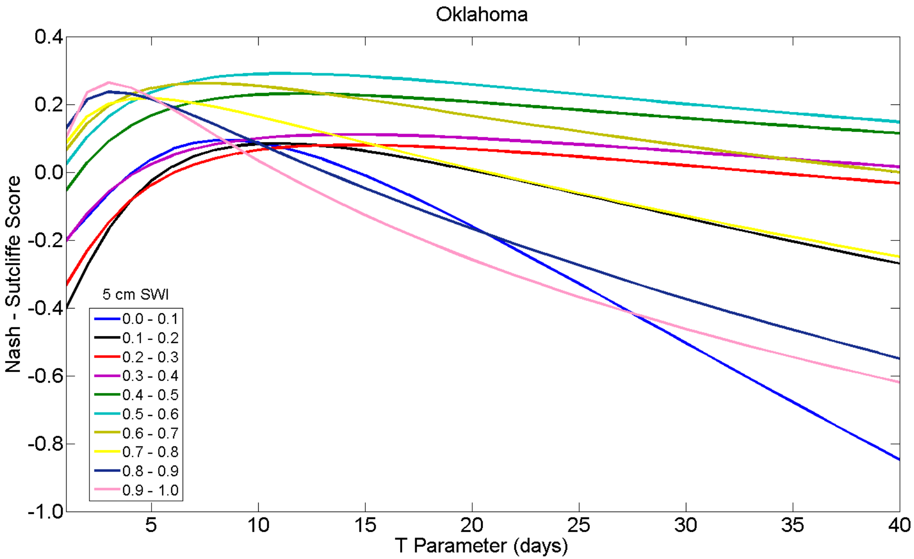

Fig. 10. Plots of the Nash–Sutcliffe score and the optimum T parameter as a function of the SWI conditions in the near-surface soil layer. Results are based on all of the Oklahoma sites.

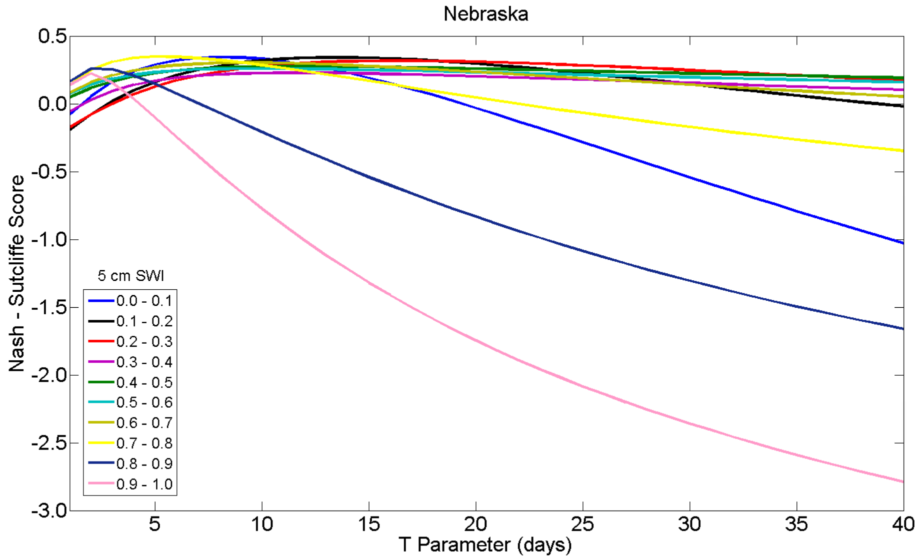

Fig. 11. Plots of the Nash–Sutcliffe score and the optimum *T* parameter as a function of the SWI conditions in the near-surface soil layer. Results are based on all of the Nebraska sites.

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

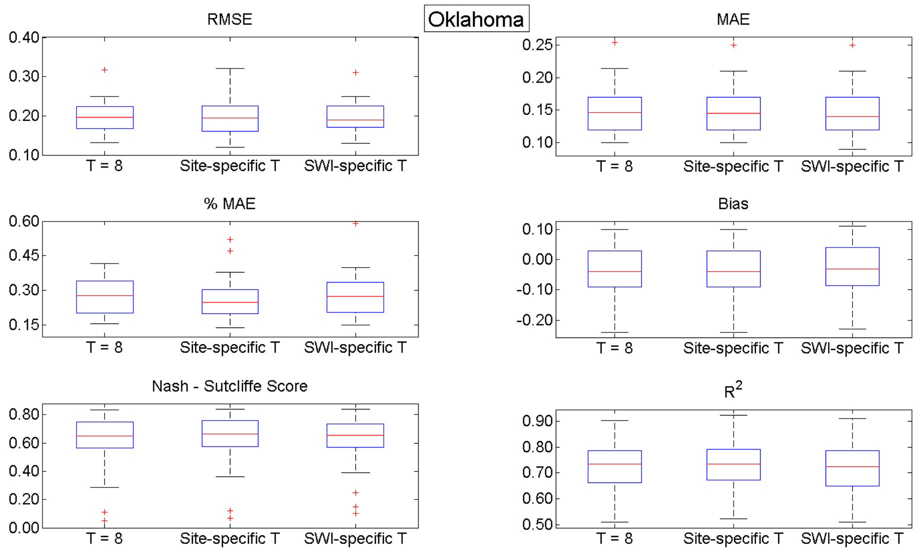

Fig. 12. Box plots of error metrics for the predicted root-zone soil moisture averaged over all Oklahoma sites. Each boxplot is generated from predictions made with one of three different optimum *T* parameters.

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.

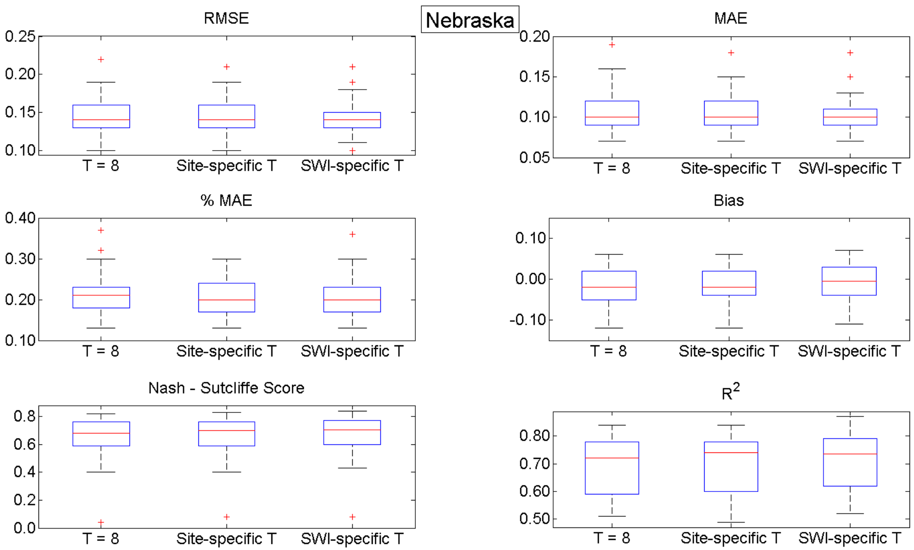

Fig. 13. Box plots of error metrics for the predicted root-zone soil moisture averaged over all Nebraska sites. Each boxplot is generated from predictions made with one of three different optimum T parameters.

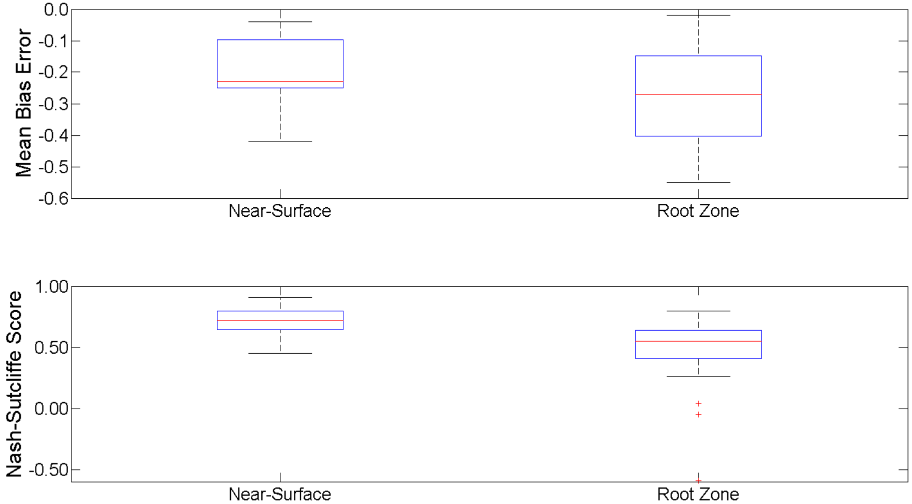

Fig. 14. Box plots of **(a)** mean bias error and **(b)** Nash–Sutcliffe score for SMOS surface soil moisture versus Oklahoma Mesonet near-surface soil moisture (left) and SMOS root zone soil moisture versus Oklahoma Mesonet root zone soil moisture (right).

HESSD
10, 8325–8364, 2013

Estimating root zone soil moisture

T. W. Ford et al.