Influence of MODIS-Derived Dynamic Vegetation on VIC-Simulated Soil Moisture in Oklahoma

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ABSTRACT

Soil moisture–vegetation interactions are an important component of land–atmosphere coupling, especially in semiarid regions such as the North American Great Plains. However, many land surface models parameterize vegetation using an interannually invariant leaf area index (LAI). This study quantifies how utilizing a dynamic vegetation parameter in the variability infiltration capacity (VIC) hydrologic model influences model-simulated soil moisture. Accuracy is assessed using in situ soil moisture observations from 20 stations from the Oklahoma Mesonet. Results show that VIC simulations generated with an interannually variant LAI parameter are not consistently more accurate than those generated with the invariant (static) LAI parameter. However, the static LAI parameter tends to overestimate LAI during anomalously dry periods. This has the greatest influence on the accuracy of the soil moisture simulations in the deeper soil layers. Soil moisture drought, as simulated with the static LAI parameter, tends to be more severe and persist for considerably longer than drought simulated using the interannually variant LAI parameter. Dynamic vegetation parameters can represent interannual variations in vegetation health and growing season length. Therefore, simulations with a dynamic LAI parameter better capture the intensity and duration of drought conditions and are recommended for use in drought monitoring.

1. Introduction

Soil moisture is vital to land–atmosphere interactions and it can modulate drought conditions, especially in semiarid environments such as the North American Great Plains (Koster et al. 2004). However, few soil moisture monitoring networks exist relative to networks observing temperature and precipitation, impeding research of land–atmosphere feedbacks critical to drought prediction and mitigation. Remote sensing and land surface models (LSMs) are commonly employed for estimation of mesoscale hydrologic and climatologic conditions. However, the spatial variability of soil moisture and factors that influence the magnitude of soil moisture (soil texture, overlying vegetation) are not consistently well represented (Xia et al. 2012).

Vegetation is a primary conduit through which soil moisture influences partitioning of surface energy. Variations in vegetation density and health modify transpiration rates (McPherson 2007) and near-surface atmospheric moisture availability (Pielke 2001). Representations of pedosphere–biosphere–atmosphere interactions must account for the innate spatiotemporal variability of the factors that influence land–atmosphere coupling.

In situ soil moisture measurements are not globally extensive, and soil moisture impacts on regional climate are difficult to attain with such limited observations. LSMS are used instead to estimate mesoscale and continental-scale hydrologic and climatologic conditions, employing temperature and precipitation data to estimate soil moisture. Despite the large temporal variability of vegetation health, several LSMS represent vegetation with an interannually invariant parameter (Tang et al. 2012). Studies have suggested that LSM-simulated vegetation health and soil moisture are not always representative of land surface and subsurface variability (Xia et al. 2012). Using interannually dynamic parameters of vegetation health are more realistic.

Dekker et al. (2007) developed a microscale vegetation–hydrology feedback model coupled with a mesoscale precipitation model to investigate the impact of infiltration on land–atmosphere feedback. Their results showed that accounting for the influence of vegetation on microscale
infiltration increased precipitation 35% over the coupled model that did not account for infiltration. Jiang et al. (2009) used the Noah LSM forced with observed vegetation conditions, represented by the normalized difference vegetation index (NDVI), to assess how this influences seasonal and intraseasonal precipitation over the central United States. Their results show that accurate depiction of vegetation enhances the persistence of intraseasonal precipitation in regional climate models. These results suggest that accurate representation of vegetation properties in LSMs is necessary for analyzing land–atmosphere interactions and that the persistence of drought in LSMs may be a function of vegetation properties such as leaf area index (LAI).

Zhang and Wegehenkel (2006) developed a soil water balance model in which remotely sensed vegetation were used to estimate spatial distributions of daily soil moisture and evapotranspiration. They found that the model was able to accurately simulate daily soil water balance in northeastern Germany when using remotely sensed vegetation. Similarly, Tang et al. (2012) used an LSM with interannually varying LAI to better represent vegetation greening in the North American monsoon region. Their results show that inclusion of LAI resulted in more accurate simulations of soil moisture and evapotranspiration over the region. Ghilain et al. (2012) derived daily biophysical vegetation parameters from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) sensor on board the geostationary satellite Meteosat Second Generation (MSG) in order to improve land surface model evapotranspiration estimates. Their results show that model-derived latent heat flux is improved when informed by the SEVIRI-based biophysical vegetation parameters, particularly in semiarid regions where evapotranspiration shows a strong seasonal variability.

Dynamic vegetation parameters have previously been employed in LSMs for hydrologic modeling. However, none of these previous studies explicitly examined the influence of dynamic LAI parameter on soil moisture simulations at the mesoscale. The purpose of this study is to evaluate how static and dynamic LAI influence VIC-simulated soil moisture.

2. Data and methods

a. Study region

Oklahoma experiences a strong west–east precipitation gradient and north–south temperature gradient (Meng and Quiring 2010). Vegetation varies from grassland–forest–cropland mix in eastern Oklahoma to rangeland and cropland in central Oklahoma. The Oklahoma panhandle land cover is characterized by rangeland and scrubland (Senay and Elliott 2000). Peak vegetation activity typically takes place between March and August, depending on the land cover type and location. Soil moisture in Oklahoma is characterized by four distinct seasonal regimes (Illston et al. 2004). Soil moisture content is normally highest between October and March and begins drying in early-to-mid spring. Soil moisture is typically driest between July and September before recharge begins again in early autumn.

This study utilizes in situ moisture observations from 20 stations in Oklahoma (Fig. 1). These sites are part of the Oklahoma Mesonet Observation Network (www.mesonet.org). The network uses Campbell 229-L heat dissipation sensors, which measure the thermal matrix potential. Volumetric soil water content (θ) is estimated from these measurements at 5, 25, 60, and 75 cm in the soil layer (Illston et al. 2008). Each Oklahoma Mesonet site is surrounded by “native” vegetation, almost exclusively grassland. Soil moisture data have been compiled and quality controlled by the North American Soil Moisture Database (NASMD) at Texas A&M University (http://soilmoisture.tamu.edu/). The stations were chosen because of the length and completeness of their data. Table 1 displays soil and land cover characteristics for each site. Soil textures range from sandy loam to silt. Land cover within 1 km of sites includes grassland, pasture, scrub, and cultivated crops; however, all Oklahoma Mesonet sites are immediately surrounded by grassland. Recent work (Cosh et al. 2010) has suggested that the range of soil moisture observations from the Oklahoma Mesonet may not reflect the actual range of soil moisture potential at some sites. If the data does contain sensor-imposed volumetric water content ranges, this could be a limitation for comparison against land surface model-derived soil moisture. However, the Oklahoma Mesonet soil moisture has been used in a variety of studies for calibration and validation of satellites (Owe et al. 2008; Albergel et al. 2012) and land surface models (Luo et al. 2003; Hossain and Anagnostou 2005). The Mesonet is also the densest mesoscale soil moisture operating system and thus is most optimal for a study of this scale.

b. VIC model

The variable infiltration capacity (VIC) hydrologic model (Liang et al. 1994) is a macroscale model that balances both surface energy and water fluxes in each grid cell. The VIC model uses the soil–vegetation–atmosphere transfer scheme (SVAT), which represents controls of vegetation on land–atmosphere moisture and energy fluxes. VIC allows for subgrid parameterization of soil, topography, and vegetation characteristics. VIC vegetation parameters for every model simulation were run...
with only one land cover type in an attempt to partially account for the scale discrepancy between in situ observations and the gridded model simulations. VIC simulates soil water content in multiple soil layers: the three used in this study are 0–10 cm, 10–40 cm, and 40–95 cm. The three soil layer intervals were chosen so that the top three Oklahoma Mesonet soil moisture sensors are located in the middle of the VIC soil layer. Soil characteristics and subgrid land cover parameters were extracted from the gridded, 1/8° resolution, dataset assimilated by Maurer et al. (2002). VIC was forced with daily observations of precipitation, minimum and maximum temperature, and wind speed from the Oklahoma Mesonet. These data are recorded at the same location as the soil moisture observations and thus are representative of the conditions at each site.

<table>
<thead>
<tr>
<th>Site</th>
<th>Dominant land cover</th>
<th>5-cm soil texture</th>
<th>25-cm soil texture</th>
<th>60-cm soil texture</th>
<th>75-cm soil texture</th>
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<tr>
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<td>Clay loam</td>
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<td>Loam</td>
<td>Loam</td>
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FIG. 1. Locations of the 20 Oklahoma Mesonet sites used in the study.
There are a number of vegetation/land cover parameters that influence VIC soil moisture simulations including roughness length, displacement height, architectural resistance, minimum stomata resistance, and rooting depth. However, LAI is the vegetation parameter that has the greatest influence on hydrologic simulations in VIC (Maurer et al. 2002). LAI quantifies canopy cover and thus influences interception and infiltration. LAI is directly employed to calculate the maximum amount of water intercepted by the canopy, canopy resistance, and root uptake and evaporative fluxes. To quantify this effect, VIC was employed in two separate model simulations. The first simulation (static LAI) was run using the mean monthly MODIS-derived LAI at each station (2000–09). The static LAI parameter varies from month to month but not interannually, typical of vegetation parameters in the VIC model. The second simulation (dynamic LAI) was run with observed monthly MODIS-derived LAI at each station. The dynamic LAI varies both monthly and interannually. Both simulations were run from 1994 to 2009, using 1994–99 as spinup, and were driven using the station-based Oklahoma Mesonet observations of minimum and maximum temperature, precipitation, and near-surface wind speed. Simulations were run on a daily time step and model output was volumetric soil water content in the 0–10-cm, 10–40-cm, and 40–95-cm layers. For convenience, the VIC soil layers will be referred to using the deepest depth (10, 40, and 95 cm). The results are organized as follows: section 3a examines the sensitivity of model-simulated soil moisture to the model LAI parameter, section 3b describes the characteristics of and differences between the simulated soil moisture datasets, section 3c evaluates soil moisture from each model simulation with in situ soil moisture observations to assess which LAI parameter leads to the more accurate soil moisture. Section 4 applies the findings of section 3 to drought monitoring using VIC-simulated soil moisture.

3. Results

a. VIC-simulated soil moisture sensitivity to LAI

Robock et al. (2003) evaluated soil moisture simulations from several land surface models, including VIC, with in situ observations from the Oklahoma Mesonet. Their results showed that simulations of seasonal variations in soil moisture during dry periods were not as accurate. These inaccuracies were attributed to the sensitivity of variable infiltration capacity to soil texture differences and hydraulic parameters. Meng and Quiring (2008) evaluated soil moisture simulations from three models, including VIC, with in situ observations from the Soil Climate Analysis Network (SCAN). Their results showed that, while VIC accurately simulated the annual cycle of soil moisture, model sensitivity to soil parameters was a function of climatic gradients, and not necessarily soil properties. These studies reported the sensitivity of VIC-simulated soil moisture to soil parameters. However, neither study quantified the sensitivity of VIC-simulated soil moisture to vegetation parameters (e.g., LAI). The
620% parameter variation approach used by Meng and Quiring (2008) was adopted in this study to test the sensitivity of VIC-simulated soil moisture to differences in LAI.

For the sensitivity analysis, VIC was used to simulate soil moisture over the 1994–2009 study periods (1994–99 spinup) using the static LAI parameter. Subsequently, two separate model simulations were run over the same time period: one in which the monthly varying LAI parameter was universally increased by 20% and another in which the LAI parameter was universally decreased by 20%. Soil moisture output from each model simulation was compared to quantify the sensitivity of VIC soil moisture simulations to the LAI parameter. The results show that increasing (decreasing) monthly LAI by 20% leads to an overall decrease (increase) in soil moisture as compared to soil moisture under “normal” LAI conditions. The change in LAI influenced the deep (95 cm) soil more than the near-surface layers. The mean soil moisture response to a 20% increase in LAI is $0.001 \pm 0.003 (2.0\%)$, $0.003 (2.1\%)$, and $0.02 (6.4\%)$ at the 10-, 40-, and 95-cm layers, respectively. Soil moisture sensitivity to LAI is more pronounced between June and October (Fig. 2) because this period corresponds to peak LAI at most of the study sites.

The sensitivity analysis suggests that VIC-simulated soil moisture is influenced by the LAI parameter. However, the sensitivity varies seasonally and is considerably stronger in the deepest (40–95 cm) soil layer. Thus, we should expect that simulations run with different LAI parameters will show the largest differences in soil moisture during the growing season and in the deepest soil layer.

b. Model-simulated soil moisture differences

The VIC model was run from 1994 to 2009 using 1994–99 as a spinup period. Two simulations were completed, one using the static LAI and the other using the dynamic LAI. Soil moisture was simulated at the 0–10-cm, 10–40-cm, and 40–95-cm layers. Tables 2a and 2b compare VIC-simulated soil moisture generated using the static and dynamic LAI parameters. The mean, standard deviation, and range of the soil moisture for both simulations (Table 2) are nearly identical. The only exception is that the soil moisture range in the 10-cm layer is larger (0.49) for the soil moisture simulated under the dynamic

<table>
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<tr>
<th>Depth</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Range</th>
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<tr>
<td></td>
<td>10 cm</td>
<td>40 cm</td>
<td>100 cm</td>
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<tr>
<td>Dynamic LAI</td>
<td>0.251</td>
<td>0.244</td>
<td>0.237</td>
</tr>
<tr>
<td>Static LAI</td>
<td>0.251</td>
<td>0.243</td>
<td>0.234</td>
</tr>
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$\pm 20 \%$ parameter variation approach used by Meng and Quiring (2008) was adopted in this study to test the sensitivity of VIC-simulated soil moisture to differences in LAI.

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LAI than the static LAI (0.39). This is the only notable difference that arises from using the different LAI parameters.

Direct comparison between the two soil moisture simulations (Table 2b) is done with the coefficient of determination ($R^2$) and mean bias, which describes the overall difference between the two datasets at each depth. The average coefficient of determination over all sites between the two datasets is 0.97, 0.99, and 0.94 for the 10-, 40-, and 95-cm depths, respectively. The coefficient of determination at each site ranged from 0.68 to 0.99, all significant at the $\alpha < 0.05$ level. The mean bias in volumetric water content between the two simulations is essentially 0 at all three depths.

A comparison of the two simulations reveals that substantial differences in the LAI parameters between the static and dynamic simulations are necessary to produce noticeable differences in the VIC-simulated soil moisture. Figure 3 shows monthly LAI and the resulting simulated soil moisture at Wister, Oklahoma, between 2000 and 2003. The timing of the maximum LAI is similar in both static and dynamic simulations. However, the static LAI is consistently higher than the dynamic LAI between July 2000 and May 2001. This difference causes a noticeable divergence between the two simulations in the soil moisture in the deepest layer. In general, when the static and dynamic LAI parameters differ, the influence is most clearly evident in soil moisture in the deepest layer, and this supports our findings from the sensitivity analysis (section 3a).

Sheffield et al. (2004) used VIC-simulated soil moisture for examining drought and showed that soil moisture in the root zone is most responsive to agricultural drought and root uptake of water. At all study sites, the largest root fractions were found in the 0–10-cm layer, while the largest soil moisture differences (both in absolute and relative terms) are in the deepest layer. Sheffield et al. also showed that deep (>50 cm) layer soil moisture anomalies are quite persistent. Wu et al. (2002) performed a soil moisture power spectrum analysis and found that deeper layer (>90 cm) soil moisture varies with a frequency of several months, implying significant persistence of soil moisture anomalies in the deep soil. This agrees with our results, which show that the influence of LAI on soil moisture is more pronounced and persistent in the deeper soil.

To better assess how the static and dynamic LAI influenced soil moisture, we calculated the persistence of the differences between the simulations in each layer. We defined persistence as the number of consecutive days during which soil water content between the two simulations differed by >10%. Figure 4 shows an example of how persistence is measured. Soil moisture differences are calculated as the difference between soil moisture in the deepest layer.

![Figure 3](image.jpg)  
**Fig. 3.** Volumetric soil water content at (from the top) 5, 25, and 60 cm from the Oklahoma Mesonet observations (blue), VIC with dynamic LAI (black), and VIC with static LAI (red); (bottom) monthly (2000–03) dynamic LAI (black) and static LAI (red).
moisture from the dynamic LAI and static LAI simulations (dynamic minus static).

Table 3 shows the results of the soil moisture persistence calculations. The mean persistence is based on all 20 sites. The range represents the difference between the sites with the greatest and least persistence. The soil moisture differences reported in Table 3 are the average differences in soil moisture (dynamic minus static) during the persistence period and are reported as a percent of the dynamic LAI soil moisture mean to facilitate comparisons between sites that have different soils. Table 3 also reports the LAI difference, which is the difference in monthly LAI (dynamic minus static) during the persistence period.

The mean length of (>10%) soil moisture divergence is much longer at the 95-cm level (62 days) than in the near-surface soil layers (1 and 9 days, respectively). There are also larger differences between the soil moisture simulations at the 95-cm level (14.2%) than the 10-cm and 40-cm levels (5.7% and 6.1%, respectively). Soil moisture in the deepest layer generally responds more strongly to differences in LAI, and the response persists longer than in the shallower soil layers. The average period of persistence at Miami, Oklahoma, is 308 days at the 95-cm depth.

Figure 5 shows the time series of 40–95-cm soil moisture from the VIC simulations and the Oklahoma Mesonet station as well as the monthly LAI. The largest differences in the soil moisture simulations occurred between 2002 and 2004. Specifically, in 2002 the static LAI peaks earlier and is larger than the dynamic LAI. This causes large differences in soil moisture between the two simulations. This is most evident in the much drier conditions in the static LAI simulation in the 95-cm soil layer. As shown in section 3a, increases in LAI lead to decreases in soil moisture, and these differences are most pronounced in the deepest soil layer. In this case, the dynamic LAI captures the vegetation response to dry conditions, and this is represented in VIC by a reduction in LAI. The lower than normal LAI reduces evaporation and transpiration; therefore, the soil is much wetter in the simulations with the dynamic LAI.

c. Model evaluation

The accuracy of VIC-simulated soil moisture using both static and dynamic vegetation is assessed using in

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<th>Depth (cm)</th>
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<th>Range</th>
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<tr>
<td></td>
<td>Persistence (days)</td>
<td>Soil moisture difference (%)</td>
</tr>
<tr>
<td>0–10</td>
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</tr>
<tr>
<td>10–40</td>
<td>9</td>
<td>0.061</td>
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<tr>
<td>40–95</td>
<td>62</td>
<td>0.142</td>
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in situ soil moisture from the Oklahoma Mesonet. Model accuracy is commonly evaluated with rms error (RMSE) and the coefficient of determination ($R^2$). However, studies have shown that the RMSE is biased when the distribution of errors is variable, regardless of the total error (Willmott and Matsuura 2005). Therefore, the simulated soil moisture data will be evaluated using multiple, complementary metrics. These include mean bias error (MBE), mean absolute error (MAE), and the coefficient of efficiency ($E$). MBE evaluates the model bias and is reported as negative if model simulations are consistently less than the observations and positive if the simulations are consistently larger than the observations. MAE is similar; however, the metric evaluates the model absolute error with respect to the observations. The coefficient of efficiency is described and applied by Legates and McCabe (1999) as the ratio of the mean square error to the variance in the observed data, subtracted from unity. When the coefficient of efficiency is greater than 0, it indicates that the model is a better predictor than the observation mean, while negative values represent models that perform worse than the observation mean. Multiple model evaluation metrics are employed to provide a holistic understanding of model performance.

Table 4 presents model evaluation metrics that have been averaged over all study sites. Our results show that the accuracy of the VIC simulations with static and dynamic LAI is nearly identical at both the 10-cm and 40-cm depths. Soil moisture simulated with dynamic LAI is slightly more accurate (as determined by MBE, MAE, and $E$) than the static LAI in the 95-cm layer. However, these differences are quite small; therefore, it is not possible to conclude that either model simulation is consistently more accurate than the other. Although the dynamic LAI is more physically realistic, it does not result in a statistically significant improvement in the accuracy of soil moisture simulations. There are a number of reasons for this. As shown in the model sensitivity study, soil moisture in the upper soil layers is not particularly sensitive to variations in LAI. Second, the differences in LAI between the static and dynamic simulations tend to be relatively small (mean difference, 1%), except during prolonged periods of drought and, therefore, have limited effect on soil moisture. Third, there are many other factors that influence the accuracy of soil moisture simulations such as the accuracy of the meteorological forcing data and soil and hydraulic parameters. Last, this comparison assumes that the observed soil moisture is without error. This is not realistic since recent work (Cosh et al. 2010) has shown that the equations used to derive soil moisture for the Oklahoma Mesonet

Table 4. Overall mean model evaluation metrics: mean bias error (MBE), mean absolute error (MAE), and coefficient of efficiency ($E$). Metrics are calculated between the model simulations and the in situ Oklahoma Mesonet observations at each of the three depths.
underestimate the true variability in soil moisture. Finally, there is a scale discrepancy between the observations (point) and the model (based on 1-km MODIS data), which could provide a source for inherent error.

Mahmood and Hubbard (2003) suggest that simulated soil moisture is sensitive to the overlying land cover, thus potentially explaining another source of inconsistency. The VIC model was run with the dominant land cover surrounding each Oklahoma Mesonet site. Therefore, the soil and vegetation parameters were consistent with the site’s dominant land cover; however, the actual parameter values were informed by those used in the Maurer et al. (2002) calibration dataset. This way, sites with land cover–type grassland exhibited the same root distribution regardless of the site’s location in Oklahoma.

4. Drought applications

VIC is used to inform the U.S. Drought Monitor (http://droughtmonitor.unl.edu/), and it is one of the models used in the NASA Land Data Assimilation Systems (NLDAS) (http://ldas.gsfc.nasa.gov/nldas/). Wood (2008) describes the University of Washington Surface Water Monitor, a drought monitoring tool that employs land surface moisture conditions from VIC simulations. The Surface Water Monitor is a near-real-time tool that provides VIC-simulated soil moisture, snow water equivalent, and runoff. It is one of the many tools/products utilized by the authors and contributors to the U. S. Drought Monitor (Svoboda et al. 2002). VIC has also been used to examine the frequency, severity, duration, and areal extent of U.S. droughts (Andreadis et al. 2005; Wang et al. 2009). Given that VIC is frequently used for drought modeling and monitoring, it is important to quantify how the use of the static LAI influences the identification of drought conditions.

VIC-simulated soil moisture from both the static and dynamic LAI models was converted from volumetric water content to total (0–95 cm) soil column water (TSCW). Daily TSCW was then converted to percentiles based on 2000–09 data and aggregated to the monthly time scale. The soil moisture percentiles were classified based on the drought categories (D0 to D4) used by the U.S. Drought Monitor (Quiring 2009). The calculations were done for each site, and then the proportion of the 20 study sites within each drought category was determined for every month. Because the largest differences between the static and dynamic LAI are observed during dry periods, the analysis focuses on two years (2001 and 2006) during which drought occurred in the majority of Oklahoma.

Figures 6 and 7 show the percentage of sites corresponding to each drought category from 2001 to 2003 and 2005 to 2008. These time periods were chosen because they capture the entire drought event as defined by the U.S. Drought Monitor. The plots show the percentage of sites in each drought category based on the static (top) and dynamic (middle) simulations. The bottom plot shows the difference between the static and dynamic plots. The areas are color coded by drought category, with D0 representing the least severe (abnormally dry, 21st to 30th percentile) and D4 representing the most severe (exceptional drought, < 2nd percentile).
Figure 6c shows that the VIC-simulated soil moisture based on dynamic LAI responds more quickly to dry conditions. Soil moisture drought is more severe in the dynamic LAI simulation from May to October 2001. However, during the latter part of 2001, the soil moisture drought from the static LAI simulation becomes drastically more severe. Over 30% more of the study sites are in classified as D2 (severe) drought under the static LAI simulation than in the dynamic LAI simulation. In the static simulation, drought is not only more severe, but it also persists longer (Fig. 6c). Drought conditions in the dynamic simulation begin to weaken in the middle of 2002 and <10% of study sites are in the D0 category by October 2002. However, based on the static simulation, >10% of sites are D0 and approximately 4% of sites are D1 until January 2003.

Figure 7 displays a similar pattern during the 2005–08 drought. The dynamic simulation soil moisture responds more quickly to the drier than normal conditions. Dynamic LAI soil moisture drought is more severe than the static simulation between March and September 2005. However, after January 2006 the static simulation indicates more severe drought conditions. By June 2006, over 30% of sites are D3 (extreme) in the static simulation, while only 12% are D3 in the dynamic simulation. These results suggest that the LAI parameter has a large influence on soil moisture simulations and it can influence how drought is depicted (both the timing and severity) in VIC soil moisture simulations. The persistence of dry soil moisture anomalies in the static simulation (which were also shown in section 3b) influence the depiction of drought conditions and tend to cause drought to persist for much longer than the dynamic simulations. Drought severity is also enhanced in the static versus the dynamic simulations. During the height of the 2001 and 2006 droughts, 20%–25% more sites were within D3 and D4 drought categories in the static simulations than in the dynamic simulations.

Over the 2001–03 drought period (Fig. 6), static LAI simulation soil moisture mean absolute volumetric water content error was 0.05 (18%), 0.06 (21%), and 0.09 (34%) at the 10-cm, 40-cm, and 95-cm layers, respectively. Dynamic LAI simulation soil moisture error was the same over the 2001–03 period. During the more severe 2005–08 drought (Fig. 7), static LAI simulation soil moisture mean absolute volumetric water content error was 0.05 (18%), 0.05 (19%), and 0.10 (37%) at the 10-, 40-, and 95-cm layers, respectively. Dynamic LAI simulation soil moisture error over the same period was 0.05 (18%), 0.05 (19%), and 0.08 (31%) at the 10-cm, 40-cm, and 95-cm layers, respectively. During these two drought events, the dynamic LAI simulations were consistently more accurate. However, owing to the factors mentioned in section 3c, the overall differences in accuracy between the two soil moisture simulations were small.

5. Summary and conclusions

Variable infiltration capacity (VIC) was used to simulate soil moisture conditions at three depths over several sites in Oklahoma between 1994 and 2010 using 1994–99 as a spinup period. Two simulations were generated; one using the standard, interannually invariant static LAI parameter prescribed using MODIS imagery and the other using interannually varying (dynamic) LAI also based on MODIS imagery. Soil moisture from each simulation was evaluated using in situ soil moisture observations provided by the Oklahoma Mesonet and quality controlled by the North American Soil Moisture...
Database. The results presented here suggest that the LAI parameter does influence soil moisture simulations from the VIC model. The static LAI parameter does not capture interannual variability in vegetation productivity and, thus, is shown to occasionally overestimate peak LAI at several of the study sites. Typically the overestimation corresponds with exaggerated soil drying, particularly in the deepest layer (Fig. 5). This is potentially due to anomalously dry soil moisture, forced by vegetation extraction in the top layer, which persists in the deepest soil layer (Wu and Dickinson 2004). Despite this issue, the dynamic LAI was not consistently more accurate in simulating soil moisture than the static LAI when compared to in situ Oklahoma Mesonet observations. The lack of consistent soil moisture estimate improvement could be due to a number of study limitations including 1) spatial scale discrepancy between the in situ soil moisture observations and the gridded soil moisture estimates from the land surface model and 2) the equations used to derive soil moisture for the Oklahoma Mesonet underestimate the true variability in soil moisture. Future research exploring the impact of vegetation parameters on land surface model soil moisture estimates could account for these two limitations through rescaling in situ soil moisture observations or using satellite-based soil moisture products.

The static and dynamic LAI can differ considerably when VIC is used for drought monitoring. The 2001 and 2006 droughts in Oklahoma were much more severe and persistent in the static LAI simulations than they were in the dynamic LAI simulations. Because the static LAI parameter does not account for drier than normal conditions that occurred throughout 2001 and 2006, the vegetation (LAI) does not respond to the below normal precipitation, and thus uptake and evapotranspiration rates are not adjusted. This is shown (Figs. 6 and 7) to result in enhanced drought severity and drought persistence as compared to the dynamic LAI simulation—the drought monitoring implication being that soil moisture generated from VIC simulations using an interannually invariant LAI parameter may produce unrealistic drought severity and persistence.

The main conclusions of this study are that 1) VIC-simulated soil moisture is sensitive to the LAI parameter, although the degree of sensitivity varies with depth, and 2) drought monitor products using model soil moisture are also very sensitive to the LAI parameter and thus require careful LAI parameterization to reflect actual vegetation conditions.

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