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IMPROVED STATEWIDE SOIL MOISTURE ESTIMATION FOR HYDROLOGIC ASSESSMENT FORECASTING

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Abstract

Soil moisture is a dominant forcing variable in the terrestrial environment. Yet, routine monitoring of soil moisture at regional scales and with temporal continuity remains a challenging task. Recognizing the potential of the undeveloped framework provided by the NC Environment and Climate Observing Network (ECONet), the goal of this project was to enhance soil moisture monitoring and estimation for North Carolina. We focused on improvements for interpretation of ECONet soil moisture data and also considered the potential for coupling this network with data from NASA's Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E). Objectives were to: 1) Characterize soil properties at the ECONet soil moisture monitoring sites, 2) Determine the distribution of NC ECONet stations with respect to soils, 3) Assess spatial and temporal relationships among ECONet and AMSR-E soil moisture observations, and 4) Gauge the potential of AMSR-E data to improve spatio-temporal estimation of soil moisture statewide. We investigated soil physical properties at 27 NC ECONet soil moisture monitoring stations in the piedmont and coastal plain regions of North Carolina. Soils at ECONet sites fall in seven textural classes. Porosities ranged from 0.36 to 0.58 $cm^3\ cm^{-3}$, suggesting a wide range of upper limits for soil water content. Diversity was also found for other parameters, such as field capacity and wilting points. Strong correlations were found between the soil physical parameters. A principal component analysis reduced 10 soil physical parameters into three principle components that explained 85% of the variability within the dataset. Analysis of variance of select, semi-qualitative soil taxonomic classes for seasonal and whole-year ECONet soil moisture revealed that the greatest significance was for the taxonomic descriptor particle size class. Multiple linear regression analysis of ECONet seasonal soil moisture with measured soil physical properties suggested two water retention parameters, along with potential evapotranspiration, were most significant. The strong relationship between individual parameters revealed through correlation and principal component analysis, as well as the significance of only a few soil parameters in the multiple linear regression, suggests that the influence of soil physical properties on ECONet soil moisture might be explained by measurement of a subset of soil properties. Coupled with results based on analysis with soil taxonomy, the most appropriate soil property measurement may be particle size distribution (i.e., texture). Poor spatial correlation of daily, statewide ECONet soil moisture was observed and may indicate that interpolation of ECONet soil moisture data is not warranted. This result may be due to the relatively low number of ECONet sites available and the distances between these. Statewide spatial correlation did improve with longer time scales, which is reasonable given that these longer time scales integrate a highly spatially and temporally variable parameter. AMSR-E soil moisture data cannot presently be used with ECONet soil moisture for interpolation since they are not correlated on a statewide scale. This may be due in part to AMSR-E's low estimates and damped variation with respect to ECONet. The correlation did improve over seasonal and annual time scales. AMSR-E soil moisture data displayed strong spatial correlation. Continuing research will look at whether AMSR-E brightness temperature is more strongly correlated with ECONet soil moisture than is AMSR-E soil moisture. Overall, results provide opportunity for improvement of soil moisture data offerings from ECONet, but further research is warranted to support efforts at continuous statewide soil moisture estimation.

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Introduction

North Carolina has recently been subject to both regional and statewide droughts. These droughts have required restrictions on water usage for more than half of the State's citizens and cost the State millions of dollars in drought-associated losses. Drought conditions are the result of large-scale climate patterns. However, rainfall's direct influence on water supplies is determined by the interaction between climate and local land conditions. Land cover, soil type, topography, and antecedent soil moisture combine to affect partitioning of rainfall between runoff, groundwater recharge, soil moisture storage, and evapotranspiration (Brocca et al., 2008; Zhang and Schilling, 2006; Maurer et al., 2004). While land cover, soil type, and topography are relatively constant on short timescales, antecedent soil moisture is a dynamic hydrologic state variable. Temporally fluctuating soil moisture conditions are important in determining the direct effects of rainfall events on water supplies. Without an adequate understanding of soil moisture conditions, predictions of event-based and seasonal variations in hydrologic response are unreliable (De Michele and Salvadori, 2002; Entekhabi et al., 1999). Soil moisture status also provides a primary indicator of drought recovery following lapses in normal rainfall (Basara et al., 1998).

The overall importance of soil moisture as a forcing variable in terrestrial environments is widely recognized (Vereecken et al., 2008; Robinson et al., 2008; Seneviratne et al., 2010; Legate et al., 2011). Soil moisture significantly influences weather and climate, plant growth and productivity, hydrology, and soil ecology (i.e., carbon/nitrogen dynamics, trace gas emissions). Because of these broad potential applications, the need for compilation of extensive and intensive soil moisture information has also been recognized for several decades (e.g., Robock et al., 2000; Western and Grayson, 1998).

Research efforts to develop new techniques for monitoring soil moisture also continue, often with focus on large scale monitoring. One prominent area of research is remote sensing (Engman and Chauhan, 1995; Jackson, 1993; Jackson and Schmugge, 2002). Remote sensing techniques offer promise; however, many provide information only for the top few centimeters of the soil (Robinson et al., 2008). Therefore application of remotely sensed soil moisture data may be limited for conditions at typical plant rooting depths or for other ecological and hydrological applications without significant complimentary information (Houser et al., 1998; Robinson et al., 2008). Most remote sensing techniques also require extensive ground-based validation before application (Arya et al., 1983; Njoku et al., 2003; Drusch et al., 2004, Cosh et al., 2004). Thus, ground-based observation of soil moisture remains important even as remote sensing techniques improve (Georgakakos and Baumer, 1996; Western et al., 2002; Robinson et al., 2008).

Efforts have also been made to develop regional-scale, ground-based soil moisture monitoring; examples include the Oklahoma Mesonet (Illston et al., 2008), the Illinois Soil Moisture Network (Hollinger and Isard, 1994), and the USDA Natural Resources Conservation Service Soil Climate Analysis Network (Schafer et al., 2007). A potential limitation of such networks is that they represent soil moisture only at the point of observation, which may differ significantly from surrounding areas (Scott et al., 2010).

Vachaud et al. (1985) proposed the concept of temporal stability for soil moisture, which attempts to explain patterns in soil moisture that persist in time. Vachaud et al. (1985) and other researchers (e.g., Martínez-Fernández and Ceballos, 2005; Western et al., 1999) have

demonstrated, beyond the idea of temporal stability, the role of soil and landscape properties in extending point soil moisture information to describe patterns in soil moisture across the landscape. It is critical that, as ground-based soil moisture networks continue to develop, soil moisture observations should be accompanied by careful inventory of soil and landscape properties in order to understand patterns in soil moisture. Furthermore, to apply or even to check quality of soil moisture monitoring data, collection of metadata is critical (Scott et al., 2010). However, a vast number of soil properties can potentially be considered in terms of characterizing soil moisture dynamics. Among the key soil parameters frequently assumed important are soil texture and particle size distribution (Loague, 1992; Saxton et al., 1986; Ritsema and Dekker, 1994; Western et al., 2002), bulk density and porosity (Gupta and Larson, 1979; Saxton et al., 1986, Rodriguez-Iturbe, 1995; Wagner et al., 1999), water retention characteristics (Rawls et al., 1982, Feddes et al., 1988; Wagner et al., 1999; Western et al., 2002), and hydraulic conductivity (Feddes et al., 1988, Western et al., 2002). Clearly, characterizing all these properties requires a significant investment in time and resources, and choice of properties to characterize must be considered carefully.

In North Carolina, the State Climate Office (SCO) currently provides soil moisture data to the public through the NC Environment and Climate Observing Network (ECONet; http://www.nc-climate.ncsu.edu). The ECONet is a near real-time, point-based, state-wide monitoring network providing soil moisture data at a single depth (20 cm). Data collection at the first sites began as early as 1998 with new sites added periodically since that time; there are currently 36 stations state-wide (Fig. 1). While this information is potentially useful, the current network was not designed to represent soil moisture conditions in major soil units. Instead, network monitoring sites were chosen to maximize spatial coverage and make use of existing meteorological monitoring frameworks irrespective of specific soil patterns. The connection between soil moisture status at these monitoring locations and regional soil moisture status for the diverse set of soil and land conditions in the State is not well defined. Thus, despite availability of soil moisture data, these data may be of limited use for characterizing conditions that contribute to regional storm response and water availability. Furthermore, within the existing monitoring framework, there have been no efforts made to characterize soil properties at the monitoring sites to aid interpretation of how monitored soil moisture conditions affect processes in the surrounding soils and landscapes.

Recognizing the potential of the undeveloped framework provided by the NC ECONet, the goal of this project was to enhance soil moisture monitoring and estimation for a diverse clientele in NC. We focused on improvements for interpretation of ECONet soil moisture data and also considered the potential for coupling this network with remote sensing data. Specific project objectives were to:

1) Characterize soil properties at the ECONet soil moisture monitoring sites to develop network metadata and new ECONet soil moisture products.

2) Determine the distribution of NC ECONet stations with respect to soils using site characterization data and existing geospatial data layers in order to define linkages between soil moisture observations at monitoring locations.

3) Assess spatial and temporal relationships among ECONet and NASA's Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) soil moisture observations.

4) Gauge the potential of the passive microwave radiometry data to improve spatio-temporal estimation of soil moisture status statewide.

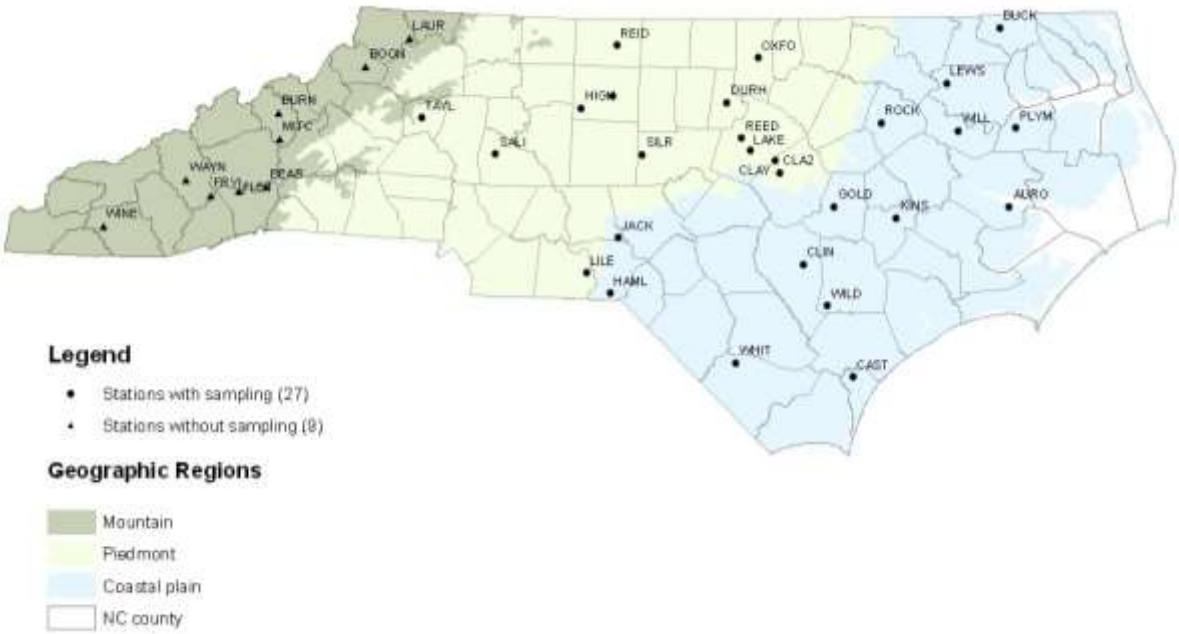


Figure 1. North Carolina, showing county boundaries and sampled and unsampled ECONet sites.

Methods

Soil Physical Property Characterization and Statistical Analysis

At the time of data collection for this study, there were 27 NC ECONet stations within the coastal plain and piedmont regions of NC (Fig. 1). Data were collected from each of these sites; data collection in the mountain region is on-going at the time of this report. The landscape at individual stations within the coastal plain and piedmont varies according to local topography, but sites are generally positioned on locally level (< 5% slope) terrain. Land use history at each site varies, but most sites can be assumed to have been used for agriculture practices at least some time during the past hundred years. Current vegetation at each site is a mix of native and introduced grasses and weeds.

For each station, soil moisture data are collected at the 20 cm depth every 30 min, producing 48 observations per station, per day. The soil moisture sensor currently installed for the NC ECONet is the Theta Probe ML2X (Delta-T Devices, Cambridge, UK). The volume measured by the

sensor is approximately 75 cm^3 (Kaleita et al., 2005). The sensor installation depth and approximate observation volume were used to guide the soil sampling protocol.

Sampling in the coastal plain and piedmont regions was conducted during the period between February 2009 and May 2010. Altogether, 81 intact soil cores, as well as additional bulk samples, were collected from the sites. Though it was not possible to sample at the exact location where sensors were installed, it was intended that the soil being collected have characteristics similar to the soil where the moisture sensor was installed. Sampling spots were randomly selected within a 3- meter radius circle centered at the approximate location of the sensor. Three 7.6 cm length, 6.3 cm diameter intact soil cores, centered at 20 cm soil depth, were collected as replicates at each site. Sampling was performed using an AMS soil sampler (AMS, Inc., American Falls, ID). A pilot hole was used to access the appropriate sampling depth. Upon retrieval, cores were sealed with caps to protect their integrity and immediately weighed in the field to determine field water content. Cores were then transported to the laboratory for the determination of water retention, saturated hydraulic conductivity and bulk density. Loose soil samples were also collected simultaneously at the 20 cm depth for additional water retention measurements and soil textural analysis.

Laboratory analyses on soils were performed during the same time period as soil sampling. The intact soil cores were used to determine saturated hydraulic conductivity values (Ks) by the constant-head method as described in Klute (1986). The falling head method (Klute, 1986) was applied to soil cores that did not exhibit measureable flow with the constant-head measurement during a 4 h period. After Ks measurements, water retention measurements at pressure of 10, 33, 66 kPa (hereafter referred to as P10, P33, and P66, respectively) were performed using a chamber method for the same intact cores (Klute, 1986). After saturation, gas pressure was applied in steps, and the volume of outflow after equilibrium at each pressure step was recorded. At the final pressure step, the samples were weighed, oven dried at 105 °C for 24 h and reweighed. Total porosity (TP) and bulk density (BD) were calculated from the dry weight and sample volume of the intact sample, assuming the particle density was 2.65 g cm^{-3}.

Water retention measurements at 100, 500 and 1500 kPa pressure (hereafter P100, P500 and P1500, respectively) were determined with disturbed samples following similar procedures as described by Klute (1986). An additional parameter, air-dried water content (AD), was measured by allowing saturated, disturbed soil samples to dry to a constant weight under constant temperature and humidity (approximately 22 ºC and 30%, respectively). Particle size distribution was determined using the hydrometer method (Klute, 1986) . Hydrometer reading were made at 0.5, 1.5, 360, and 960 minutes to determine the percentage of clay, silt and sand.

Parameter values for the three replicate cores at each site were arithmetically averaged to obtain a single value for each parameter except for Ks. The skewness test (Tabachnick and Fidell, 1996) revealed that Ks values are highly skewed among replicates compared with all the other variables. Thus, they were transformed using the log transfer method to a nearly normal distribution, then back transformed after averaging. Based on analyses, a soil properties dataset including 13 parameters for each of 27 ECONet station was generated. Selected variables were analyzed using classical statistical methods to obtain the minimum, maximum, mean, median, standard deviation and coefficient of variation (CV).

A correlation analysis was performed on 10 of the 13 parameters (excluding Ks, TP and silt content) via a correlation matrix. Values for Ks were excluded because of local heterogeneity amongst replicates. Porosity and silt content were excluded since they were derived from BD and total content of sand and clay, respectively, and were therefore directly related to other subsets of parameters. Following correlation analysis, a principle component analysis (PCA) was used to assess the overlap of individual parameters and collapse correlated parameters into a smaller subset of uncorrelated parameters. Prior to this analysis, the data were normalized to an average of zero and standard deviation of one.

Analysis of Relationships between ECONet Soil Moisture Observations and Soils

Continuous observations of soil volumetric moisture content (θ), along with climatological parameters of precipitation and potential evapotranspiration (PET), at the sampling sites were retrieved from the NC ECONet database. For this work, we used the ECONet dataset from May, 2008 to April, 2009, which was the most recently available complete annual cycle (Pan, 2010). The average one-year precipitation across all sites was 98 cm, which was 25 cm lower than the 30-year normal. However, this period was chosen because it provided the most complete dataset across all sites. With the exception of six stations with unavailable or problematic data (Pan, 2010), 21 stations provided a total of 7665 θ observations (on a daily basis) included in this study. We further subdivided this period into two intervals: 'growing season' from May, 2008 to October, 2008 and 'non-growing season' from November, 2008 to April, 2009. Whole-year and seasonal average soil moisture content at sampling sites were compiled from daily monitoring records for corresponding ECONet stations. Other desired parameters, precipitation and PET, were obtained in the same manner. A paired-sample T-test was performed for differences in precipitation, soil moisture and PET in discrete periods in the studied area.

Physical properties were also extracted from the taxonomic descriptions for each soil family. Rather than numeric parameters, physical properties at the family level were qualitative taxonomic descriptors shown in the form of classification. Soil moisture content at the sensor depth is not only controlled by soil properties at the measurement depth, but also by the characteristics of the soil profile including multiple horizons (Ghosh, 1980; Hillel, 1971). Thus, we chose these taxonomic descriptors based on the pedological horizon (20-100cm) that represents the major characteristic of the profile and, according to Wosten et al. (1985), are highly related to soil hydraulic properties. The taxonomic descriptors and their classes for soils are summarized in Table 1. Once the descriptor classification had been determined for all the sites, the analysis proceeded to investigate the correlation between soil moisture content and soil taxonomic descriptors.

One-way analysis of variance (ANOVA) was performed for each taxonomic descriptor to determine if θ varied over the classes of that descriptor. That is, we attempted to identify if some known taxonomic descriptor of the soils could be used as the determinant factor for the soil moisture pattern. ANOVA was chosen since the parameters for the entire soil profile were only available as qualitative descriptors. In ANOVA, means of θ with sites in the same descriptor category were used for comparison. If ANOVA results specified significant differences from one class (based on a single descriptor) to another, that descriptor was identified as a property associated with θ variation. Further analysis was performed to determine if the variation in θ

pattern could be better explained by the combination of two determined descriptors identified in the previous ANOVA test. For instance, results suggested θ was influenced by particle size and wetness class (in descriptor classifications) of the soil in individual one-way ANOVAs. A two-way ANOVA analysis could show the proportion of total variation in θ attributed to each descriptor. Here, a combination of descriptor classes was used instead of two-way ANOVA because of the absence of descriptors for two sites with "Udorthents" soil (classified as "other" in descriptors). It essentially serves the same purpose as two-way ANOVA by simultaneously including statistically important factors in the previous step. If the P-value is improved over results when using either descriptor alone, the information contained in one descriptor could not be enough to describe θ patterns in the studied area.

In addition to using soil descriptors available from soil maps, an attempt was made to quantify the relationship between observed θ and measured soil physical properties. Forward stepwise (SPSS, 2000) multiple linear regression (MLR) analysis was performed using the means of daily θ at each sampling site. In order to include both locational and temporal variation in precipitation and PET, seasonal means were selected. The MLR was designed to pick the most important influences on θ (in the sense of the significance level for each parameter). In the preliminary test, 10 soil hydraulic parameters (the same parameters analyzed in PCA), and two climatological parameters (precipitation and PET) were included. The number of predictive variables was reduced by evaluating the corresponding P-value for each parameter leading to a reduced model containing only significant variables.

Spatial and Temporal Correlation of ECONet Soil Moisture Observations

Assessments of ECONet θ data quality by Pan (2010) suggest that there are stations that have had more than half of several years with either missing or poor quality data. Data quality was particularly bad before 2005. Three stations maintained poor quality through 2009: Durham, High Point, and Siler City (DURH, HIGH, SILR). Based on station number and data quality considerations, we chose to use data from 2007 through 2009 for this portion of the analysis. Also, the AMSR-E data (next section) are available beginning in 2004. There were 31 stations at the start of 2007, but two were removed from study because of poor data quality (HIGH and SILR), leaving 29 stations for analysis.

We began by examining the difference in spatial correlation between wet and dry days across the ECONet. To do this, we examined precipitation records from the State Climate Office to determine the months of highest and lowest rainfall. These were September 2008, and May and November 2009 for wet months, and November 2007, June 2008, and February 2009 for dry months. NC's Storm Event Database was used to find a large precipitation event that might have covered the whole state. We expected such an event to provide a short period of relatively uniform θ across the state. Tropical Storm Hanna in September 2008 was the only storm found in the study period that generally went east to west over the state.

Daily-averaged ECONet θ data were then used to find specific wet and dry days within the wet and dry months noted. These were chosen considering representative sites, peaks of wet and dry, and uniformity across the state. The SCO provided a subset of stations that represent average conditions for the state's three physiographic regions. These were: Waynesville (WAYN) and Fletcher (FLET) in the mountains; High Point (HIGH), Rockingham (ROCK), and Jackson

Springs (JACK) in the piedmont; and Plymouth (PLYM), Aurora (AURO), and Castle Hayne (CAST) in the coastal plain. Their daily averaged θ data were reviewed for peak dry and wet days within the considered months. The most coincident peaks (for wet and dry conditions) for all eight stations were chosen as the representative dates. The wet dates were 6 September 2008, 18 and 19 May 2009, and November 2009. The dry dates were 14 November 2007, 18 June 2008, and 17 February 2009. This task was inherently difficult in that what happens on the coast is not generally occurring in the mountains, and vice versa. The dates, therefore, were an average of the wettest days for most stations, and were weighted toward the date when most stations had received rainfall.

In order to quantify spatial correlation, a semivariogram is used. It is a graph of the semivariance, i.e., half the average variance between all pairs of points a selected lag distance h_i apart, as a function of h_i. Practically, the semivariance is calculated for pairs of points that lie within a range of lag distances, the bin, which results in a corresponding range of semivariances. These so-called semivariance clouds are plotted and modeled via regression to produce the semivariogram model. Conceptually the semivariogram tells us at what distances values are more alike, i.e., more correlated (low semivariance) and at what distance the semivariance reaches or approaches the population variance. This semivariance plateau is called the sill. The distance at which the sill occurs, i.e., where the variance between points approximates the sample variance, is called the range of spatial correlation. The nugget is the semivariance extrapolated to a lag distance $h = .0$. In theory the nugget should be zero; that it often is not is due to experimental error and spatial correlation at scales smaller than the shortest sampled lag distance. The degree of spatial correlation is indicated by the nugget:sill ratio, which indicates what proportion of the population variance is non-spatial. The smaller the nugget:sill, the greater the degree of spatial correlation; 1- (nugget/sill) is the proportion of variance attributable to spatial correlation. We used the geostatistical software GS+ (Gamma Design, Plainwell, MI) to generate our semivariograms.

Analysis of AMSR-E Soil Moisture Data and Comparison with ECONet

AMSR-E is one instrument on board NASA's AQUA satellite. AQUA's mission is to gain more understanding about Earth's water cycle in all its forms: ice, snow, ocean water, atmospheric water, soil moisture, etc. Also on board is the Moderate Resolution Imaging Spectroradiometer (MODIS), which gives vegetation indices that might be useful in refining AMSR-E's θ estimation. Accuracy of estimation of θ via passive microwave radiometers is affected by the extent and magnitude of vegetative cover. In addition, vegetation affects θ directly via evapotranspiration. These datasets are global in scale, so the information can be applied beyond NC if warranted. AMSR-E data are available without cost via a variety of data pulls from the National Snow and Ice Data Center (NSIDC) in Boulder, CO.

AMSR-E estimates soil moisture by sensing the microwaves emitted by the surficial 1 cm of soil. It records these as brightness temperature (Tb). Because of the contrast between the dielectric properties of water versus soil solids, the strength of the microwave, (i.e., the brightness temperature, Tb) is a function of θ. AMSR-E passes over NC every other day with a statewide view using the ascending pass. The data are sampled at varying spatial densities, but averaged and served in a standardized global Equal-Area Scalable Earth Grid (EASE grid) with 25- by 25-

km cells. The State contains 209 such cells. In theory, θ is sensed with an accuracy of 0.06 g cm^{-3} in low vegetation conditions. Large water bodies, high vegetation biomass, and changes in topography all negatively affect accuracy of estimation of θ via passive microwave radiometry.

To correct for these interferences, an algorithm that incorporates parameters for soil types, vegetation, surface roughness, and quality checks is used to estimate θ from the raw temperature brightness data. The data are also flagged for ice, permafrost, snow, precipitation, radio frequency interference, and vegetation density. To date, we have been unable to find the actual algorithm well described in the literature. For example, other than Tb, we do not know exactly which auxiliary parameters appear in the model and which of these are dynamic and which are static. An R script was used to pull Tb, θ, Date, Latitude, and Longitude from L3 data for a rectangular area over the entire state in order to examine relationships between θ estimated by the algorithm and Tb.

The AMSR-E θ data comes in hierarchical data files (.hdf) and requires special procedures to view and manipulate. Using grid georeferencing, we subset the data to select only the grid cells covering NC. So-called Level 3 data, which include the θ estimates in EASE grid cells, were viewed in ArcGIS. L2B data is also averaged into the EASE grid, but is stored in a table format. It can be loaded into ArcMap by adding it as XY data. Using L2B also has lower memory requirements (L2B: 1 MB; L3: 63 MB). We also used HDFView (HDF Group, 2011) to view the data, copy tables, and other limited options. Both data types and programs were used to analyze AMSR-E θ data.

Results and Discussion

Characteristics of Soil Physical Properties

It is necessary to recognize that there is natural variation amongst sampling locations at each station site which may limit representativeness of individual samples for describing the soil properties at the actual sensor location (Scott, 2010). For example, in the present dataset the CV for Ks among replicates at a given site exceeded 50%. The rest of the parameters, however, were relatively consistent between the three replicates at each site with CV's < 5% (data not shown). Limited local variation in soils data obtained from small soil cores obtained within a spatially confined area has also been reported by others in similar approaches (Basara and Crawford, 2000) or on similar soils (Cassel, 1983). Because variation among individual parameters was small for all parameters except Ks, we focus the remaining discussion on comparison of mean properties from site to site rather than local variation at a given site. The full data set for parameters measured at each site is provided in Pan (2010).

Descriptive statistics of selected soil physical properties among the 27 ECONet stations are shown in Table 1. Based on the skewness and CV, several of the variables can be described as having a normal distribution. Soil bulk density was normally distributed from 1.10 to 1.69 Mg m^{-3} with normality indicated by the slight difference between mean and median. Similarly TP, derived from BD, was normally distributed. While sand content was normally distributed, clay and silt content were skewed judging by their skewness values and the difference between mean and median. The texture distribution (i.e. combination of sand, silt, and clay) of sampling sites is shown within an alternative texture triangle in Fig. 2. The soil texture at ECONet sites is

distributed within seven classifications, with most points falling within the four classifications loam, sandy clay loam, sandy loam and loamy sand. Texture points clustered in the area with sand percentage greater than 40% and clay percentage less than 40%. The relatively higher CV (80%) for clay content could be explained by noting that one station had observed clay content of 55% while all other stations had clay content < 40%. The reason for a CV of 50% in AD may be caused by a similar reason since AD may be highly dependent on the content and mineralogy of the clay fraction (Sumner and Kamprath, 2000).

Table 1. Descriptive Statistics for Selected Physical Properties at ECONet sites in the Piedmont and Coastal Plain.

Parameter	Mean	Median	Max	Min	SD	Skewness	CV (%)
BD, Mg m^{-3}	1.42	1.43	1.69	1.10	0.17	-0.34	12
TP, m^{-3} m^{-3}	0.46	0.46	0.59	0.36	0.06	0.33	13
Log Ks, cm h^{-1}	0.65	0.70	1.15	-0.32	0.33	-1.1	47
Clay, %	15	11	53	2	12	1.54	80
Sand, %	63	64	90	24	17	-0.30	27
Silt, %	22	16	49	4	13	0.72	59
AD, m^3 m^{-3}	0.02	0.02	0.07	0.01	0.01	1.84	50
P33, m^3 m^{-3}	0.28	0.29	0.50	0.13	0.09	0.14	31
P1500, m^3 m^{-3}	0.10	0.09	0.19	0.04	0.04	0.56	44
PAW, m^3 m^{-3}	0.18	0.19	0.33	0.07	0.06	0.43	32

Field capacity and wilting point, corresponding approximately to P33 and P1500, are two commonly used reference points for soil moisture observations. There are wide ranges for both of these parameters among the 27 stations; P33 ranged from 0.13 to 0.50 m^3 m^{-3} and P1500 ranged from 0.04 to 0.13 m^3 m^{-3}. Strong positive correlations with clay content were observed for both P33 and P1500, with r^2 of 0.66 and 0.80, respectively, for the best fit power model (Fig. 3). Another common parameter of interest for soil moisture observation, plant available water content (PAW), the difference between field capacity and wilting points, is shown as the area between the two curves in Fig. 3 as well as in Table 1. The general trend for plant available water content is apparent as it increases with clay content for these sites. However, the correlation ($r^2 = 0.18$, fitted power model not shown) was much weaker.

Results from simple statistical analysis clearly indicate that soil physical properties are highly varied among the 27 studied ECONet stations of the piedmont and coastal plain. More importantly, the physical heterogeneity would be reflected in distinct hydraulic behavior. For example, the maximum possible θ (i.e., TP) at sites within the network ranges from 0.36 to 0.59 m^3 m^{-3}. The difference between the upper and lower end of this TP range would result in a very different interpretation for the same numerical value of θ observed at different sites. Though slightly less pronounced, differences at the dry end of the soil moisture range (e.g. P1500) are also substantial. The wide range in observed soil characteristics within the network illustrates the importance of collecting soil physical properties data for soil moisture monitoring in an expansive network such as NC ECONet. This information is not only potentially useful for

quality control of soil moisture data collected in the network but also enhances the potential for interpretation of soil moisture data.

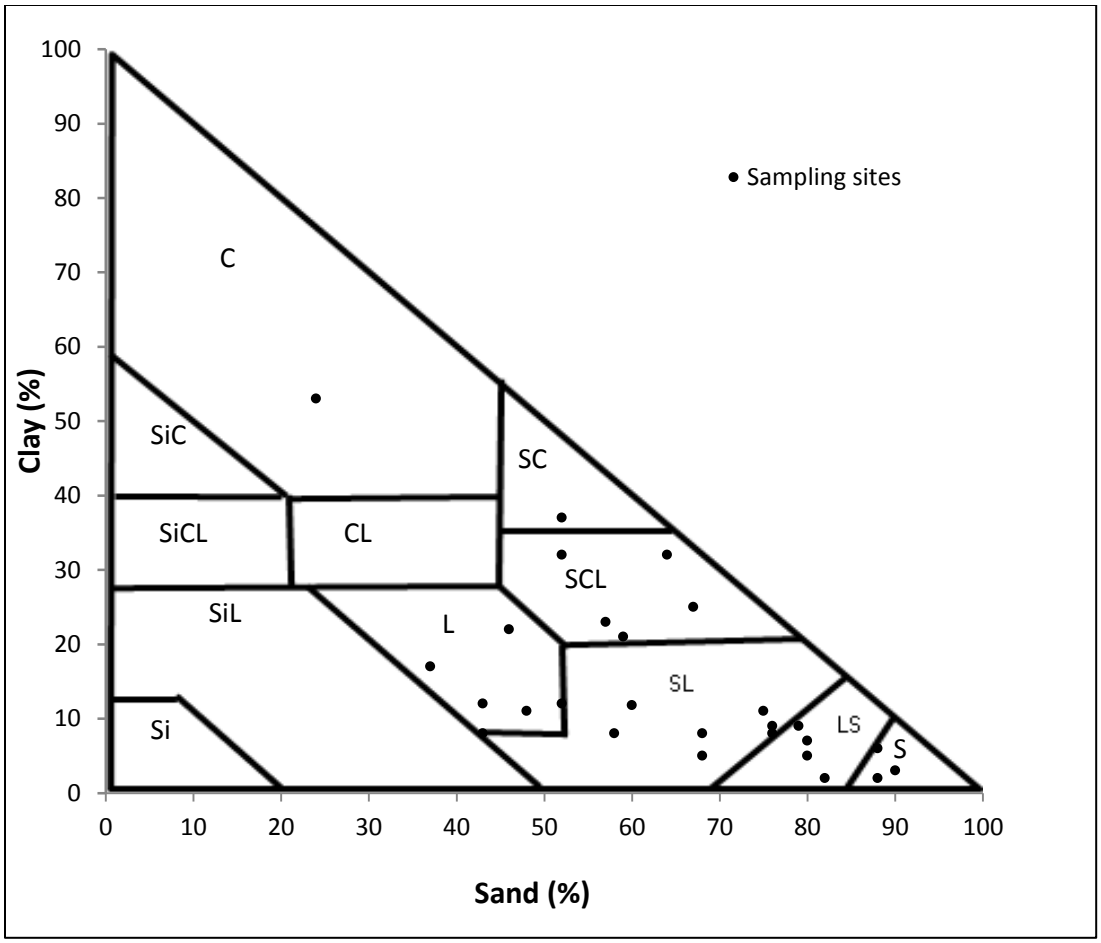


Figure 2. Textural Triangle with Distribution of Sampled ECONet Sites. Texture classes are as defined by the USDA classification system.

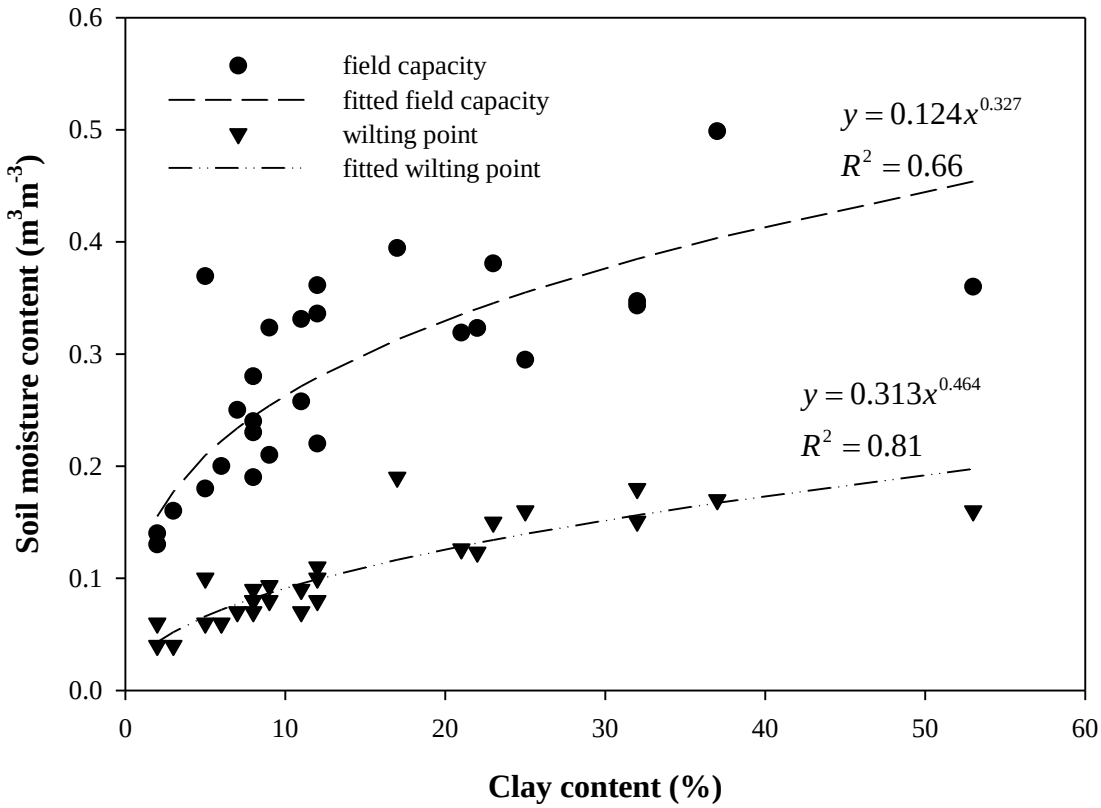


Figure 3. Field Capacity and Wilting Point Relationships to Clay Content. The equations for the fitted lines are given next to the lines.

Correlations and Parameter Reduction for Soil Physical Properties

The soil physical parameters are generally linearly correlated; Table 2 is the correlation matrix, listing the correlation coefficients and significance level. Bulk density is only weakly statistically correlated with most other parameters. The literature on the relationships between BD and other soil physical properties are not very conclusive. For example, Manrique and Jones (1991) noted that the nature of the relationship between bulk density and clay content was different between soil types, while Williams (1970) found that the relationship between bulk density and soil texture was dependant on landuse and management. Considering that ECONet sites are located in the different land parcels with variable soil type and historical land use, these prior observations are compatible with our observation of the weak relation between BD and other soil physical properties.

Table 2. Correlation Matrix (lower triangle) for Measured Soil Physical Parameters.

Parameter	BD	Clay	Sand	AD	P10	P33	P66	P100	P500	P1500
BD	1.00									
Clay	0.047 ns	1.00								
Sand	-0.19 ns	-0.65***	1.00							
AD	0.018 ns	0.48***	-0.35**	1.00						
P10	-0.37**	0.54***	-0.50***	0.17ns	1.00					
P33	0.24ns	0.67***	-0.71***	0.21 ns	0.50***	1.00				
P66	0.22 ns	0.65***	-0.72***	0.18 ns	0.47***	0.96***	1.00			
P100	0.47***	0.68***	-0.68***	0.29 ns	0.25 ns	0.80***	0.78***	1.00		
P500	0.28*	0.72***	-0.70***	0.048 ns	0.35**	0.73***	0.70***	0.82***	1.00	
P1500	0.26*	0.83***	-0.68***	0.223*	0.44**	0.83***	0.81***	0.85***	0.89***	1.00

ns, non-significant; ***,** and *, significant at p = 0.01, 0.05, 0.1, respectively.

Water retention parameters are positively correlated to clay content with the strength of the correlation increasing at the highest pressures (e.g. P1500). This is as expected since the amount of water held at and after 1500 kPa pressure is primarily a function of soil texture, especially clay content (Stewart and Howell, 2003). The correlation for AD and clay content is weaker, but at very dry conditions mineralogy, not just clay content, may also be important. The more narrow range in observed AD also likely weakens the correlation. Individual water retention parameters are highly correlated in most cases, which is not surprising given that all represent a portion of the same pore-size distribution for a given soil. It may be noteworthy that P10 tended to be less strongly correlated with other parameters, or in the case of P100, uncorrelated. AD may also be viewed as another water retention parameter; AD showed no significant correlation to all other water retention parameters besides P1500 (P = 0.1), which is the next driest water retention parameter. As indicated above, AD may be more closely related to mineral type (and possibly specific surface area) than other water retention parameters.

There are two main exceptions to the positive correlation observed for most parameters. One is sand which is negatively correlated with all the other parameters. Strong negative correlation (P = 0.01) between sand and clay content observed in our study is well recognized (Coffin and Lauenroth, 1992; Kaiser et al., 1992; Rostagno, 1989). The negative correlations between sand content and water retention parameters are consistent with the positive correlations between clay content and water retention parameters. Another expection is negative correlation between BD and P10 (P = 0.05), which may be explained by the negative physical relationship between BD and soil porosity (i.e. void space) for retaining water at low pressures.

The dataset yields a Kaiser-Meyer-Olkin index value of 0.778 which indicates that the degree of variance among the tested parameters is greater than the minimally accepted level of 0.7 to conduct a PCA (Pallant, 2001). A significance value of 0.000 for Bartlett's test of sphericity also reinforced that the parameters are suitable for a PCA (Pallant, 2001). In PCA, latent roots and vectors of the correlation matrix were extracted to reaveal a more clear relationship among the parameters. The first three eigenvalues are listed in Table 3. The first principle component (PC)

accounts for more than 59% of the variance, whereas the second and the third PCs account for only an additional 15% and 10%, respectively. This confirms the results of the above correlation analysis that all the variables are generally strongly correlated as the first 3 PCs could explain 85% of the total variance.

Table 3. Eigenvalues of Correlation Matrix for Principal Component Analysis of Soil Physical Properties.

	Initial Eigenvalues		
Component	Parameters	Variance	Cumulative Variance
		%	%
1	6	60	60
2	2	15	75
3	1	10	85

In Table 4, the configuration rotated by varimax of the first three PCs is reported with the correlation coeffiecients between the original variates and the PCs. The parameters clay, sand, P33, P66, P100, P500, and P1500 appear closely related, loading on the first PC. The close correlation suggests that, as described above, soil texture has a strong influence in determination of soil water retention characteristics. Bulk density and P10 are strongly correlated with the second PC, but in opposed positions. Air-dried water content has the strongest association with the third PC.

Table 4. Correlations Between Original Variates and the First Three Principle Components.

	Component		
	1	2	3
Parameter	Weights[1]		
BD	27	87	18
Clay	85	-24	20
Sand	-83	9	-8
AD	33	-26	90
P10	53	-71	-22
P33	92	2	-14
P66	90	2	-16
P100	89	30	7
P500	87	16	-21
P1500	94	7	-8

[1]Values were muliplied by 100 and rounded to the nearest integer.

Loading plots (Fig. 4) project the linear objects onto the new reduced space representing the main part (85.1%) of total data variance, thus it is possible to investigate interelations through the cluster of points. If a variable is close to another, the variables will have influence on each other. Conversely, if a variable is distant from another, the influence will be inverse. The projections onto the axes indicate the relative contributions for the corresponding components (Norušis, 1993). The loading plots delineate separate groups of highly intercorrelated, or similar variables, allowing a visual observations of all the variables and investigation of the physical meaning of components. From Fig.4, it is noted that parameters clay, P10, P33, P66, P100, P500, P1500 are very close to each other. This cluster of points might represent the water retaining function of the soil. Parameter sand was distant form this cluster but negatively correlated ($P < 0.05$) with all the parameters comprising it. The strong negative correlation could be explained as sand is unfavorable for water storage. Bulk density and AD are clearly separated from the cluster of points. They can be considered as the two parameters that account for the last two PCs, since no apparent correlation is found between them. As for physical meanings, BD (via its relationship to TP) and AD may be representative of the maxium and minium limits of water content in the soil, respectively. While a water content substantially below that observed at P1500 (e.g., corresponding to AD) may not be likely in the subsurface soil, the AD parameter may be of greater importance when considering near surface soil moisture content for soil exposed directly to atmospheric drying. When it is not feasible to measure all soil parameters, the analysis of parameters BD and AD along with soil texture (i.e. sand, silt and clay content) could be an option. These parameters could reveal the inherent locational differences in soil physical properties at soil moisture monitoring sites, thus aiding data interpretaion without the added costs of water retention measurements.

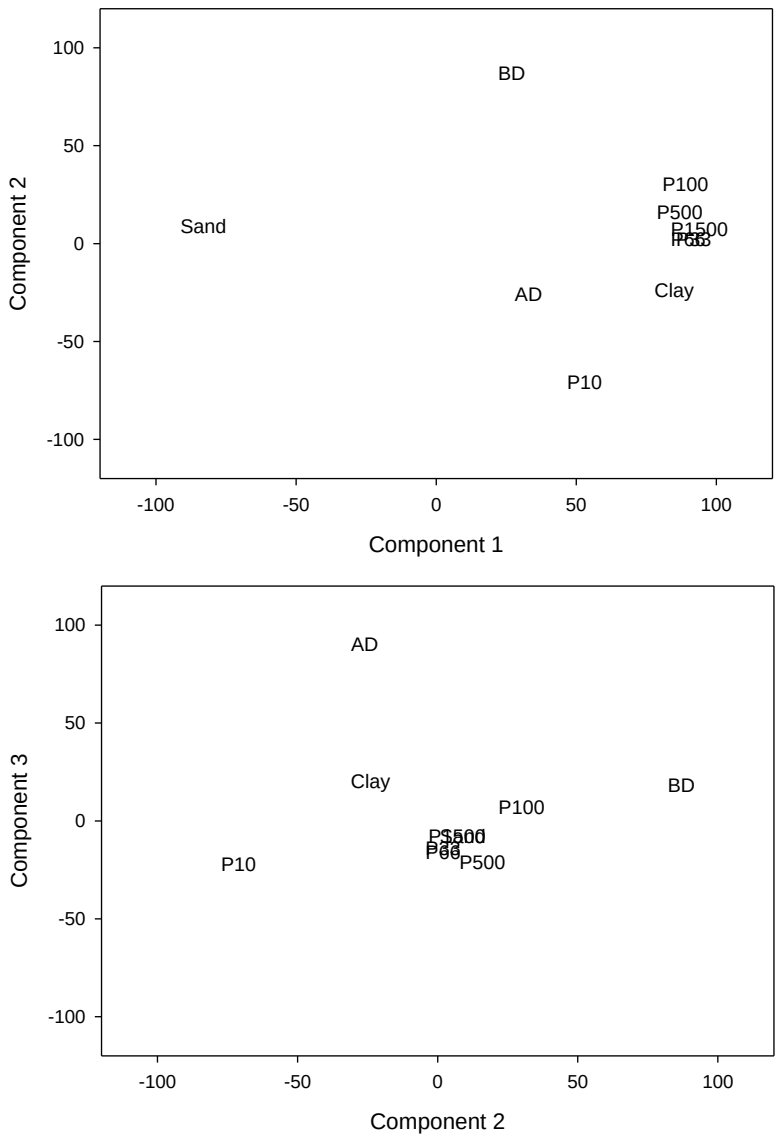


Figure 4. Two-dimensional Loading Plots of the Weights of the First Three Principle Components. Parameters labels indicate coordinates within the plots. Parameters are defined in the text.

Relationships of ECONet Soil Moisture Observations to Soils

Table 5 presents the taxonomic classes and descriptors used for ANOVA tests. Figure 5 and Table 6 present the results of the ANOVA tests. The number of degree of freedom for each ANOVA test can be found from data given in Table 5 (number in parentheses). The height of each bar in Fig. 5 represents the F-ratio derived from the one-way ANOVA test for θ at sites with different descriptors. F is the ratio of the θ variance between groups to the θ variance within groups; a large value of F indicates a significant change in average soil moisture content from one soil classification to another. With the exception of suborder, θ varied (P = 0.05) by single descriptors (wetness class and particle size) for each time interval (Table 6). The finding that

suborder was not a significant soil descriptor for moisture content is not surprising. Although, suborder could reduce the variance of soil properties in the dataset (Heuscher et al., 2005), it is a broader classification than family. It is not specific enough to account for moisture variation among the groups since the property differences existing within a suborder could cause heterogeneous in-group hydraulic behavior.

Generally, the F ratio was higher for the non-growing season than the growing season, which suggests that the soil properties play a more dominant role for θ in non-growing season (Fig. 5). This could be explained by the vegetation at the sampling sites. Soil moisture content is influenced by the actual evapotranspiration related to the vegetation cover (Douville, 2003). The vegetation cover is grasses for most sites, but the species differ (i.e. wild short grass, hay for cattle consumption). In the non-growing season, the vegetation is in the dormant stage with low and similar evapotranspiration rate. However, evapotranspiration increases and differs largely between species, and depending on site maintenance, in the growing season and thereby exerts different levels of control on water in the soil (Zavaleta et al., 2003). As a result, the significance of soil properties for θ is lessened in the growing season.

Table 5. Site Descriptors and Classes for Each Descriptor Extracted from Family-level Soil Classification. Descriptor classes are treated as categories in one-way ANOVA.

Descriptor	Classes[1]
Suborder	Udic (13), Aguic (6), other (2)
Particle size class	fine (8), fine-loamy (7), coarse-loam (4), other (2)
Wetness class	poorly/very poorly drained (3), somewhat poorly drained (3), mod. well drained (4), well drained (2), somewhat excessively drained (2), other (2)
Combined wetness and particle size classes	poorly/ very poorly drained, fine (1); poorly/very poorly drained, loamy (2) somewhat poorly drained, fine (1); somewhat poorly drained, loamy (2); moderately well drained, loamy (4), well drained, fine (6); well drained, loamy(1); somewhat excessively drained, loamy (2); other (2)

[1]Numbers in parentheses are the number of sampling sites in each classification. Two sites designated with Udorthents were treated as "other" in every class.

Table 6. P-values from One-way ANOVA of Soil Moisture and Taxonomic Descriptors.

	P-value			
Period	Sub order	Particle size	Wetness class	Particle size and wetness class
Whole year	0.37	0.01	0.01	0.007
Non-growing season	0.28	0.007	0.005	0.0025
Growing season	0.52	0.04	0.05	0.039

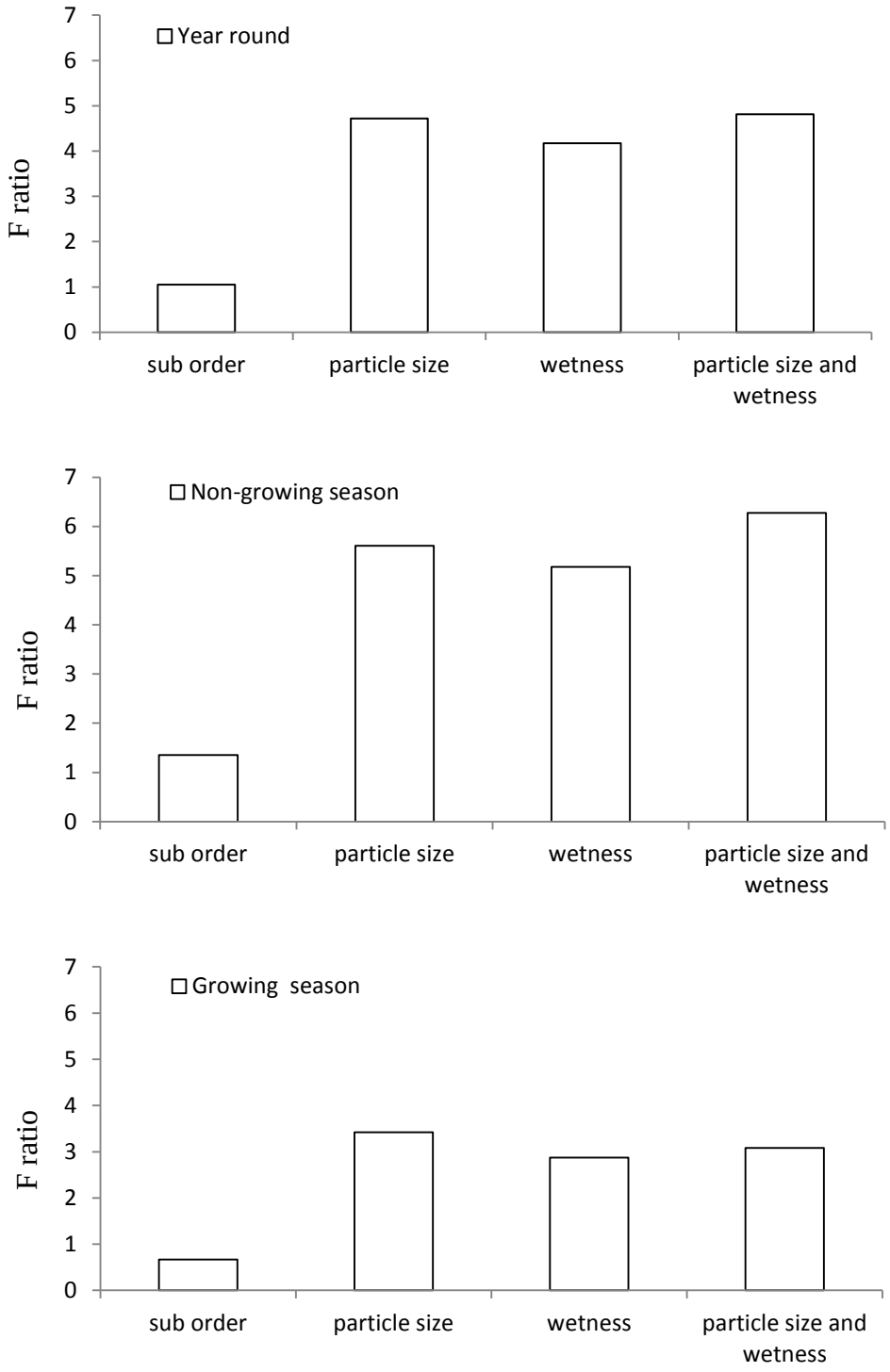


Figure 5. Values of the F ratio from One-way ANOVA with Whole Year (top), Non-Growing season (middle), and Growing-season (bottom) Soil Moisture Data based on Soil Taxonomic Descriptors.

In all cases, the combination of wetness and particle size classes partitioned soil moisture best with a P-value less than 0.01. However, the F ratio only slightly changed by including two significant predictors at the same time (e.g. 4.17 compared to 4.81 in whole-year data). Because

it provided the highest F ratio in all cases, the largest difference in θ between groups due to a single class was from particle size class. But its significance level may not be as much as wetness class groups, suggested by comparing their P-value. In the combination of particle size and wetness class, there was only a small portion of total variance explained by the additional descriptor wetness class when particle size was treated as the first parameter. This implies that the information about θ variability may be described by soil particle size alone. On the other hand, wetness class alone should also suffice to describe θ if we treat it as the first factor. This led us to conclude that there is an overlap in information between wetness class and particle size class.

Our next step was to investigate the dependence of soil properties based on hydraulic data obtained from lab measurements and to explore the relative significance of these parameters. Before proceeding, we should point out that we are interested in an exploratory statistical analysis which can lead us to determine the importance of soil property controls on θ. The choice of MLR model here is intended to compare the importance of soil with other factors known to influence θ. We are concerned with exposing "robust" parameters in the data, but not the precision of the predictive equation.

The prelimary MLR model included 12 parameters: precipitation, PET and 10 parameters representing measured soil physical properties (Table 7). After close examination of the importance for each parameter in the initial MLR, it was reduced to its three most important parameters with significance level at P = 0.10. After dropping the insignificant factors shown in the prelimary MLR model, the reduced MLR used to describe θ was:

$$\theta = 0.079 - (0.0291*PET) + (0.680*P10) + (0.503*P1500)$$

The development of this model was based on 42 seasonal (divided by growing and non-growing season) means in 21 stations which include 7665 daily observations altogether. The model includes both time stable (soil propety parameters) and non-stable (climate observations) influences on θ. The P value for this model is < 0.001 with an r^2 of 0.51. Results show a linear combination of independent parameters PET (P = 0.002), P10 (P = 0.006), P1500 (P = 0.087) predict θ. This suggests that θ varied as a combined function of climate and soil properties. This is consistent with findings of others (e.g., Robock et al. 1995) that soil moisture is controlled by interactions between atmospheric and land surface conditions and soil characteristics.

PET represents the amount of water that could evaporate and transpire from the landscape based on atmospheric demand (Lu et al., 2005). It accounts for part of atmospheric and land surface conditions with temperature and solar radiation as inputs for its calculation (Allen et al., 1998). The slope of -0.029 suggests PET is negatively related to θ which is consistent with water loss from soil by evapotranspiration.

Another dominant part of atmospheric and land surface conditions is precipitation (Koster et al., 2004). The dominant role precipitation plays in controlling soil moisture conditions cannot be overlooked, although the parameter precipitation is not significant as one of the three parameters in the MLR model. In the experimental area, the locational variability is similar for PET and precipitation, with coefficients of variation of 0.34 and 0.31. But the impact of event-driven,

short-term differences in precipitation is not apparent when dealing with seasonal θ data. Soil moisture content could increase greatly after a rainfall event, but the seasonal mean data used in the model smooths the change following individual events.

Table 7. 12-Variable Multiple Linear Regression (MLR) Results of PET, Precipitation and Soil Physical Properties on Soil Moisture Content. Overall MLR model: P value = 0.004, r^2=0.51.

Variable	Coefficient	P-value
Intercept	0.08	0.57
PET	-0.03	0.02
Precipitation	-0.01	0.65
TP	-0.05	0.81
Clay	-0.13	0.59
Sand	-0.02	0.83
AD	-1.60	0.22
P10	0.85	0.01
P33	0.46	0.26
P66	-0.78	0.05
P100	0.24	0.64
P500	-0.79	0.18
P1500	2.19	0.06

P10 and P1500 represent control on θ from soil. The simultaneous appearance of these two variables could be explained by their weak correlation in the first PC which is highly related to the water retaining function of soil (Table 4). However, as indicated by the correlation matrix (Table 2), P10 and P1500 are both highly dependent on clay and sand content (P = 0.01). Thus, the two parameters may essentially represent the same source of influence from soil that could be interpreted as soil texture.

The regression equation accounted for 51% of the variability of the soil moisture content over different soils. The remaining variability might be reduced if the actual evapotranspiration rate were known rather than the approximate values estimated from other climate parameters. There could be alternative explanations. For example, the model tested here may not completely describe all the soil property factors that influence θ since not only the value but also the co-variation of the testing parameters could be affected by soil properties (refer to PCA section).

Besides PET, combined results from MLR and PCA suggest soil texture (via water retention behavior) is the most important factor for describing the observed θ variation between stations, at least on a longer-term basis (i.e. seasonal and whole-year patterns). This result is of high practical value since soil texture information could be easily extracted from soil survey datasets at multiple taxonomic classification levels. Currently, texture information is restricted to qualitative estimates based on the properties of "representative" profiles. Quantitative values for

soil parameters rather than qualitative estimates will be more favorable for increasing the accuracy of soil moisture interpolation. Even with qualitative classification, it may be feasible to develop regional soil moisture maps with the combination of climate influence (monitored on station) and soil property influence (integrated by GIS).

Spatial Variation and Correlation of ECONet Soil Moisture Observations

Basic descriptive statistics for ECONet daily average θ on the dates chosen for spatial analysis are shown in Table 8. Soil moisture on days chosen as wet was generally wetter than for dry days. The variability of θ was similar for wet and dry days. We first conducted semivariography of ECONet θ using these daily averages (Table 9). The active lag distance used was 257,400 m, keeping with a convention to limit consideration to approximately half the maximum lag in the data, which removes noise at greater distances and to keep a minimum of 10 pairs in the first lag class. This resulted in a reasonable number of points with which to assess spatial correlation. On the daily scale, spatial correlation was found to be poor (Table 9). Two of the dry dates (18 Jun 2008; 17 Feb 2009) were found to have no spatial correlation, showing linear models. The latter is plotted in Fig. 6. The GS+ software forced the nugget to zero with a spherical fit. The semivariogram, however, is all nugget effect and would be better modeled as linear. Of the dates examined, 12 Nov 2009, a wet day, exhibited the strongest spatial correlation (Fig. 7) with a nugget:sill of 0.08, or 92% spatial correlation. All other models exhibited spatial correlation < 77%.

Longer time scales (seasons and years) were then examined to see how spatial correlation might change. Spatial correlation for the seasons and year examined (Table 10) had a narrower range of generally lower nugget:sill ratios, indicating stronger correlation than the individual days examined. Among the time periods examined, the yearly data (Fig. 8, 2009) generally had the strongest spatial correlation. Spatial correlation was found, on average, to increase with the time scale: the average daily nugget:sill was 0.313 versus 0.20 for the monthly average, with higher maximum values also occurring at the longer time scales.

Table 8. Summary Statistics for ECONet θ on Select Wet and Dry Days, 2007 through 2009.

Date	N	Mean	SD	Minimum	Maximum	CV
		---------- $cm^3\ cm^{-3}$ ----------				%
Wet						
6/9/2008	29	0.32	0.11	0.11	0.65	0.34
18/05/2009	29	0.30	0.10	0.12	0.49	0.34
19/05/2009	29	0.29	0.09	0.12	0.46	0.32
12/11/2009	28	0.35	0.11	0.17	0.57	0.31
Dry						
14/11/2007	28	0.25	0.08	0.12	0.42	0.33
18/06/2008	29	0.23	0.08	0.09	0.38	0.36
17/02/2009	29	0.28	0.09	0.13	0.45	0.31

Table 9. Semivariogram Parameters for ECONet θ on Select Wet and Dry Days, 2007 through 2009.

Date	Active Lag	Lag Class	Best-Fit Model	r^2	Nugget	Sill	Range	Nugget: Sill
	------ m ------				--- cm^6 cm^{-6}---		--- m ---	
Wet								
6/9/2008	257400	32175	Gaussian	0	0.003	0.013	5,543	0.231
18/05/2009	"	"	Gaussian	0.68	0.005	0.010	144,799	0.510
19/05/2009	"	"	Gaussian	0.65	0.004	0.009	180,999	0.444
12/11/2009	"	"	Spherical	0	0.001	0.012	20,300	0.083
Dry								
14/11/2007	"	"	Exponential	0.67	0.000	0.007	166,800	0.000
18/06/2008	"	"	Linear	0.19	0.006	0.006	239,257	0.925
17/02/2009	"	"	Spherical	0	0.000	0.007	20,300	0.000

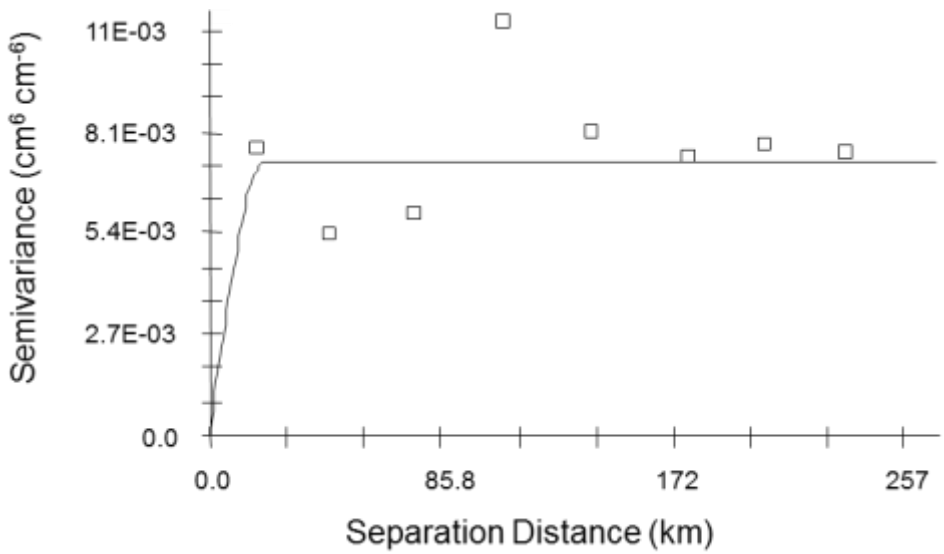


Figure 6. Semivariogram of Statewide ECONet θ for 17 Feb 2009, a Dry Day.

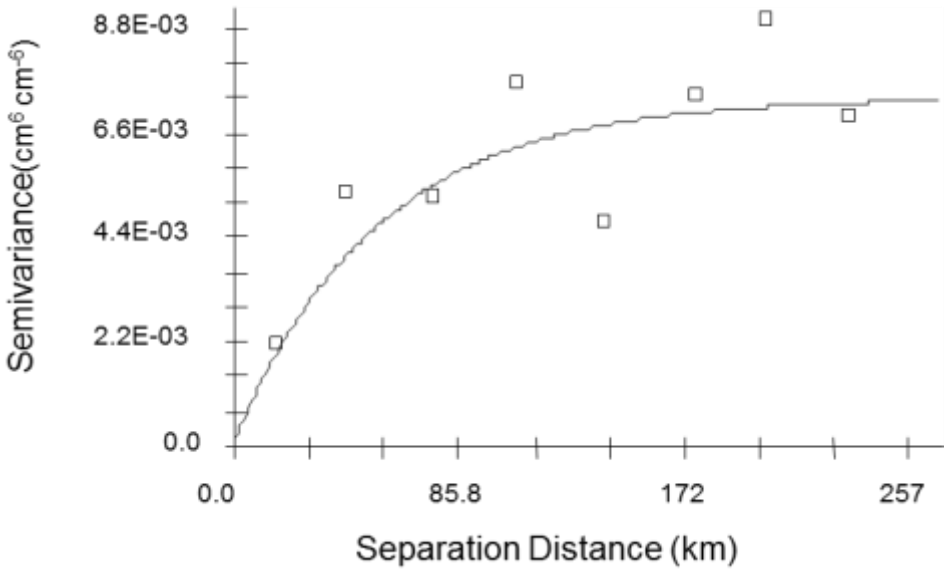


Figure 7. Semivariogram of Statewide ECONet θ for 12 Nov 2009, a Wet Day; Nugget:Sill = 0.08.

Table 10. Semivariogram Parameters for ECONet θ for Months Containing Select Wet and Dry Days, 2007 through 2009.

Date	Active Lag	Lag Class	Best Fit Model	r^2	Nugget	Sill	Range	Nugget: Sill
	------ m ------				--- cm^6 cm^{-6}---		--- m ---	
Wet								
Sep-08	257400	32175	Gaussian	0	0.003	0.010	5,716	0.300
May-9	"	"	Exponential	0.67	0.001	0.009	229,500	0.111
Nov-09	"	"	Exponential	0.50	0.005	0.015	11,820,000	0.333
Dry								
Nov-07	"	"	Exponential	0.7	0.001	0.007	204,000	0.143
Jun-08	"	"	Exponential	0.25	0.001	0.006	63,000	0.167
Feb-09	"	"	Exponential	0	0.001	0.007	17,400	0.143

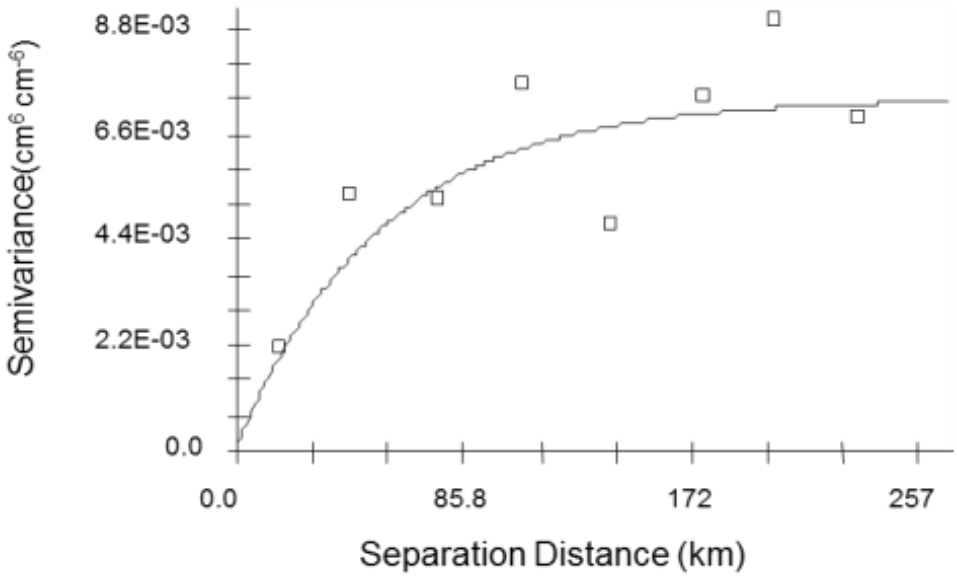


Figure 8. Semivariogram of 2009 Annual Average Statewide ECONet θ.

AMSR-E and ECONet Comparisons

Descriptive statistics for AMSR-E θ for the 209 NC cells on the same wet and dry days used in the ECONet analyses are summarized in Table 11. AMSR-E θ were lower and less variable than ECONet θ. Semivariograms of AMSR-E θ were well modeled (r^2 = 0.89 – 0.99; Table 12) and showed very strong spatial correlation that ranged from 90 to 99% of the total variability (nugget:sill from 0.0004 to 0.02, respectively). Figure 9 shows one semivariogram that demonstrates the strong spatial correlation of AMSR-E θ. The nugget is very low with a well-defined sill. Compared to the ECONet's spatial correlation, AMSR-E had upwards of 183 data points on the study days, leading to the first lag classes having more than 50 pairs. The average range of spatial correlation was greater on dry days than wet days (732 vs. 502 km, respectively). Comparing the ECONet and AMSR-E θ datasets was difficult due to not having AMSR-E data on the majority of the study days, or only partial data over the state. AMSR-E data from the day before and after were compared to the study day. We found no correlation of ECONet θ with AMSR-E in any date pairs. Figure 10 shows the best simple linear regression, which had an r^2 of 0.07. While disappointing relative to the objectives of this research, the lack of correlation is not unexpected considering that the ECONet θ are point observations at ~ 20-cm depth and AMSR-E senses surficial (0 – 1 cm) θ integrated over large-area cells.

Table 11. Summary statistics for AMSR-E θ on Select Wet and Dry Days, 2007 through 2009.

Date	N	Mean	SD	Minimum	Maximum	CV
		----------cm^3 cm^{-3}----------				%
Wet						
5/9/2008	195	0.129	0.021	0.031	0.195	16
7/9/2008	205	0.143	0.018	0.077	0.218	13
17/05/2009	183	0.135	0.026	0.01	0.18	19
19/05/2009	201	0.151	0.019	0.081	0.201	13
11/11/2009	184	0.130	0.026	0.026	0.173	20
13/11/2009	209	0.139	0.018	0.064	0.196	13
Dry						
13/11/2007	206	0.128	0.016	0.053	0.17	13
15/11/2007	208	0.132	0.028	0.009	0.175	21
17/06/2009	206	0.138	0.017	0.074	0.191	12
19/06/2008	207	0.139	0.021	0.074	0.204	15
17/02/2009	186	0.122	0.021	0.082	0.174	17

We examined the temporal correlations of ECONet θ with AMSR-E θ from the individual cells that contained each ECONet station to see if their variability through time was similar. Representative sites were selected using the added criteria of being two AMSRE footprints away from water (Njoku et al., 2003). Among the potential representative sites, WAYN, FLET, ROCK and JACK remained applicable choices. Of these, FLET is near Asheville which has higher potential of radio frequency interference (RFI), so it was eliminated. Then taking into account potential for observation distortion in the mountains, JACK was eliminated. ROCK is mostly viable except that the Tar River Reservoir, not much larger than the river itself, may be in the footprint. Looking outside of the suggested stations, CLIN seemed the best option in the state, being distant from the ocean, mountains, large cities, and reservoirs and having one of the better data histories. Thus, we began the analysis on temporal correlation using CLIN, OXFO, ROCK, and WAYN.

Table 12. Semivariogram Parameters for AMSR-E θ on Select Wet and Dry Days, 2007 through 2009.

Date	Active Lag	Lag Class	Best-Fit Model	r^2	Nugget	Sill	Range	Nugget: Sill
	------- m ------				$cm^3\ cm^{-3}$		m	
Wet								
5/9/2008	405947	27063	Spherical	0.99	21	612	458,900	0.03
7/9/2008	"	"	Spherical	0.89	28	370	232,700	0.08
17/05/2009	"	"	Spherical	0.99	30	1650	908,900	0.02
19/05/2009	"	"	Exponential	0.99	14	435	404,100	0.03
11/11/2009	"	"	Gaussian	0.99	83	1177	522,213	0.07
13/11/2009	"	"	Exponential	0.98	38	391	482,700	0.10
Dry								
13/11/2007	"	"	Exponential	0.98	18	347	674,100	0.05
15/11/2007	"	"	Gaussian	0.99	102	1554	586,299	0.07
17/06/2009	"	"	Spherical	0.98	52	506	782,800	0.10
19/06/2008	"	"	Exponential	0.99	28	650	716,700	0.043
17/02/2009	"	"	Gaussian	0.98	1	2112	902,572	0.005

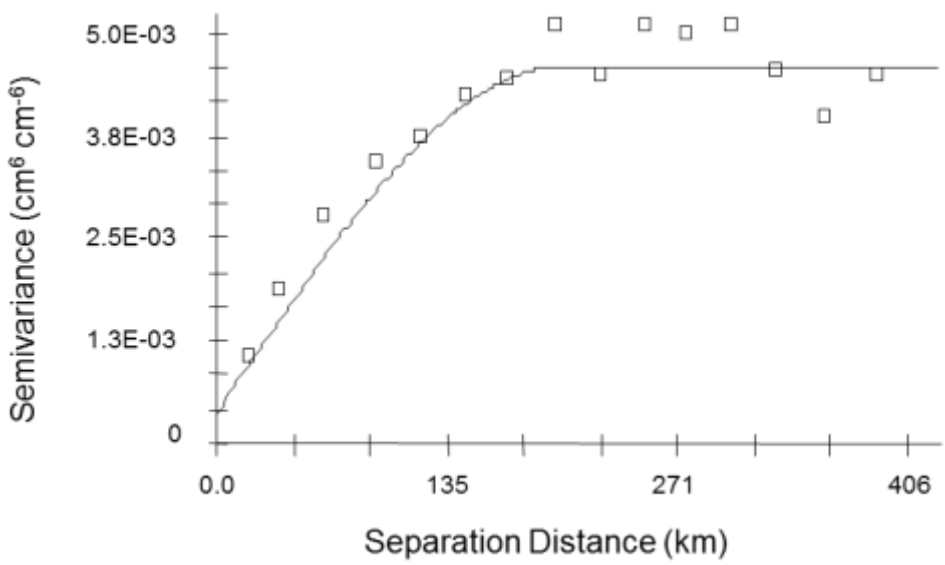


Figure 9. Semivariogram of AMSR-E θ on 5 Sep. 2008, a Wet Day; Nugget:Sill = 0.03.

The closest AMSRE cells to ECONet sites were not always predictable. The lat and long in the L2B datasets are not coincident with the L3 cell's centroid location, but offset by about (-0.04663˚, 0.01534˚). We choose to use L2B data because L3 data does not allow one to access the EASE Grid cell locations through HDFView, nor by subsetting in ArcMap. HDFView does not have a "Find" function, so visual scanning for the points nearest the ECONet sites is

necessary. However, since the AMSRE Lat/Long are not in the center of the cell, the wrong cells may be selected and validation is needed (Figure 11).

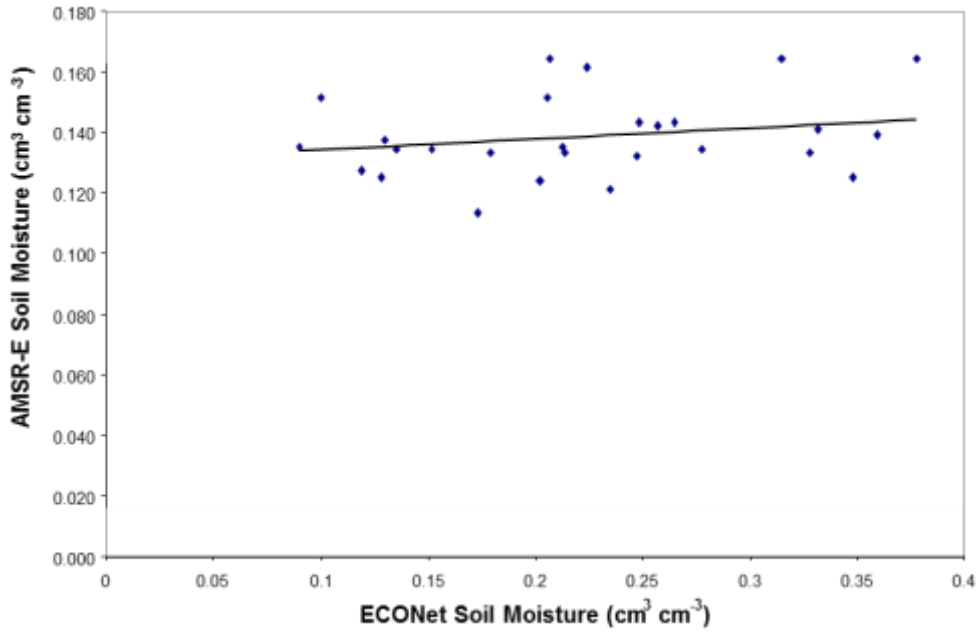


Figure 10. Simple Linear Regression of AMSR-E vs. ECONet θ on 17-18 June 2008, r^2=0.07.

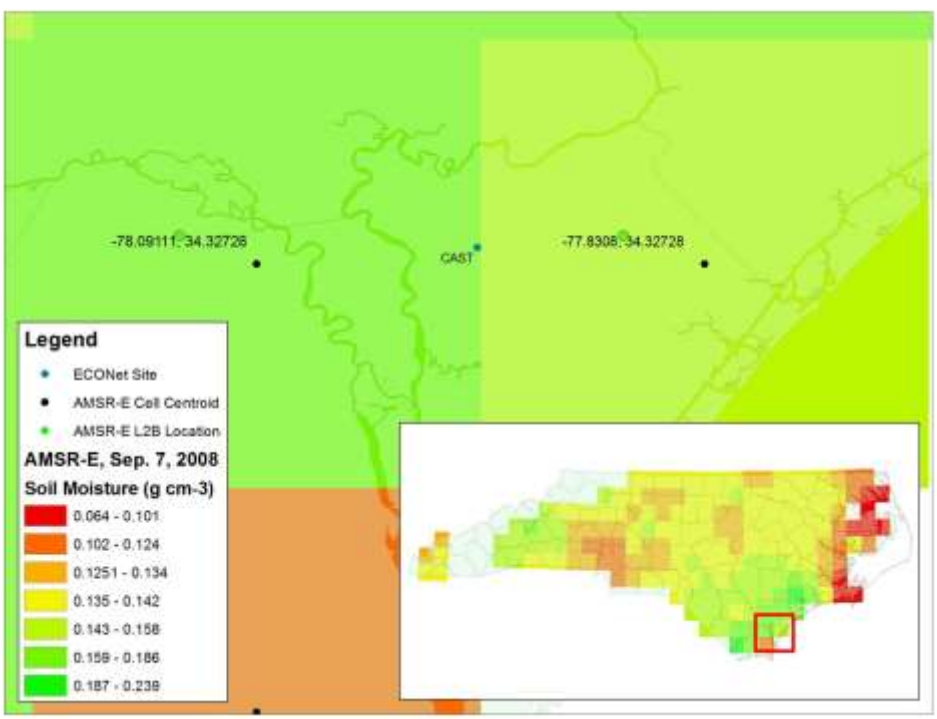


Figure 11. Spatial Offset of AMSR-E L3 Data (cell centroid) and AMSR-E L2B data. Inset Map Shows AMSR-E L3 θ as Interpolated into the Equal-Area Scalable Earth (EASE) grid. Red Bounded Area on Inset Map is Shown Behind at Larger Scale.

Table 13 shows the temporal correlations of AMSR-E and ECONet θ by season in 2008, starting with January to March as winter at select, individual ECONet sites. Correlations ranged from 0.02 to 0.52, a large improvement from statewide SLR. A scatterplot of ECONet and AMSR-E θ for winter, 2008 at Clinton is shown in Fig. 12. Though the regression of Clinton's θ values gave a moderate correlation ($r^2 = 0.44$), the numerical agreement was somewhat poor. A time series comparison is shown in Figure 13. First, ECONet θ shows clearly defined wetting and drying cycles, whereas AMSR-E was much less variable. Secondly, the physical values of AMSR-E were very low compared to ECONet values, and lower than physically expected over many rain events. The regression model did not improve with removal of extreme ECONet values. Similar results were observed at other sites. Figure 14 shows daily θ for spring 2008 for the Oxford ECONet station and the AMSR-E cell containing it. The ECONet data exhibit dynamic moisture release, while the AMSR-E data showed very little variation and very low magnitude relative to ECONet θ.

Table 13. Coefficients of Determination (r^2) of Site-specific ECONet θ versus AMSR-E θ from Grid Cell Containing the ECONet Station Over Seasons and Year, 2008.

Period	Wayne (WAYN)	Oxford (OXFO)	Clinton (CLIN)	Rockingham (ROCK)
Winter	0.02	0.02	0.44	0.04
Spring	0.50	0.13	0.46	0.09
Summer	0.08	0.11	0.52	0.19
Fall	0.04	0.05	0.13	0.01
2008	0.21	0.05	0.25	0.00

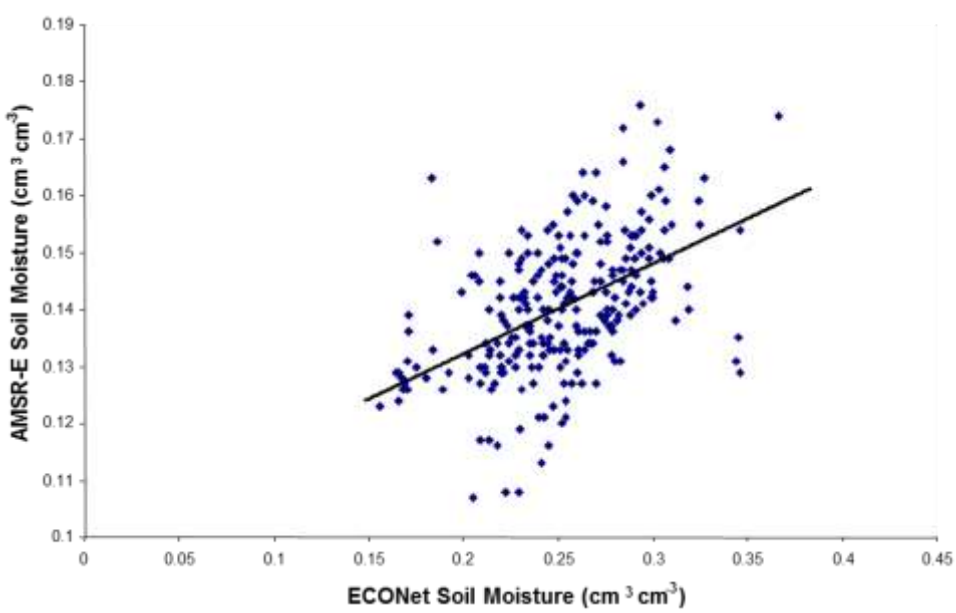


Figure 12. Simple Linear Regression of AMSR-E Soil Moisture from the Grid Cell Containing the Clinton ECONet Station versus Clinton ECONet Soil Moisture, Winter 2008; r^2=0.44.

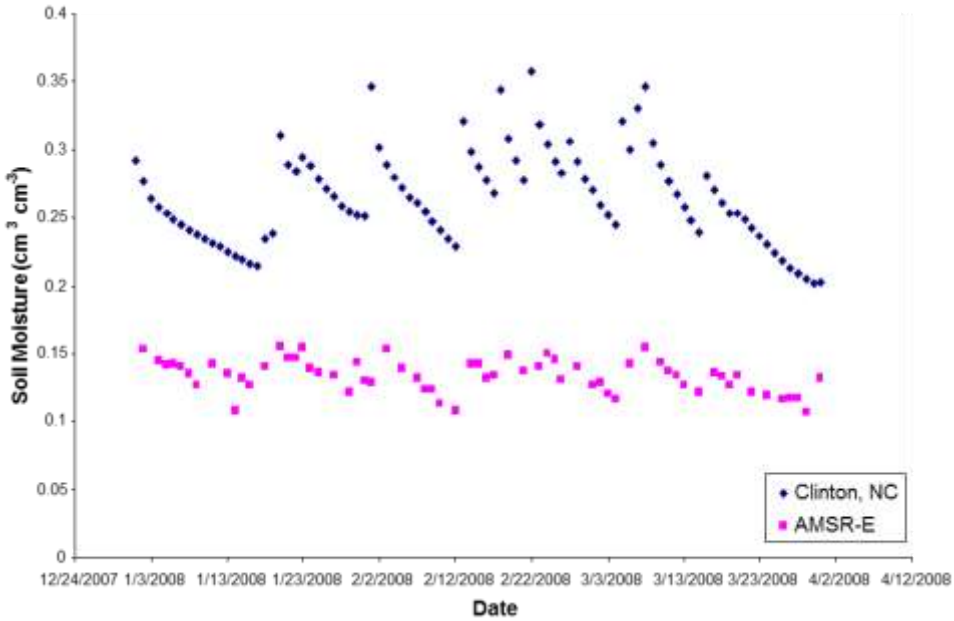


Figure 13. Daily Soil Moisture from ECONet Station at Clinton, NC and from the AMSR-E Grid Cell Containing the Clinton Station, Winter into Spring 2008.

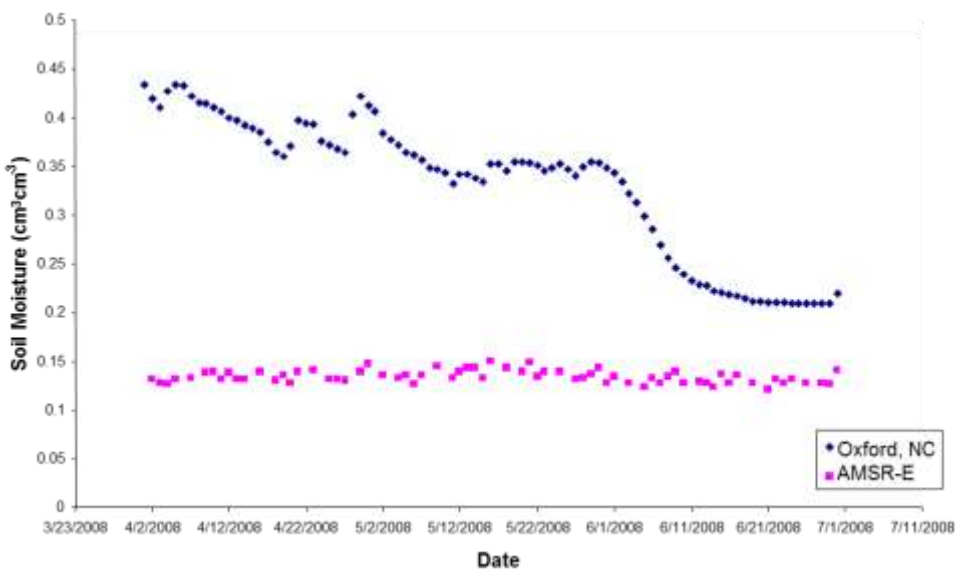


Figure 14. Daily ECONet Soil Moisture at the Oxford, NC Station and for the AMSR-E Cell Containing It for Spring 2008. Linear Regression of the Two had $r^2 = 0.13$.

While the lack of spatial and temporal correlation between ECONet and AMSR-E θ may be due to the grossly different sampling of area (point vs. large cell) and depth (20 vs. 1 cm), the accuracy and precision of the algorithm used to estimate θ is also in question. There has been little actual validation of this AMSR-E algorithm, which estimates θ as a function of AMSR-E Tb and other parameters. According to the National Snow and Ice Data Center (http://nsidc.org/data/docs/daac/ae_land_l2b_soil_moisture.gd.html), which serves the data:

> "The soil moisture algorithm uses Polarization Ratios (PR), which are sometimes called normalized polarization differences of the AMSR-E channel Tbs. PR is the difference between the vertical and horizontal Tbs at a given frequency divided by their sum. This effectively eliminates or reduces surface temperature effects, which is necessary since no dynamic ancillary surface temperature data are input to the algorithm. The algorithm first computes a vegetation/roughness parameter g using PR 10.7 GHz and PR 18.7 GHz, plus three empirical coefficients. Soil moisture is then computed using departures of PR 10.7 GHz from a baseline value, plus four additional coefficients. The baseline values for PR 10.7 GHz are based on monthly minima at each grid cell over an annual cycle. AMSR-E/Aqua L2A Global Swath Spatially-Resampled Tbs (Tb) are used as input to calculating soil moisture variables. Static input databases are used for surface classification and to identify valid grid points for retrieval. Surface topography data are derived from the United States Geological Survey (USGS) GTOPO30 global digital elevation model. Horizontal grid spacing is 30 arc seconds. Preprocessing of these data enables screening out points over ocean, mountains, and areas where the topographic variability within a grid cell is likely to degrade geophysical retrievals. Sand and clay fraction are derived from a 1 degree x 1 degree latitude/longitude global soil type database that estimates soil dielectric properties as a function of soil moisture content. A mask of permanent ice and snow is used to screen out these areas over land. Vegetation type is derived from the USGS 1 km global land cover characteristics database. These data estimate the dependence of vegetation type on the model coefficient that relates vegetation water content to vegetation opacity. Finally, precipitable water and surface air temperature are derived from National Center for Environmental Prediction (NCEP) or European Centre for Medium-Range Weather Forecasts (ECMWF) global reanalysis climatologies, or from real-time forecast model outputs. These data are used for estimating atmospheric contributions in the geophysical retrieval algorithm (Njoku 1999)."

Our understanding of this description is that the algorithm uses temporally and spatially variable AMSR-E Tbs from at least two frequencies, as well as ancillary data that are spatially variable but static. We have sought, but not yet obtained, the actual program code of the AMSR-E soil moisture algorithm.

Given that the accuracy and precision of the AMSR-E soil moisture algorithm is unknown, we decided to examine the relationship between AMSR-E θ and the 10.7 GHz Tb that is the basis of the estimation. This might indicate how well the algorithm estimates soil moisture via model parameters other than Tb, as well as indicate whether and how model fidelity to Tb changes over time and space.

Tables 14 and 15 show summary statistics for both vertical and horizontal Tb on the wet and dry dates studied, as well as their coefficients of determination (r^2) with AMSR-E θ. For both polarizations, the ranges of Tb for wet and dry days were similar except for two dry days (15 November 2007 and 17 February 2009) when the ranges were about one third lower. The r^2 for correlations of Tb with AMSR-E θ ranged from 0.04 to 0.56. The correlations were somewhat stronger on wet versus dry days, with an average r^2 of 0.33 for wet days and 0.24 for dry days.

Table 14. AMSR-E Vertical Brightness Temperature (Tb) Summary Statistics and r^2 for Correlation with AMSR-E θ on Select Wet and Dry Days, 2007 through 2009.

Date	N	Min.	Max.	Range	Mean	SD	CV	r^2
		----------K----------					%	
Wet								
9/5/2008	330	220	291	71	282	10	3.6	0.20
5/17/2009	305	215	285	71	273	9	3.4	0.44
5/19/2009	341	207	285	78	276	12	4.3	0.32
11/13/2009	356	206	280	74	269	12	4.4	0.32
Dry								
11/13/2007	349	209	284	76	275	11	4.1	0.37
11/15/2007	353	231	281	50	267	8	3.2	0.46
6/17/2008	351	215	296	81	287	12	4.1	0.10
6/19/2008	344	212	293	81	284	12	4.1	0.04
2/17/2009	322	221	275	53	268	6	2.1	0.07

Table 15. AMSR-E Horizontal Brightness Temperature (Tb) Summary Statistics and r^2 for Correlation with AMSR-E θ on Select Wet and Dry Days, 2007 through 2009.

Date	N	Min.	Max.	Range	Mean	SD	CV	r^2
		----------K----------					%	
Wet								
9/5/2008	330	167	287	121	275	17	6.1	0.21
5/17/2009	305	159	279	120	264	16	5.9	0.50
5/19/2009	341	148	278	130	266	20	7.7	0.33
11/13/2009	356	149	274	126	258	20	7.7	0.32
Dry								
11/13/2007	349	150	279	129	266	19	7.2	0.45
11/15/2007	353	196	275	79	258	13	5	0.56
6/17/2008	351	153	291	138	277	20	7.3	0.15
6/19/2008	344	151	288	138	275	20	7.4	0.06
2/17/2009	322	176	269	93	260	10	3.7	0.13

On average and across polarization (Tables 16 and 17), the spatial correlation of Tb was somewhat stronger for dry days than wet days with nugget:sill of 0.20 and 0.04 (i.e., proportion of variability that was spatial was 80 and 96%, respectively). This stronger spatial correlation

compared to AMSR-E θ suggests that there may be some promise in using these data for interpolation, but interpretation will be aided when additional information on the AMSR-E algorithm can be obtained.

Table 16. Semivariogram Parameters for AMSR-E Vertical Brightness Temperature (Tb) on Select Wet and Dry Days, 2007 through 2009.

Date	Active Lag	Lag Class	Best Fit Model	r^2	Nugget	Sill	Range	Nugget: Sill
	---degrees---				---- K^2 K^{-2} ----		degrees	
Wet								
9/5/2008	2	0.294	Exponential	0.99	2590	6465	5.571	0.401
5/17/2009	“	“	Spherical	0.99	1950	5669	3.709	0.344
5/19/2009	“	“	Spherical	0.99	10	7385	1.984	0.001
11/13/2009	“	“	Spherical	0.99	10	5850	2.041	0.002
Dry								
11/13/2007	2	0.294	Spherical	0.99	10	7372	1.823	0.001
11/15/2007	“	“	Exponential	0.97	110	4297	2.262	0.026
6/17/2008	“	“	Gaussian	0.99	770	7350	1.306	0.105
6/19/2008	“	“	Gaussian	0.99	740	8013	1.320	0.092
2/17/2009	“	“	Spherical	0.62	1	2267	0.370	0.000

Table 17. Semivariogram Parameters for AMSR-E Horizontal Brightness Temperature (Tb) on Select Wet and Dry Days, 2007 through 2009.

Date	Active Lag	Lag Class	Best Fit Model	r^2	Nugget	Sill	Range	Nugget: Sill
	---degrees---				----- K^2 K^{-2} -----		degrees	
Wet								
9/5/2008	2	0.294	Exponential	0.99	8500	18510	5.316	0.459
5/17/2009	"	"	Exponential	0.97	6280	17750	9.363	0.354
5/19/2009	2.3	"	Spherical	0.99	10	22600	2.275	0.000
11/13/2009	2	"	Spherical	0.99	10	17860	1.946	0.001
Dry								
11/13/2007	2	0.294	Spherical	0.99	10	19070	1.730	0.001
11/15/2007	"	"	Exponential	0.95	10	8803	1.338	0.001
6/17/2008	"	"	Gaussian	0.987	2080	20130	1.297	0.103
6/19/2008	"	"	Gaussian	0.991	2160	22210	1.342	0.097
2/17/2009	"	"	Spherical	0.378	10	6717	0.344	0.001

Summary, Conclusions, and Recommendations

We investigated soil physical properties at 27 NC ECONet soil moisture monitoring stations in the piedmont and coastal plain regions of North Carolina. Prior to this study, and despite collection of soil moisture data for the past twenty years, few soils metadata existed to support NC ECONet. Soils at ECONet sites fall in seven textural classes. Porosities ranged from 0.36 to 0.58 $cm^3\ cm^{-3}$, suggesting a wide range of upper boundaries for soil water content. Diversity was also found for other parameters, such as field capacity and wilting points. As these properties individually and cumulatively influence soil moisture dynamics, it is beneficial to understand soil properties for each monitoring site as well as the potential range of characteristics across monitored sites within the network.

Strong correlations were found between the soil physical parameters tested in the dataset. A PCA reduced 10 soil physical parameters into three principal components (PCs) that explained 85% of the variability within the dataset. We interpret the first PC to represent the soil water retaining function (closely related to soil texture), and the second and third PCs, associated with bulk density (and TP) and air-dried water content, respectively, represent the upper boundary and lower boundaries for soil moisture values under field conditions. The PCA results suggests that soil texture, bulk density and air-dried water content may be three of the most important physical properties to characterize because they accounted for much of the variance for soil physical properties considered here. Thus, it may not be necessary to test a large number of parameters in order to develop understanding of soil physical properties at a given location within the network.

We highly recommend including basic soil physical information in monitoring station metadata in similar regional networks. Based on results obtained here, it may be possible to limit data collection to a subset of relatively easy to obtained soil physical properties. Nonetheless we expect that the data can be very helpful to evaluate soil moisture data quality on a physically realistic basis and/or for extending network products for additional applications. Information obtained in this study is currently being implemented into routine reporting procedures for the NC ECONet (see *Appendix 2*).

Analysis continued with direct examination of soil relationships with ECONet θ observations. Evaluation of the relationship of select, semi-qualitative soil taxonomic classes to seasonal and whole-year ECONet θ (via ANOVA) revealed that the greatest significance was for the taxonomic descriptor particle size class. Additional MLR analysis of ECONet seasonal θ with measured (i.e. quantitative) soil physical properties suggested two water retention parameters, along with potential evapotranspiration, were most significant. The strong correlation of individual parameters revealed through correlation analysis and PCA, as well as the significance of only a few soil parameters in the MLR, again suggests that the influence of soil physical properties on ECONet θ might be explained by measurement of a small subset of soil properties. Coupled with results based on analysis with soil taxonomy, the most appropriate soil property measurement may be particle size distribution (i.e. texture).

Poor spatial correlation of daily, statewide ECONet θ was observed and may indicate that interpolation is not warranted. However, this result may be due to the relatively low number of

ECONet sites available and the distances between these. As the network grows and increases in density, the resulting larger datasets will need to be examined to determine whether stronger spatial correlation is evident, increasing the likelihood that interpolation would yield reasonable θ estimates. Statewide spatial correlation did improve with longer time scales, which is reasonable given that these longer time scales integrate a highly spatially and temporally variable parameter, θ. In continuing research, we will analyze correlation of θ with other parameters like precipitation and evapotranspiration, for which data are available from many more stations (~12,000). If soil moisture is correlated with either or both of these, co-kriging θ with them should improve estimation.

AMSR-E θ cannot presently be used with ECONet θ to interpolate θ since they are not correlated on a statewide scale. At least in part, this was due to AMSR-E's low θ estimates and damped variation with respect to ECONet. The correlation did improve over seasonal and annual time scales. AMSR-E θ displayed strong spatial correlation. This might be due to the "drop-in-the bucket" processing which averages the multiple raw data returns within an EASE grid cell to determine the cell's θ. AMSR-E θ was weakly correlated to its Tb across the state, somewhat more strongly on wet versus dry days. Brightness temperature had longer ranges on dry days, whereas θ showed no trend. Brightness temperature was more spatially correlated on drier than wetter days, and on par with the spatial correlation of its θ.

Continuing research will look at whether Tb is more strongly correlated with ECONet θ than is AMSR-E θ. We will also see if we can improve estimation by incorporating auxiliary parameters like precipitation and evapotranspiration, which are monitored much more intensively ($n \approx 12{,}000$) than are ECONet and AMSR-E θ. Vegetation characteristics such as type and biomass can be estimated from vegetation indices based on data from the Moderate Resolution Imaging Spectroradiometer (MODIS), also aboard AQUA, to improve AMSR-E θ estimation. The accuracy and precision of θ estimation via passive microwave radiometry generally decreases as vegetation biomass increases. The temporal and spatial correlation could be expanded to more sites and years.

References

Allen, R., L. Pereira, D. Raes, and M. Smith. 1998. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome 300.

Arya, L., J. Richter, and J. Paris, 1983. Estimating profile water storage from surface zone soil moisture measurements under bare field conditions. Water Resour. Res.,19:403-412.

Basara, J., and T. Crawford, 2000. Improved installation procedures for deep-layered soil moisture measurements. J. Atmosph. Oceanic Tech., 17:879-884.

Basara, J.B., D.S. Arndt, H.L. Johnson, J.G. Brotzge, and K.C. Crawford. 1998. An analysis of the drought of 1998 using the Oklahoma Mesonet. EOS Trans., Am. Geophys. Union 79: 258.

Brocca, L., F. Melone, and T. Moramarco. 2008. On the estimation of antecedent wetness conditions in rainfall-runoff modeling. Hydr.Processes 22(5): 629-642.

Cassel, D.. 1983. Spatial and temporal variability of soil physical properties following tillage of Norfolk loamy sand. Soil Sci. Soc. Am. J., 47, 196-201.

Coffin, D., and W. Lauenroth. 1992. Spatial variability in seed production of the perennial bunchgrass Bouteloua gracilis (Gramineae). American Journal of Botany 79:347-353.

Cosh, M.H., T.J. Jackson, R. Bindlish, and J.H. Prueger, 2004. 2002 soil moisture experiment (SMEX02): Watershed scale temporal and spatial stability of soil moisture and its role in validating satellite estimates. Remote Sensing Env.,92:427-435.

De Michele, C., and G. Salvadori. 2002. On the derived flood frequency distribution: Analytical formulation and the influence of antecedent soil moisture condition. J. Hydrol. 262:245-258.

Douville, H. 2003. Assessing the influence of soil moisture on seasonal climate variability with AGCMs. Journal of Hydrometeorology 4:1044-1066.

Drusch, M., E. F. Wood, H. Gao, and A. Thiele, 2004. Soil moisture retrieval during the Southern Great Plains Hydrology Experiment 1999. A comparison between experimental remote sensing data and operational products. Water Resour. Res., 40: 2504.

ECONet Management Plan, State Climate Office of NC, NC State University, Raleigh, NC, 2005.

Engman, E.T., and N. Chauhan, 1995. Status of microwave soil moisture measurements with remote sensing. Remote Sensing Enviro. 51:189-198.

Entekhabi, D., G.R. Asrar, A.K. Betts, K.J. Beven, R.L. Bras, C.J. Duffy, T. Dunne, R.D. Koster, D.P. Lettenmaier, D.B. McLaughlin, W.J. Shuttleworth, M.T. van Genuchten, M.Y. Wei, and

E.F. Wood. 1999. An agenda for lands surface hydrology research and a call for the second international hydrological decade. Bull. Am. Meteor. Soc. 80:2043-2058.

Feddes, R.A., P. Kabat, P.J.T. Van Bakel, J.J.B. Browswijk, and J. Halberstma. 1988. Modelling soil water dynamics in the unsaturated zone – State of the art. J. Hydrol. 100:69-111.

Georgakakos, K.P., and O.W. Baumer, 1996. Measurement and utilization of on-site soil moisture data. J. Hydrol 184:131-152.

Ghosh, R. 1980. Estimation of soil-moisture characteristics from mechanical properties of soils. Soil Science 130:60.

Gupta, S., and W. Larson. 1979. Estimating soil water retention characteristics from particle size distribution, organic matter percent, and bulk density. Water Resour. Res. 15:1633-1635.

HDF Group. 2011. HDFView. http://www.hdfgroup.org/hdf-java-html/hdfview/. Champaign, IL.

Heuscher, S., C. Brandt, and P. Jardine. 2005. Using soil physical and chemical properties to estimate bulk density. Soil Science Society of America Journal 69:51.

Hillel, D. 1971. Soil and water; physical principles and processes. Physiologial Ecology:288.

Hollinger, S.E., and S.A. Isard.1994. A soil moisture climatology of Illinois. J. Climate, **7**, 822-833.

Houser, P.R., W.J. Shuttleworth, J.S. Familietti, H.V. Gupta, K.H. Syed, and D.C. Goodrich, 1998. Integration of soil moisture remote sensing and hydrologic modeling using data assimilation. Water Resour. Res. 34:3405-3420.

Illston, B., J. Basara, C. Fiebrich, K. Crawford, E. Hunt, D. Fisher, R. Elliott, and K. Humes, 2008. Mesoscale monitoring of soil moisture across a statewide network. J. Atm. Oceanic Tech. 25:167-182.

Jackson, T., and T. Schmugge, 2002. Passive microwave remote sensing system for soil moisture: Some supporting research. *IEEE Trans.* Geosci. Remote Sensing 27:225-235.

Jackson, T.J., 1993. Measuring surface soil moisture using passive microwave remote sensing. Hydrol. Processes **7**:139-152.

Kaiser, E., T. Mueller, R. Joergensen, H. Insam, and O. Heinemeyer. 1992. Evaluation of methods to estimate the soil microbial biomass and the relationship with soil texture and organic matter. Soil Biology and Biochemistry 24:675-683.

Kaleita, A.L., J.L. Heitman, and S.D. Logsdon, 2005. Field calibration of the theta probe for Des Moines Lobe soils. Appl. Eng. Ag.21:865-870.

Klute, A. 1986. Methods of Soil Analysis, Part 1: Physical and Mineralogical Methods. Am. Soc. Agron., Madison, WI, 1188 pp.

Koster, R., P. Dirmeyer, Z. Guo, G. Bonan, E. Chan, P. Cox, C. Gordon, S. Kanae, E. Kowalczyk, and D. Lawrence. 2004. Regions of strong coupling between soil moisture and precipitation. Science 305:1138.

Legates, D.R., R. Mahmood, D.F. Levia, T.L. DeLiberty, S.M. Quiring, C. Houser, and F.E. Nelson, 2011. Soil moisture: A central and unifying theme in physical geography. Progress in Physical Geography 35:65-86.

Loague, K., 1992. Using soil texture to estimate saturated hydraulic conductivity and the impact on rainfall-runoff simulations. Water Resour. Bull. 28:687-693.

Lu, J., G. Sun, S. McNulty, and D. Amatya. 2005. A comparison of six potential evapotranspiration methods for regional use in the southestern United States JAWRA Journal of the American Water Resources Association 41:621-633.

Manrique, L., and C. Jones. 1991. Bulk density of soils in relation to soil physical and chemical properties. Soil Science Society of America Journal 55:476.

Martínez-Fernández, J., and A. Ceballos, 2005. Mean soil moisture estimation using temporal stability analysis. J. Hydrol. 312:28-38.

Maurer, E.P., D.P. Lettenmaier, and N.J. Mantua. 2004. Variability and potential sources of predictability of North American runoff. Water Resour. Res. 40, WO9306.

Njoku, E.G., T.J. Jackson, V. Lakshmi, T.K. Chan, S.V. Nghiem, 2003. Soil moisture retrieval from AMSR-E. *IEEE* Trans. Geosci. Remote Sensing 41:215-229.

Norušis, M. 1993. SPSS for Windows: base system user's guide, release 6.0 Prentice Hall.

Pallant, J. 2001. SPSS survival manual. A step by step guide to data analysis using SPSS for Windows (Version 10). Buckingham Open University Press. 15 pp.

Pan, Weinan. 2010. Soil Moisture Characterization with North Carolina Environment and Climate Observing Network. M.S. Thesis. North Carolina State University, Raleigh.

Rawls, W., D. Brakensiek, and K. Saxton. 1982. Estimation of soil water properties. Trans. ASAE 25:1316-1320.

Ritsema, C.J., and L.W. Dekker. 1994. Soil moisture and dry bulk density patterns in bare dune sands. J. Hydrol. 154:107-131.

Robinson, D.A., C.S. Campbell, J.W. Hopmans, B.K. Hornbuckle, S.B. Jones, R. Knight, F. Ogden, J. Selker, J., and O. Wendroth, 2008. Soil moisture measurements for ecological and hydrological watershed scale observatories: A review. Vadose Zone J.**7:**358–389

Robock, A., K. Vinnikov, C. Schlosser, N. Speranskaya, and Y. Xue. 1995. Use of midlatitude soil moisture and meteorological observations to validate soil moisture simulations with biosphere and bucket models. Journal of Climate 8:15-35.

Robock, A., K.Y. Vinnikov, G. Srinivasan, J.K. Entin, S.E. Hollinger, N.A. Speranskaya, S. Liu, and A. Namkhai. 2000. The Global Soil Moisture Data Bank. Bull. Am. Meteor. Soc. 81:1281-1299.

Rodriguez-Iturbe, I., G.K. Voge, R. Rigon, D. Entekhabi, F. Castelli, and A. Rinaldo. 1995. On the spatial organization of soil moisture fields. Geophys. Res. Letters 22:2757-2760.

Rostagno, C. 1989. Infiltration and sediment production as affected by soil surface conditions in a shrubland of Patagonia, Argentina. Journal of Range Management 42:382-385.

Saxton, K., W. Rawls, J. Romberger, and R. Papendick, 1986. Estimating Generalized Soil-water Characteristics from Texture. Soil Sci. Soc. Am. J. 50:10-31.

Schaefer, G. L., M.H. Cosh, and T.J. Jackson, 2007. The USDA Natural Resources Conservation Service Soil Climate Analysis Network (SCAN). J. Atmos. Oceanic Technol. 24:2073–2077.

Scott, R.W., E.C. Krug, S.L. Burch, 2010. Illinois doil moisture under sod experiment. J. Hydrometeor 11:683–704.

Seneviratne, S.I., T. Corti, E.L. Davin, M. Hirschi, E.B. Jaeger, I. Lehner, B. Orlowsky, A.J. Teuling, 2010. Investigating soil moisture–climate interactions in a changing climate: A review. Earth-Science Reviews 99:125–161.

SPSS, Inc. 2000. SigmaPlot 2000 User's Guide.

Stewart, B.A., and T.A. Howell. 2003. Encyclopedia of water science Marcel Dekker, New York.

Sumner, M.E., and E.J. Kamprath. 2000. Handbook of soil science CRC Press, Boca Raton.

Tabachnick, B.G., and L.S. Fidell, 1996.Using multivariate statistics.Language 519:535.

Vachaud, G., A. Passerat De Silans, P. Balabanis, and M. Vauclin. 1985. Temporal stability of spatially measured soil water probability density function. Soil Sci. Soc. Am. J. 49:822-828.

Vereecken, H., J.A. Huisman, H. Bogena, J. Vanderborght, J.A. Vrugt, J.W. Hopmans, 2008. On the value of soil moisture measurements in vadose zone hydrology: A review. Water Resour. Res. 44:W00D06.

Wagner, W., G. Lemoine, and H. Rott. 1999. A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sensing Env.70:191-207.

Western, A.W., and R.B. Grayson, 1998. The Tarrawarra data set: Soil moisture patterns, soil characteristics, and hydrological flux measurements. Water Resour. Res. 34:2765-2768.

Western, A.W., R.B. Grayson, and G. Bloschl, 2002. Scaling of soil moisture: A hydrologic perspective. Annu. Rev. Earth Planet. Sci. 30:149-180.

Western, A.W., R.B. Grayson, G. Bloschl, G.R. Willgoose, and T.A. McMahon, 1999. Observed spatial organization of soil moisture and its relation to terrain indices. Water Resour. Res. 35:797-810.

Williams, R. 1970. Relationships between the composition of soils and physical measurements made on them. Rep. Rothamsted Exp. Stn. for 1970 2:5-35.

Wosten, J., J. Bouma, and G. Stoffelsen. 1985. Use of soil survey data for regional soil water simulation models. Soil Science Society of America Journal 49:1238.

Zavaleta, E., B. Thomas, N. Chiariello, G. Asner, M. Shaw, and C. Field. 2003. Plants reverse warming effect on ecosystem water balance. Proc. Nat'l Acad. of Sci. 100:9892.

Zhang, Y.K., and K.D. Schilling. 2006. Effects of land cover on water table, soil moisture, evapotranspiration, and groundwater recharge: A field observation and analysis. J. Hydrol. 319:328-338.

Appendix 1

AD: Air-dried water content

AMSR-E: Advanced Microwave Scanning Radiometer

ANOVA: Analysis of variance

AURO: Aurora ECONet Station

BD: Bulk density

CAST: Castle Hayne ECONet Station

CLIN: Clinton ECONet Station

CV: Coefficient of variation

DURH: Durham ECONet Station

ECONet: Environment and Climate Observing Network

FLET: Fletcher ECONet Station

EASE-Grid: Equal-Area Scalable Earth Grid

HIGH: High Point ECONet Station

JACK: Jackson Springs ECONet Station

Ks: Saturated hydraulic conductivity

MLR: Multiple linear regression

MODIS: Moderate Resolution Imaging Spectroradiometer

NC: North Carolina

NSIDC: National Snow and Ice Data Center

OXFO: Oxford ECONet Station

PLYM: Plymouth ECONet Station

P10: Water retained at 10 kPa

P33: Water retained at 33 kPa

P66: Water retained at 66 kPa

P100: Water retained at 100 kPa

P500: Water retained at 500 kPa

P1500: Water retained at 1500 kPa

PC: Principal component

PCA: Principal component analysis

PET: Potential evaportranspiration

ROCK: Rockingham ECONet Station

SCO: North Carolina's State Climate Office

SILR: Siler City ECONet Station

SD: Standard deviation

Tb: Brightness Temperature

WAYN: Waynesville ECONet Station

θ: Soil moisture content

Appendix 2

Publications

Theses

Pan, W. 2010. Soil Moisture Characterization with North Carolina Environment and Climate Observing Network. M.S. Thesis, NCSU.

Presentations (listed chronologically)

Pan, W., J.L. Heitman, R.P. Boyles, and J.G. White. Soil Moisture Characterization with the North Carolina Environmental and Climate Observing Network. Soil Sci. Soc. Am. Meeting. Pittsburgh, PA. Nov. 5-9, 2009.

Pan, W., J.L. Heitman, R.P. Boyles, and J.G. White. Soil Moisture Characterization with the North Carolina Environmental and Climate Observing Network. Soil Sci. Soc. of NC Annual Meeting. Raleigh, NC. Jan. 19-20, 2010.

Pan, W. Soil Moisture Characterization with NC Environment and Climate Observing Network. NCSU Graduate Student Research Symposium, Raleigh, NC. March 10, 2010.

Pan, W., J.L. Heitman, R.P. Boyles, and J.G. White. A Study to Improve Soil Moisture Observations with the NC ECONet. NC WRRI Annual Conference, Raleigh, NC. March 30-31, 2010.

Heitman, J.L. Soil Physics Research at NCSU: Evapotranspiration, Heat Flux, Temperature, and Water. Southern Region Environmental Soil Physics (SDC333) Annual Meeting, Nashville, TN. May 20, 2010.

Heitman, J.L., C. D'Aiuto, W. Pan, J.G. White, and R. Boyles. Soil Moisture Maps for Agricultural Management Decision Support. Southeast Climate Consortium (SECC) Annual Program Review, Raleigh, NC. May 24-25, 2010.

D'Aiuto, C. 2010. Passive Microwave Remote Sensing of North Carolina Soil Moisture for Hydrologic Assessment and Forecasting. NCSU Soil Science Department Seminar. Raleigh, Sep. 29, 2010.

D'Aiuto, C., J. White, J.L. Heitman and R.P. Boyles. Passive Microwave Remote Sensing of NC Soil Moisture for Hydrologic Assessment and Forecasting. ASA-CSSA-SSSA Int'l Annual Meetings. Long Beach, CA. Nov. 2, 2010.

Pan, W., J.L. Heitman, J. White, R. Boyles and R. Austin. Improved Soil Moisture Products From the North Carolina Environment and Climate Observing Network. ASA-CSSA-SSSA Int'l Annual Meetings. Long Beach, CA. Nov. 3, 2010.

Pan, W., J.L. Heitman, J. White, R. Boyles and R. Austin. Improved Soil Moisture Products From the North Carolina Environment and Climate Observing Network. Soil Sci. Soc. of NC Annual Meeting. Raleigh, NC. Jan. 18-19, 2011.

D'Aiuto, C., J. White, J.L. Heitman, and R.P. Boyles. Passive Microwave Remote Sensing of NC Soil Moisture for Hydrologic Assessment and Forecasting. NC WRRI Annual Conference, Raleigh, NC. Mar. 22-23, 2011.

Technology Transfer

Soil moisture indices based on ECONet data and data reported herein are now publically available online through the State Climate Office's data retrieval interface known as CRONOS < http://www.nc-climate.ncsu.edu/cronos>. These include a saturation index (SI), defined as the ratio between observed soil moisture content and measured porosity, and plant available water (PAW), defined as the observed water content minus the measured water retention at 1500 kPa (set with max at water retention at 33 kPa minus water retention at 1500 kPa, min at zero). Both PAW and SI can be retrieved on an hourly, daily, and monthly basis for 27 ECONet stations for which soil properties have been established. As additional stations are sampled and analyzed, PAW and SI will become available for those locations as well.

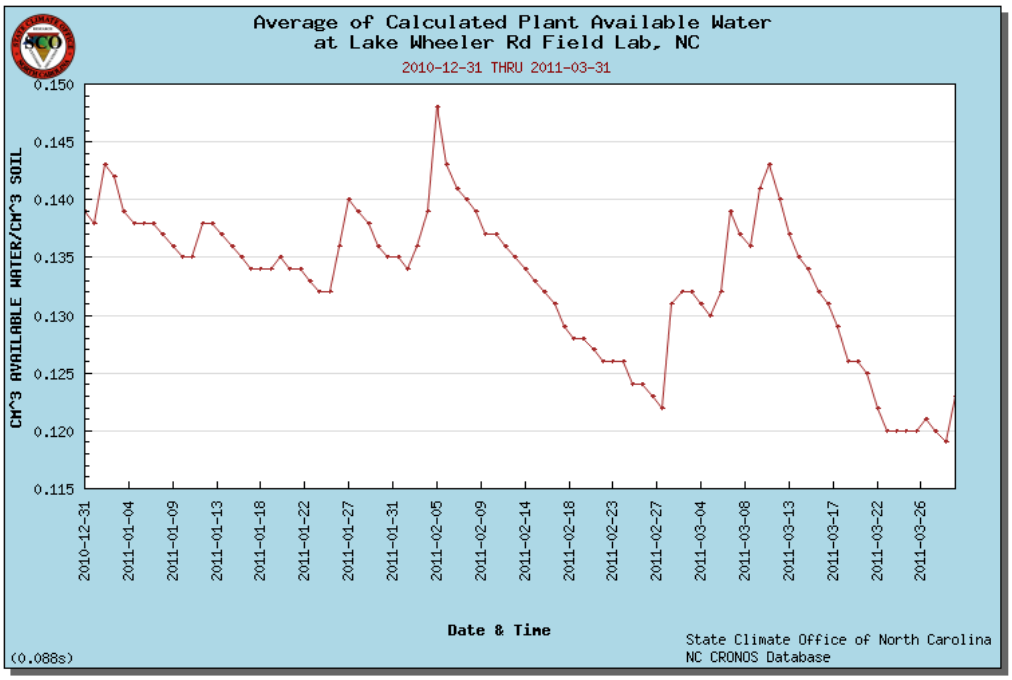
Calculations of PAW and SI were encoded into on-demand functions using PHP scripting, which allows for easy interaction between the front end web pages and the backend climate databases. Upon visiting a data retrieval page for ECONet stations such a Lake Wheeler Road Field Lab, users will see both PAW and SI available in the "Soil Parameters" section of the page:

Soil Parameters	Unit	Depth
Soil temperature hour average	Fahrenheit	0.1m
Soil moisture hour average	m^3 water / m^3 soil	0.2m
Soil temperature	Fahrenheit	0.1m
Soil moisture	m^3 water / m^3 soil	0.2m
Calculated Plant Available Water	cm^3 available water / cm^3 soil	0.2m
Calculated Saturation Index	cm^3 water / cm^3 pore space	0.2m

Once either parameter is selected and a date range for data retrieval has been chosen, users can retrieve the observations in an Excel spreadsheet, web page, or delimited format (tab, comma):

```
Date/Time (EST), Average of Calculated Saturation Index (cm^3 water/cm^3 pore space)
03/15/2011,0.443
03/16/2011,0.439
03/17/2011,0.437
03/18/2011,0.433
03/19/2011,0.426
03/20/2011,0.426
03/21/2011,0.424
03/22/2011,0.417
03/23/2011,0.413
03/24/2011,0.413
03/25/2011,0.413
03/26/2011,0.413
03/27/2011,0.415
03/28/2011,0.413
03/29/2011,0.411
03/30/2011,0.42
```

Upon selecting to retrieve data in a web page format, users will also be able to graph each parameter:



Metadata for soil observations will also be made available through the SCO to aid in data interpretation. Development of additional products based on incorporation of AMSR-E data may be pursued pending outcomes of ongoing analyses.