INVESTIGATION OF SOIL MOISTURE – VEGETATION INTERACTIONS IN OKLAHOMA

A Thesis

by

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ABSTRACT

Land-atmosphere interactions are an important component of climate, especially in semi-arid regions such as the Southern Great Plains. Interactions between soil moisture and vegetation modulate land-atmosphere coupling and thus represent a crucial, but not well understood climate factor. This study examines soil moisture-vegetation health interactions using both *in situ* observations and land surface model simulations. For the observational study, soil moisture is taken from 20 *in situ* Oklahoma Mesonet soil moisture observation sites, and vegetation health is represented by MODIS-derived normalized difference vegetation index (NDVI). For the modeling study, the variable infiltration capacity (VIC) hydrologic model is employed with two different vegetation parameterizations. The first is the model default vegetation parameter which is interannually-invariant leaf area index (LAI). This parameter is referred to as the control parameter. The second is MODIS-derived LAI, which captures interannual differences in vegetation health. Soil moisture simulations from both vegetation parameterizations are compared and the VIC-simulated soil moisture's sensitivity to the vegetation parameters is also examined.

Correlation results from the observation study suggest that soil moisture-vegetation interactions in Oklahoma are inconsistent, varying both in space and time. The modeling results show that using a vegetation parameterization that does not capture interannual vegetation health variability could potentially result in dry or wet biased soil moisture simulations.

DEDICATION

This work is dedicated to my fiancé Molly for enduring my stress and complaints, and for moving to a very hot place for me. Also to my parents for always pushing me to follow my dreams and work hard to be able to do what I love. Lastly to my Grandmother who used board games to teach me Geography, and initiated my interest in Geographic ideas and thinking.

ACKNOWLEDGEMENTS

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Finally, thanks to my mother and father for their encouragement and to my fiancé for her patience and love.

NOMENCLATURE

AGCM	Atmospheric General Circulation Model
d	Degree of Agreement
E	Coefficient of Efficiency
LAI	Leaf Area Index
LSM	Land Surface Model
MAE	Mean Absolute Error
MBE	Mean Bias Error
MODIS	Moderate Resolution Imaging Spectroradiometer
NASMD	North American Soil Moisture Database
NCDC	National Climate Data Center
NDVI	Normalized Difference Vegetation Index
NLCD	National Land Cover Database
RMSE	Root Mean Square Error
SCAN	Soil Climate Analysis Network
SST	Sea Surface Temperatures
SVAT	Soil-Vegetation-Atmosphere Transfer Scheme
USGS	United States Geological Survey
VCI	Vegetation Condition Index
VIC	Variable Infiltration Capacity (model)

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CHAPTER I

INTRODUCTION

1.1. Background

1.1.1 Soil Moisture and Land-Atmosphere Interactions

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). However, few soil moisture monitoring networks exist globally relative to networks observing temperature and precipitation, impeding research and elucidation of land-atmosphere feedbacks critical to drought prediction and mitigation. Remote sensing imagery and land surface models (LSMs) are commonly employed for estimation of mesoscale hydrologic and climatologic conditions; however, the spatial variability of soil moisture and the factors that influence the magnitude of soil moisture (soil texture, overlying vegetation), are not consistently well represented (Xia *et al.* 2008). The influence of local soil moisture on near-surface atmospheric moisture variability and related precipitation variability has been widely examined; however, the spatial inconsistency of this relationship is not well understood (Meng and Quiring, 2010a).

Soil moisture significantly influences land-atmosphere interactions as soil moisture modifies energy and wetness fluxes in the boundary layer through evaporation and transpiration (Pal and Eltahir, 2001). Dry soil can induce and amplify warm and dry conditions, especially during the summer, by reducing local evaporation and modifying patterns of moisture convergence/divergence and atmospheric circulation (Namias, 1991). Thus soil moisture can have a strong impact on the Bowen ratio (Basara and Crawford, 2002), convective available potential energy (Pal and Eltahir, 2001), convective inhibition (Myoung and Nielsen-Gammon, 2010), and the persistence of precipitation, which can correspond to an intensification of anomalous soil moisture conditions. Koster *et al.* (2004) identified regions of strong land-atmosphere interactions through sixteen ensemble simulations of a dozen climate models. The results showed these "hot spot" regions are typically located in transition zones between wet and dry climates, where potential evapotranspiration is consistently high, while actual evapotranspiration is sensitive to soil moisture availability, such as the North American Great Plains. Similarly Taylor *et al.* (2011) examined the frequency of Sahelian convective storms and the mesoscale soil moisture patterns underlying convective initiation. They found that horizontal gradients in soil moisture at the mesoscale can have a significant impact on convective rainfall initiation in Sahel, and potentially several other semi-arid regions.

1.1.2 Vegetation – Soil Moisture Interactions

Schubert *et al.* (2004) examined the causes of droughts in the Great Plains using ensembles of a long-term general circulation model forced with observed sea surface temperatures and found that two-thirds of low frequency rainfall variance can be explained by land-atmosphere interactions. In contrast the observational study of Findell and Eltahir (1997) only attributed 16% of summer precipitation variance to spring soil moisture conditions. The inconsistencies of soil moisture-atmosphere coupling strength are due in part to spatial variability of influential variables such as vegetation and soil texture. Discrepancies in the estimates of land-atmosphere coupling strength have implications for accurate modeling and drought predictability.

Vegetation is a primary conduit through which soil moisture influences near-surface atmospheric conditions. Therefore variations in vegetation density and health have significant influences on transpiration (McPherson, 2007) and corresponding soil moisture-atmosphere interactions (Pielke, 2001). Dekker *et al.* (2007) found that the inclusion of microscale vegetation-soil feedback increased evapotranspiration, which in turn increased simulated mesoscale precipitation feedback up to 35%. Although vegetation-soil moisture interactions have been shown to significantly alter near-surface atmospheric moisture at the mesoscale, these interactions have not been thoroughly investigated or quantified. Therefore this research proposes to examine the interactions between soil moisture and vegetation using both observations and LSMs.

1.1.3 Objectives

The objectives are twofold for this research. The first objective is to investigate the interactions between soil moisture and vegetation during the growing season (May-October) using soil moisture observations and remote sensing-derived vegetation health. This will provide an observation-based assessment of soil moisture-vegetation relationship variability as well as elucidation of the factors which have the most influence on land-atmosphere interactions in Oklahoma.

The second objective will examine the sensitivity of the Variable Infiltration Capacity (VIC) LSM when simulating soil moisture using two different vegetation parameterizations. Many LSMs including VIC use an interannually-invariant vegetation health parameter, which will be converted to a dynamic vegetation parameter. Soil moisture will be simulated for several sites in Oklahoma under both control and variable vegetation parameters. Soil moisture simulations from both vegetation parameterizations will be compared and the accuracy of each will be assessed using *in* situ soil moisture observations.

CHAPTER II

OBSERVATION-BASED VEGETATION-SOIL MOISTURE INTERACTIONS

2.1. Introduction

2.1.1 Background

Soil moisture controls land-atmosphere interactions by modifying energy and moisture fluxes in the boundary layer. Soil water content influences evapotranspiration and corresponding near-surface atmospheric moisture availability (Pal and Eltahir, 2001). Dry soil can induce and amplify warm and dry conditions, especially during the summer, by reducing local evaporation and modifying patterns of moisture convergence/divergence (Namias, 1991). Overlying vegetation is a key pathway through which soil moisture influences atmospheric moisture. Therefore variations in vegetation density and health modify transpiration rates and corresponding near-surface atmospheric moisture availability (Pielke, 2001). Myoung and Nielsen-Gammon (2010) found that summer precipitation variability in the southern Great Plains is primarily explained by convective inhibition, a strong function of near-surface moisture. Their results suggest soil moisture and vegetation are significantly related to convective precipitation. Fig. 2.1 shows a simple schematic representing moisture related interactions between vegetation and soil.

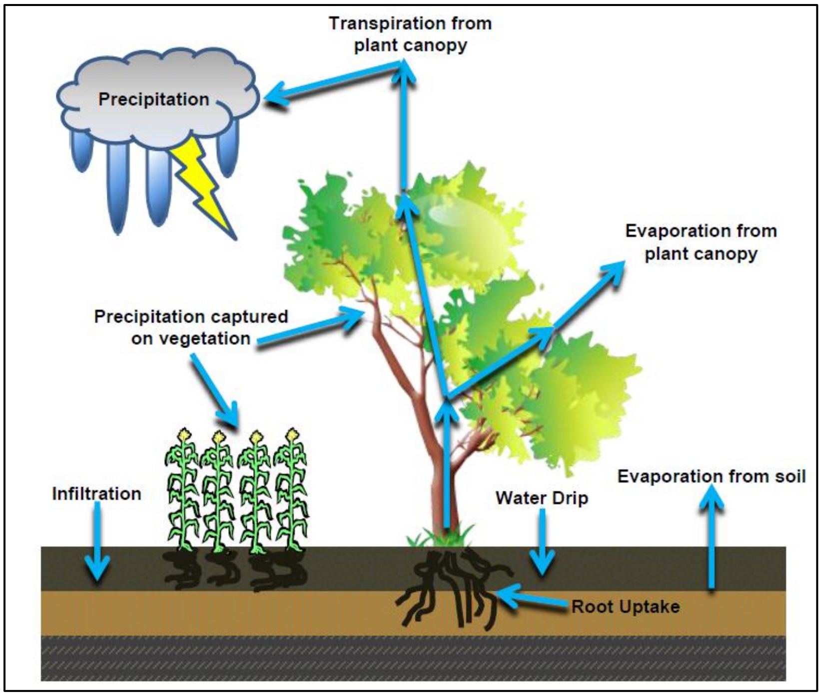


Figure 2.1. Schematic of moisture-related interactions between vegetation and soil.

2.1.2 Previous Research

Gu *et al.* (2008) examined the relationship between vegetation health and soil moisture at several sites in Oklahoma. Their correlation analysis suggested that vegetation-soil moisture relations varied as a function of soil texture and land cover heterogeneity, also that soil moisture-vegetation correlations tended to be highest at a 7-8 day lag. Méndez-Barroso *et al.* (2009) investigated the relationship between vegetation greenness, precipitation and soil moisture in the North American Monsoon Region. Their results suggested that vegetation greenness responded best to concurrent soil moisture conditions, as lagged correlations were generally smaller. Their results also showed that soil moisture-vegetation correlation strength was dependent on the vegetation type, as thorn-scrub greenness was consistently highest correlated with immediate soil moisture observations. The results of the limited number of past investigations suggest that vegetation-soil moisture interactions vary considerably both in space and time. It also suggests that pedosphere-biosphere coupling is dependent both on vegetation type and soil texture.

In order to appropriately evaluate land surface model output for drought prediction, observed land-atmosphere interactions must be well documented and understood. The objective of this study is to document the observed relationship between soil moisture and overlying vegetation health. Simultaneous and lagged correlations are used to measure the strength of the relationships. Spatial and temporal patterns are observed, and potential sources of such variability are identified.

2.2. Data and Methods

2.2.1 Study Region

Oklahoma experiences a significant west-east precipitation gradient and north-south temperature gradient (Meng and Quiring, 2010b). Vegetation and soil conditions exhibit great spatial variability across the state, thus providing the potential for soil moisture-vegetation interactions to vary spatially and temporally. This study utilizes *in situ* soil moisture observations from 20 stations in Oklahoma (Fig. 2.2). These sites are part of the Oklahoma Mesonet Observation Network, *www.mesonet.org*. Volumetric soil water content (θ) is estimated using a heat dissipation sensor at 5, 25, 60 and 75 cm depths (Illston *et al.* 2008). The soil moisture data have been compiled and quality controlled by the North American Soil Moisture Database (NASMD) at Texas A&M University. The stations were chosen because of the length and completeness of their data. Table 2.1 displays soil and land cover characteristics from each site. Soil textures range from sandy loam to silt and overlying land cover includes grassland, pasture, scrub and cultivated crops.

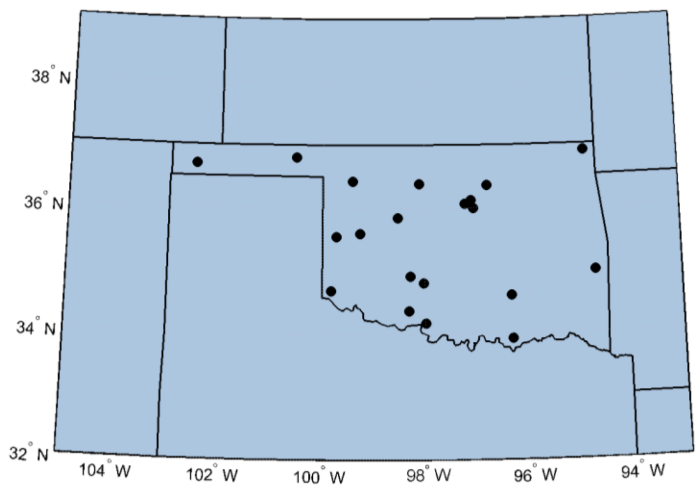


Figure 2.2. Site map of 20 Oklahoma Mesonet observing sites used in the study.

2.2.2 Vegetation and Soil Moisture Data

Vegetation health is estimated using the Normalized Difference Vegetation Index (NDVI). NDVI is derived from reflectance values that are calculated separately in wavelength bands in the visible (0.5 – 0.7 μm) and near infrared (0.7 – 0.9 μm) regions of the spectrum (Carlson and Ripley, 1997). NDVI data are calculated from eMODIS surface reflectance, a product of the Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensing tool. eMODIS is derived from real-time 250 m Modis L1B data over the contiguous United States. The United States Geological Survey process the data, correct for atmospheric noise and calculate NDVI from the surface reflectance product. eMODIS images are then reprojected into a Lambert Azimuthal projection and converted to the GeoTIFF format for ease of distribution. eMODIS data are provided at 7-day rolling composites over the contiguous United States (Gu *et al.,* 2012). The data were downloaded for each growing season (May – October) between 2000 and 2009.

Table 2.1. Study site land cover and soil characteristics.

Site	Dominant Land Cover	5 cm Soil Texture	25 cm Soil Texture	60 cm Soil Texture	75 cm Soil Texture
Acme	Grassland	Sandy Loam	Sandy Loam	Sandy Loam	Sandy Loam
Marena	Grassland	Sandy Loam	Loam	Sandy Loam	Sandy Loam
Wister	Pasture/Hay	Silt Loam	Silt Loam	Silt Loam	Clay
Durant	Deciduous	Sandy Loam	Sandy Loam	Clay	Clay
Cheyenne	Grassland	Sandy Loam	Sandy Loam	Loam	Loam
Apache	Cropland	Sandy Loam	Sandy Loam	Clay	Clay
Stillwater	Cropland	Silt Loam	Loam	Loam	Clay Loam
Pawnee	Grassland	Silt Loam	Silt Loam	Clay Loam	Silt Loam
Waurika	Cropland	Sandy Loam	Sandy Loam	Sandy Loam	Sandy Loam
Miami	Grassland	Silt Loam	Silt Loam	Clay	Clay
Hollis	Cropland	Silt Loam	Clay	Clay	Clay
Watonga	Grassland	Loam	Loam	Loam	Loam
Boise City	Grassland	Loam	Clay Loam	Silt Loam	Silt Loam
Walters	Developed	Silt Loam	Clay	Clay	Clay Loam
Centrahoma	Grassland	Sandy Loam	Loam	Clay Loam	Clay Loam
Beaver	Grassland	Loam	Clay Loam	Loam	Loam
Woodward	Evergreen	Sandy Loam	Loam	Loam	Loam
Butler	Grassland	Silt Loam	Silt Loam	Silt Loam	Silt Loam
Lahoma	Grassland	Silt Loam	Clay Loam	Silt Loam	Silt Loam
Perkins	Grassland	Loam	Loam	Loam	Loam

Because NDVI varies seasonally as vegetation “greens” during the growing season, weekly NDVI values had to be standardized in order to remove seasonal bias. Vegetation Condition Index (VCI) was calculated and used to represent vegetation health condition. VCI has been previously employed in land-atmosphere interaction studies (Quiring and Ganesh, 2010). The VCI is calculated as

$$VCI_i = \frac{NDVI_i - NDVI_{min}}{NDVI_i - NDVI_{max}} \qquad (1)$$

where $NDVI_i$ is the NDVI value of the current week and $NDVI_{min}$ and $NDVI_{max}$ represent the minimum and maximum NDVI values measured during that week at that site over the 10 year period. Daily soil moisture observations were averaged into 7-day composites for compatibility with the VCI data.

2.2.3 Methods

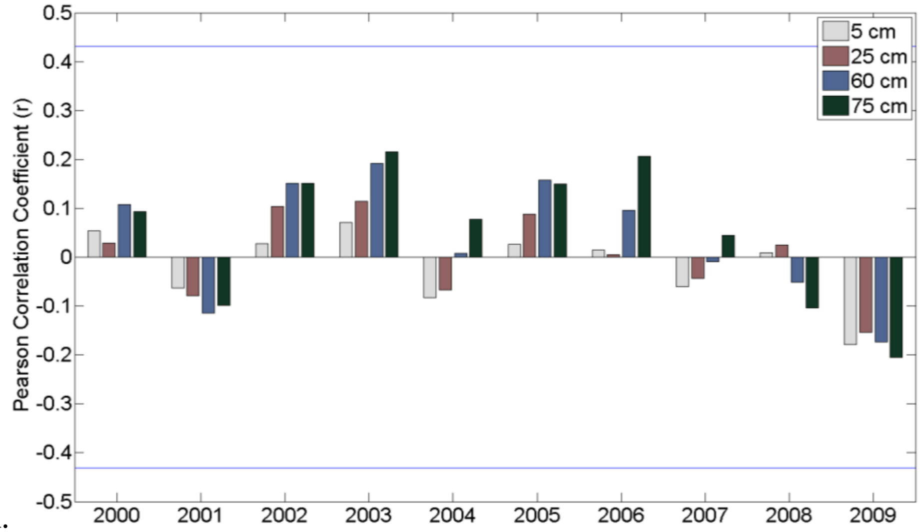
Soil moisture-vegetation interactions were evaluated using simultaneous and lagged correlations. Pearson correlation coefficients (R) are used to indicate whether the relationship is positive or negative and the coefficient of determination (R^2) is used to represent the relationship magnitude/strength. Data were subdivided and correlations were calculated to assess whether the soil moisture-vegetation health strength varies both spatially (between sites) and temporally (between growing seasons).

2.3. Results and Discussion

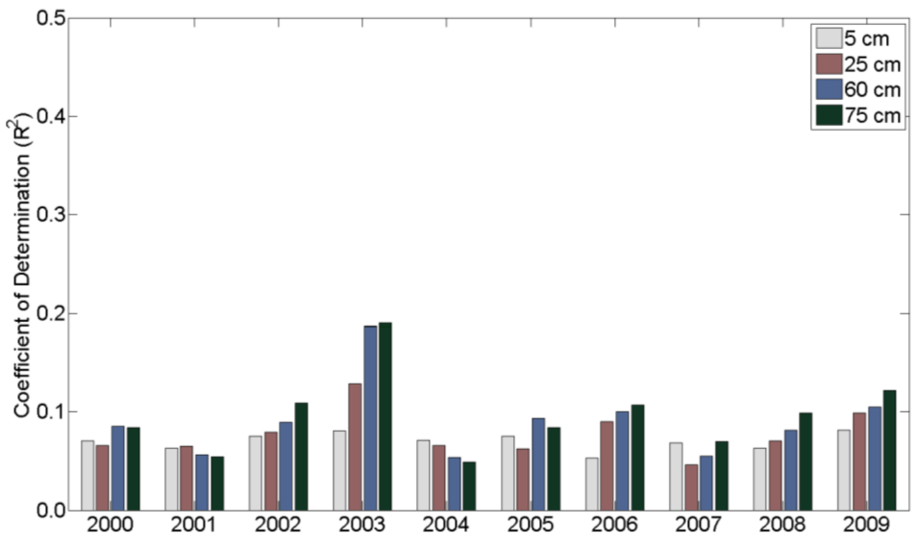
2.3.1 Soil Moisture – VCI Correlations

Soil moisture - vegetation interaction strength varied significantly between growing seasons. Figures 2.3a and 2.3b show correlation coefficients and the coefficient of determination representing the sign and strength, respectively of the soil moisture-vegetation health relationship at each depth averaged over all sites by growing season. As shown, the correlations exhibit considerable interannual variability, even changing sign from one growing season to the next. Correlations at all depths are positive in 2000, 2002, 2003, 2005 and 2006 and they are negative in 2001 and 2009. Soil moisture – VCI correlations are not noticeably higher at any depth than any other. None of the reported correlation values in Fig. 2.3a are significant at the alpha < 0.05 level suggesting that high correlation variability between growing seasons and between sites degrades any significant relationship signal. It is worth mentioning here that the same analysis was conducted using range-based standardized soil moisture instead of raw volumetric soil water content. This was done as soil moisture can exhibit a seasonal magnitude pattern, typically less dramatic than that of vegetation health. Correlations between standardized soil moisture and VCI (not shown) were similarly varied and not statistically significant.

Similarly the coefficient of determination reported in Fig. 2.3b shows high interannual variability. For example the site-averaged coefficient of determination between 60 cm soil moisture and VCI in 2003 is 0.19 and significant at the alpha < 0.05 confidence level, while the coefficient of determination at the same soil depth just a year later in 2004 is less than 0.1.



a.



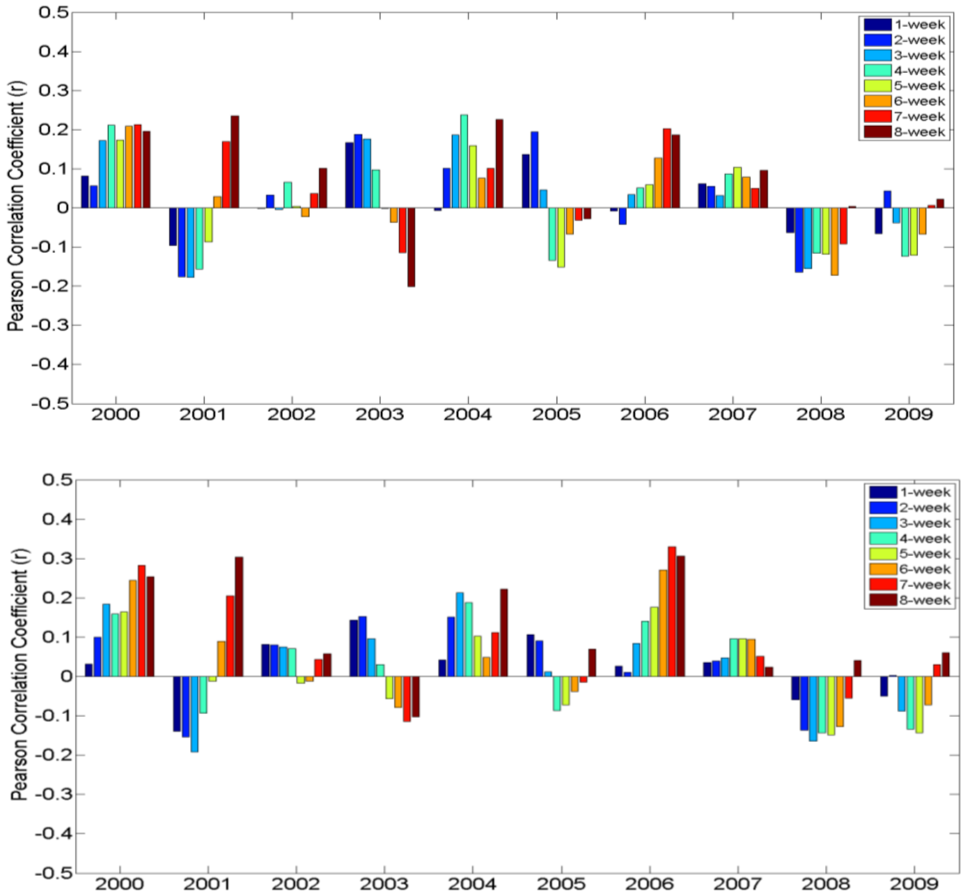
b.

Figure 2.3. Growing season (May-October) correlations between soil moisture and VCI (a) and coefficient of determination (b) at each depth in the soil averaged across all 20 sites. Blue line represents significance threshold at the alpha < 0.05 level.

2.3.2 Lagged Correlations

Soil moisture can exhibit a memory in which anomalously dry or wet conditions will persist for several weeks (Wu and Dickinson, 2004). Gu *et al.* (2008) found that soil moisture – vegetation interactions were strongest at a one-week lag, attributable to the soil moisture memory. In this study, soil moisture was lagged 1 – 8 weeks and lagged correlations were calculated between soil moisture and VCI. Figs. 2.4 and 2.5 display bar graphs of lagged correlations at each soil depth. Similar to the simultaneous correlations, lagged correlations averaged over all sites vary in sign. For example, Fig. 2.5b shows that 75 cm soil moisture – VCI correlations in 2001 at the 7 – 8 week lag exceed 0.3, while correlations at a 1 – 2 week lag are actually negative (-0.14). However, in 2003, correlations at the same depth with a 7 – 8 week lag are slightly negative (-0.06), while 1 – 2 week lag correlations are positive (0.18). Furthermore, 1-week lagged correlations were not consistently stronger than simultaneous correlations, suggesting that the time interval at which soil moisture and vegetation most strongly interact varies spatially and temporally.

Because of the high level of variability in both simultaneous and lag correlations, precipitation, land cover and soil texture characteristics were examined to explain the variability in the soil moisture-vegetation relationships.

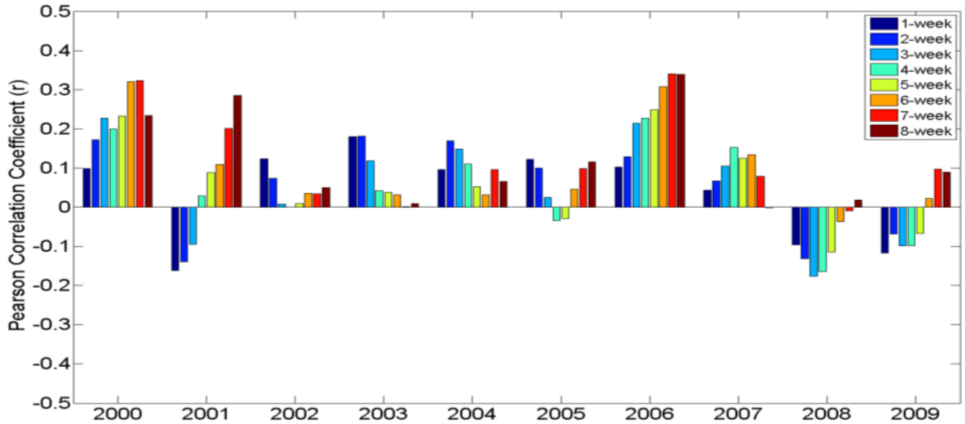


a.

b.

Figure 2.4. Bar graphs of soil moisture-VCI lag correlation coefficients. Correlations were averaged overall all 20 sites and reported by individual growing seasons. Plots are shown at (a) 5 cm and (b) 25 cm.

a.



b.

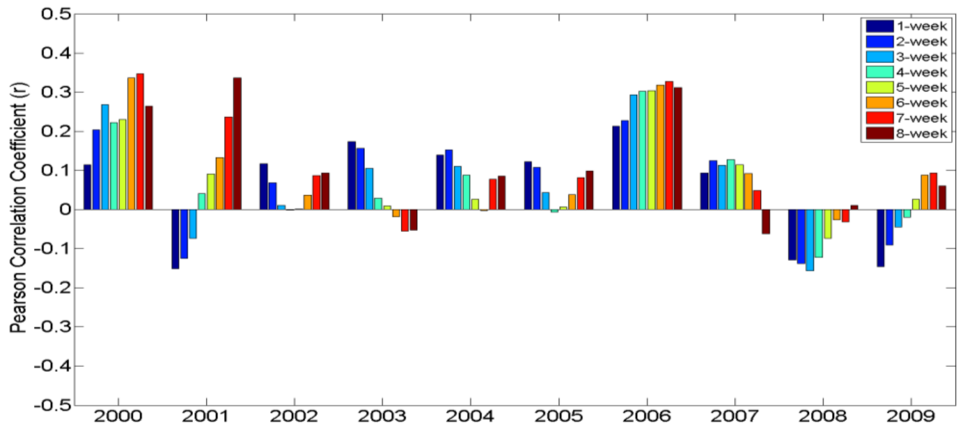


Figure 2.5. Bar graphs of soil moisture-VCI lag correlation coefficients. Correlations were averaged overall all 20 sites and reported by individual growing seasons. Plots are shown at (a) 60 cm and (b) 75 cm.

2.3.3 Precipitation Influence on Soil Moisture-Vegetation Interactions

Precipitation is widely accepted as the principal forcing of soil moisture, and several studies have shown that precipitation variability influences vegetation health (Wang *et al.*, 2001; Ji and Peters, 2004). Thus the timing and quantity of growing season precipitation has the potential to influence the interaction between soil moisture and vegetation. Wang *et al.* (2001) correlated precipitation with NDVI to quantify the influence of precipitation variability on vegetation health. They found that the strongest precipitation-NDVI correlations were seen during and immediately after a prolonged drying period. This was attributed to plant response to relatively low soil moisture caused by below normal precipitation. Thus when there is little precipitation, soil moisture will limit plant health and correlations between soil moisture and vegetation health will be stronger.

To quantify how variable growing season precipitation influences vegetation-soil interactions, daily growing season (May – October) precipitation data was acquired from the Oklahoma Mesonet at each of the 20 study sites. Each year's percent departure from the 1994 – 2010 mean total growing season precipitation was calculated and related to the soil moisture-VCI correlation coefficient during that particular growing season. Fig. 2.6 shows scatter plots of precipitation departure and 5 cm soil moisture-VCI correlation coefficients at each site. Plots are presented by growing season; each point represents one study site. The coefficient of determination is also calculated for each growing season.

The relationship between precipitation departures and soil moisture-VCI correlations is variable in sign. However, the relationship is not statistically significant during any growing season. The relationship sign does not show any pattern between anomalously dry and wet growing seasons. The scatter plots of 25, 60 and 75 cm soil moisture-VCI correlations (not shown) demonstrate similar results. These plots suggest that the data used here does not show any relationship between the amount of precipitation that falls during a growing season and the coupling strength between soil moisture and vegetation health in Oklahoma.

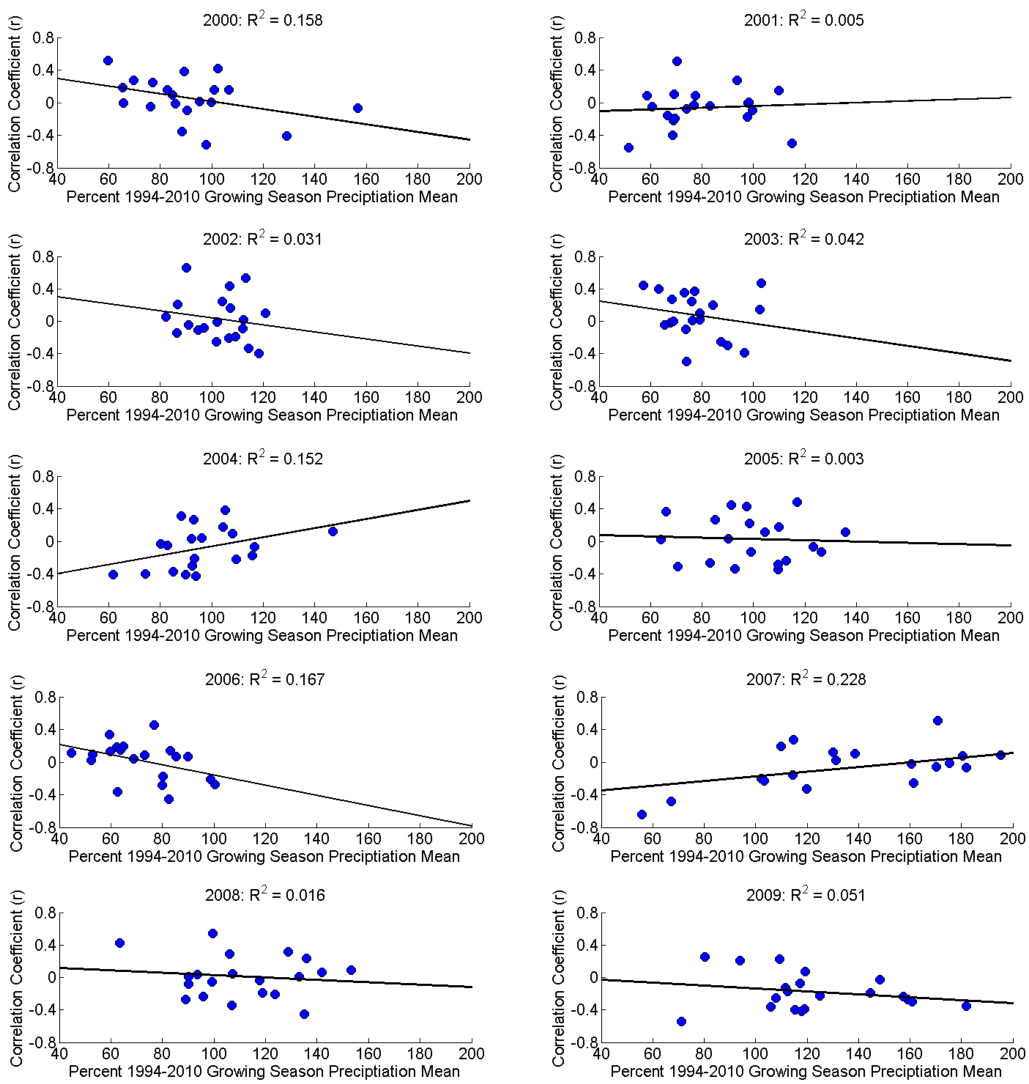


Figure 2.6. Scatter plots of growing season (May-Oct) precipitation departures (%) and soil moisture-VCI correlation coefficients. Each point represents one site. Plots are shown for 5 cm.

Results from previous studies suggest that soil moisture-VCI relationships should be generally stronger under drier conditions. Dirmeyer *et al.* (2000) performed a sensitivity analysis using several land surface models to investigate the relationship between evaporative fraction and soil moisture. They found that evaporative fraction, a strong function of overlying vegetation production (McPherson, 2007), was strongly, linearly correlated with soil moisture under anomalously dry conditions. Similarly Méndez-Barroso *et al.* (2009) evaluated the soil moisture-vegetation coupling under varying conditions and found that generally stronger interactions occurred under dry or drying conditions. The results shown here do not corroborate these previous findings. One possible explanation is that precipitation does not influence vegetation health directly, but instead through soil moisture. Thus the magnitude of the soil moisture should be more strongly related to the coupling strength between soil moisture and vegetation health.

Koster *et al.* (2009) describe two idealized “evaporative regimes” in which evaporation is characterized from the land surface. The drier or moisture-limited regime is associated with strong land-atmosphere interactions. In the moisture-limited regime, soil moisture exerts strong control on evaporation. The wetter or energy-limited regime is distinguished by evaporation variability that is independent of soil moisture conditions. Koster *et al.* (2009) use AGCM simulations corroborated by observations of precipitation and temperature to examine the manifestation of the two regimes. Their results show that these evaporative control regimes are evident in the observations; however, they are much stronger in the AGCM simulations (Koster *et al.*, 2009).

The physical explanation for the observed phenomena is that relatively dry soil moisture provides a moisture-limited circumstance for vegetation, constricting the stomata apertures and reducing transpiration. In this situation, increases (decreases) in soil moisture will lead to increased (decreased) stomata expansion and increased (decreased) transpiration (Koster *et al.* 2009). However, as soil moisture increases beyond the threshold of the moisture-limited regime, stomata no longer respond as markedly to soil moisture changes, and thus transpiration is essentially decoupled from soil moisture conditions. Thus anomalously dry soils, forced by below normal precipitation, has a stronger influence on vegetation health than if moisture for vegetative root uptake was not limited. These results suggest that under anomalously dry conditions (i.e., moisture-limited regime) we should see stronger land-atmosphere interactions, a phenomenon that is generally corroborated by the results seen here.

2.3.4 Soil Moisture-VCI Interactions Under Varying Moisture Conditions

Several studies have suggested that soil moisture is coupled to surface and near-surface atmospheric processes only under specific energy and moisture conditions. Seneviratne (2010) describes three climate/soil moisture regimes related to the impact of soil moisture on evapotranspiration, a variable strongly related to NDVI (Nemani and Running, 1989). The wet and dry regimes describe soil moisture conditions that are greater than a critical soil moisture value and conditions less than the soil wilting point, respectively. Under these two regimes, soil moisture is generally decoupled from evapotranspiration. However, when soil moisture is between the critical value and wilting point, strong land-atmosphere coupling is observed (Seneviratne, 2010). Thus it is during this transition period that soil moisture-vegetation interactions should be strongest (Koster *et al.*, 2004).

To test the hypothesis that soil moisture-VCI interactions are strongest during the transition regime (when soil moisture is between the critical value and wilting point), soil moisture-VCI correlations were computed using all of the observations associated with the transition regime during each growing season. Soil moisture conditions that fall between the soil wilting point and the critical value, approximately 80% of field capacity (Seneviratne, 2010), are considered ideal for strong surface-subsurface coupling. The Oklahoma Mesonet provides soil texture, but not wilting point or field capacity for any of their observation sites, and thus these parameters had to be estimated. Instead of using pedotransfer functions or other generalized physically-based methods, field capacity and wilting point were estimated by examination of the soil moisture data. Field capacity (wilting point) was estimated by first sub-setting the top 98% (bottom 2%) of soil moisture values for each station at each depth. Histograms of the top and bottom 2% of data were drawn and field capacity (wilting point) was estimated as the average of the respective histogram bins with the greatest frequency of occurrence. Thus both parameters are an approximation of the points at which the soil moisture data most frequently peaks and troughs, respectively. The soil moisture critical value was set as 80% of the estimated soil field capacity.

Fig. 2.7 shows the percent of growing season soil moisture observations which fell in the transition regime and the corresponding soil moisture-VCI correlation. Each point represents one growing season at one site and so each plot contains 10 points from each site (200 points total). The coefficient of determination was calculated to evaluate the relationship between the number of transition regime days and the soil moisture-vegetation relationship during that period. The soil moisture-VCI correlations do not vary as a function of the number of observations in the transition regime. The slopes of the linear fits between the two variables at each depth are positive, however, the relationship is not statistically significant. Fig. 2.8 shows the same relationship averaged over all sites. Thus each point represents one growing season at one of the four depths, thus accounting for 40 points (10 years X 4 depths). Although the overall fit is positive (R^2 of 0.07), the relationship is not statistically significant.

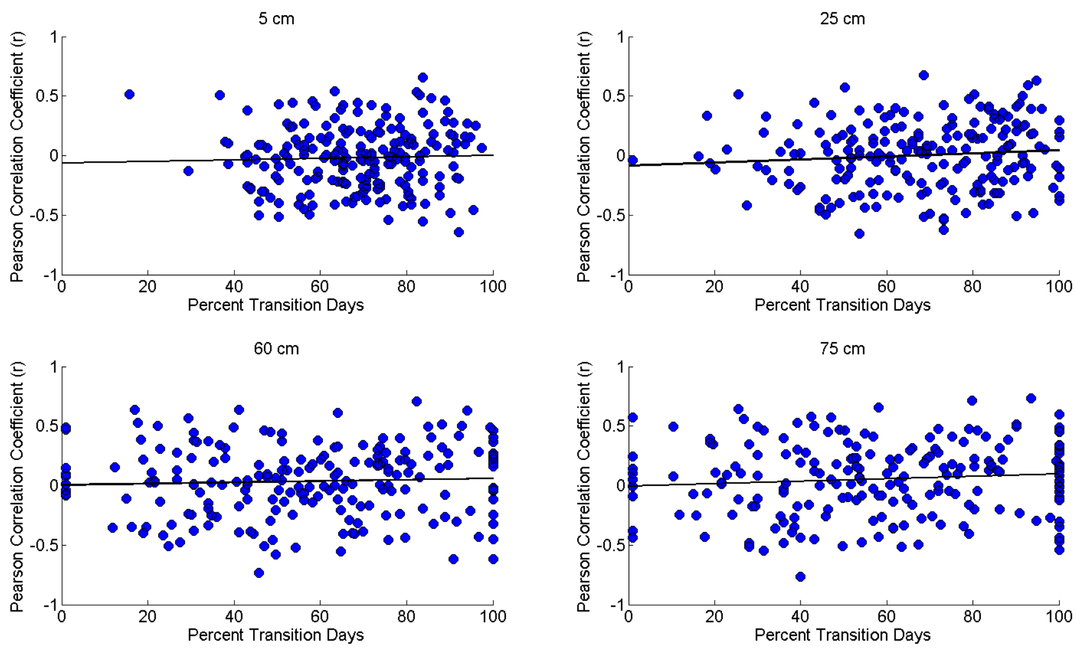


Figure 2.7. Scatter plots of the percent of growing season daily soil moisture observations in the transition regime and the soil moisture-VCI correlation coefficients. Each point represents one growing season at one site.

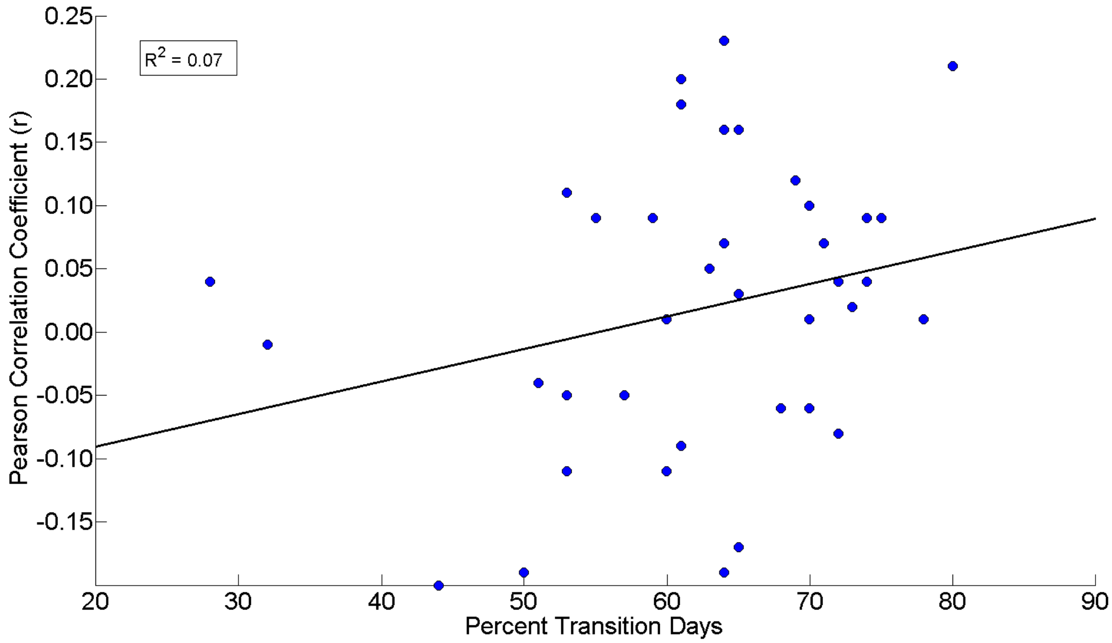


Figure 2.8. Scatter plot of percent transition days and soil moisture-VCI correlation coefficient. Each point represents one growing season at one soil depth.

These results suggest that although soil moisture conditions within the transition regime defined by Seneviratne (2010) can lead to stronger soil moisture-vegetation interactions, the influence is not consistent nor statistically significant when averaged over all sites. These results are surprising because vegetation health should be influenced by soil moisture, especially when soil moisture is between the critical value and the wilting point. Findell and Eltahir (2003) evaluated soil moisture-convection feedbacks over the contiguous United States, and found that the Southern Great Plains exhibited both positive and negative land-atmosphere feedbacks during the summer. Regions with strong positive feedbacks were observed in the eastern Great Plains and strong negative feedbacks were found in the western Great Plains. Thus the strength and sign of land-atmosphere interactions in the Southern Great Plains were characterized by high variability, potentially explaining the variability in R^2 values in this study. Although land-atmosphere interactions do respond to transitional moisture conditions, other factors also influence the strength of soil moisture-VCI relationships.

2.3.5 Soil Moisture – VCI Correlation Spatial Variability

Spatial variability is also observed within soil moisture-VCI correlations, although not nearly as pronounced as the temporal variability. Figure 2.9 shows maps of station-averaged soil moisture-VCI coefficient of determination (R^2) at 4 soil depths across the study region. No consistent spatial patterns are noticeable in the maps, suggesting that the influence of spatially-heterogeneous variables (soil texture, land cover, etc.) are site specific.

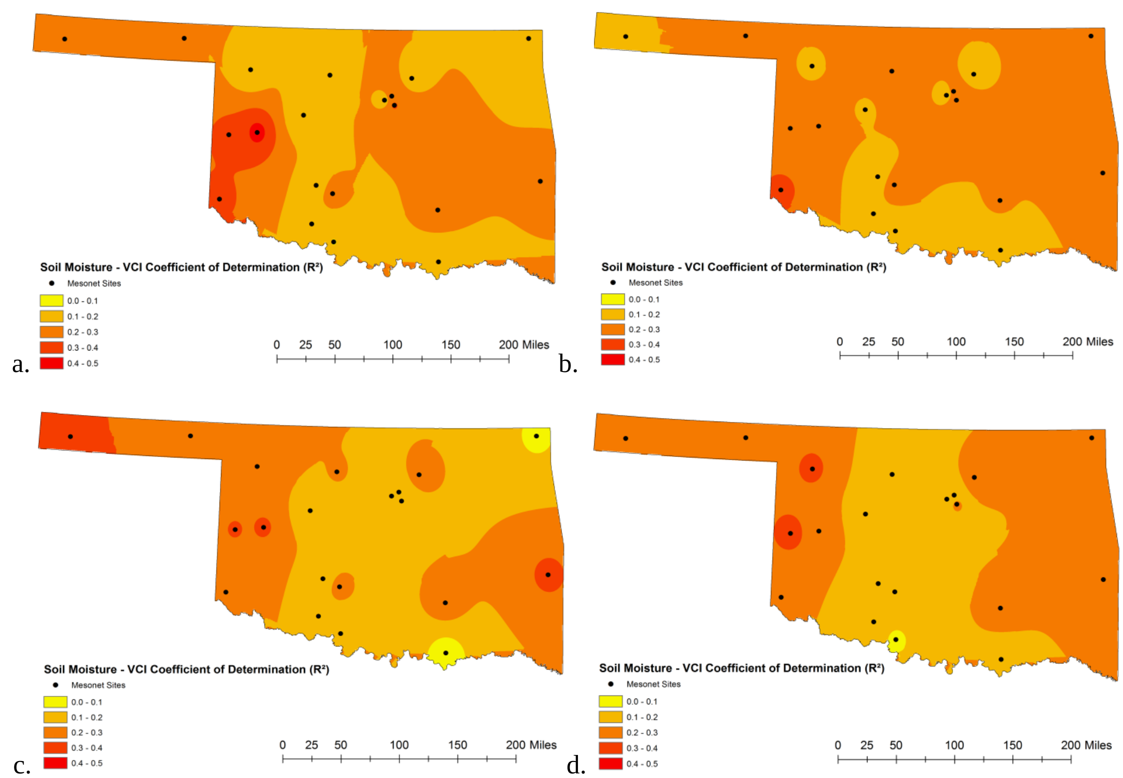


Figure 2.9. Contour maps of soil moisture-VCI correlation coefficients (R) at (a) 5 cm, (b) 25 cm, (c) 60 cm and (d) 75 cm.

To test the influence of land cover and soil texture on soil moisture-VCI interactions, data were composited according to their dominant land cover and soil porosity at each depth. Fig. 2.10 displays bar graphs of soil moisture-VCI correlations by growing season averaged over all sites of similar land cover. This suggests that sites dominated by grassland as well as grassland-mixed land cover exhibit more frequent positive correlations.

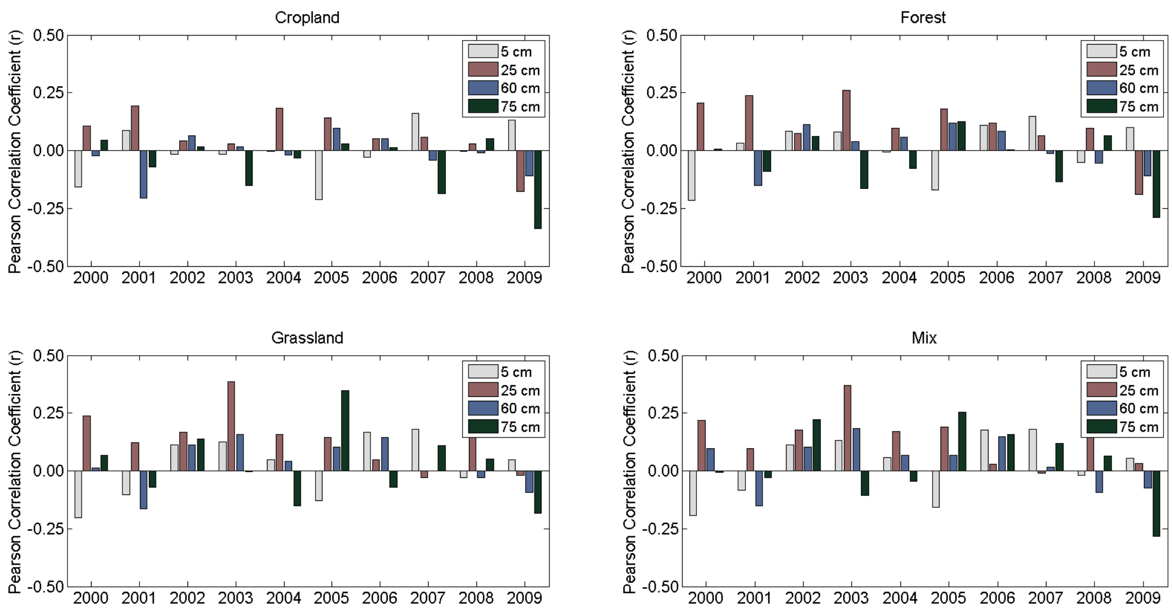


Figure 2.10. Bar graphs of soil moisture-VCI correlation coefficients averaged by growing season over all sites of similar overlying land cover. Correlations are provided at each of the 4 soil depths.

Boxplots of soil moisture-VCI correlations were created for each group of sites, classified by their land cover. Fig. 2.11 displays these boxplots, which show that the mean correlations of sites with forest, grassland and grassland-mix land cover are higher than those with cropland cover. However, a student's paired t-test (results not shown) shows that the mean soil moisture-VCI correlations for sites with grassland and grassland-mix land cover types are not significantly higher than those with cropland cover types. This suggests that although sites with native grassland cover do tend to have more positive soil moisture-vegetation interactions, the overall differences between land cover classes are not statistically significant.

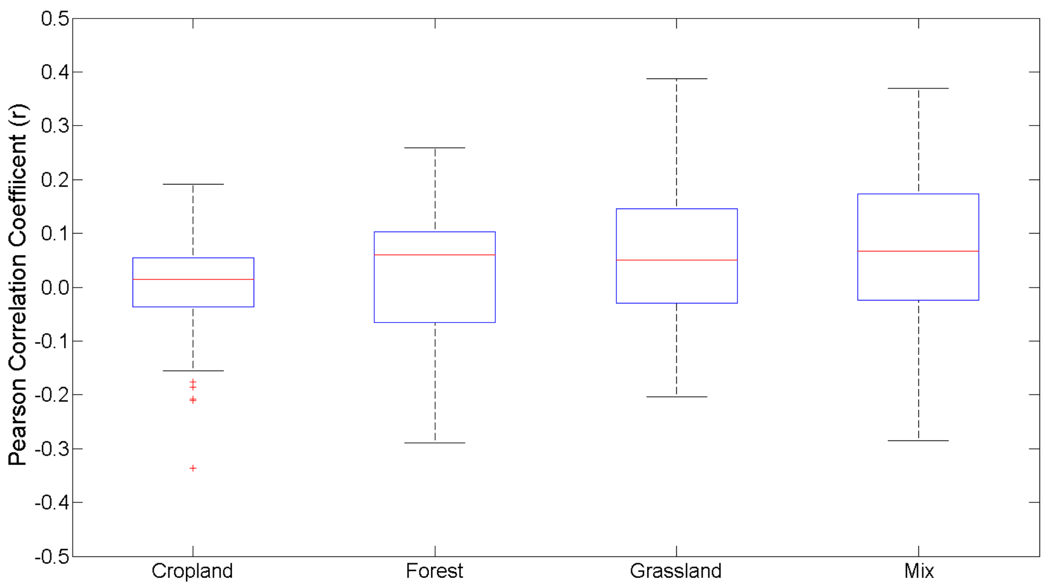


Figure 2.11. Box plot of soil moisture-VCI correlation coefficients averaged over all sites with similar land cover.

Soil texture, specifically the porosity of a soil, influences the water retention abilities of the soil and thus can affect the interactions between soil moisture and vegetation. Fig. 2.12 displays scatter plots of soil porosity and the site averaged soil moisture-VCI correlation at each site. The results indicate that at 3 out of the 4 depths there is a negative relationship between soil porosity and the strength of the soil moisture-vegetation relationship. This suggests less porous soils retain more moisture in the upper soil layers. Although this makes sense physically, none of the relationships between porosity and soil moisture-VCI correlations are statistically significant. Therefore, although both land cover and soil texture seem to influence soil moisture-vegetation interactions, these effects are not strong.

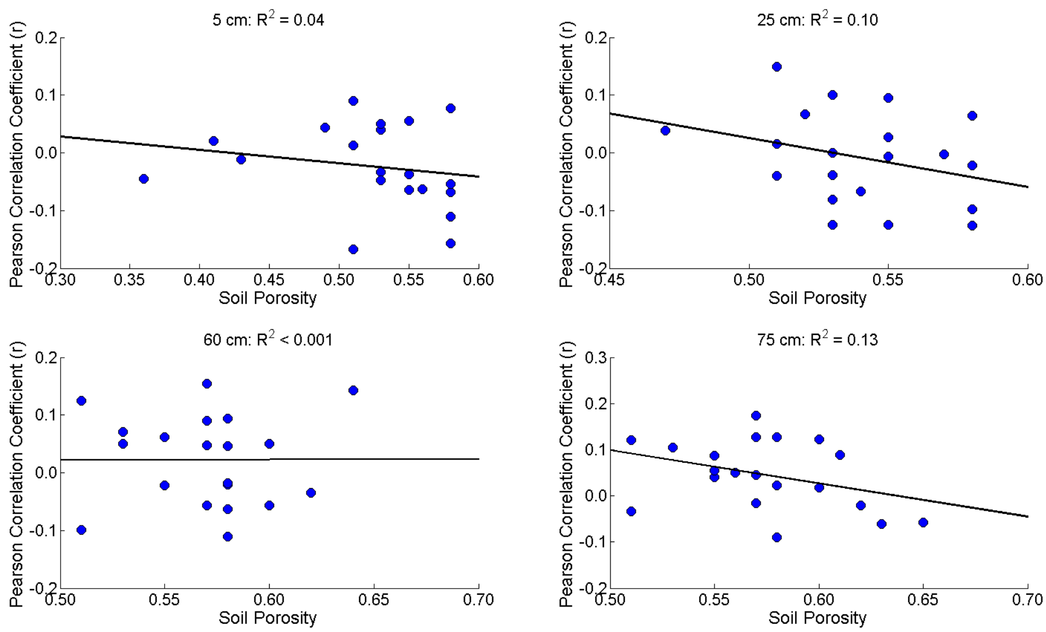


Figure 2.12. Scatter plots of soil porosity and soil moisture-VCI correlations. Each point represents one study site.

Gu *et al.* (2008) found that soil moisture-vegetation correlations varied according to land cover and soil texture and sites with homogeneous land cover and silt loam soil texture exhibited the highest soil moisture-vegetation correlations. To test whether similar results could be attained here, study sites were selected based on land cover homogeneity and soil texture class. Land cover homogeneity was assessed using the National Land Cover Database 2006 land cover classification data. Land cover homogeneity was computed as the percent of each land cover class represented in a 1 km box surrounding each Mesonet site. Six sites were identified as having homogeneous land cover. Following the results from Gu *et al.* (2008) these sites should have stronger soil moisture-VCI correlations than sites with more heterogeneous land cover. The average correlation of the six homogeneous land cover sites was evaluated against the average correlation of six randomly chosen sites. A bootstrapping method (Efron and Tibshirani, 1993) was used to repeat this procedure 10,000 times to ensure that the comparison is robust. Fig. 2.13 displays histograms of average correlation coefficients generated by the bootstrapping procedure. The mean correlation for the six sites with homogeneous land cover is not statistically significantly different from the mean of 10,000 iterations, contrasting the results of Gu *et al.* (2008).

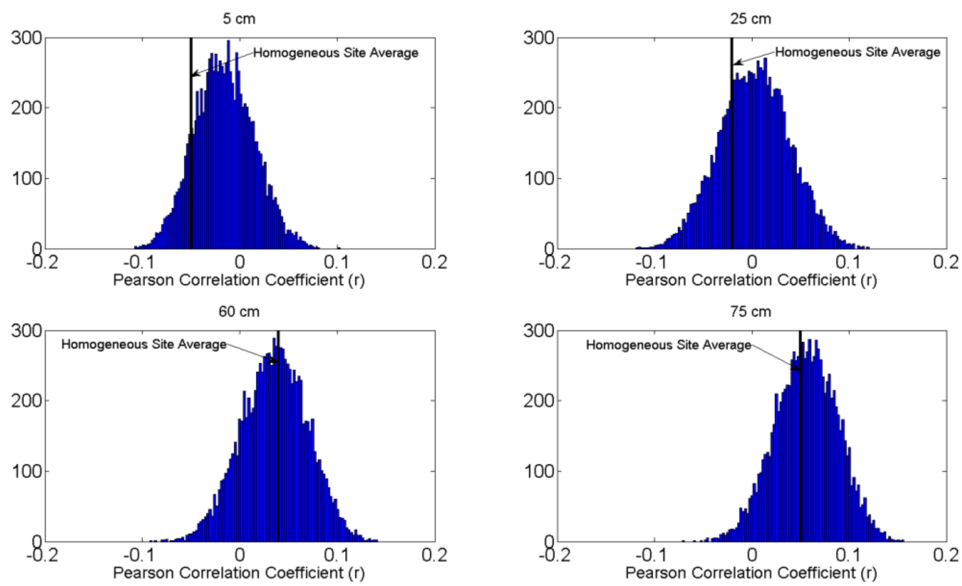


Figure 2.13. Histograms of soil moisture-VCI correlations generated using a bootstrapping procedure with 10,000 iterations. The average correlation of all 6 homogeneous land cover sites is shown with the thick black line.

A similar approach was taken to evaluate the potential increase in soil moisture-VCI correlations at sites with silt loam soils. For this test, 8 sites had silt loam soils at the 5 cm, while only 4 had silt loam soils at the 3 deeper depths. Thus the bootstrapping method randomly chose 8 sites for comparison at the 5 cm depth, and 4 sites for comparison at the remaining depths. Fig. 2.14 displays the resulting histograms, similar to those in Fig. 2.13. The results at the 60 and 75 cm depths are similar to those from Fig. 2.13, as the mean correlation from silt loam sites is not different from the overall mean. However, the silt loam-site correlation mean at the 5 and 25 cm depths is considerably higher than the mean of the 10,000 iterations. In fact the mean from the silt-loam sites at the 5 and 25 cm depths represent the 90^{th} and 80^{th} percentiles, respectively, based on the 10,000 iterations.

The explanation provided in Gu *et al.* (2008) for why sites with silt loam soils exhibited significantly higher correlations than those with loam or sandy loam soils is that the heat dissipation sensors used to estimate volumetric soil water content do not perform well in soils with high sand contents and may not accurately reflect soil moisture variations. In this study, sites with silt loam soils at the 5 and 25 cm depths exhibited generally higher correlations; however, sites with silt loam soils at the 60 and 75 cm depths did not. This is possibly due to the time interval used, as only simultaneous correlations were analyzed.

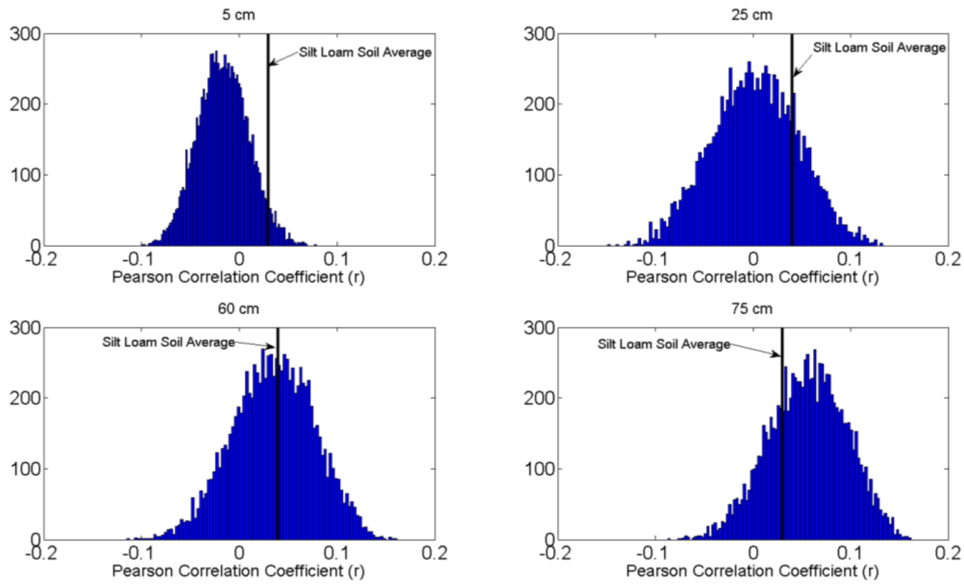


Figure 2.14. Histograms of soil moisture-VCI correlations generated using a bootstrapping procedure with 10,000 iterations. The average correlation of all silt loam soil texture sites is shown with the thick black lines.

Previous literature is in general consensus that land cover and soil characteristics greatly influence soil moisture magnitude and variability (Mahmood and Hubbard, 2003; Vicente-Serrano, 2007; DeLiberty and Legates, 2008). In fact, Mahmood and Hubbard (2003) found that under certain precipitation conditions, land use land cover is the most influential factor for soil moisture variability. Thus it is surprising that soil moisture-VCI correlations are not influenced by land cover and soil texture in this study. Vegetation response to soil moisture is site specific due to differences in vegetation type, soil characteristics, overall climate and ecosystem health and diversity. These complicating factors could potentially explain the inconsistent behavior of soil moisture-VCI correlations as well as the lack of strong influence from land cover, soil texture and moisture conditions.

2.4. Potential Study Limitations

The results from this study suggest that soil moisture-vegetation coupling is far more complicated than a simple, linear relationship. Some of the potential limitations of this work include the use of VCI to represent vegetation health. One potential consequence of using VCI is that the influence of land cover on the relationship strength could be diluted due to either erroneously high VCI variability and/or the relatively short (> 10 years) time series of NDVI used to calculate VCI. Another limitation is the use of linear correlations when evaluating the interactions between soil moisture and vegetation. Because correlations evaluate the absolute influence of soil moisture on vegetation, the inconsistent results are not surprising. Vegetation health is influenced by several, non-soil related factor. These influential factors include temperature, precipitation amount and precipitation variability (Pielke, 2001) as well as biogeographical factors such as the diversity and health of the biome (Symstad and Jonas, 2011), and fire and grazing management practices (Fuhlendorf and Smeins, 2009). Because of the numerous variables influencing vegetation health, a measurement of the relative influence of soil moisture on vegetation health would be more insightful; however requiring far more complexity than linear correlations can provide.

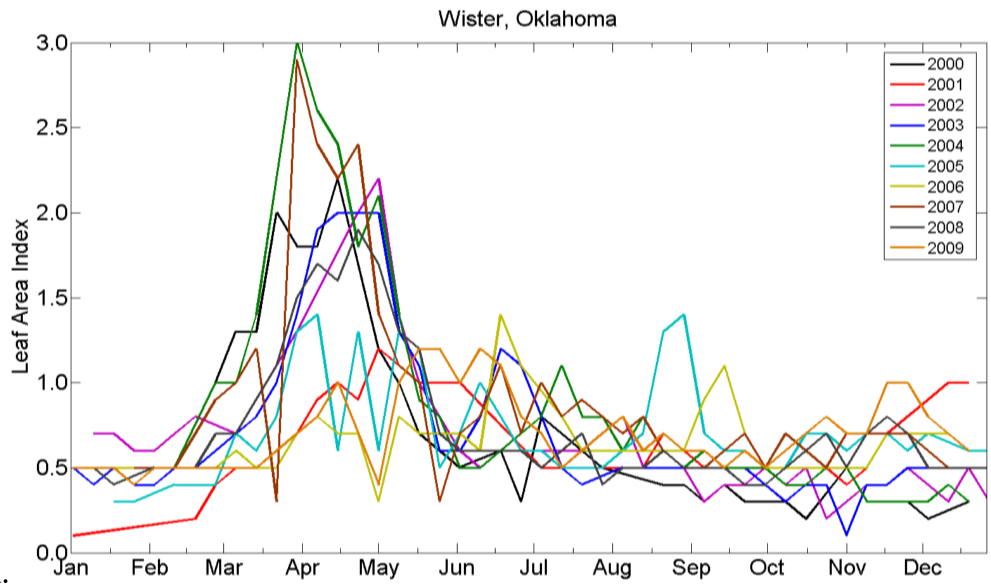
Lastly the time period defined as the growing season (May – October) is a study limitation. Vegetation phenology timing is a strong function of the regional climate (Stöckli and Vidale, 2004; Badeck *et al.* 2004; Zhang *et al.* 2004) and thus peak vegetation greening occurs at different times based on the climate of the vegetation's biome. Fig. 2.15 shows two-week composites of leaf area index (LAI) derived from 1-

km MODIS imagery over Wister and Boise City sites between 2000 and 2009. The plots show that vegetation greening at Boise City (primarily scrub) is typical of the central Great Plains. Peak vegetation health occurs between May and September, followed by a decrease in health which continues throughout the winter season. However the LAI plot at Wister (primarily grassland) shows that vegetation health consistently peaks between March and April. This suggests that even within the domain of Oklahoma, vegetation in climatologically diverse areas experience greening at noticeably different times. Thus a May – October study period does not capture the peak vegetation health at Wister and may not be the time period in which vegetation most strongly interacts with soil moisture. The static study time period is a study limitation because of this.

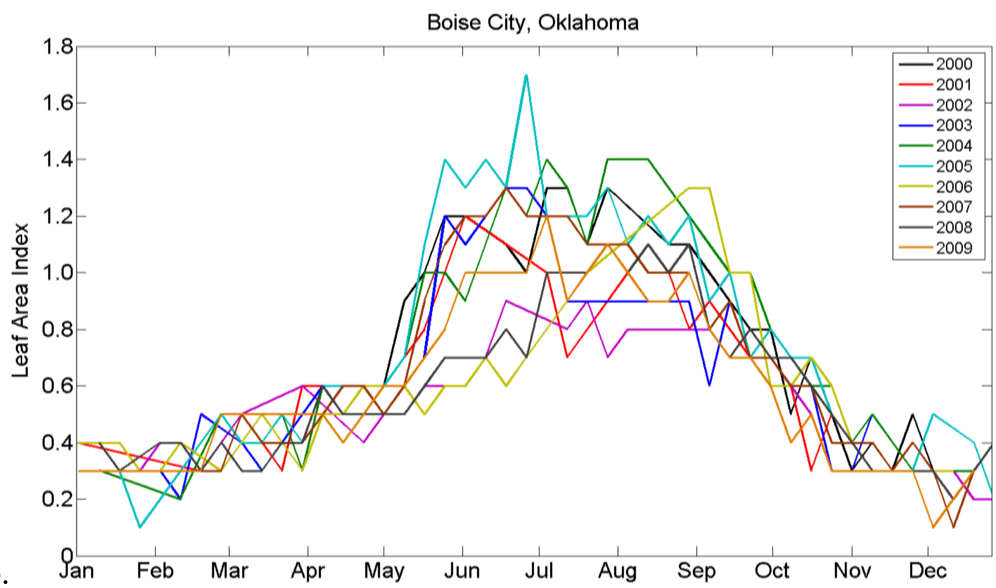
2.5. Conclusions

Interactions between soil moisture and vegetation were evaluated using simple linear correlation analysis at 20 Oklahoma Mesonet sites throughout Oklahoma. Temporal variability was observed in the soil moisture-VCI relationship. Moisture condition analysis suggests that the soil moisture-VCI correlation strength does not vary as a function of the amount of precipitation nor the soil moisture magnitude.

The impacts of land cover and soil characteristics on correlation coefficients were also examined. The results suggested that soil moisture-VCI interactions exhibited noticeable spatial variability. Sites with grassland cover exhibited more frequent positive soil moisture-VCI correlations; however, the differences between the mean correlations of each land cover group were not statistically significant. Soil texture analysis suggested that soil moisture-VCI coupling strength did not vary as a function of the underlying soil texture at any depth. However, the results from the bootstrapping procedure suggest that sites with silt loam soils at the 5 and 25 cm generally have higher correlations than other soil textures.



a.



b.

Figure 2.15. Two week composites of leaf area index between 2000 and 2009 at (a) Wister and (b) Boise City.

CHAPTER III

INFLUENCE OF REMOTELY-SENSED VEGETATION CONDITIONS ON THE VIC HYDROLOGIC MODEL

3.1. Introduction

3.1.1 Background

Land-atmosphere coupling is an important component of Great Plains hydroclimate variability; however, local interactions between land and atmosphere exhibit strong spatiotemporal variability. Schubert *et al.* (2004) examined the causes of droughts in the Great Plains using ensembles of a general circulation model forced with observed sea surface temperatures (SST) and found that two-thirds of low frequency rainfall variance can be explained by land-atmosphere interactions. In contrast the observational study of Findell and Eltahir (1997) attributed only 16% of summer precipitation variance to spring soil moisture conditions. The inconsistency between studies is due in part to strength and sign variability of land-atmosphere forcings over the central United States (Meng and Quiring, 2010b). Land surface and subsurface heterogeneity impose pronounced land-atmosphere modeling and prediction implications.

Overlying vegetation is a primary conduit through which soil moisture influences partitioning of surface energy flux. Therefore variations in vegetation density and health modify transpiration rates (McPherson, 2007) and corresponding near-surface atmospheric moisture availability (Pielke, 2001). Vegetation-soil moisture interactions at all scales have been shown to significantly alter near-surface atmospheric moisture.

However, our concept of pedosphere-biosphere-atmosphere interactions must appreciate the innate spatiotemporal variability of the factors which 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. Land surface models (LSMs) are used instead to estimate mesoscale and macroscale hydrologic and climatologic conditions, employing temperature and precipitation parameters to estimate soil moisture. Despite the large temporal variability of vegetation health, most LSMs represent vegetation as a pre-determined, interannually invariant parameter (Tang *et al.* 2012). Studies have suggested that the estimation of vegetation health and soil moisture do not always well represent land surface and subsurface variability (Xia *et al.* 2012). Thus expressing vegetation health with temporally dynamic parameters should result in a better representation of vegetation conditions and provide more detailed insight as to the impact of vegetation on land-atmosphere interactions.

This research proposes to examine soil moisture-vegetation interactions simulated by an LSM using both interannually-variant and invariant vegetation parameters. Model simulations are compared and contrasted, and model-derived soil moisture is evaluated against *in situ* soil moisture observations.

3.1.2 Previous Research

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 microscale infiltration as a vegetation parameter, mesoscale precipitation increased 35% over the coupled system which 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 seasonal and intraseasonal precipitation are influenced by vegetation parameter modification over the Central United States. Their results showed that accurate depictions of vegetation growth patterns play a significant role in enhancing the persistence of intraseasonal precipitation in regional climate models. These results suggest that accurate representation of micro-to-mesoscale vegetation properties in LSMs is necessary for analyzing land-atmosphere interactions and that the persistence of drought in LSMs may be a function of temporally-invariant vegetation properties such as leaf area index (LAI).

Chapter II results show that soil moisture-vegetation health relationships are highly variable both over space and time. Thus analyses of soil moisture-vegetation interactions and their representation in LSMs are necessary to better understand the sign and strength of land-atmosphere coupling in semi-arid regions. Zhang and Wegehenkel (2006) developed a soil water balance model in which remotely sensed vegetation data were used to estimate spatial distributions of daily soil moisture and evapotranspiration. They found that by using long-term, remotely-sensed vegetation data, the model was able to accurately simulate daily soil water balance in Northeastern Germany. 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 the LAI resulted in more accurate calculations of soil moisture and evapotranspiration over the region. These results suggest that the current LSM representation of vegetation health as an interannually-invariant parameter may lead to inaccurate LSM simulations.

3.2. Data and Methods

3.2.1 Study Region

Similar to Chapter II, the study region is Oklahoma. This analysis employs hourly *in situ* soil moisture, precipitation, temperature and wind speed observations from 20 Oklahoma Mesonet stations (Fig. 2.2). Volumetric soil water content is observed at each site between 2000 and 2009 at 5, 25, 60 and 75 cm. The soil moisture data has been compiled and quality controlled by the North American Soil Moisture Database (NASMD) at Texas A&M University. The data were also previously subject to a rigorous quality control procedure by the Oklahoma Mesonet. The 20 stations were chosen because of the length and completeness of their data. Soil textures at the sites range from sandy loam to silt and overlying vegetation includes grassland, pasture, scrub, cultivated crops, and forest. Table 3.1 displays land cover characteristics for each site. Soil data were provided by the Oklahoma Mesonet, land use/land cover was taken from the National Land Cover Database (NLCD) 2006 dataset.

Table 3.1. Study site predominant land cover, as reported by NLCD 2006 dataset.

Site	Immediate LULC	Predominant LULC
Acme	Grassland	Grassland
Apache	Grassland	Grassland
Beaver	Grassland	Grassland
Boise City	Grassland	Grassland
Butler	Grassland	Grassland
Centrahoma	Grassland	Deciduous Forest
Cheyenne	Scrub/Shrub	Grassland/Shrub
Durant	Grassland	Deciduous Forest
Hollis	Pasture/Hay	Scrub/Cultivated Crop
Lahoma	Pasture/Hay	Cultivated Crop
Marena	Grassland	Grassland
Miami	Grassland	Grassland
Pawnee	Pasture/Hay	Grassland
Perkins	Grassland	Deciduous Forest/Grassland
Stillwater	Pasture/Hay	Cultivated Crop
Walters	Scrub/Shrub	Mix
Watonga	Grassland	Grassland/Evergreen Forest
Waurika	Grassland	Grassland
Wister	Grassland	Pasture/Hay
Woodward	Grassland	Grassland

3.2.2 VIC Model

The variable infiltration capacity (VIC) hydrologic model (Liang *et al.* 1994) is a macroscale model that balances both surface energy and water over a grid. A soil-vegetation-atmosphere transfer scheme (SVAT) represents controls of vegetation on land-atmosphere moisture and energy fluxes. VIC is unique in that the model allows for subgrid parameterization of soil, topography and vegetation characteristics. The VIC model allows for multiple soil layers, three were used in this study (0 to 10 cm, 10 to 40 cm, and 40 to 95 cm). The three soil layer depths were chosen in order for the top three Oklahoma Mesonet soil moisture observation depths to represent the middle point of the

VIC soil layer. Soil characteristics and subgrid land cover parameters were taken from the gridded 1/8° resolution dataset compiled by Maurer *et al.* (2002). This dataset provides land surface characteristics for the entire contiguous United States. VIC was forced with daily observations of precipitation, minimum and maximum temperature and wind speed from the Oklahoma Mesonet. These data are recorded directly above the soil moisture observations and thus are most representative of the synoptic conditions at each site.

3.2.3 MODIS Data

LAI is the vegetation parameter that most influences VIC-simulated hydrologic fluxes and soil moisture (Maurer *et al.* 2002). LAI data used in this study were computed using daily global spectral reflectance from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) instrument at a 1 km resolution (http://modis.gsfc.nasa.gov/data/dataprod/dataproducts.php). These data are available as 8-day composite products, and have been used in several studies to represent vegetation conditions. Fensholt *et al.* (2004) evaluated the MODIS LAI product with *in situ* sites in semi-arid Senegal, West Africa. Their results showed that MODIS LAI captured seasonal dynamics of grassland vegetation accurately. MODIS LAI is used to represent observed vegetation conditions in this study.

3.2.4 Experiment Design

VIC model representation of vegetation health change consists of monthly-varying LAI which is interannually-invariant (Maurer *et al.*, 2002). Thus the VIC model should be able to capture seasonal variability and vegetation green up; however, lack of interannual LAI variability could be a source of error during years of anomalously high/low vegetation greenness. Significant differences between model and actual LAI magnitude could introduce error in model soil moisture and evaporative flux output data. To test this, VIC was employed in two separate model simulations, one in which LAI remains interannually-invariant (control) and the second in which the model utilizes monthly average MODIS-derived LAI (Modis). The model input parameters for both simulations were 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 to 10 cm, 10 to 40 cm and 40 to 95 cm layers. For convenience, the VIC soil layers will be referred to by their bottom point (10, 40 and 95 cm). The results section is organized as follows: section 3.1 examines the differences between the interannually-invariant LAI used in the control VIC simulation and the observed LAI used in the Modis simulation. Section 3.2 describes the influence of dissimilar LAI datasets on model soil moisture simulations and examines the sensitivity of soil moisture to LAI perturbations. Section 3.3 evaluates soil moisture from each model simulation with *in situ* soil moisture observations to assess whether the model simulates soil moisture more accurately using remotely-sensed LAI or the interannually-invariant LAI.

3.3. Results

3.3.1 LAI Dataset Differences

Differences between the two LAI datasets were documented to better understand the parameters influencing model output soil moisture. Fig. 3.1 shows the relationship between the VIC control LAI and MODIS LAI datasets. The plot displays the control LAI data on the x-axis and corresponding Modis LAI data on the y-axis. Each point represents one month during one growing season at one site. When the control LAI data is between 0 and 1 there is good correspondence between the two LAI parameters; however, beyond an LAI of 1, the control parameter is frequently higher than the Modis parameter. Part of this is due to drier than normal growing seasons, when the Modis LAI responds to less than normal vegetation health and the control LAI does not. However some of the points beyond a control LAI value of 1 represent the LAI parameter over the Wister, Oklahoma site.

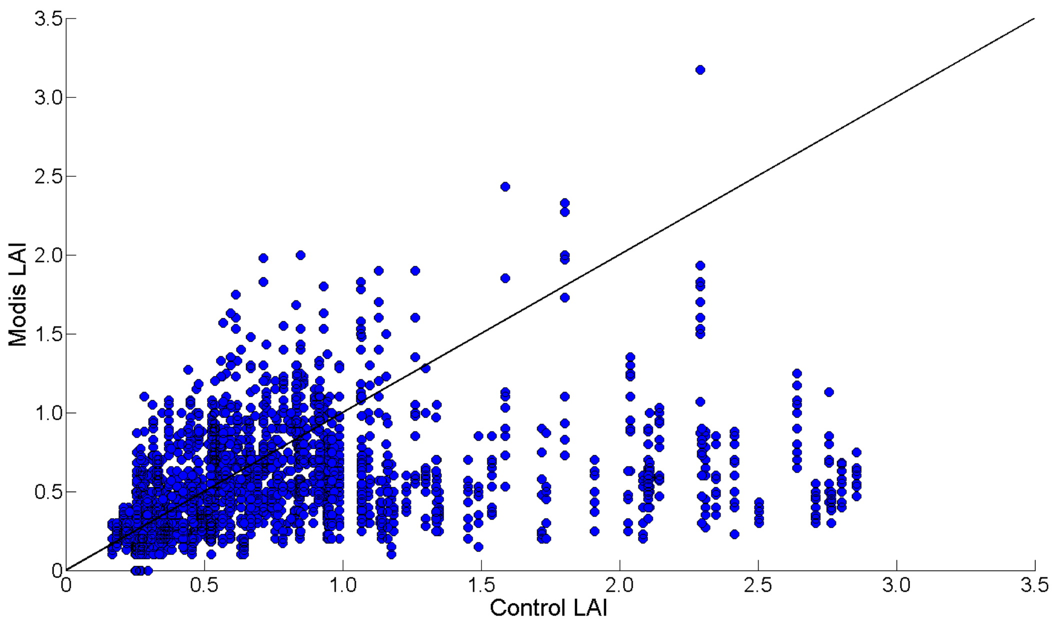


Figure 3.1. Scatter plot of control LAI and Modis LAI parameters. Each point represents one month during one growing season at one site.

Wister is located in East-Central Oklahoma and the mesonet site is surrounded by prairie grassland, which is reflected in both the Modis imagery and the Maurer *et al.*

(2002) model calibration data. Fig. 3.2 shows a plot of the control LAI and Modis LAI over Wister during the study period. The Modis LAI parameter frequently peaks between February and March, while the control LAI parameter peaks in June. This suggests that although the control land cover parameterization is good and the control LAI parameter magnitude is accurate during meteorological "average" years, the time period during which the two LAI parameters peak is much different, driving differences in soil moisture simulations. These results are similar to those from Tang *et al.* (2012) who found that timing of peak vegetation greening in the North American Monsoon region was more accurate in a Modis-derived LAI parameter than the VIC control parameter.

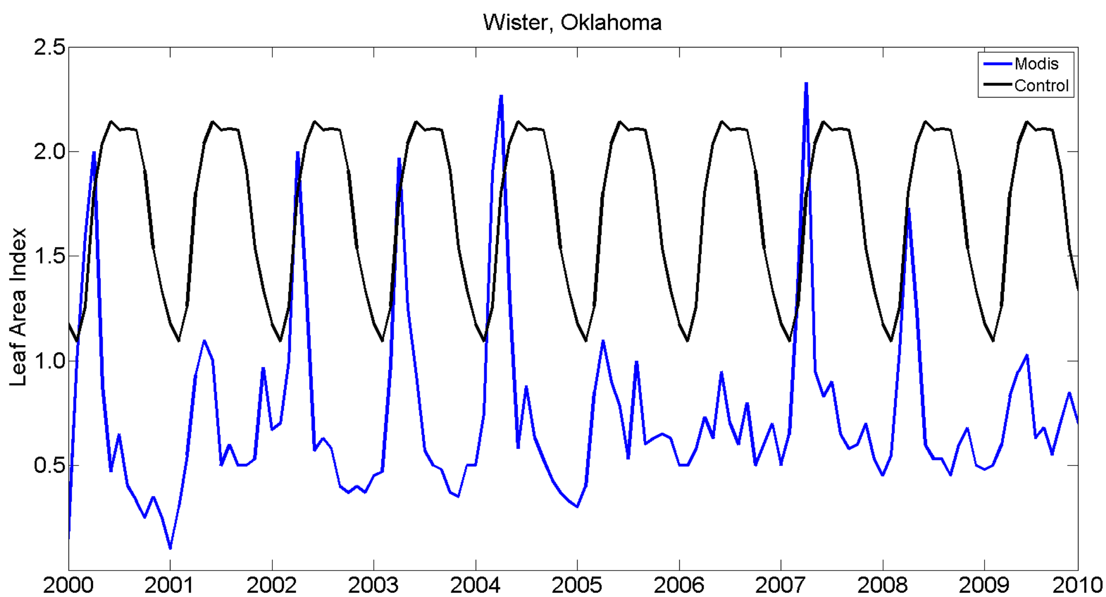


Figure 3.2. Plot of (blue) Modis LAI parameter and (black) control LAI parameter during the study period.

To further examine the differences between the two LAI parameters, a paired student's t-test was employed. The t-test results show whether the Modis LAI parameter at a specific site is significantly (alpha < 0.05) higher or lower than the control LAI parameter. The results (not shown) demonstrate that the control LAI parameter mean is significantly higher than the Modis parameter mean at 7 sites (Centrahoma, Marena, Miami, Pawnee, Perkins, Stillwater and Wister), while the Modis parameter mean is significantly higher than the control parameter mean at 2 sites (Durant and Boise City). Fig. 3.3 displays LAI plots from 2 of the sites at which the control LAI parameter was significantly higher than the Modis parameter, Centrahoma and Miami. These sites are representative of the other 7 sites at which the control LAI parameter is significantly higher. The plots show that the control LAI parameter is systematically higher than the Modis LAI parameter. This suggests that the land cover classification of the Maurer *et al.* (2002) calibration data does not accurately reflect the land cover type captured in the MODIS imagery.

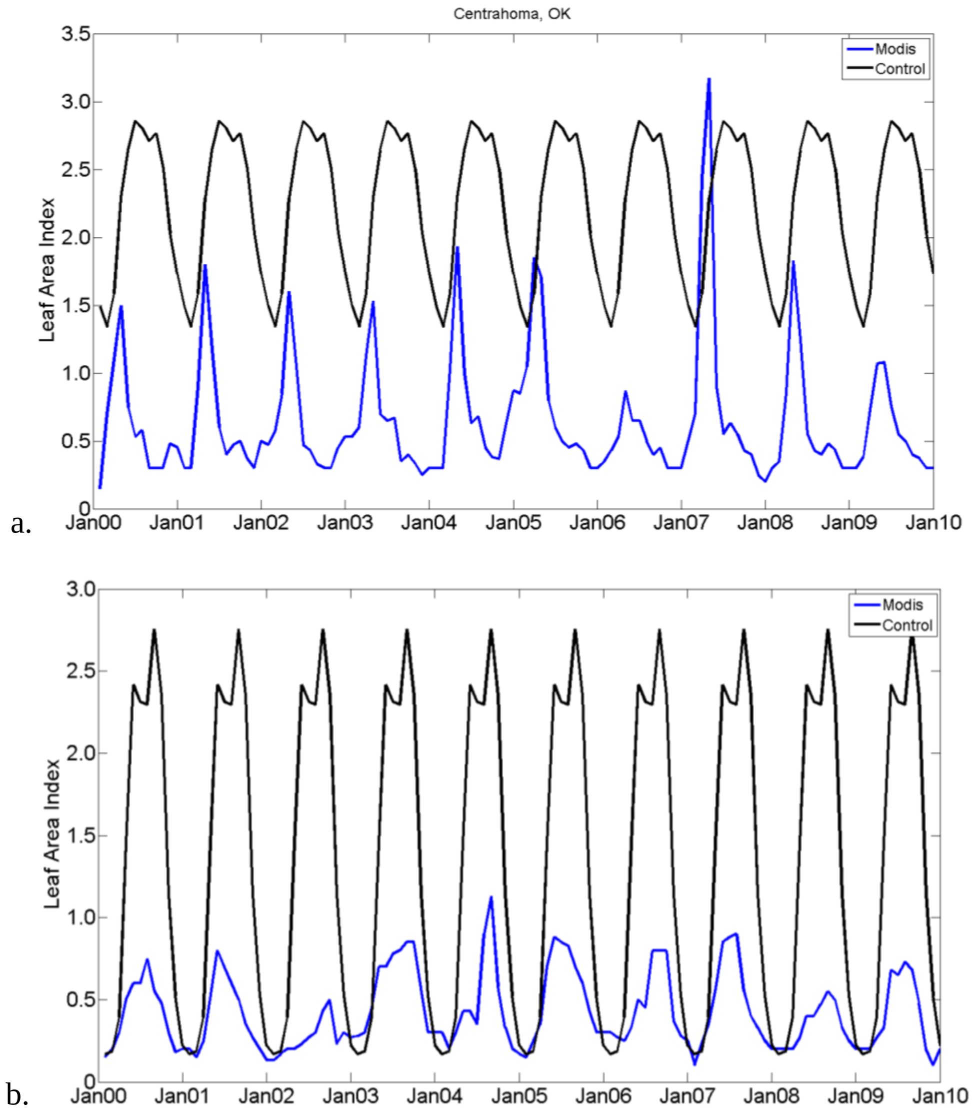


Figure 3.3. Plots of (blue) Modis LAI and (black) control LAI parameter values. The plots are shown for (a) Centrahoma and (b) Miami between January 2000 and January 2010.

Fig. 3.4 shows LAI plots from the 2 sites at which the Modis parameter is significantly higher than the control parameter. The plots show that the vegetation peaks are similar temporally, but the magnitude of the Modis LAI is consistently higher than that of the control LAI parameter.

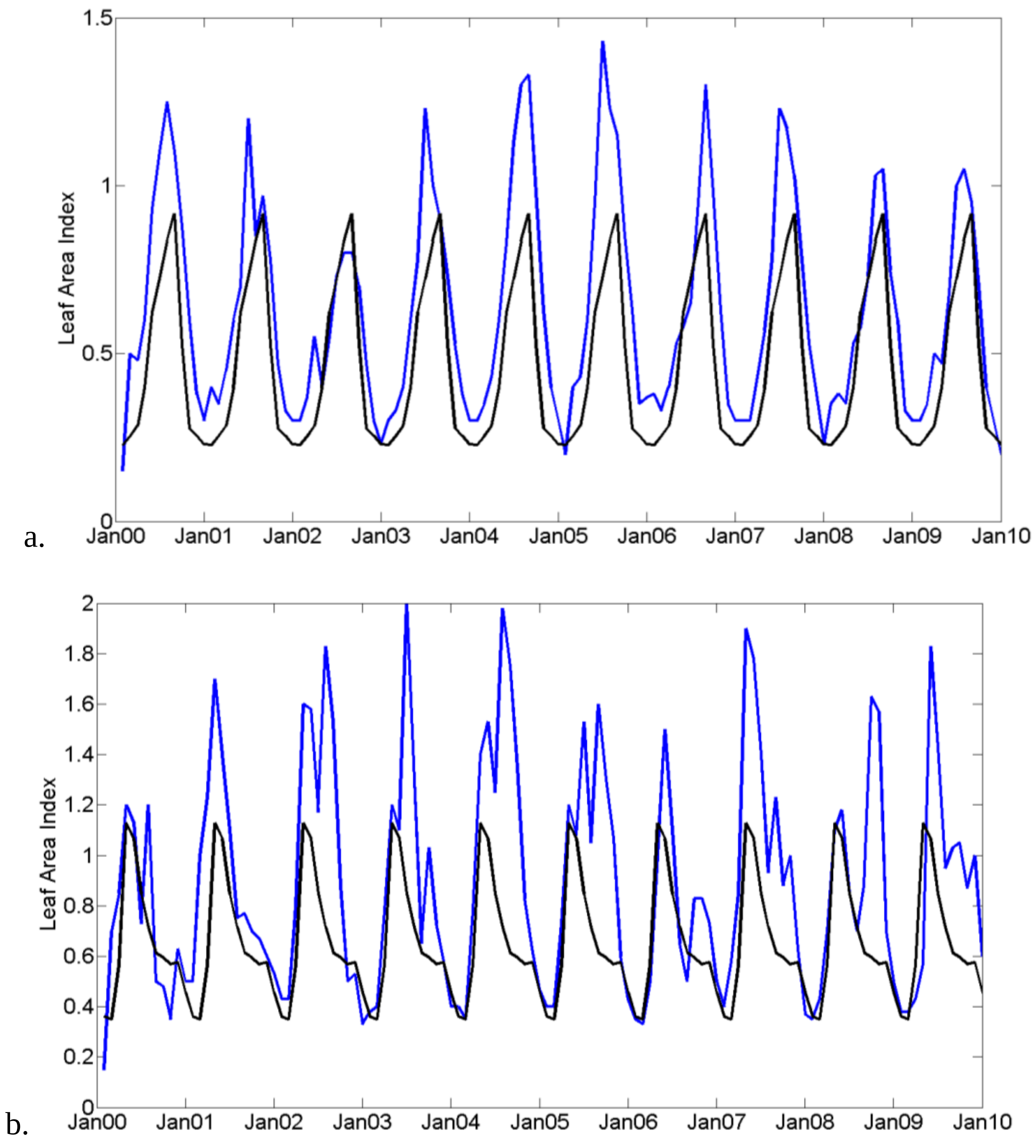


Figure 3.4. Plots of (blue) Modis LAI and (black) control LAI parameter values. The plots are shown for (a) Boise City and (b) Durant between January 2000 and January 2010.

Fig. 3.5 shows percent mean absolute difference between the two LAI datasets by month. The largest percent difference occurs during the winter (November, December, and January) and spring (April - May) months. The large deviation between LAI datasets in the beginning of the growing season makes sense, as anomalously dry/wet growing season conditions can cause significant differences in vegetation health from normal conditions. Thus we should expect the largest deviations during the early summer months. The most dominant land cover type is native prairie grassland, which is typically dormant during the winter season. Suyker and Verma (2008) show that native prairie grasses in Oklahoma and Kansas exhibit LAI and net ecosystem CO_2 exchange values near 0 during the Northern Hemisphere winter. Thus the relatively large difference between the LAI datasets in winter is most likely due to the relatively small LAI magnitudes during the winter season.

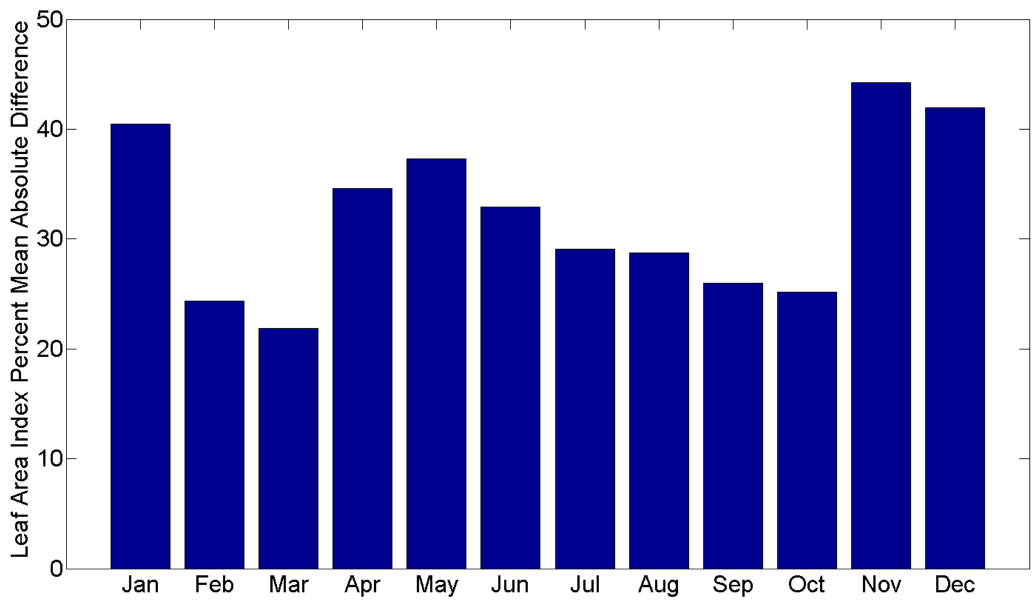


Figure 3.5. Monthly LAI percent mean absolute difference averaged between all sites and growing seasons.

Fig. 3.6 provides a more in depth look at LAI differences, as it displays monthly LAI percent mean difference separated by the dominant land cover at each site. The dominant land cover type was identified as the NLCD 2001 land cover class which represented > 60% of a 1 km radius surrounding the observation site. If no one land cover type represented over this threshold, the site was considered a mix land cover. Fig. 3.6 shows that the land cover types in which the LAI datasets diverge the most are prairie grassland, pasture/hay and the mix types. LAI difference over these sites is greatest during the early growing season (April – July) as well as December and November.

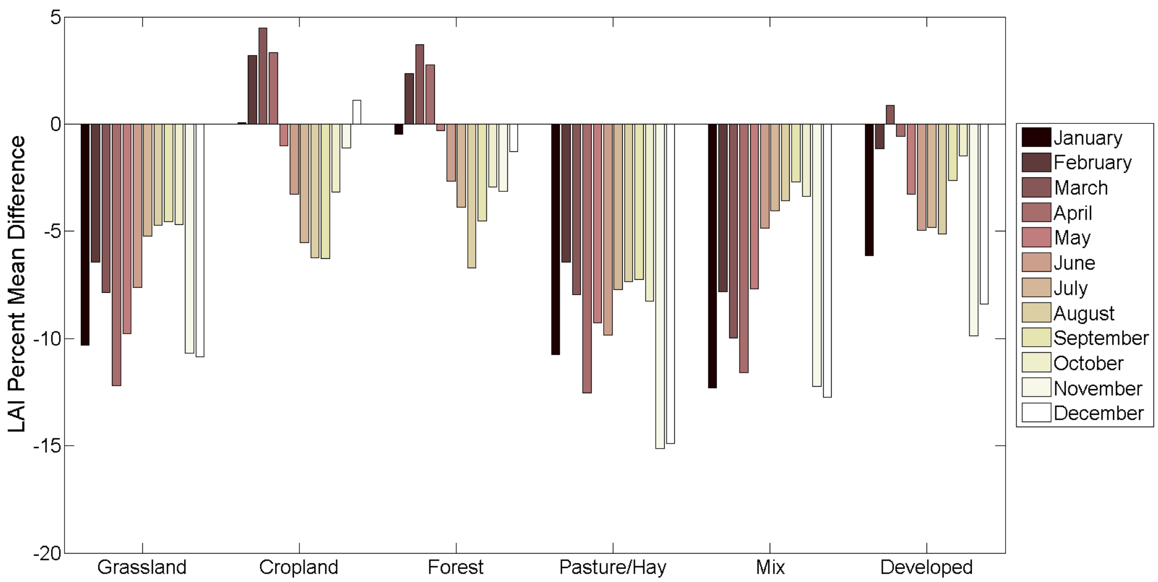


Figure 3.6. Monthly LAI percent mean differences separated by dominant land cover. Values are averaged between 2000 and 2010.

Overall results show that differences between VIC control and MODIS LAI datasets vary by land cover and soil moisture magnitudes. Modis LAI over several grassland sites frequently peaks during the early spring while the control LAI peaks in early – mid-summer. At some sites, the control LAI parameter is systematically higher than the Modis LAI parameter; and at fewer sites the Modis LAI parameter is systematically higher than the control parameter. One would expect these differences to noticeably influence model-simulated soil moisture, for example consistently higher vegetation health during the spring should equate to more root uptake of subsurface moisture and overall lower root zone soil moisture values. The following section explores the differences between VIC-simulated soil moisture using the control LAI and the MODIS LAI data.

3.3.2 Model-Simulated Soil Moisture Differences

Table 3.2 displays evaluation results comparing VIC-simulated soil moisture generated using VIC control LAI and MODIS LAI. The metrics used to examine the differences between the datasets include the coefficient of determination (R^2) and the percent mean absolute difference. The average coefficient of determination between the two datasets is 0.96, 0.94 and 0.87 for the 10, 40 and 95 cm depths respectively. Coefficient of determination values ranged from 0.68 – 0.97, all significant at the alpha < 0.05 level. This suggests that although noticeable differences in LAI data exist, the two simulated soil moisture datasets correlated strongly. The average percent mean absolute difference was 4, 6 and 14 for the 10, 40 and 95 cm depths respectively. Percent mean absolute difference values ranged from less than 1 to 32; however, variability at the 95 cm level is much more pronounced than the 10 cm depth. The percent mean absolute difference coefficient of variation at the 95 cm depth is 0.57 compared to 0.38 at 10 cm. Similarly the R^2 coefficient of variation at 95 cm is 0.08 compared to only 0.01 at the 10 cm level. Although slight, the variability difference suggests that the use of different LAI datasets influences the simulated soil moisture more at the deeper soil depths than the surface.

Table 3.2. Comparison metrics between VIC simulated soil moisture using control and Modis LAI.

	Coefficient of Determination (R^2)			Percent Mean Absolute Difference		
Site	**10 cm**	**40 cm**	**95 cm**	**10 cm**	**40 cm**	**95 cm**
Acme	0.95	0.87	0.91	4	9	13
Marena	0.96	0.95	0.80	3	4	18
Wister	0.96	0.98	0.93	4	2	7
Cheyenne	0.96	0.98	0.92	2	3	8
Apache	0.96	0.87	0.93	4	11	13
Stillwater	0.96	0.98	0.91	4	2	8
Pawnee	0.96	0.97	0.89	2	4	13
Waurika	0.96	0.97	0.87	3	4	14
Miami	0.96	0.95	0.86	7	10	27
Hollis	0.98	0.98	0.97	1	2	3
Watonga	0.96	0.96	0.86	3	5	18
Boise City	0.97	0.96	0.78	4	12	11
Walters	0.95	0.94	0.82	4	9	27
Centrahoma	0.95	0.94	0.81	7	9	32
Beaver	0.96	0.96	0.80	3	7	8
Woodward	0.96	0.94	0.88	5	5	14
Butler	0.97	0.96	0.96	2	4	7
Lahoma	0.93	0.78	0.68	4	9	27
Perkins	0.96	0.98	0.90	4	2	7
Average	**0.96**	**0.94**	**0.87**	**4**	**6**	**14**

Fig. 3.7 shows VIC control LAI and MODIS LAI as well as the resulting simulated soil moisture at Boise City, Oklahoma between 2000 and 2003. Boise City is shown here as the Modis LAI is consistently higher than the control LAI parameter. This results in systematically lower soil moisture generated from MODIS VIC simulations. Differences between the LAI parameters corresponded to differences in simulated soil moisture; however, differences between the soil moisture simulations varied by depth. For example, the percent mean difference between VIC control and MODIS LAI over Boise City between 2000 and 2010 is 0.31, meaning that the MODIS

LAI is on average 31% higher than the VIC control LAI. This difference results in a percent mean soil moisture difference of -3%, -10% and -12% at the 10, 40 and 95 cm levels respectively. These results mean that a 31% higher input LAI parameter resulted in a 3% decrease in VIC-simulated soil moisture at the 10 cm level, compared to a nearly 12% decrease in 95 cm soil moisture.

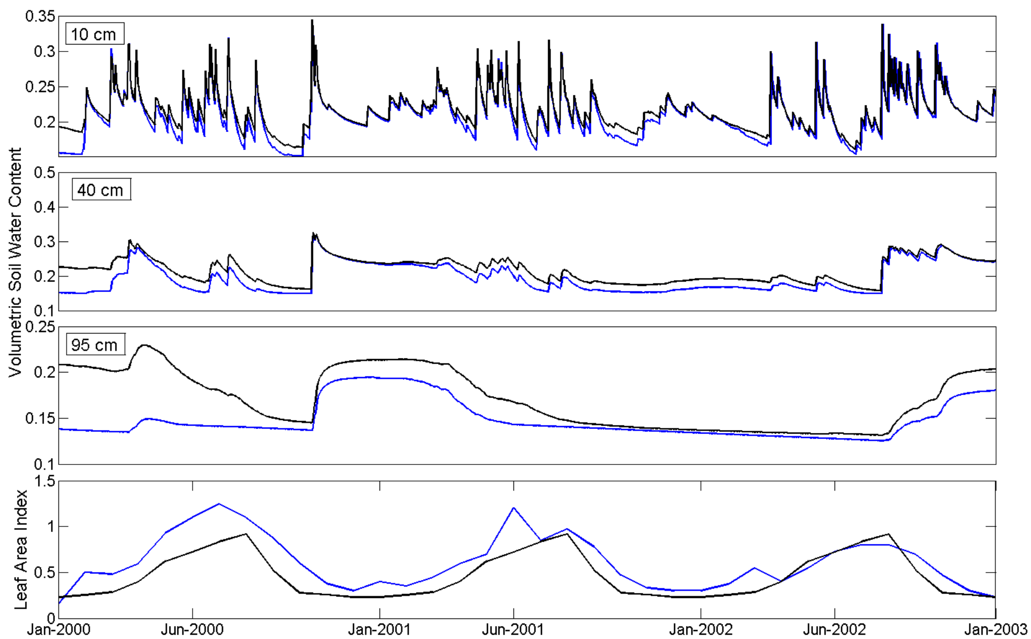


Figure 3.7. Bottom plot shows Modis (blue) and control (black) LAI over Boise City, Oklahoma between 2000 and 2003. Top figures show corresponding soil moisture from the two simulations at the 10, 40 and 95 cm depths.

At all sites where MODIS LAI consistently exceeds VIC control LAI, the average percent mean difference is 17.6%. The 18% LAI increase results in a 1.1%, 3.1% and 4.8% decrease of soil moisture at the 10, 40 and 95 cm depths respectively. Similarly, at all sites in which VIC control LAI exceeds MODIS data, the average percent mean difference is -36.6%. The nearly 37% decrease in LAI leads to a 1.4%, 0.9% and 2.5% increase of soil moisture at the 10, 40 and 95 cm depths respectively.

These results show that LAI parameter has the greatest influence on VIC-simulated soil moisture in the deep soil layers. Sheffield *et al.* (2004) simulated soil moisture using the VIC model for drought analysis and showed that soil moisture in the root zone layer is the most responsive to agricultural drought and root uptake of water, thus we should expect LAI changes to influence deeper-layer simulated soil moisture more than near surface layers. Sheffield *et al.* (2004) 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 deep layer soil moisture anomalies. Because deep soil moisture anomalies are persistent, VIC-simulated soil moisture sensitivity to the LAI parameter could potentially lead to added or diminished anomaly persistence. For example, when the control LAI is higher than the MODIS LAI, this results in decreased soil water content, especially in the 10 to 40 cm and 40 to 95 cm layers.

Added anomaly persistence caused by VIC vegetation parameterization was tested by marking points in the daily soil moisture simulations in which both datasets exhibited equal soil moisture conditions. Persistence of LAI-forced anomalies was measured as the amount of time that elapsed while the soil water content from the two different LAI parameterizations differed by greater than 10%. Fig. 3.8 shows an example of how persistence is measured. Because MODIS LAI over the majority of study sites is consistently less than the VIC control, only these instances are considered. Persistence was averaged by site and the mean LAI difference between VIC control and MODIS was calculated and averaged over each persistence period. Table 3.3 shows average soil moisture persistence (memory) forced by LAI differences. Soil moisture persistence is reported in days.

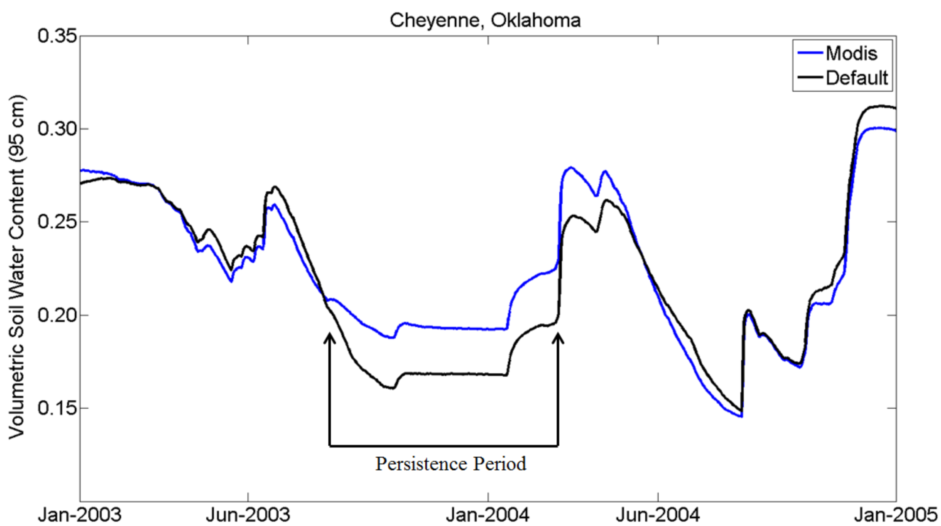


Figure 3.8. Example of how LAI-forced soil moisture persistence period is calculated

The average soil moisture anomaly persistence due to increased VIC control LAI over MODIS data is 29, 74 and 169 days at the 10, 40 and 95 cm depths respectively. Average persistence ranges from 10 to 67 days at 10 cm, 24 to 137 days at 40 cm and 108 to 295 days at 95 cm. Results show that higher LAI values in the VIC control lead to drier soils, than if MODIS LAI is employed. This effect is amplified at deeper soil layers, as the average persistence was well over 5 months. These results corroborate the findings of Wu *et al.* (2002) in that soil moisture persistence, forced by anomalous moisture and/or vegetation conditions are much longer at deeper layers than near surface layers. Our results are also in agreement with Sheffield *et al.* (2004) since we found that when conditions near the surface were drier than normal, these conditions persisted for a significantly shorter period of time than in deeper layers. This is partly due to the sensitivity of VIC-simulated deep layer soil moisture to the LAI parameter. However, because VIC bottom layer soil is not as responsive to precipitation events as the top layers, the influence of LAI on 95 cm soil moisture is primarily modulated by the soil column root distribution (Liang *et al.* 2004).

Table 3.3. Persistence of soil moisture divergence at each depth for every site. Also shown is the average percent difference between control and Modis LAI parameters during the persistence period

Site	10 cm Persistence (days)	40 cm Persistence (days)	95 cm Persistence (days)
Acme	18	96	177
Marena	67	129	131
Wister	19	36	219
Cheyenne	10	30	133
Apache	37	137	204
Stillwater	27	61	155
Pawnee	14	68	151
Waurika	18	46	136
Miami	54	117	118
Hollis	29	66	210
Watonga	14	86	194
Boise City	43	84	172
Walters	45	101	151
Beaver	64	60	164
Woodward	12	40	208
Butler	12	92	295
Lahoma	19	65	108
Perkins	21	24	115
Average	**29**	**74**	**169**

3.3.3 Model Evaluation

Section 3.2 results show considerable differences in VIC-simulated soil moisture when the VIC control and MODIS LAI data differ. This section examines which simulated soil moisture dataset is most accurate compared to *in situ* soil moisture observations. Model accuracy is most commonly evaluated with root mean square error (RMSE) and the coefficient of determination (R^2); however, studies have shown that the RMSE parameter is biased when the distribution of errors is variable, regardless of the total error (Wilmott and Matsurra, 2005). Therefore the simulated soil moisture data will be evaluated using multiple, complementary metrics. These include mean absolute error and percent mean absolute error (MAE), root mean square error, mean bias error (MBE), coefficient of determination, degree of agreement (d) and the coefficient of efficiency (E). The evaluation metric formulas are each described and applied in Legates and McCabe (1999). Several model evaluation metrics are employed because each has its own bias and assumptions, thus making model accuracy evaluation based on a single metric inadequate.

3.3.3.1 Influence of Land Cover on Model Performance

Table 3.4 displays model accuracy evaluation results averaged between all 20 sites. Overall the VIC-simulated soil moisture at 10 and 95 cm under MODIS LAI conditions is more accurate according to MAE, MBE, d and E. The VIC-simulated soil moisture at 40 cm under control LAI conditions are more accurate according to MAE, MBE, R^2, d and E. However, the general interpretation of the model evaluation results is that neither of the datasets is noticeably more accurate than the other according to any evaluation metric. This is surprising as one would expect that a more accurate depiction of vegetation conditions should lead to a more accurate soil moisture simulation. Mahmood and Hubbard (2003) suggest that simulated soil moisture is sensitive to the overlying land cover, thus potentially explaining the inconsistent accuracy evaluation results. One possible explanation is that one of the LAI parameters was consistently higher than the other at only 9 out of the 20 study sites. This means that at the other 11 sites, the control LAI parameter was sometimes higher than the Modis and sometimes lower, resulting in inconsistent soil moisture simulations. Averaging model performance across the entire study period could potentially dilute accuracy differences between the two vegetation parameters at these 11 sites.

Table 3.4. Model accuracy evaluation. Numbers in bold represent the more accurate evaluation score.

	MODIS			Control		
Metric	10 cm	40 cm	95 cm	10 cm	40 cm	95 cm
Mean	0.252	0.242	0.230	0.250	0.242	0.229
Standard Deviation	0.058	0.059	0.076	0.057	0.057	0.074
RMSE	0.068	0.072	**0.087**	0.068	0.072	0.091
MAE	**0.055**	0.058	**0.071**	0.056	**0.057**	0.075
Percent MAE	**0.199**	0.198	**0.241**	0.020	**0.195**	0.254
MBE	**-0.024**	-0.050	**-0.065**	-0.026	-0.050	-0.067
R^2	0.233	0.363	**0.421**	**0.237**	**0.372**	0.325
Degree of Agreement (d)	**0.668**	0.685	**0.641**	0.667	**0.688**	0.598
Coefficient of Efficiency (E)	**-0.043**	-0.481	**-1.480**	-0.053	**-0.452**	-1.710

To explore the impact of land cover on model accuracy, results were summarized by the dominant land cover. Fig. 3.9 shows the how percent mean absolute error varies as a function of land cover. Percent mean absolute error differs very little between simulated soil moisture under MODIS and control LAI parameters. A paired student's t-test showed that neither was significantly different (alpha = 0.05) under any land cover. These results suggest that although land use/land cover strongly influences underlying soil moisture, it does not significantly influence differences in model performance when using simulated and observed LAI parameters.

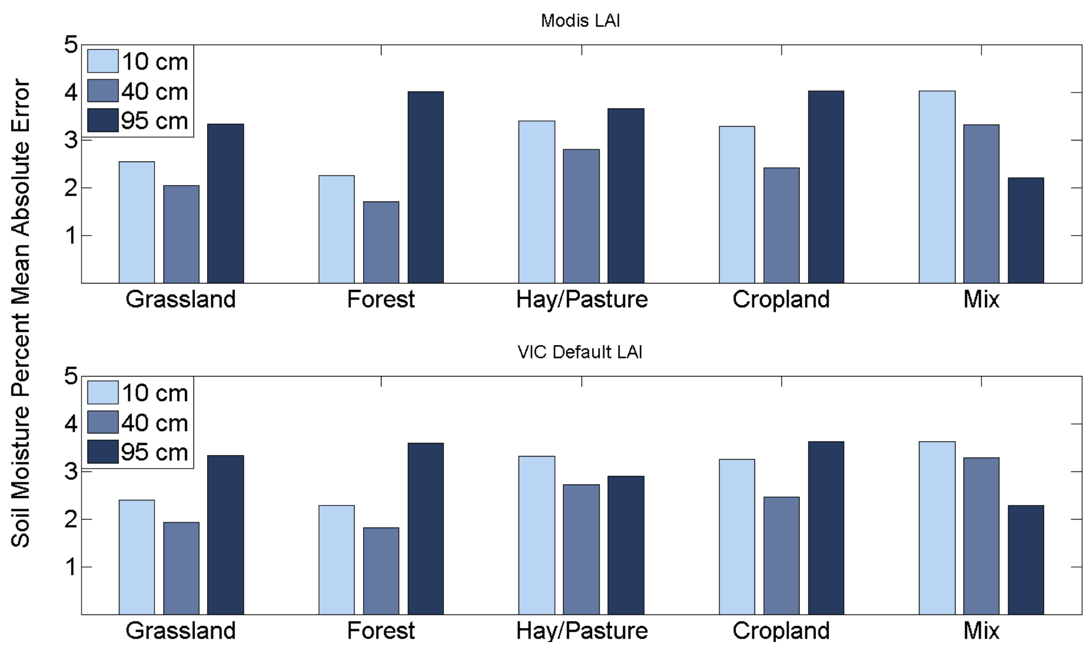


Figure 3.9. Bar plots of percent mean absolute error separated by the dominant land cover.

3.3.3.2 Influence of Moisture Conditions on Model Performance

This research was motivated by the lack of interannual variability in LAI in the VIC model. Vegetation health is the same during both anomalously wet and dry periods. Thus one would expect that VIC would more accurately simulate soil moisture using observed vegetation conditions under anomalously dry conditions, reflecting the limited moisture availability in the subsurface. To test this, precipitation conditions between May and September of each study period year were categorized with respect to total precipitation deviation from the 1895-2011 mean. Growing seasons were then separated by total precipitation deviation from mean and only seasons exhibiting a > 20% precipitation decrease remained for analysis. Mean absolute difference was calculated during the anomalously dry periods by comparing the simulated and observed soil moisture. The results show that even under these conditions, there was no significant difference in model performance. The average MODIS – VIC control LAI difference was -1.08, demonstrating the decreased vegetation health reflected in MODIS is not captured in the control LAI. Despite more accurate vegetation depictions, the mean absolute error for MODIS LAI at 10, 40 and 95 cm (0.05, 0.04, and 0.04) was not significantly less than the control LAI (0.05, 0.03, and 0.06).

The lack of considerable improvement in model accuracy when using MODIS LAI is thought to be due to a combination of complicating factors. The first of which is that VIC-simulated soil moisture is overly sensitive to changes in LAI. Small decreases in the LAI parameter will sometimes cause erroneously large increases in underlying soil moisture. Similarly small increases in LAI can correspond with large decreases in VIC-simulated soil moisture. Fig. 3.10 shows two examples of this phenomenon particularly that VIC-simulated soil moisture responds much more strongly to LAI changes than the *in situ* observations. The top plot in Fig. 3.10 shows both simulated soil moisture data with the observations as well as both MODIS and VIC control LAI data. Apache, Oklahoma experienced relatively normal growing season precipitation (-0.2 mm departure) in 2004; however, the VIC control LAI significantly underestimated vegetation health between June and September. This underestimation lead to relatively higher soil moisture conditions because of decreased root uptake compared to soil moisture under MODIS LAI conditions, and a more accurate soil moisture simulation using the MODIS data.

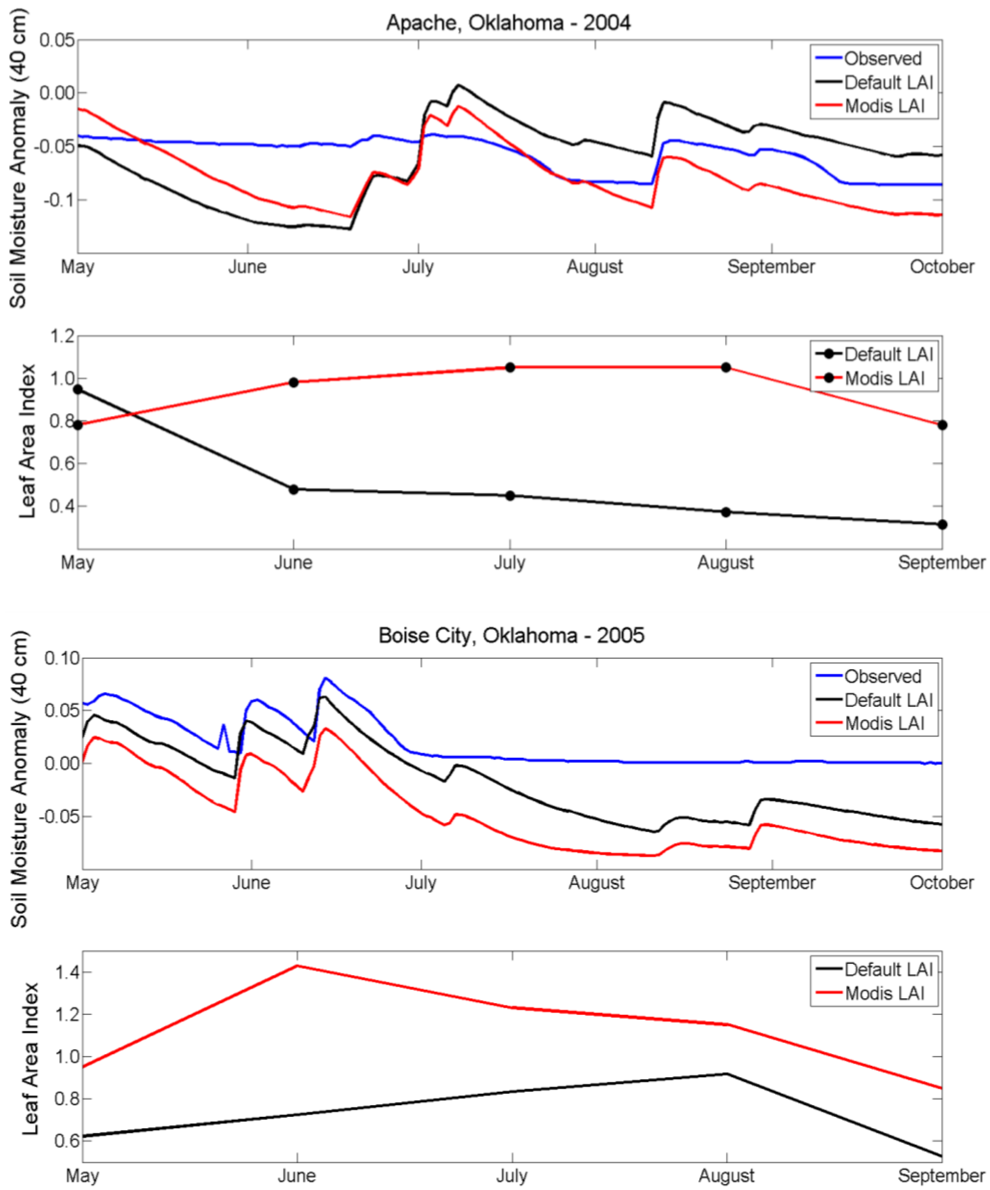


Figure 3.10. Plots of VIC-simulated soil moisture and observed soil moisture at 40 cm with corresponding VIC control and MODIS LAI plots.

However, the second plot shows the same data only for Boise City, Oklahoma during the 2005 growing season. This period of time corresponds with higher than normal precipitation over Boise City (+68.5 mm departure), demonstrated by the significantly higher MODIS LAI compared to the control LAI. Despite the more accurate depiction of vegetation conditions, the simulated soil moisture conditions were less accurate because the increased LAI lead to an overestimate of evapotranspiration (and therefore a decrease in soil water content). The control LAI did not capture the increased vegetation health (and increased evapotranspiration) and therefore simulated soil moisture was higher and more representative of actual soil moisture conditions. This is an example of the model getting it right, but for the wrong reasons. This suggests that soil moisture magnitude response to changes in LAI are overly sensitive compared to the response of *in situ* soil moisture observations.

3.3.3.3 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 although VIC simulations were relatively close to the observations, the seasonal variation and simulated soil moisture during dry periods were not as accurate. Robock *et al.* (2003) attributed some of these issues to model sensitivity to soil texture differences and hydraulic parameters. Meng and Quiring (2008) evaluated simulated soil moisture form three models including VIC with *in situ* observations from three Soil Climate Analysis Network (SCAN) sites. 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-related parameter changes; however, neither effectively quantified the influence of LAI variability on the soil moisture simulations. Thus the ±20% parameter variation approach was adopted from Meng and Quiring (2008) to test the sensitivity of VIC soil moisture to 20% increases and decreases to LAI.

The sensitivity analysis was performed by generating soil moisture from VIC over the same 1994-2010 period using the control LAI data, only increasing (Plus20) and decreasing (Minus20) each month’s LAI by 20%. Thus the only different model parameter is the ±20% LAI values. As expected, increasing LAI by 20% leads to an overall decrease in soil moisture with respect to the “normal” LAI conditions, and vice versa when decreasing LAI. The change in LAI influenced the deep (95 cm) layer soil more than the shallower layers. The average soil moisture percent differences corresponding to a 20% increase in LAI are -0.6, -1.4 and -5.7% at the 10, 40 and 95 cm layers respectively. Similarly the average soil moisture percent differences corresponding to a 20% decrease in LAI are 0.07, 1.5 and 7.4% at the 10, 40 and 95 cm layers respectively. These results show that VIC-simulated soil moisture in the deeper soil layers is more sensitive to changes in LAI than the near-surface soil layers. Fig. 3.11 shows monthly percent differences in soil moisture corresponding to Plus20 and Minus20 simulations. Soil moisture at the 95 cm depth responds more strongly to changes in LAI; however, Fig. 3.11 shows that soil moisture sensitivity to LAI is heightened during the late growing season (June – October). In addition, it is evident that

VIC is slightly more sensitive to increases in LAI than it is to decreases. The sensitivity of VIC-simulated soil moisture to LAI perturbations, along with sensitivity to soil parameters explains some of the differences between the simulated and observed soil moisture.

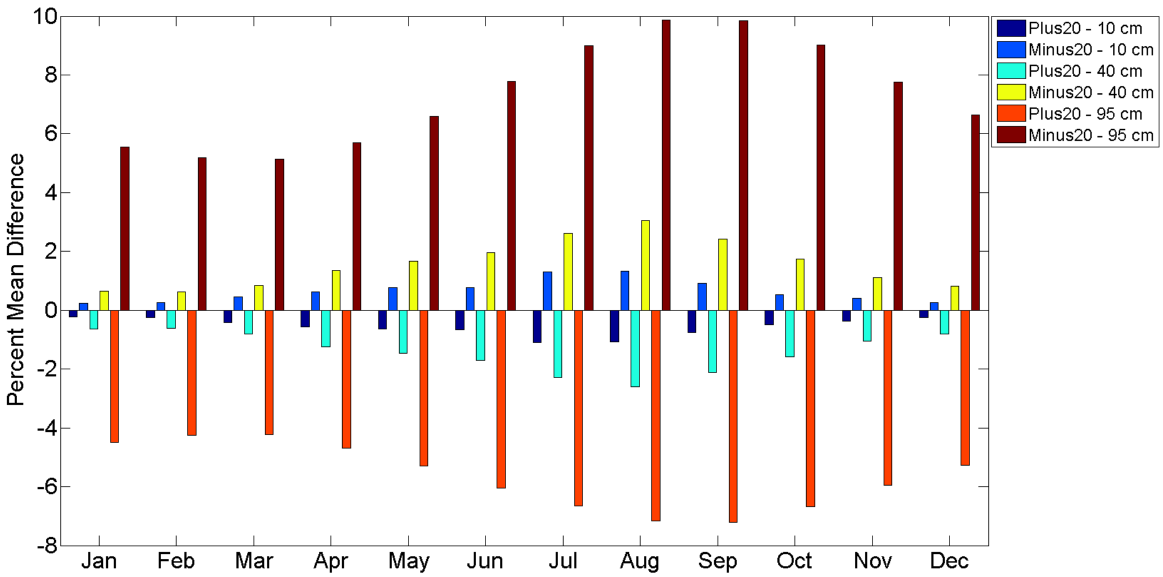


Figure 3.11. Monthly soil moisture percent difference between control LAI and LAI increased/decreased by 20%.

3.3.3.4 VIC-simulated Soil Moisture-LAI Interactions

The sensitivity of VIC-simulated soil moisture to LAI has potential impacts for drought modeling and drought monitoring. Section 3.1 discusses the difference between the interannually-invariant control LAI parameter used by VIC and the MODIS-derived LAI. Specifically, the control LAI does not capture actual vegetation conditions. This systematic overestimation of LAI leads to an overestimation of root uptake and this further decreases soil moisture levels.

To test the impact of changes in LAI to VIC-simulated soil moisture, model simulations were generated from 1994-2001 using a spinup period of 1994-1999. The VIC control (interannually-invariant) LAI parameter was used during the spinup period. Beginning in 2000 five separate simulations was generated, each with a different LAI parameter. Four of the simulations used a different three month period (Jan-Mar, Apr-Jun, Jul-Sep, Oct-Dec) in which LAI was increased by 20% over the control values; these are the variable simulations. The final simulation continued to use the same interannually-invarying control LAI parameter; the control simulation. Changes in soil moisture corresponding to the varied LAI parameter were recorded; particularly the elapsed time during which the control and variable simulated datasets diverged by more than 1%. As expected, the 20% increase in LAI lead to the greatest change at the deep (95 cm) layer. The average time through which the soil moisture datasets diverged by more than 1% when LAI was increased in January-March were 3, 13 and 110 days at the 10, 40 and 95 cm levels respectively. Also as anticipated, the greatest soil memory corresponded with increased LAI during the late growing season (July-September), the average length of time during which soil moisture diverged by more than 1% during this period were 68, 96 and 243 days at the 10, 40 and 95 cm levels respectively.

During the period of divergence, the average percent difference in soil moisture ranged from < 1% to nearly 5%. At some sites the percent difference between the variable and control soil moisture data simulations exceeded 15%, representing a strong response to LAI perturbations. Fig. 3.12 shows percent mean absolute error averaged by depth for each 3-month analysis period, demonstrating that the greatest response to changes in LAI occurred growing season soil moisture. Changes in growing season LAI influence soil moisture more strongly than during the winter season.

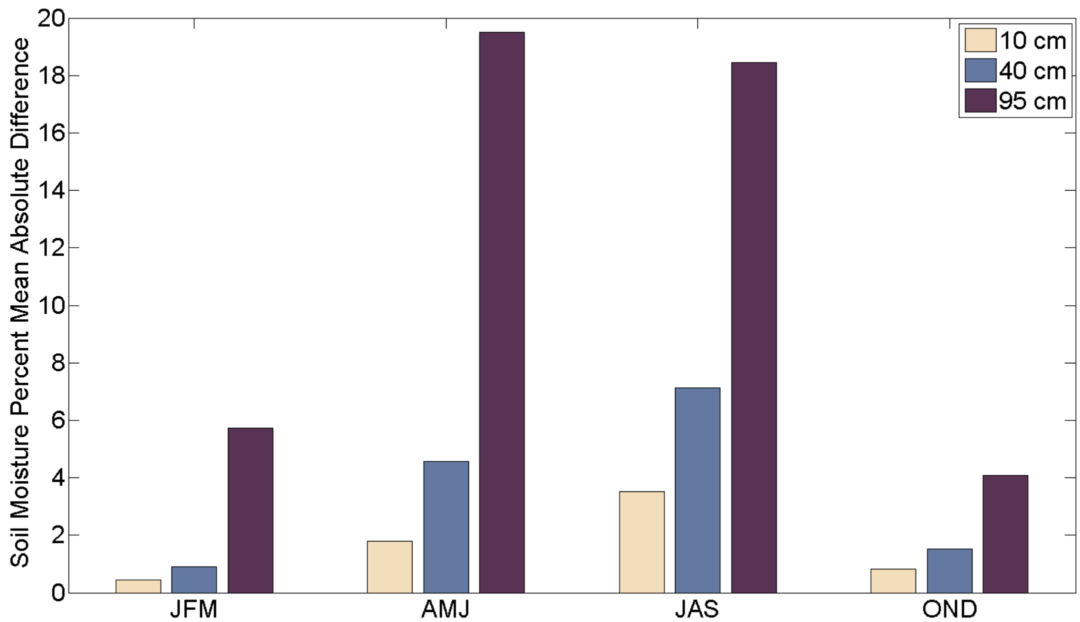


Figure 3.12. Percent mean absolute error between variable and control soil moisture data

3.4. Discussion

Land surface models such as VIC are frequently employed for drought monitoring. Wood (2008) describes the University of Washington Surface Water Monitor, a useful drought monitoring tool which employs land surface moisture conditions, including soil moisture from land surface model simulations. Andreadis *et al.* (2005) used the VIC hydrologic model to construct a United States 20th century drought history. Wang *et al.* (2009) used six land surface models to simulate soil moisture during the 20th century over the United States. Their results showed that soil moisture at the deepest soil column had the longest memory.

The results presented here suggest that static vegetation parameters in the VIC model cannot capture interannual and interseasonal vegetation dynamics. At 9 of the 20 study sites, the control LAI parameter systematically overestimated LAI with respect to the dynamic, Modis LAI parameter. This was primarily due to two factors: 1) differences in land cover classes between the model calibration data and the MODIS surface reflectance data and 2) the inability of the control LAI to accurately represent peak LAI. The peak LAI (as derived from Modis) at these 9 sites occurred at least 2 months before the peak occurred in the control LAI parameter. The Modis LAI parameter was systematically higher than the control parameter at 2 of the 20 sites. This is likely caused by differences between the magnitude of LAI for each land cover class between the control LAI parameter and what is captured by the MODIS imagery.

However, with respect to drought monitoring, the 9 sites at which there were systematic differences in LAI parameters and corresponding soil moisture simulations are not as problematic as the other 11. Systematic soil moisture simulation bias forced by the control LAI parameter can be accounted for, but inconsistent differences between the two LAI parameters at the other 11 sites cannot be accounted for. Therefore, using a land surface model which does not accurately represent vegetation conditions dynamically could introduce error in soil moisture simulations. This has implications for drought monitoring as well as for studies that examine land-atmosphere interactions and soil moisture memory.

3.5. Summary and Conclusions

The VIC hydrologic model was used to simulate soil moisture conditions at three depths over several sites in Oklahoma between 1994 and 2010. Two simulations were generated, one using the standard, interannually-invariant control LAI parameter as described in Maurer *et al.* (2002) and the other using MODIS LAI. 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 primary conclusions of the study are:

1) VIC-simulated soil moisture using MODIS LAI was not consistently more accurate than soil moisture simulated with the control LAI. However, the simulations using MODIS LAI were generally more accurate at the 0 to 10 cm and 40 to 95 cm depths and the control LAI was generally more accurate at the 10 to 40 cm depth.
2) The control LAI parameter systematically overestimated vegetation health at 9 sites. This overestimation was exacerbated during anomalously dry growing seasons and cause significant differences in simulated soil moisture during these periods.
3) A sensitivity analysis showed that VIC-simulated soil moisture is quite sensitive to perturbations in LAI. A 20% increase and a 20% decrease in LAI resulted in a ~6% decrease and 7% increase in soil moisture, respectively.
4) Control LAI is independent of soil moisture availability and this can result in drier soil moisture conditions than those actually observed. A sensitivity test

showed that this phenomenon could cause differences between actual soil moisture conditions and those simulated by VIC exceeding 15%.

5) The results of this study suggest that accurate parameterization of vegetation health, both seasonally and interannually, are essential for accurately simulating soil moisture.

CHAPTER IV

SUMMARY & CONCLUSIONS

4.1. Objective 1 Summary

Chapter 2 documented the observed interactions between soil moisture and vegetation health using data from 20 sites in Oklahoma. The relationship between soil moisture and remote sensing-derived vegetation health varied in sign. Three site-specific factors expected to influence soil moisture-vegetation coupling strength were examined in depth: precipitation, land cover and soil texture. The data showed no relationship between any of these three variables and correlation strength. This suggests that linear correlations cannot capture the influence of soil moisture on vegetation with respect to the multitude of other factors influential to the growth and health of vegetation.

The most important finding is that soil moisture-vegetation coupling strength varies as a function of space and of time. Under anomalously wet conditions, particularly those in which moisture is not a limiting factor, vegetation health is essentially decoupled from soil moisture variations (Dirmeyer *et al.* 2000). The use of agricultural drought indices derived from remotely-sensed vegetation health accounts for temporal variability in soil moisture-vegetation coupling. For example under soil moisture conditions below the permanent wilting point, vegetation health may not respond as strongly to soil moisture variations. The strength and timing (lagged versus simultaneous) of vegetation response to soil moisture is controlled by vegetation type and soil texture. Thus drought indices derived from vegetation health may include inherent biases and error due to spatial variability of soil texture and vegetation type, a phenomenon which necessitates further investigation.

4.2. Objective 2 Summary

Chapter 3 evaluated the influence of remote sensing-derived vegetation parameters on VIC-simulated soil moisture at 20 Oklahoma Mesonet sites. Model simulations were generated from 2000-2010 using both the standard, interannually-invariant LAI as well as the MODIS-derived LAI. An accuracy assessment based on *in situ* soil moisture observations showed that the MODIS LAI did not consistently improve the accuracy of the soil moisture simulations. This was attributed to the sensitivity of VIC to changes in LAI.

Large differences between VIC-simulated soil moisture using the control versus the MODIS LAI parameters were found during anomalously dry conditions. Using the invariant LAI can accentuate and elongate drought conditions because vegetation health does not change during drought conditions and therefore evapotranspiration is over-estimated. During anomalously dry periods, MODIS LAI decreases; however, the control LAI cannot respond to decreased moisture availability and continues at the "climatological" or average vegetation production. Essentially with the VIC control LAI parameter, root uptake remains steady despite continuously decreasing soil moisture availability, which reduces soil moisture even further, intensifying dry conditions.

The control LAI was also not able to account for spatial variability in peak "greening" times. Spatially-variable factors such as vegetation type, general climate an synoptic conditions influence the timing of peak vegetation health, thus making this peak variable over space. Because the control LAI parameter has one greening timeline for each vegetation class, regardless of the factors listed above, it could not account for the spatially-dynamic peak greenness variability.

Land surface models such as VIC typically employ these interannually-invariant vegetation parameters (http://ldas.gsfc.nasa.gov/nldas/, http://www.hydro.washington.edu/forecast/monitor/index.shtml). These LSMs are commonly used for a variety of drought monitoring/drought modeling applications. However, the ability of these models to accurately simulate soil moisture is hindered by invariant vegetation parameters, potentially resulting in biased estimates of agricultural and hydrological drought.

Soil moisture-vegetation interactions are vital to land-atmosphere coupling and the precipitation recycling; however, these interactions exhibit considerable spatial and temporal variability. These aspects are not accurately simulated in land surface models, resulting in biased soil moisture estimates. In order to understand and properly model land-atmosphere interactions, variations in soil moisture-vegetation coupling have to be documented and examined. Clearly further research utilizing both *in situ* observations and models is necessary to increase our ability to understand and simulate land-atmosphere interactions.

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