ABSTRACT

PAN, WEINAN. Soil Moisture Characterization with North Carolina Environment and Climate Observing Network. (Under the direction of Dr. Joshua Heitman).

Soil moisture content has important implications for agriculture, hydrology, weather prediction and climatology. In North Carolina, soil moisture content is monitored as a routine parameter in a statewide surface network, North Carolina Environment and Climate Observing Network (NC ECONet). Networks of this extent and potential value are found in few other U.S. states. A series of investigations were conducted in order to provide a foundation for efforts to use soils information and ECONet observations to provide spatially continuous soil moisture maps for NC. Soil samples were collected from 27 ECONet stations in the Piedmont and Coastal Plain regions. A soil physical property dataset was generated from lab analysis with 11 soil physical parameters collected for each sampling site. The dataset reveals that the soil properties are highly diverse among individual ECONet stations, e.g. porosity ranging from 0.38 to 0.59 cm^3 cm^{-3} and textures representing seven USDA texture classifications. As an enhancement for metadata and network applications, the dataset will be added to the online ECONet system. Seven million soil moisture data documented at the 27 stations within the past 11 years were further involved in quality assurance (QA) of ECONet using the soil physical property data to provide a basis for data tests. The main problems concerning QA are missing data and failure of data to fall within a physically-realistic range. For each individual station, the QA passing rate ranges from 67 to 100%. Individual site-year QA reports were also developed to serve as a reference for deriving research quality data from sites considered unacceptable in terms of having

complete records. Overall, the estimated standard error between currently-used sensor (Theta probe) readings from ECONet and independent gravimetric samples is 0.06 cm^3 cm^{-3}. Additional analyses were conducted to determine which, if any, soil characteristics were most closely related to observed soil moisture patterns. ANOVA tests were used to test if the mean soil moisture content differed among groups of ECONet sites which share similar soil properties according to the family-level descriptors extracted from the Soil Survey database. Using seasonal soil moisture averages, results suggest soil moisture is likely to be influenced by two taxonomic descriptors: wetness class and particle size class. Principle component analysis was used to assess the overlap between measured soil physical properties in terms of site characteristics. A multiple linear model including both climate influence (potential evapotranspiration, precipitation) and soil property parameters indicated significant control of soil properties on soil moisture variation. Result suggests that existing soil mapping delineations may provide information for soil moisture interpolation.

Soil Moisture Characterization with North Carolina Environment and Climate Observing Network

by
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DEDICATION

This work is dedicated to my parents, Qingping Fang and Genxing Pan, without whose love and caring supports I would not be the person I am today.

And to the memory of my beloved grandfather Wenzhe Fang (1925 to 2008). I will miss him greatly and hope I have made him proud.

BIOGRAPHY

Weinan Pan was born in Nanjing, a beautiful city in southeast China, on November 22, 1985. As the only child in the family, Weinan grew up with endless love and support from her parents and grandparents. Influenced by her father, a soil scientist, she developed a love for environmental science since childhood. Weinan graduated from Jinlin High School in 2004 and received her bachelor degree from Nanjing Agricultural University in Agricultural Resources and Environments. She came to North Carolina State University in fall of 2008 to pursue her M.S. in soil science. She has since worked under the guidance of Dr. Joshua Heitman.

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This thesis arose from the two years of work I have done since I came to Dr. Heitman's group. During that time, I have worked with a number of great people whose help enabled me to complete this research.

In the first place, I am heartily thankful to my supervisor, Joshua Heitman, who has supported me throughout my master study with his patience and knowledge. At the time I started, I was a fresh college graduate knowing little about research and science. He encourages me to think and work in my own way, but whenever I met difficulties he is always there providing guidance for me. It is the continuous encouragement and inspiration from Dr. Heitman that helped me keep improving myself and enriching my growth as a researcher and a scientist that I want to be in the future. I am indebted to him more than he knows.

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Chapter 1 Literature Review

1.1 Introduction

Soil water performs a number of important functions in soils. It is essential for mineral weathering and organic matter decay, chemical reactions that provide soluble nutrients in the plant-soil system. Water also serves as the medium in which nutrients move to plant roots. The retention of rain or irrigation water for direct plant use is another primary function of soil. An ample supply of water is necessary for the maintenance of turgidity in plant cells, especially for newly formed cells (Hausenbuiller, 1978). It is also utilized by plants in structural and protoplasmic tissue, although this only accounts for a small part of the total water taken by plants. About 99% percent of plant-absorbed water is lost to the atmosphere through transpiration.

Soil water is also crucial to the physical behavior of soils. Soil water content has a marked effect on consistence properties and on the suitability of soil for cultivation. Similarly, variation in the water content can affect the compressibility of the soil, its load-bearing capacity, and its stability on sloping surfaces. These latter properties are often of great significance to the use of soils for engineering purposes (Schofield and Wroth, 1968).

Furthermore, soil water plays an important role in determining regional climate and hydrology. Research indicates that soil moisture conditions on a large scale can lead to droughts or floods (Delworth and Manabe, 1989). Fluctuation in soil moisture at the large scale affects the distribution of evaporation and precipitation (Yeh *et al.*, 1984) and the relative partitioning between latent and sensible heat fluxes, both spatially and temporally

(Illston et al., 2008). Thus, knowledge of soil moisture at the mesoscale provides an opportunity to investigate the influence that land surface processes have on climate. As indicated by Namias (1989), changes in the soil moisture regime at the end of spring/beginning of summer can significantly impact summer precipitation in North America. During North American drought, soil moisture information also fosters a potential for drought prediction (Oglesby and Erickson III, 1989).

Knowledge of soil moisture storage, and temporal and locational variations in this storage, is valuable for a variety of purposes. However, obtaining this knowledge is challenging, because soil moisture is directly and indirectly affected by a large number of factors, and relationships to these factors vary widely from location to location.

1.2 Factors influencing soil moisture

1.2.1 Precipitation

Soil moisture status reflects past occurrences of precipitation (i.e., rainfall). The state of soil moisture is regulated by inputs of water from precipitation and losses from evapotranspiration and drainage. On the other hand, the soil moisture status and soil characteristics determine the hydraulic properties of the soil, and for this reason, soil moisture exerts significant control on the rates of infiltration (i.e., regulates the input of precipitation) and subsequent evaporation and drainage (i.e., regulates the retention of precipitation) (Eltahir, 1998). Soil moisture may also influence rainfall through regulating atmospheric variables. Soil–precipitation correlations have been widely studied. As early as 1937, Holzman (1937) described this correlation as “year by year as cultivation of the soil is extended, more of the rain that falls is absorbed and retained to be given off by evaporation

or to produce springs. This of course must give increasing moisture and rainfall." Similar statements were offered by Horton (1944), McDonald (1962), and Hillel (1998). They reinforce the general idea that precipitation enhances regional soil moisture content, but that this is not a one-way relationship.

In recent years, studies on the inter-annual variability of soil wetness and precipitation show the significance of studying soil moisture for wet and dry seasons. For instance, in a recent observational study of Findell and Eltahir (1997) it was demonstrated that during summer there are lag correlations between soil moisture anomalies and subsequent rainfall anomalies over Illinois. Lagged-correlation effects in the wet season can also been seen in precipitation-soil moisture model in summertime in Australia (Simmonds and Hope, 1997) and could give rise to a bimodal distribution of wet and dry seasons under some climatic regimes (Entekhabi *et al.*, 1992). Soil-precipitation relations have been further related to the feedback mechanism between soil moisture and rainfall using General Circulation Models (GCMs) for performing numerical experiments (Findell and Eltahir, 1997; Oglesby and Erickson III, 1989; Rind, 1982; Shukla and Mintz, 1982; Walker and Rowntree, 2006). Findings in general are that that change in soil moisture conditions at the late spring/early summer may significantly impact the simulated summer rainfall over continental land regions. A relatively wet initial soil moisture condition results in relatively more rainfall, which supports the existence of a positive soil moisture–rainfall feedback. However, most of these modeling experiments involving extreme anomalies (extreme changes of soil moisture conditions) which are not likely to be observed frequently.

1.2.2 Evapotranspiration

Evapotranspiration (ET) is a term used to describe the sum of evaporation and plant transpiration from the Earth's land surface to atmosphere. ET is a major pathway for water loss from soil. The processes of evapotranspiration are closely linked to the quantity of water found in soil (Korzun et al., 1974). In addition to ET, potential evapotranspiration (PET) is also used as a non-plant-community-specific gauge of ET. Thornthwaite (1948) was the first to introduce the concept of PET. He defined PET as the maximal water quantity transferred to the atmosphere, from a vegetation cover in a state of full physiological activity and unlimited water and nutrient availability. In a grass lawn-covered experiment plot, Choisnel, (1997) showed PET corresponds with soil moisture content during the grass active phase and without restriction of water and nutrient uptake. Incorporating soil-plant-water relations, studies for evapotranspiration influences on soil moisture have been performed using various approaches including remote sensing (Soer, 1980) and model simulation based on plot-scale hydrometeorological variables (Zappa and Gurtz, 2003).

1.2.3 Soil properties

Besides external inputs (i.e. precipitation and irrigation) and outputs (ET), soil properties greatly influence the amount of water held in soil. Soil-water characteristics refer to the properties determining how water is held in soil due to capillarity and adsorption on surfaces. Soil hydraulic conductivity refers to the property describing how water flows through soil in, for example, drainage. Soil-water characteristics and hydraulic conductivity vary widely and nonlinearly with water content for different soils (Arya et al., 1999), thus determining these properties for a given soil is challenging. Arya et al. (1982) presented a

model for estimating the soil-water retention curve (i.e. soil-water characteristics) from particle size distribution and bulk density data. Their model calculates a pore size distribution from particle size distribution, bulk density, and particle density. Then the pore radii are converted to equivalent soil-water tensions using the equation of capillarity at the corresponding volumetric water content. These types of relationships have also been extended to describe soil hydraulic conductivity (Arya and Heitman, 2010).

Statistically-based approaches have also been employed. Soil texture is generally considered a dominate determinate for the water-holding characteristics of most agricultural soils (Loague, 1992). Textural information can be estimated by simple methods and could readily serve as reference for estimating soil-water relationships in soil. As reviewed by Saxton et al. (1986), correlations have been developed between soil texture and hydraulic properties. Quantitative representations of these correlations are found in many studies. For example, Gupta and Larson (1979) and Rawls et al. (1982) used multiple linear regression equations for prediction of soil moisture storage characteristics, based on sand, silt, clay, and organic matter contents and bulk density.

Numerous investigations indicate that soil moisture is influenced by many complex factors including organic matter content (Hudson, 1994), topography (Burt and Butcher, 2006; Qiu et al., 2001; Tromp-van Meerveld and McDonnell, 2006), depth of the water table (Price, 1997), vegetation (Eagleson, 1978), etc. Soil properties are highly variable in space, and thus. within a few meters soil moisture can vary as much as within a distance of kilometers (Quattrochi and Goodchild, 1997). This makes physically-based prediction of soil moisture storage challenging, even using known relationships.

Vachaud et al. (1985) introduced the concept of temporal stability to describe the observation that spatial soil moisture patterns tend to persist in time. Using this concept they demonstrated that soil moisture measured at single points is often highly correlated with the mean soil moisture content over an area. This suggests that temporal stability of spatial soil moisture patterns should allow one to estimate the areal mean soil moisture from point measurements. And it has been hypothesized that soil/landscape/vegetation properties can be used to explain this pattern, but the pattern tends to vary widely from study to study (Grayson et al., 1997). However, based on this concept, it should be noted, a point-based observation not chosen to maximize spatial coverage of major land surface properties may risk ignoring moisture patterns for major land-surface areas in the intended covered area. Because of all the factors influencing soil moisture, direct observations of soil moisture on the large scale are critical for understanding temporal and spatial patterns, and also because of immense complexity, we can expect to face serious challenges for developing a comprehensive, large-scale approach for on-site soil moisture monitoring.

1.3 North Carolina and NC ECONet

1.3.1 Climate in North Carolina

North Carolina lies between 33.5 °and 37 °north latitude and between 75 °and 84.5 ° west longitude. The extreme length from east to west is 809 km, and its extreme breadth from north to south is 300 km. The range of altitude is also the greatest of any state east of the Mississippi River, ranging from sea level along the Atlantic coast to 2026 m at the summit of Mount Mitchell. The three principal physiographic divisions of the eastern United States are

particularly well developed in North Carolina. From east to west, they are the Coastal Plain, the Piedmont, and the Mountains. With its nearly 2,100-m range in elevation from the ocean, North Carolina has one of the most complex climates in the United States (Robinson, 2005).

In all seasons of the year, the average temperature varies more than 6.7 ℃ from the lower coast to the highest elevations. While there are no distinct wet and dry seasons in North Carolina, rainfall patterns do vary seasonally. Summer precipitation is normally the greatest, and July is the wettest month. Summer rainfall is also the most variable, occurring mostly in connection with showers and thunderstorms. Autumn is the driest season, and November the driest month (Hardy *et al.*, 1988). Precipitation during winter and spring occurs mostly in connection with migratory low pressure storms, which appear with greater regularity and in a more even distribution than summer showers. In winter, snow and sleet occur on an average once or twice a year near the coast, and not much more often over the southeastern half of the State (Boyles, 2000). The variation of climate in North Carolina produces a wide range of vegetation. While the traditional agricultural cash crops of North Carolina are tobacco and cotton, currently the greatest row crop revenues are from soybean and corn. Soils and climate combine to provide optimum conditions for the former, with acreage scattered throughout the state. The Piedmont is the center of population for the state, while the Coastal Plain is the major area for extensive agricultural crops. Agricultural production is much smaller in the mountain region (United States National Agricultural Statistics Service., 2004).

1.3.2 North Carolina Environment and Climate Observing Network (NC ECONet)

NC ECONet is a state-of-the-art surface network of automated weather stations designed to observe climate and environmental phenomena in North Carolina. The network was designed and implemented by scientists at the State Climate office with cooperation from other state agencies. The ultimate goal of NC ECONet is to provide full coverage for North Carolina with at least one ECONet weather station in each county. Now under construction, it is currently composed of 37 weather observation sites scattered across the State (Fig.1.1). The three physiographic divisions are well covered with 10, 13, and 14 stations for the Mountains, Piedmont, and Coastal Plain, respectively.

At each site, a 10-m tower is installed with two sets of thermometers/hygrometers, anemometers, and pyranometers at heights of 2- and 10-m off the ground (Fig 1.2). They help to measure the difference between surface and tree line characteristics. A tipping-bucket rain gauge is installed around 1meter away from tower. Soil moisture and temperature sensors are installed at a depth of 20-cm below the ground, approximately 3-m away from the tower. A data logger is also installed on the tower to receive and store all the data transferred from instruments. In total, 42 parameters from four major categories - atmospheric, wind, soil and solar radiation - are recorded at least once every hour (Dake, 2003). A full list of ECONet measured parameters is shown in Table.1.1. Data from these stations are provided to government agencies to improve severe weather management, weather forecasts, energy planning, and natural resource management. They are also made available to the general public for a variety of uses. Parameters extracted for the research reflected in following Chapters 2-4 included soil moisture, precipitation, and potential evapotranspiration (PET).

Potential evapotranspiration (mm d^{-1}) values are automatically generated in ECONet stations with Penman-Monteith equation(Allen et al., 1998). Real-time data of temperature, wind speed, relative humidity, and solar radiation are used in the PET generation.

1.4 Soil moisture monitoring networks

1.4.1 Data collection

In the NC ECONet, soil moisture data were collected beginning in January 1999. At that time, ECHO (Decagon Devices, Inc.,Pullman, Wash.) sensors were installed in the network for soil moisture monitoring. In 2003, a completed upgrade of soil moisture sensors was performed and Theta probe (Model ML 2X, Dynamax, Houston, TX) has been used for soil moisture observation since that time. Theta probe is one of a group of soil moisture sensors based on measurement of soil electrical impedance. Somewhat similar to other common dielectric methods such as time-domain reflectometry (TDR), it determines the impedance of a sensing rod array and this measurement is used with a standardized calibration relationship to estimate the volumetric water content of the soil matrix (Miller and Gaskin, 1996). Specific details about operation of the Theta probe can be found in the Theta probe user manual (Delta-T Devices, 1999).

In the US, there are currently several other state-scale on-site climate networks besides NC ECONet which include soil moisture monitoring (Brock et al., 1995). Oklahoma Mesonet is an automated network of 116 remote meteorological stations across Oklahoma. In situ soil moisture monitoring was deployed in 1996 at 60 sites at four different depths, where possible: 5, 25, 60 and 75cm. The sensor used in Oklahoma Mesonet is the Campbell

Scientific 229-L (Illston et al., 2008). It is a heat-dissipation sensor which measures temperature response to a fixed heat input; these data are used to calculate soil moisture based on the thermal properties of the sensor. The Illinois Soil Moisture Network (Hollinger and Isard, 1994) includes 19 locations throughout the State of Illinois as part of The Water and Atmospheric Resources Monitoring Program (WARM). The network provides observations of soil moisture for the top 10 cm and then for 20 cm layers (e.g. 10-30 cm, 30-50 cm) down to a depth of 2 m. Data are measured by neutron probe on a monthly basis, available from 1981. Other examples include Nevada Cooperative Soil Climate Study project where soil moisture measurements are collected by Hydraprobe at 10-cm depth intervals to 1 m at eight sites (NCAR, 2008).

1.4.2 Data quality assurance (QA)

NC ECONet and Oklahoma Mesonet deploy quality assurance procedures to test the quality of all data recorded in their networks. Both use a routine QA procedure to check all the measured parameters with automated computer programs. QA tests are based on simple statistical distributions across all observations and locations (ECONet technical notes, 2010; (Shafer et al., 2000). Results from each test are then passed to a decision-making algorithm that incorporates the results from all tests into a single QA flag, similar to the approach suggested by Gandin (1988).

The Mesonet has recorded over 10 million soil moisture data points, but no report was found regarding the percentage of data that passed the statistical QA (Shafer et al., 2000). Specific QA procedures for state scale *soil moisture* observations were first discussed by Illston et al.(2008). In their research, Mesonet readings were compared to both values

obtained from gravimetric and neutron probe sampling to estimate the average error from Mesonet observations. The results yielded an average estimated error of 0.066 and 0.052 cm^3 cm^{-3} for gravimetric and neutron measurements, respectively. They concluded that the maximum uncertainty of the derived soil water content from Mesonet is approximately 0.05 cm^3 cm^{-3}. Gleason and Basara (2003) found that the Mesonet sensor readings were usually higher than the gravimetric samples for dry samples and considerably lower than the gravimetric samples for extremely wet soil samples. Basara and Crawford (2000) pointed out that the inconsistency between gravimetric and Mesonet readings is likely related to sensor properties, and that the accuracy of monitoring could be improved if soil types of the Oklahoma Mesonet could be used to develop specific calibration for the Campbell 229-L. Laboratory calibration of the sensors was introduced by Illston et al.(2008).

Theta Probe, the sensor employed in NC ECONet, is now widely used for in situ soil moisture measurements. Though no specific investigation on its performance has yet been recorded for ECONet, several other sources discuss the accuracy of Theta Probe for similar applications. Giraldo (2008) found that Theta probe readings averaged 6.6% lower than gravimetric readings among their study area of 49 sites in south Georgia. Cosh et al. (2005) performed a calibration on Theta Probe over a large region in Ames, Iowa (50×100 km). They concluded that field specific calibration is necessary for reducing bias and error in large scale soil moisture monitoring. Correspondingly, a Theta probe calibration study in Graysville, MB, Canada also indicates that a field calibration of Theta Probe with gravimetric water measurements improved sensor accuracy (Bullied et al., 2007). Kaleita et al. (2005a) conducted both field and laboratory calibration by regression with numerous

gravimetric samples from a field site in Iowa. They reported that Theta Probe could be field calibrated for a given soil type and that the number of samples necessary to adequately calibrate the probe was 20.

1.4.3 Data utilization

Continous, automated soil moisture observations have proven of great value for scientific research (Emanuel et al., 1995; Georgakakos and Baumer, 1996). Datasets from soil moisture networks have been used in many studies, including weather and climate studies (Brotzge and Crawford, 2000; Brotzge and Weber, 2002; Marshall et al., 2003; Raman et al., 2005), real-time flow prediction (Fiebrich and Crawford, 2001) and agricultural studies (Brooks, 2006). Unfortunately there exist few soil moisture networks with long-term monitoring records. Instrument maintenance and calibration problems, and the high-level of human resources required for such networks may be reposnsible for this situation (Georgakakos and Baumer, 1996). The Global Soil Moisture Data Bank (GSMDB: http://climate.envsci.rutgers.edu/soilmoisture/), established by Robock, was a notable initiative to provide a centralized dissemination portal for in situ soil moisture measurements over the world. It includes long-term (with at least 6 year observation), in-situ soil moisture observations in over 600 stations from a large variety of global climates, including the former Soviet Union, China, Mongolia, India, and the United States (Robock et al., 2000). Through the Global Soil Moisture Data Bank GSMDB actual soil moisture dataset from stations can be extracted for a variety of research interests.

The recent development of remotely sensed soil moisture measurements (e.g. (Bindlish et al., 2006; Jacobs et al., 2004) provides an alternative solution for soil moisture

measurement on large scales. These measurements, however, correpsond to the top few centimeters (e.g. 0-6 cm) of soil. The application of remotely sensing moisture data may be limited since these data only weakly represent moisture condtions at typical plant rooting depths (Ulaby and Stiles, 1980). The measurements are indirect by microwave, thus they also require validation before application (Arya et al., 1983). There is a possibility to improve remote sensing soil moisture data by integaration of on-site soil moisture data. This task requires good quality, extensive on-site soil mositure data, and in addition, some method of interpolation between points based observations (Georgakakos and Baumer, 1996).

1.5 Problem statements

A thorough knowledge of soil properties at monitoring locations is required to investigate data accuracy and assesses the performance of a soil moisture network. The lack of knowledge in site soil properties as well as data quality will limit the application of network products. Few studies are available on data quality assurance for soil moisture data. They either focus on long-term QA results from automated algorithms or sensor bias results from point to point comparison between network extracts and gravimetric samples. Research on long-term, quantitative soil moisture QA with a realistic soil physical basis has not been reported.

Soil moisture is influenced by numerous factors. Most soil moisture variability studies are limited to a single influencing factor and based on small study sites (e.g., sampling area of m^2) of uniform soil and land surface properties. To date, very few studies have been made to quantitatively understand soil moisture variation at a large scale. The weights for each major factor are of great importance when we attempt to interpolate soil

moisture conditions between point observations. Yet, spatial variability of soil physical properties creates serious difficulties. Information extracted from soil survey may be possible for solving the problem. Relating soil survey delineations to soil moisture variations can be the first step. However, no report is available on this effort as of yet. The focus for this work is to explore relationships between soil moisture observations and soil physical properties within the NC ECONet. The impetus for this work is to provide a foundation for efforts to use soils information and network observations in order to provide spatially continuous soil moisture maps.

1.6 Research objectives and thesis organization

The objectives of this study are to 1) characterize soil physical properties at NC ECONet stations and enhance ECONet meta data, 2) assess data quality of historical soil moisture data documented in NC ECONet and determine possible problems limiting overall quality, and 3) investigate relationships between soil physical properties and soil moisture.

The investigation starts with lab analysis in Chapter 2 to obtain soil physical parameters for each ECONet station; variations of soil properties within the network are also discussed. Chapter 3 focuses on evaluating historical soil moisture data with available physical parameters obtained in Chapter 2. Chapter 4 focuses on assessing the influential factors for soil moisture variation based on soil properties and the high-quality data period determined in Chapter 3. Emphasis is placed on determining which soil properties exhibited the strongest relationships to observed soil moisture to suggest a possible means for future interpolation using soil physical properties. Chapter 5 provides general conclusions based on this investigation.

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Table 1.1 List of parameters reported in ECONet system. Data are available for download at http://www.nc-climate.ncsu.edu/cronos.

Categories				
Atmospheric Parameters	Wind Parameters	Moisture Parameters	Soil Parameters	Solar Parameters
Air Temperature (bulb) Air Temperature (hourly average) Dew Point Heat Index Wind Chill Station pressure Station pressure (hourly average) Sea level pressure estimate	Calculated Log Wind Profile Wind speed Wind direction Wind speed (hourly average) Wind speed max for the past hour Time of max wind speed for past hour Wind direction of maximum wind speed for past hour Wind direction (hourly average) Wind gust Standard deviation of direction	Relative humidity Relative humidity (hourly average) Hourly precipitation	Soil temperature hour average Soil moisture hour average Soil temperature Soil moisture	Photosynthetically active radiation Photosynthetically active radiation (hour average) Solar radiation Solar radiation (hourly average)

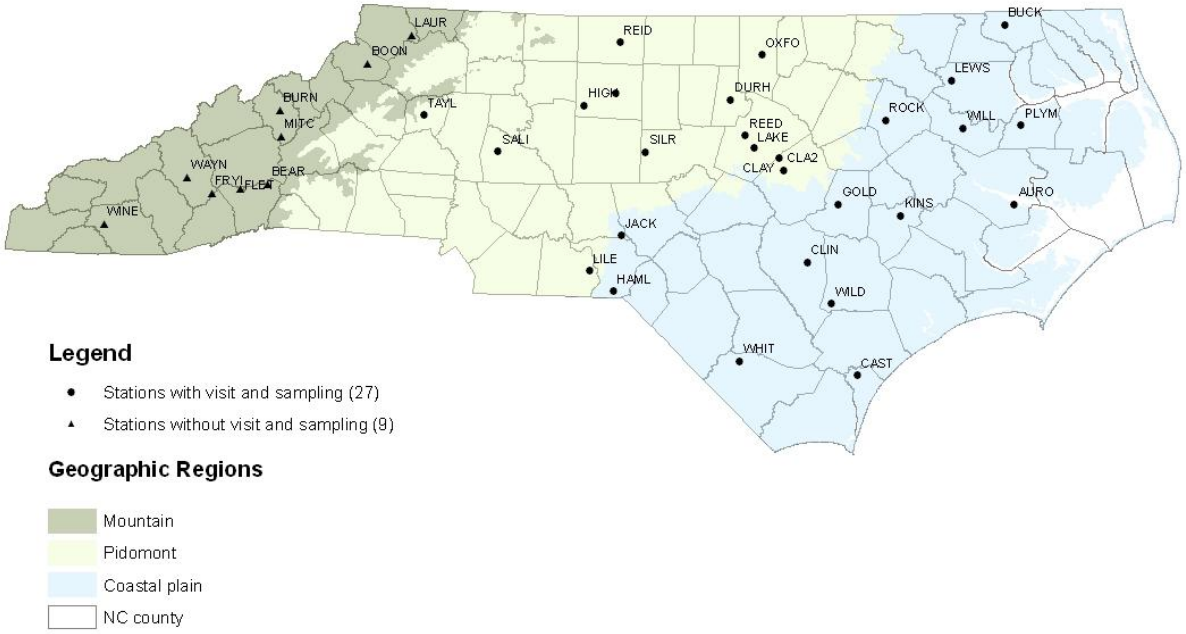

Figure 1.1 Map of North Carolina showing physiographic regions, county lines and ECONet stations.

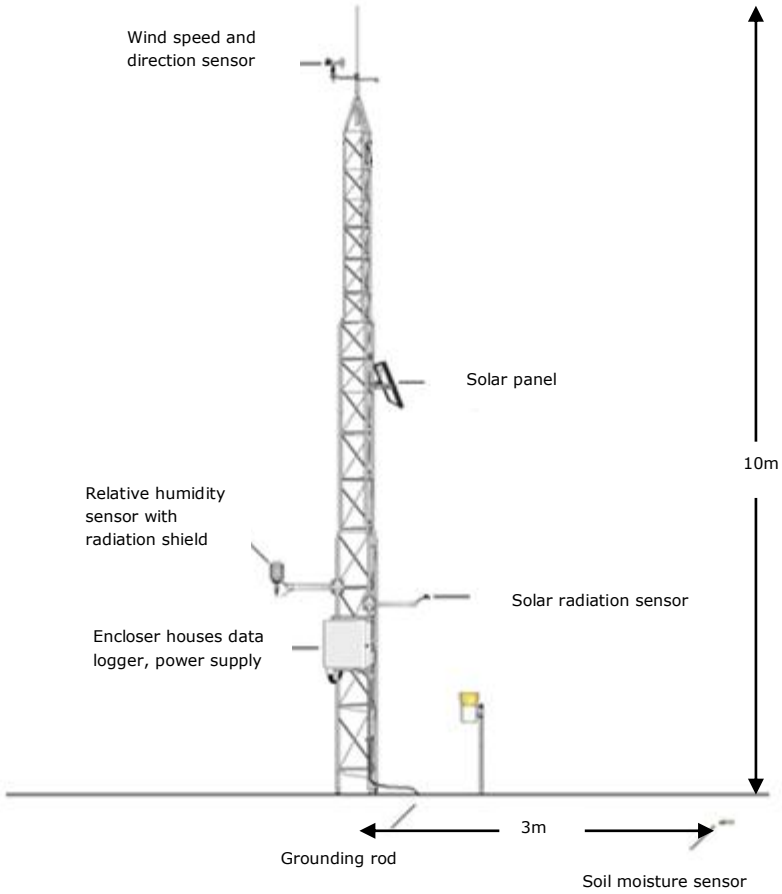

Figure 1.2 Schematic of ECONet station instruments site layout

Chapter 2 Metadata for Enhancing Soil Moisture Monitoring Across a State Network

2.1 Introduction

Soil moisture has important implications for agriculture, hydrology, weather prediction, and climatology. Long term soil moisture data will assist in agriculture, emergency response, natural resource management, tourism, economic development, education, and many other applications that affect our day-to-day lives. A continuous, automated mesoscale soil moisture monitoring network may lead to dramatic improvement in soil moisture observations and forecasts (Dabberdt et al., 2000). In North Carolina, soil moisture data are collected as routine climatological parameters in the North Carolina Environment and Climate Observing Network (NC ECONet) operated by the State Climate Office. Currently, 37 ECONet stations are operated on a continuous basis across the state with soil moisture data collected at the 20 cm depth at each of these sites.

The selection of station locations was intended to be representative of as large an area as possible (Ryan Boyles, personal communication 2009). Ideally, for soil moisture monitoring, the sites should be located on uniform terrain, standing on the major soil unit of a given station's coverage area (Shafer et al., 1993). However, the location of ECONet stations was constrained by a lack of suitable available sites, and the network was not specifically designed for only soil moisture observation (Ryan Boyles, personal communication 2009). Therefore, many ECONet sites are located on land parcels such as existing agricultural

research stations, irrespective of major soil units in a given ECONet station's intended coverage area.

Metadata are crucial for understanding soil moisture data collected at weather stations (Martinez et al., 2005). Currently, available metadata can be found under "station details" in the web portal for each station. Information included there is 1) station name, first observation and type, 2) geographic location, 3) maintenance information, and 4) site photos. Among the many factors which influence field soil moisture content, e.g., vegetation, topography, precipitation, and evapotranspiration (Sumner and Kamprath, 2000), some additional information is also available. Most sites are covered by similar grass species, and topography is somewhat uniform. Rainfall and potential evarpotranspiration are monitored by ECONet. However, site-specific soil properties are not available for any sites. In addition to already quantified factors (rainfall and evarpotranspiration), soil properties are hypothesized to be the major factor controlling soil moisture variations observed at individual sites. The amount of moisture retained by a given location and the physical bounds on the range of soil moisture at a given location are controlled by various soil properties, such as texture, percent organic matter, coarse fragment, bulk density, hydraulic conductivity, water characteristics, and structure (Beven and Kirkby, 1979; Hudson, 1994; Shukla and Mintz, 1982; Sørensen et al., 2006). The interrelations of soil and water differ as soil properties differ. Thus, knowledge of the characteristics of soil properties at ECONet stations is expected to be valuable for understanding soil moisture conditions across the State.

This chapter provides information about characterization and analysis of soil properties at 27 ECONet stations (Table A.1 in Appendix), located in the coastal plain and

piedmont physiographic regions. The original data included 891 data points in total, with 11 soil physical parameters for each sample (Table A.3 and Table A.4 in Appendix). In addition, taxonomic information for each ECONet station was extracted from the Soil Survey database. The resulting dataset was used for multiple purposes in this thesis. Specific analyses include investigation of the locational variability in soil properties (discussed below), quality assurance of sensed soil moisture data (Chapter 3), and analysis of relationships between physical properties and soil moisture (Chapter 4). While we have conducted our own analyses of this data set, we also intend to add these soil properties to ECONet metadata for the wider research community so that it may be used to its fullest potential.

2.2 Methods

2.2.1 Field Sampling

During the period between February 2009 and May 2010, 27 stations located in the Piedmont and Coastal Plain physiographic regions were sampled (Fig.2.1.). Three intact soil cores, as well as additional bulk samples, were collected from each site. Lab analyses on soils were performed during the same time period.

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 ECONet 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. 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 (discussed below). Loose soil samples were also collected simultaneously at the 20cm depth for soil textural analysis.

2.2.2 Laboratory Analyses

The intact soil cores were used to determine saturated hydraulic conductivity values (K_s) by the constant-head method as described by Klute and Dirksen (1986a). One end of the cylinder was covered with cheese cloth and placed in a water bath until completely saturated from the bottom. Thereafter, cores were moved to a stand for measurement, and downward flow was maintained under a constant hydraulic gradient of about 4.2 cm. The falling head method (Klute and Dirksen, 1986b) was applied to soil cores that did not exhibit measureable flow with the constant-head measurement.

After conductivity measurements, water retention measurements at pressure of 10, 33, 66 kPa (P10, P33, and P66) were performed (Klute and Page, 1982). Intact soil cores were removed to the pressure cell and set on pre-wetted ceramic plate which permitted raising the water level to the top of the core and saturating the entire sample. The excess water was removed by siphon before water retention measurements. Gas pressure was applied in steps, and the volume of outflow after equilibrium at each pressure step was recorded. Before disturbing the intact soil cores, the samples were oven dried at 105 ℃ for 24 h to determine

dry weight per volume. Total porosity and bulk density were calculated, assuming the particle density was 2.65 g cm^{-3} (Troeh and Thompson, 2005).

Samples were ground and passed through a 2 mm sieve before water retention measurements in the high pressure system. Water content at 100, 500 and 1500 kPa pressure (P100, P500 and P1500) was determined following similar procedures as described by Klute and Dirksen (1986c) . Soil samples were packed in a rubber ring and placed on the pre-wetted ceramic plate. Three replicates were used at each desired pressure. Samples were wetted on the plate by immersing the plate and the samples in the water to a level just below the top of the samples. Soil samples and plate were moved to the chamber after saturation, and the outflow tube on the plate was connected to the pass-through connector in the wall of the chamber. Air pressure was applied after the chamber was closed. Hydraulic equilibrium at each applied pressure was assumed upon cessation of outflow. After equilibration, soil cores were removed by wide blade and weighed. Volumetric water content at each pressure was calculated from bulk density and the sample weights after equilibrium.

Air-dried water content measurement was also performed using disturbed soil. The saturation process was the same as described in water retention procedures. Before oven drying, samples were left at room temperature (22 ℃) and humidity (~30%) until their mass reached a constant value.

Simultaneously, particle size distribution was determined by sedimentation using the hydrometer methods as proposed by Day (1965) . Sodium hexametaphosphate solution was used to soak sample overnight for dispersion. Hydrometers reading were made at 0.5, 1.5,

360, and 960 minutes to determine the percentage of clay, silt and sand (Klute and Dirksen, 1986d).

2.2.3 Statistical Methods

In order to minimize potential error and ensure the representativeness of the samples, measurements from the three replicates at each site were arithmetically averaged to obtain a single value for each variable except for K_s. The skewness test (Tabachnick et al., 2001) revealed that K_s values were highly skewed among three 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. All soil parameters for the 27 stations were analyzed using classical statistical methods to obtain the minimum, maximum, mean, median, and standard deviation. A one-way ANOVA was also performed with SAS JMP 7.0 (SAS, 2007) to determine if the physical difference between Piedmont (n=13) and Coastal plain (n=14) were significant using Fisher's protected least significant difference ($P< 0.10$) test.

2.2.4 Taxonomic Information

In addition to quantitative parameters, an alternative way for characterizing soil physical properties is based on the qualitative descriptions contained in Soil Taxonomy. Taxonomic information is obtained through knowledge of the soil series at sampling sites. Sampling sites were georeferenced by geographic coordinates extracted from ECONet metadata (http://www.nc-climate.ncsu.edu/cronos) and then projected to North Carolina State

Plane NAD83 meters using Arc GIS (Esri). Soil Series information at the sites was obtained from the SSURGO database (USDA-NRCS, 1995). It includes digitized soil maps (1:20,000) composed of polygons representing various map units defined with a soil series name (or other designations such as urban land, water and quarries) based on county soil surveys. The SSURGO soil map was re-projected to the same spatial resolution and geographic coordinate system as for ECONet station locations. Hence, attribute "Soil Series" at each location could be extracted from the attribute table provided with soil survey map (Table 2.1). In order to justify that it is appropriate to use soil survey data, we chose to use what we consider to be the most determinant parameter, texture, to evaluate the accuracy of soil survey. As shown in Table 2.1, lab-analyzed texture was matched to textural classification in NRCS soil series description (Hirekerur et al., 1989) at corresponding depth. The soil series coverage rate on the county basis was calculated using the equation:

$$\textbf{Coverage rate}\ (\%) = \frac{\textbf{Area covered by identical map units as ECONet stations}}{\textbf{The total area of tested county}}$$

2.3 Result and Discussion

2.3.1 Soil Physical Properties at ECONet Sites

It is necessary to recognize that there is natural variation at each sampling spot and that the properties (e.g., bulk density) of any particular soil can and do change with seasons and cultural practices, etc. These changes may be hard to quantify, but parameters were relatively consistent between three replicates at each site. Except for K_s, replication error in soil

physical parameters tested here is <5%. Similar observations were reported by (Basara, 1998) and (Cassel, 1983) for laboratory data obtained from small soil cores from areas adjacent to the desired sampling spot. Their results indicate the typical observed range of bulk density at any given depth interval was approximately ± 0.03 g cm^{-3} and the horizontal soil texture varied slightly.

Descriptive statistics of site soil physical properties are shown in Table 2.1. Based on the skewness, most of the variables could be described as having a normal distribution. The possible exceptions were Log(Ksat), air dried water content, clay content and silt content. Soil bulk density (ρ_b) satisfactorily fell in a normal distribution from 1.10 to 1.69 cm^{-3} cm^{-3} as indicated by the slight difference between mean and median, and a skewness of -0.34. The case is similar for porosity, derived from ρ_b. While sand content was normally distributed, clay and silt content were skewed judging by the skewness value and the difference between mean and median.

The texture distribution of sampling sites within an alternative texture triangle is shown in Fig. 2.2. The soil texture at ECONet sites is distributed within seven classifications, with most points falling within the four classifications loam, sandy clay, sandy loam and loamy sand. Texture points clustered in the area with sand percentage greater than 40% and clay percentage less than 40%. The higher skewness in clay content could be explained by the only clay-texture soil site. The reason for the 1.84 skewness in air-dried water content is caused by the similar reason as skewness in clay percentage since air-dried water content (i.e.

minimum water retained by soil under field condition) is highly dependent on the content and mineral component of clay portion (Sumner and Kamprath, 2000).

Although there were wide ranges for both field capacity and wilting points, these values are evenly distributed in different water content intervals (Fig.2.3.). Strong positive relationship of clay content with water content at both field capacity and wilting point were observed, with R^2 of 0.66 and 0.80, respectively. Plant available water (PAW) content was calculated as the difference between field capacity and wilting points, which is the difference between the two curves in Fig.2.3. The general trend of PAW was apparent as it increased with clay content. However, the relation (R^2=0.18, fitted curve not shown) was much weaker. A possible reason could be the higher inherent variability for PAW, since it was the difference between two measurements.

2.3.2 Comparison of Soil Physical Properties Between the Piedmont and Coastal Plain

The descriptive statistics for measured soil physical characteristics separated into the Piedmont and Coastal Plain physiographic regions are shown in Table 2.2. There was no significant different in ρ_b between the Piedmont and the Coastal Plain. This observation may be somewhat surprising when considering the factors influencing ρ_b. The particle size distribution together with packing controls the range of possible ρ_b value at a particular location (Sumner and Kamprath, 2000), thus it is highly dependent on the soil texture as well as the management history at a given site. Significant difference was observed in particle size distribution in Piedmont and Coastal plain soils (discussed next). However, the ρ_b may be primarily the result of compaction associated with different management at the sites (e.g.

heavy machinery on the research farm) with likely no tillage in the vicinity of the sensor since installation.

The average clay content in the Piedmont was more than two times that in the Coastal Plain with a significance level of 0.01. A similar trend was observed for the maximum and minimum values in clay content. It is obvious that dominant particle sizes were distinct in these two regions. The Piedmont soils were relatively clayey, while Coastal plain soils relatively sandy. Associated with clay content (described above), field capacity and wilting point in the Piedmont were also greater compared to the Coastal Plain ($P<0.01$), with a difference of 50% on average. The difference between plant available water is still pronounced but less apparent (20% greater in the Piedmont) at $P<0.1$ level. Air-dried water content was also greater for Piedmont with significance level of $P<0.10$.

Results clearly indicate that soil physical properties are spatially heterogeneous by physiographic regions. More importantly, the regional physical heterogeneity would be reflected in the distinct hydraulic behaviors in Piedmont and Coastal Plain soils. With the differences in field capacity and wilting points, the same water content values in the two regions may represent very different water supply conditions. Thus, it is valuable to realize the soil properties difference in these two regions with respect to both understanding and utilizing soil moisture data.

2.3.3 Taxonomic Information at ECONet Sites

Soil properties differ among individual sites and also show distinct characteristic between two major regions. Knowledge of soil properties in the study area is beneficial for regional

soil moisture assessment. While collection of soil physical data throughout the experiment area is operationally and economically prohibitive, some information is available in taxonomic descriptions in the SUURGO database. With four sites lacking soil survey data, the remaining 27 stations unevenly distribute on 21 soil series and 2 special designations (Table 2.3). Station HAML is built on a soil series which represents 24% of its county's soils. For stations other than HAML, the series at each site only covers a small portion (mostly below 5%) for the entire area of the county in which it is located. This high diversity of soil series is not surprising, since series is the most detailed "mappable" taxonomic entity (Buol, 1997) in SUURGO base, with 14000 series existing for US soils. Soil texture in 19 out of 23 sampling sites were in the same textural class as the description found in Soil Survey (Table 2.3). This implies that soil survey data were reliable in the experimental area, and it may be feasible to utilize soil properties extracted from the soil survey database to further explore the value of soil moisture data. However, we should also note that practical value will be limited if soil series are chosen as the criteria to classify soils since it is too narrow to represent major soil units at the scale of our study. A higher level of taxonomic classification may need to be considered to permit soil moisture investigation.

2.4 Development of New Network Products Based on Enhanced Metadata

The enhanced metadata collected for the soils as described above allow us to add new network products to the current ECONet system which may be of immediate value. Plant available water (PAW) is a crucial parameter in the context of agriculture and urban lawn management. It is one of the fundamental soil factors affecting crop yield (Morgan et al.,

2003). With knowledge of detailed soil parameters obtained in this study, instantaneous PAW (cm cm^{-1}) at each ECONet station could be simultaneously calculated by equation [1].

$$PAW = \theta_{sensed} - \theta_{wp} \quad [1]$$

where, θ_{sensed} is sensed soil moisture content ($cm^3 cm^{-3}$) determined by ECONet and θ_{wp} is volumetric soil moisture content at the wilting point (cm^3 cm^{-3}).

Saturation index (SI) is the ratio between real-time soil moisture and porosity (i.e. maximum water content) of soil. The SI is of significant importance for engineering construction. It The compressibility and load-bearing capacity are highly correlated with soil moisture condition (Aswathanarayana, 2001). The SI could easily be obtained with known soil properties using equation [2].

$$SI = \frac{\theta sensed}{f} \quad [2]$$

where, θ_{sensed} is sensed soil moisture content ($cm^3 cm^{-3}$) determined by ECONet and *f* is soil porosity ($cm^3 cm^{-3}$). Traditionally, these two variables are considered challenging to obtain. However, with soil properties now available, they could be calculated and reported in real time in the same manner that soil moisture content is currently reported. The dataset for soil physical properties at each ECONet station could also be used to develop other network outputs (e.g. soil water potential) to fit the interest of individual end users.

2.5 Summary

In this chapter, we investigated soil physical properties at 27 ECONet stations in the Piedmont and Coastal Plain regions of North Carolina. The resulting dataset of soil physical properties suggests that soils are highly variable in the studied regions. According to particle size analysis, soils at ECONet sites fall in seven textural classes, with texture often considered to be the most influential factor for soil hydraulic properties (Cosby et al., 1984). As observed in the lab analysis, air-dried water content is highly related to soil texture (especially clay content). The skewness value of 1.84 and CV of 50% indicate the high variability in the lower boundary of soil moisture content under field conditions. 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. Investigation continued by comparing soil parameters by physiographic regions. Five of 10 analyzed variables (clay content, silt content, wilting point, plant available water and air-dried water content) exhibited significant differences by region suggesting a general soil characteristic difference between the Piedmont and Coastal Plain. Considering this variability, we reason that regional soil moisture observations will be better explained with knowledge of soil properties in the area of the observation sites, especially for comparison among sites. Simple comparisons to soil survey information suggest some potential for obtaining useful information when field sampling is prohibitive. However, results also show that, according to series designations, ECONet sites may not reflect a large land area within individual counties. Some suggestions for how metadata could be immediately implemented were also discussed. Overall, we believe soil physical property

information described herein will be valuable for refining and improving ECONet capabilities.

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Table 2.1 Descriptive Statistics for Selected Physical Properties at ECONet sites in the Piedmont and Coastal Plain

Variable	Mean	Median	Max	Min	SD	Skewness	CV
Bulk density, g cm^{-3}	1.42	1.43	1.69	1.10	0.17	-0.34	0.12
Porosity, cm^{-3} cm^{-3}	0.46	0.46	0.59	0.36	0.06	0.33	0.13
Log Sat. Cond., cm h^{-1}	0.65	0.70	1.15	-0.32	0.33	-1.1	0.47
Clay content, %	15	11	53	2	12	1.54	0.80
Sand content, %	63	64	90	24	17	-0.30	0.27
Silt content, %	22	16	49	4	13	0.72	0.59
AD, cm^3 cm^{-3}	0.02	0.02	0.07	0.01	0.01	1.84	0.50
FC, cm^3 cm^{-3}	0.28	0.29	0.50	0.13	0.09	0.14	0.31
WP, cm^3 cm^{-3}	0.10	0.09	0.19	0.04	0.04	0.56	0.44
PAW, cm^3 cm^{-3}	0.18	0.19	0.33	0.07	0.06	0.43	0.32

AD= air dried water content; FC= field capacity, volumetric water content at -33 kPa; WP= wilting point, volumetric water content at -1500 kPa. PAW= plant available water content, calculated as difference between -33 kPa and -1500 kPa.

Table 2.2 Descriptive Statistics for Selected Physical Properties at ECONet Sites of the Piedmont (n=13) and Coastal Plain (n=14).

Variable	Location	Mean	Median	Max.	Min.	SD.	CV
Bulk density, g cm^{-3}	Piedmont	1.46	1.48	1.63	1.22	0.12	0.08
	Coastal Plain	1.38	1.36	1.69	1.10	0.20	0.14
Porosity, cm^3 cm^{-3}	Piedmont	0.45	0.44	0.54	0.38	0.05	0.11
	Coastal Plain	0.48	0.49	0.59	0.36	0.08	0.17
Log Sat. Conductivity, cm h^{-1}	Piedmont	0.58	0.70	0.95	-0.31	0.37	0.64
	Coastal Plain	0.71	0.69	1.14	0.29	0.29	0.41
Clay content***, %	Piedmont	21	17	53	7	14	0.67
	Coastal Plain	9	8	23	2	7	0.78
Sand content, %	Piedmont	58	59	80	24	17	0.29
	Coastal Plain	68	68	90	43	16	0.24
Silt content, %	Piedmont	20	15	46	4	14	0.70
	Coastal Plain	23	22	49	6	13	0.57
AD*, cm^3 cm^{-3}	Piedmont	0.03	0.03	0.07	0.01	0.02	0.67
	Coastal Plain	0.02	0.02	0.04	0.01	0.01	0.50
FC***, cm^3 cm^{-3}	Piedmont	0.33	0.34	0.50	0.21	0.07	0.21
	Coastal Plain	0.24	0.23	0.38	0.13	0.08	0.31
WP***, cm^3 cm^{-3}	Piedmont	0.13	0.13	0.19	0.07	0.04	0.30
	Coastal Plain	0.08	0.08	0.15	0.04	0.03	0.38
PAW*, cm^{-3} cm^{-3}	Piedmont	0.20	0.19	0.33	0.13	0.05	0.25
	Coastal Plain	0.16	0.15	0.27	0.07	0.06	0.38

AD= air dried water content; FC= field capacity, volumetric water content at -33 kPa; WP= wilting point, volumetric water content at -1500 kPa. PAW= plant available water content, calculated as difference between -33 kPa and -1500 kPa. ***, * refer to significant levels of 0.01 and 0.10, respectively.

Table 2.3 Soil Series Coverage on ECONet Sites and Texture Comparison between Lab Analysis and Series Description Extracted from SUURGO Database

Site ID	Soil map unit	Defined soil series or special designations	Coverage in the county	Consistency with taxonomic descriptions in SUURGO
			%	
AURO	AaA	Altavista	1.38	Yes
BUCK	LeA	Lenoir	2.69	Yes
CAST	St	Stallings	1.52	n/a
CLA2	Tn	Toisnot	1.06	No
CLAY	VrB	Varina	0.40	Yes
CLIN	Ln	lynchburg	3.45	Yes
DURH	Ur	Urban land[a]	5.32	n/a
GOLD	Jo	Johns	1.12	Yes
HAML	WcB	Wakulla/candor soils	23.77	Yes
HIGH	MuB	Mecklenburg	2.79	Yes
JACK	Aab	Ailey	1.77	Yes
KINS	Nb	Norfolk	6.54	No
LAKE	ApB	Appling	2.92	No
LEWS	GoA	Goldsboro	5.55	Yes
LILE	Udc	Udorthents[b]	1.12	n/a
NCAT	MhB2	Mecklenburg	5.21	Yes
OXFO	VaB	Vance	2.98	Yes
PLYM	Cf	Cape fear loam	2.54	Yes
REED	CgB2	Cecil	2.17	Yes
REID	CaB	Casville	1.09	Yes
ROCK	GoA	Goldsboro	7.57	Yes

Table 2.3 Continued

Site ID	Soil map unit	Defined soil series or special designations	Coverage in the county %	Consistency with taxonomic descriptions in SUURGO
SALI	LdC2	Lloyd	0.73	Yes
SILR	UdC	Udorthents[b]	0.66	n/a
TAYI	CeB2	Clifford	1.28	No
WHIT	Gt	Grifton	6.72	Yes
WILD	NbA	Norfolk	3.64	Yes
WILL	GoA	Goldsboro	9.25	Yes

a, Special designation, with no taxonomic information available; b, Special designation assigned to cutting and filling areas, with no taxonomic information.

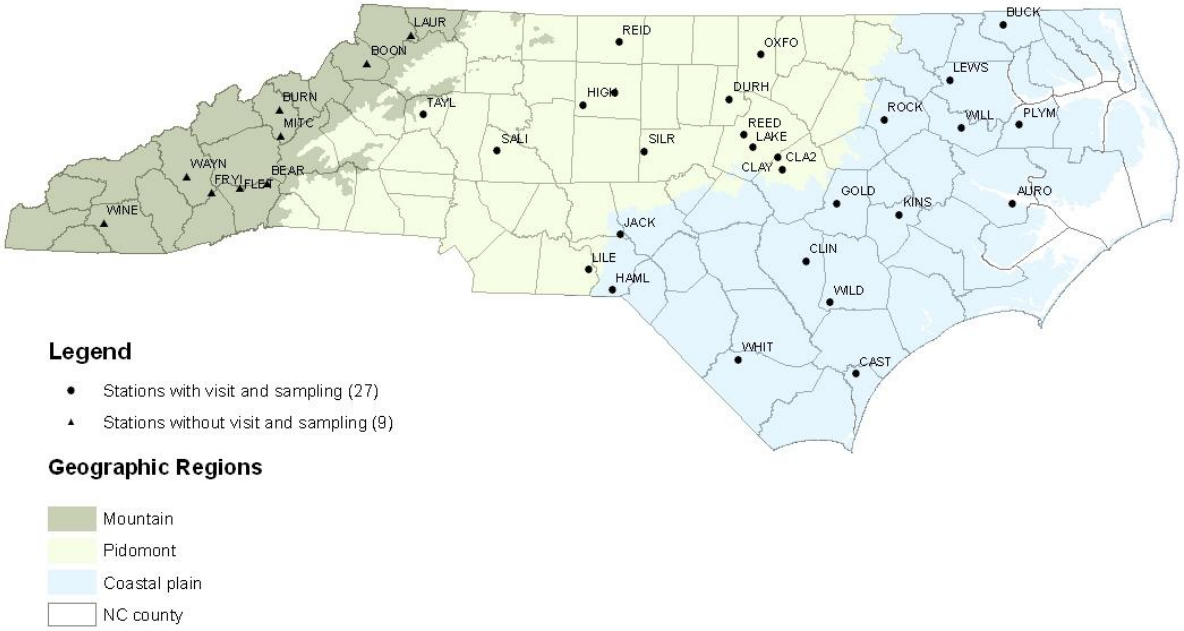

Figure 2.1 Map of Study Area with Sampled and Unsampled ECONet Sites.

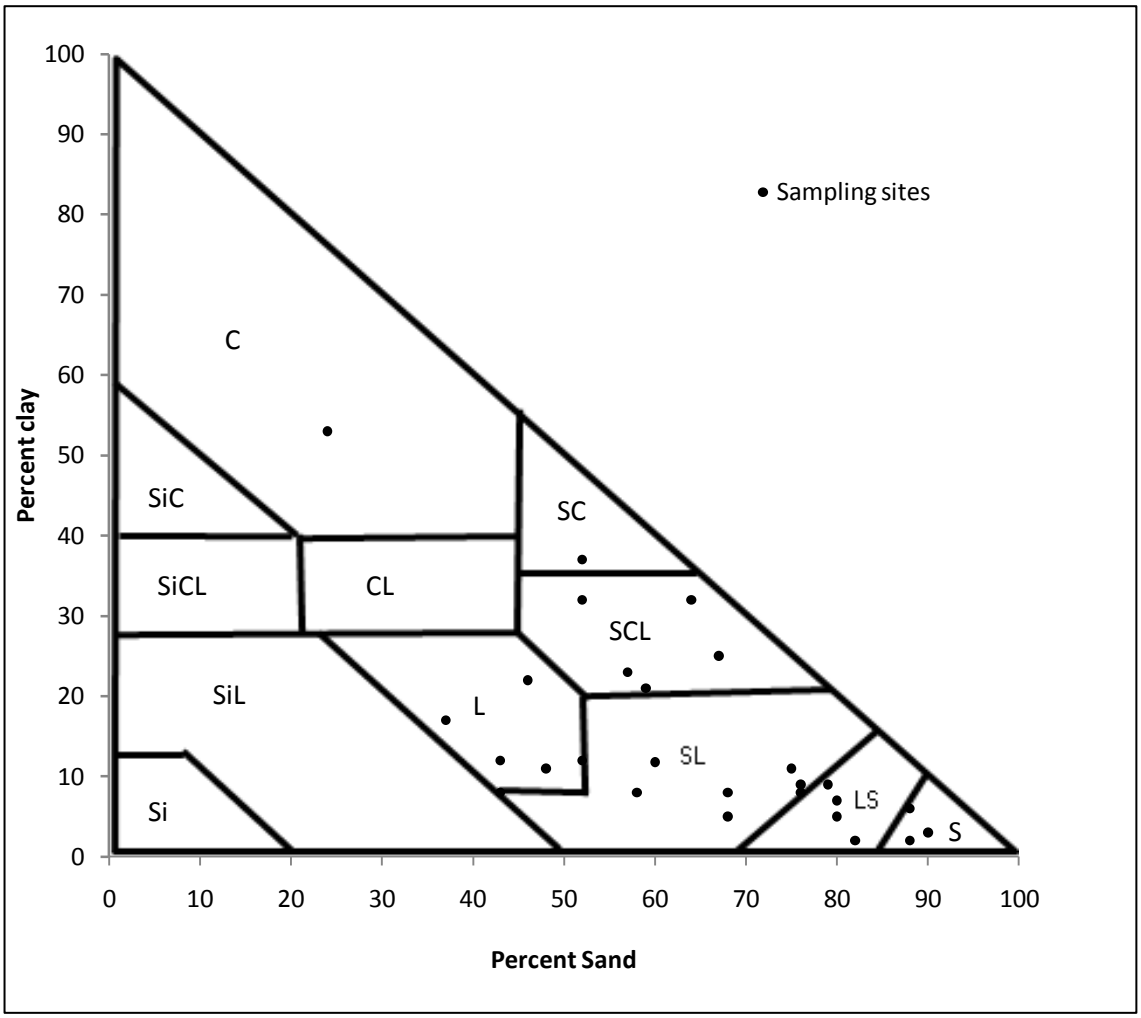

Figure 2.2 Alternative Texture Triangle with the Distribution of Sampled ECONet Sites.

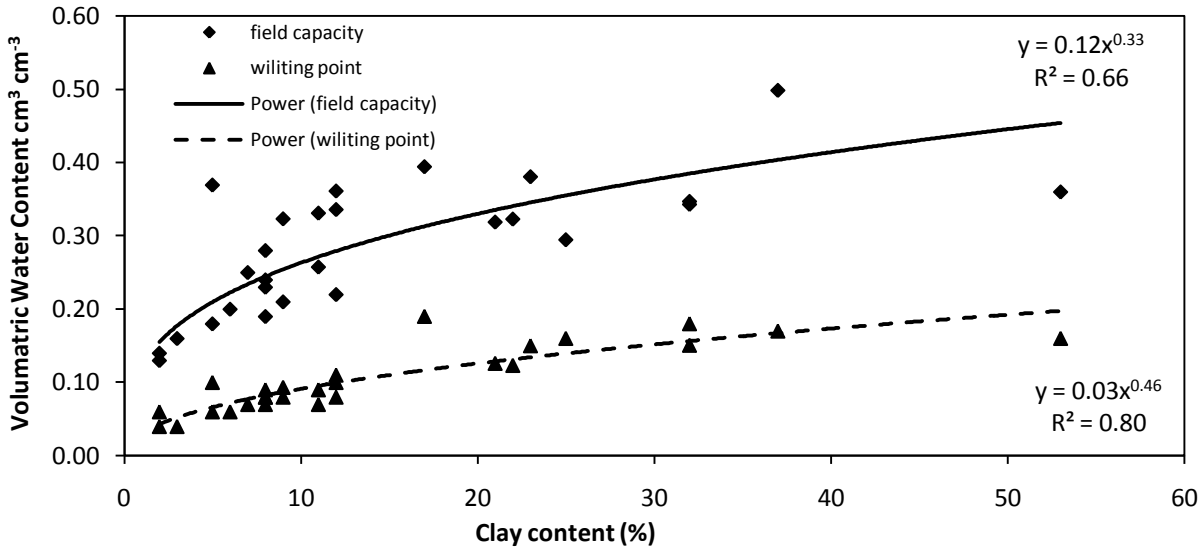

Figure 2.3 Relationships of Field Capacity and Wilting Point to Clay Content

Chapter 3 Quality Assurance of Soil Moisture Observations from NC ECONet

3.1 Introduction

In North Carolina, the NC ECONet provides soil moisture observations to the public. Volumetric soil moisture data are recorded every 60 min, producing 24 observations per station, per day. The ECONet has collected over eight million soil moisture observations since its commissioning in January 1999 through November 2009. Modifications during this period, including changes in the type of soil moisture sensor installed at monitoring sites, have been implemented in a continuous effort to improve ECONet performance. The soil moisture sensor currently installed for the NC ECONet is the Theta Probe ML2X manufactured by Delta-T Devices, Cambridge, UK. Previously, another impedance-based sensor, ECHO (Decagon Devices, Inc.,Pullman, Wash.), had been installed for soil moisture monitoring at ECONet sites. Both sensors make use of the relationship between soil dielectric constant, determined via impedance, and volumetric water content (Topp et al., 1980). As the NC ECONet has continued to develop, ECHO sensors were replaced by Theta Probe in succession (after 2003) to improve the accuracy of soil moisture observation.

All documented data are publicly accessible from the NC State Climate Office website (http://www.nc-climate.ncsu.edu/econet), available in both hourly and daily formats. A generic quality assurance (QA) procedure was applied to this dataset, with appropriate flags denoted beside data after they pass through this automated QA procedure. As noted in Chapter 1, with little knowledge of soil properties at monitoring sites, the QA procedure was

limited. The QA check could only be based on the simple statistical distributions of soil moisture readings across stations, irrespective of soil physical properties expected to influence these distributions. With soil physical parameters provided in Chapter 2, we examined ECONet observations on a more physically-realistic basis. Improved QA investigation based on soil physical properties will provide guidance for utilizing historical data recorded in ECONet and should also strengthen ECONet performance in the future.

The objective of this chapter is to assess the quality of soil moisture data collected by NC ECONet based on the soil physical parameters determined in Chapter 2. Research reports on quality assurance procedures used in monitoring networks are presently sparse. A key concept used here is measurement of soil porosity and air dried water content to allow real physical bounds be integrated into the data checks. Historical, physically-based QA results for the entire network, as well as for each individual station are presented. In addition, comparison of water content from field sampling at ECONet sites is used to further assess the sensor accuracy. The factors influencing sensor accuracy are also considered and discussed. The impetus for this work is to enhance soil moisture monitoring in the NC ECONet and extend its application in water management for North Carolina citizens.

3.2 Method

3.2.1 Quality Assurance for ECONet Data Based on Physical Bounds

To enhance the soil moisture QA procedures already implemented by the State Climate Office, we sought to implement additional QA procedures based on soil physical property data. The overarching assumption in this new QA protocol is that observations

collected by the sensors should fall within realistic physical bounds, established at each site through measurement of soil properties. Our aim was to detect the appearance and frequency of "unreasonable" data that include missing points and outliers. A flowchart demonstrating general QA steps in this procedure is shown in Fig. 3.1.

Raw data for each site are soil moisture readings documented every 60 minutes in 'ASCII txt' format, based on manufacturer-recommended calibrations between sensor output and soil water content. The duration for available records at sites varies from one to 12 years. For practical feasibility in working with this large data set, we converted hourly data into daily soil moisture data by averaging available hourly observations. This conversion was completed using a FORTRAN program. New datasets were generated in MS 'Excel' format including date, daily average soil moisture content, and number of data points available each day. Consistent with the physical property data collected in Chapter 2, 27 stations from the Piedmont and Coastal Plain were considered in the analysis.

The first step to accomplish data quality assurance was to investigate the sensor operation. A preliminary evaluation on the number of successfully archived data at each ECONet site can test if the sensor is consistently functional. The MS Excel function COUNTIF(range, criteria) was used to count the total number of missing data at each ECONet station during its operation.

Subsequently, a range test was performed for each set of observations. At each station, the physical maximum and minimum soil moisture bounds were determined from measured soil properties (Table 3.1). The upper bound for soil moisture content was

determined by soil porosity, obtained as described in the previous chapter. Errors from field sampling and sensor performance were taken into consideration. There is an average variation of ± 0.03 cm^3 cm^{-3} between the three replicate porosity measurements collected at each site (see Chapter 2). An error of ± 0.05 $cm^3 cm^{-3}$ is commonly associated with the Theta Probe soil moisture sensor (Miller and Gaskin, 1996). Therefore, the upper bound of sensed soil moisture reading was assumed to be the soil porosity plus an error of 0.05 cm^3 cm^{-3}. Similarly, the lower bound of field soil moisture is approximated by the air-dried water content. Again an error of 0.05 cm^3 cm^{-3} was assumed from the sensor; variation among air dried replicates was insignificant (around 2%). Across all sites, using air dry water content with an assumed error of 0.05 cm^3 cm^{-3} gave an effective lower bound of 0.00 cm^3 cm^{-3}. The Range test was conducted in MS Excel; failing days were identified and counted using the COUNTIF (range, criteria) function.

Archived data passing the missing data and range checks were accepted as " reasonable" data, and those failing were considered "problematic" data. In this case, an ECONet site with above 95 % "reasonable" data since its commission was considered to have acceptable performance. The 95% threshold was chosen because confidence level "95% " is typically used in statistical analysis (Zar, 1999).

Further analysis was performed for sites that had < 95% "reasonable" data. In this analysis we attempted to indentify both the period and the reasons for "problematic" data for each site-year. This record should thereby serve as not only an evaluation for sensor performance, but should also provide a guide for retrieval of acceptable site-year soil

moisture data from historical records. Specific site-year examinations were done by MS Excel FILTER and COUNTIF functions based on yearly available observations.

3.2.2 Correlation between Water Contents from ECONet Observations and Field Sampling

After QA, a second test was used to examine the accuracy of sensed soil moisture data. Sensor readings were compared to field measurements from gravimetric sampling (discussed in previous chapter) at corresponding times and depths. A linear regression model was fit in SAS JMP (SAS, 2007) to acquire the standard error of sensor measurements. Twenty-six of 27 sites from the Piedmont and Coastal Plain were tested altogether; site NCAT was excluded because of missing sensor readings at the time of sampling. The soil parameter dataset was also used in this study to investigate if certain soil properties were related to the performance of the soil moisture sensors.

3.3 Result and discussion

3.3.1 Quality Assurance for Historical ECONet Data

Table 3.1 shows the bounds (used as thresholds) in the range test of soil moisture at each ECONet site. As described above, low values of air-dried water content (< 0.05 cm^3 cm^{-3}) give 0.00 cm^3 cm^{-3} as the possible minimum sensor reading for all the sites. However, the upper bound differed between sites, reflecting the unique soil properties at each site. The upper boundaries ranged from 0.41 cm^3 cm^{-3} (CLIN) to 0.64 cm^3 cm^{-3} (BUCK), with a standard deviation of 0.06 cm^3 cm^{-3}. This suggests more variable soil moisture readings could be observed in the upper boundary compared to lower boundary.

Overall QA results are shown in Table 3.2. The QA results presented here cover an average of 8 years for each ECONet site, with 72,138 daily reading and 198 site-years involved. Among all 27 ECONet stations, the percentage for station records per site passing QA examination range from 67 to 100%. Seventeen sites passed the missing data and range test with > 95% "reasonable" data, with four of these having 100% "reasonable" data. These 17 stations were considered acceptable and excluded from further QA analysis.

QA procedures were continued for separate site-year examination on the remaining sites. Three of 10 "problematic" stations, SILR, WILL and NCAT, suffered mainly from missing data (Table 3.3). It appeared that no data were collected during periods ranging from several days (SALI) to months (REED) to years (SILR), which could often be traced via maintenance logs to a power outage or connection loss. Data were stored in the data logger supported by a battery. If the battery was not replaced frequently enough, a loss of saved data occurred because the recovery function could only backup the most recent data. Power outage leads to the loss of all the parameters collected on site, while connection loss only affects soil moisture recording. One example was REED 2004 when missing data was attributed to a damaged underground cable connecting the probe to the data logger.

Range test failure also occurred at a number of sites. No data failed the examination for the lower boundary, since 0.00 cm^3 cm^{-3} is a forced lower bound in the sensor algorithm. However, for the upper boundary, we observed that up to 29% data failed for total records documented at a single site (e.g. REED), and up to 99% data failed at a particular site in a single year (e.g. REED, 2001) (Tables 3.2 and 3.3). An example of data that failed the upper limit range test and thus required further investigation is shown in Fig.3.2. The plot depicts

the soil moisture change for site REED in 2001 with only 1% of data points passing QA procedures. In 2001, 99% of data taken at REED were > 0.52 cm^3 cm^{-3} which exceeded the established upper bound (Table 3.1). Although the absolute reading was unreasonable, the pattern in soil moisture reasonably follows the pattern of rainfall events. This trend was also observed in other range test failure cases, which suggests the problem here is more likely tied to sensor malfunction or inaccuracy in the general calibration relationship. Two sensors, ECHO2 (Decagon Devices, Inc.,Pullman, Wash.) and Theta Probe (Delta-T Devices, Cambridge, UK), have been installed at ECONet sites since 1999 when the ECONet database is first available. Both are dielectric probes working on the principle that there is a consistent relationship between soil dielectric constant and volumetric water content. After 2003 ECHO sensors were replaced by Theta Probe in succession to improve the accuracy of soil moisture observations. As shown in Table 3.3, at each of 10 stations failing the range test, all the highest single-year failure percentages were observed prior to year 2003. Figure 3.3 shows the percentage of total available data passing the range test, recorded at all the problematic sites from 1999 to 2009. A low point was observed from 2000 to the end of 2003 which is the same period when ECHO2 sensors was used for soil moisture monitoring in ECONet. The percentage of soil moisture observations that passed the range test increased substantially after the completion of sensor upgrade in the end of 2003. It is evident that Theta Probe has been superior to ECHO2 sensor for ECONet with much less possibility for overestimation of soil moisture conditions.

The site-year examination in Table 3.3 provides detailed QA results, which could serve as a reference for deriving research quality data from sites considered as unacceptable

in terms of complete records. Among all the 84 site-year dataset recorded as unacceptable by overall examination, 47 individual site-years have > 95% reasonable data (Table 3.4). This suggests that partial datasets from unacceptable stations still could be used as long as the appropriate site-year archives were selected.

Specific missing and range-test failing data are not likely recoverable. Data such as the example shown in Fig. 3.2 cannot be calibrated without some independent measure of soil moisture at the site. With no gravimetric sampling data available for this time period, calibration based on neighboring stations may be one option to correct data. But this requires selecting neighboring stations with similar soil properties, precipitation, and evapotranspiration. Unfortunately, ECONet stations are sparse across the whole state and usually more than 65 km from their neighboring stations. Another option is correcting data through an empirical calibration model which could be developed by relating gravimetrically determined water content to sensor measured water content. However, the challenge here is ensuring the timely collection of soil samples right after the problem is detected. Periodic and standard site visits including soil sampling could be used to improve ECONet soil moisture data. The more often sensors are inspected, the better they will perform. Real-time data quality may be much improved if soil moisture data accuracy assessment is conducted during each site visit.

3.3.2 Correlation Between Water Contents from ECONet Observations and Field Sampling

The comparison between field measurements acquired using the gravimetric technique and the ECONet sensor reading at corresponding times is shown in Fig. 3. 4.

According to the regression model, the root mean squared error (RMSE) between field and sensor measurements is 0.067 cm^3 cm^{-3}. The readings from the sensors tend to be wetter than the condition established with field sampling, showing an average overestimation of 0.058 cm^3 cm^{-3}. The overestimation of soil moisture appeared more frequently in the relatively dry condition, particularly when soil moisture contents were less than 0.25 cm^3 cm^{-3}. Similar findings were reported by Illston et al. (2008), where an RMSE of 0.066 cm^3 cm^{-3} was detected between the field measurements obtained from destructive soil samples and their Mesonet soil moisture sensor estimation. Furthermore, our results were consistent with their conclusion that soil moisture appeared to be more likely overestimated in dry conditions (< 0.15 cm^3 cm^{-3}).

There also appeared to be a tendency for the values derived from ECONet sensor to be wetter than the gravimetric sampling values especially for those sites with high clay content (Fig. 3.5). For example, the sensed soil moisture content is 0.24 cm^3 cm^{-3} higher than field sampling at site OXFO with clay content of 53% and 0.16 cm^3 cm^{-3} higher at site REED with clay content of 32%. This can probably be explained from the working principle of sensors used in ECONet. The use of dielectric probes as a non-destructive method of soil moisture measurement is based on the calibration between square root of soil dielectric constant (ε) and volumetric water content (θ) (Topp et al., 1980; Zegelin et al., 1989) . It is commonly accepted that ε is most strongly dependent on θ, and almost independent of soil density, texture, temperature and salt content (Kaleita et al., 2005b; Topp et al., 1980). For a first approximation, soils with a large range of properties could have a similar calibration function, which led to the proposal of a “universal” relation usually represented by a linear

regression equation for field use (Delta-T Devices, 1999; Topp et al., 1980; Whalley, 1993). However, some researchers suggest modification of the "universal relation" for peat soils and soils with high clay content (Dirksen and Dasberg, 1993; Roth et al., 2006). The "universal" ε and θ relationship was developed under the ideal condition that soil is a perfect dielectric with zero or negligible dielectric loss assuming soil has no magnetic permittivity (Davis and Chudobiak, 1975). It works remarkably well in coarse-textured soil since its relatively uniform structure is favorable for zero dielectric loss (Topp, 2003). However, in heavier-textured clay soil, the dielectric loss becomes appreciable as the clay percentage increases (White et al., 2006). As reviewed by (Whalley, 1993), the dielectric loss by magnetic permittivity in the fine-textured soil does influence the slope and intercept of the linear fit model representing the "universal" relation. This phenomenon was likely observed for high clay content sites in this study. The standard error (RMSE derived from comparison of sensor and gravimetric reading) is 0.038 $cm^3\ cm^{-3}$ in the soils with clay content < 25%, but increased to 0.079 $cm^3\ cm^{-3}$ for the soils with > 25% clay content. Though maybe not practical at all sites, site-specific calibration could be considered to obtain unique slope and intercept in order to increase soil moisture estimation accuracy for the sites with high clay content.

Despite the value of on-site sampling, several issues concerning sensor accuracy from the comparison between sensor reading and sampling must be considered. As discussed in the previous chapter, three replicates can only partly address the heterogeneity of soil at the site. Samples will never perfectly represent the condition of instrumented spots. A range of $\pm 0.035\ cm^3\ cm^{-3}$ in soil moisture content was observed between replicates from the same site.

Also, as pointed out by Illston et al.(2008), the sensitivity of these two techniques is varied. Although centered at 20 cm, the gravimetric technique is actually measuring the vertical average of soil moisture content from depth of 16.2 to 23.8 cm. However, the sensor is sensitive to the horizontal volume of soil surrounding the sensor centered at depth of 20 cm. Furthermore, both techniques have inherent error. Considering all these possibilities, the range of sensor accuracy could be somewhere between ± 0.03 and ± 0.10 cm^3 cm^{-3} (taking into consideration soil heterogeneity between replicates).

A field evaluation of TDR performance (also a dielectric probe) by Topp and Davis (1985) suggests RMSE between sensor and gravimetric values was ± 0.06 cm^3 cm^{-3} when measured locations were different but decreased to ± 0.02 cm^3 cm^{-3} when measured locations were the same. The results from a field calibration on Theta Probe sensor over a large region in Iowa (50×100 km) also correspond to our result (Cosh et al., 2005). In their study, a greater than ± 0.05 cm^3 cm^{-3} error was detected without field specific calibration; and field specific calibration reduced the error to less than ± 0.04 cm^3 cm^{-3}. Given these sampling issues and the typical range of RMSE values found in prior research, the approximately $\pm$ 0.06 cm^3 cm^{-3} accuracy of the soil moisture records from ECONet appears reasonable and acceptable.

3.4 Summary

Physically-based QA was used to assess the overall performance of soil moisture monitoring with NC ECONet. The two major areas considered in the QA procedure were missing data and range test failure. Among all 27 ECONet stations tested, the percentage for

station records per site passing QA examination differs, ranging from 67 to 100%. Seventeen of 27 stations had > 95% observations that were physically reasonable; four had 100% reasonable data. Further investigation of data recorded at seven problematic stations revealed that the rate of reasonable data collection increased after 2003, suggesting the superior performance of Theta Probe in soil moisture monitoring compared to ECHO sensor. The individual site-year examinations provide a guide to obtaining viable data from problematic stations by avoiding site-years with < 95% reasonable data instead of abandoning the entire dataset.

Comparison between field measurements of soil moisture content using the gravimetric technique and the ECONet readings indicated an estimated standard error of 0.06 cm cm^{-3} for the current ECONet soil moisture sensor, Theta Probe. We related sensor performance to soil conditions and found that soil moisture appeared more likely overestimated in dry conditions (soil moisture < 0.15 cm^3 cm^{-3}). High clay content also tended to lessen sensor accuracy. The bias averaged less than 0.05 cm^3 cm^{-3} in the soils with clay content from 0 to 25%, but increased with clay content as the clay content in soils increased above 25%.

We highly recommend periodical routine site visit to each ECONet station. The more often sensors are examined, the greater the opportunity to obtain a continuous record of high quality data. Real-time data quality will be much improved if soil moisture data accuracy assessment is conducted during each site visit. Another valuable approach is to develop specific calibration equation for individual soil, if operationally feasible. Instead of a

“universal” equation, the employment of soil-specific calibration will increase monitoring accuracy by decreasing the inherent bias between soil types.

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Table 3.1 Physical Bounds for Water Content Observations at ECONet Stations

Site ID	Porosity	Upper boundary	Air dried water content	Lower boundary
	$cm^3\ cm^{-3}$			
AURO	0.39	0.44	0.01	0
BUCK	0.59	0.64	0.01	0
CAST	0.47	0.52	0.01	0
CLA2	0.44	0.49	0.03	0
CLAY	0.47	0.52	0.03	0
CLIN	0.36	0.41	0.01	0
DURH	0.40	0.45	0.03	0
GOLD	0.48	0.53	0.01	0
HAML	0.56	0.61	0.01	0
HIGH	0.41	0.46	0.02	0
JACK	0.56	0.61	0.02	0
KINS	0.40	0.45	0.02	0
LAKE	0.46	0.51	0.03	0
LEWS	0.57	0.62	0.02	0
LILE	0.45	0.50	0.02	0
NCAT	0.44	0.49	0.01	0
OXFO	0.53	0.58	0.07	0
PLYM	0.50	0.55	0.04	0
REED	0.47	0.52	0.02	0
REID	0.38	0.43	0.04	0
ROCK	0.38	0.43	0.02	0
SALI	0.40	0.44	0.03	0
SILR	0.54	0.62	0.01	0
TAYI	0.43	0.48	0.01	0
WHIT	0.52	0.57	0.02	0
WILD	0.44	0.49	0.03	0
WILL	0.49	0.54	0.02	0

Table 3.2 Quality Assurance Results for 27 ECONet Stations

Site ID	First observation	Total obs.	Available years	Missing data	Range test failure	Reasonable data	Main problem
				%			
SILR	11/14/2000	3294	9	26	7	67	Missing data
REED	10/14/1998	4056	11	2	29	70	Fail range
REID	5/19/1999	3849	11	2	27	71	Fail range
SALI	9/17/1999	3718	10	0	23	77	Fail range
WILL	7/13/2000	3418	9	20	0	80	Missing data
DURH	3/3/2009	263	1	9	11	81	Fail range
NCAT	2/14/2006	1366	4	13	6	81	Missing data
CLAY	11/11/1999	3663	10	1	12	87	Fail range
HIGH	4/11/2002	2781	8	1	7	92	Fail range
AURO	9/14/2000	3355	9	0	7	93	Fail range
ROCK	12/8/1999	3636	10	4	0	96	N/A
BUCK	9/20/2006	1158	3	4	0	96	N/A
GOLD	4/5/2002	2787	8	1	3	97	N/A
OXFO	10/8/1999	3697	10	3	0	97	N/A
HAML	11/27/2007	725	2	3	0	97	N/A
CAST	8/25/1999	3741	10	1	2	97	N/A
JACK	10/4/1999	3601	10	3	0	97	N/A
CLIN	1/29/2000	3584	10	2	0	98	N/A
TAYI	11/6/2008	380	1	2	0	98	N/A
WILD	9/25/2008	422	1	1	0	99	N/A
LAKE	6/26/2001	3070	8	1	0	99	N/A
LILE	5/18/2007	918	3	1	0	99	N/A
KINS	5/2/2000	3440	9	1	0	99	N/A
CLA2	8/2/2003	2303	6	0	0	100	N/A
PLYM	11/19/2004	1818	5	0	0	100	N/A
WHIT	6/19/2001	3077	8	0	0	100	N/A
LEWS	11/21/1998	4018	11	0	0	100	N/A

Table 3.3 Site-year Examination for 10 Sites with < 95% reasonable data (shown in No. of failed observations)

	Year																					
	1999		2000		2001		2002		2003		2004		2005		2006		2007		2008		2009	
Site	M[a]	F[b]	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F	M	F
REED	0	35	0	35 2	0	36 1	1	27 1	35	95	44	0	0	0	0	0	0	0	0	0	0	0
DURH	N/A[c]		N/A		N/A		N/A		N/A		N/A		N/A		N/A		N/A		N/A		23	28
CLAY	N/A		11	69	3	15 9		12 6	75	27	4	0	0	0	0	0	0	0	0	0	0	0
WILL	N/A		N/A		14 6	0	36 5		15 8	0	0	0	0	0	0	0	0	0	0	0	0	0
HIGH	N/A		N/A		N/A		43	3	0	0	0	0	0	21	7	37	1	27	0	26	0	7
SALI	0	7	0	45	27 2	0	0	34 8	0	16 8	10	0	0	0	0	0	0	0	0	0	0	0
SILR	0	0	0	0	26 3	1	36 5	0	15 1	0	53	39	0	71	0	0	2	10	0	52	38	37
HAML	N/A		N/A		N/A		N/A		N/A		N/A		N/A		N/A		0	0	23	0	0	0
REID	39	0	0	17 6	24	32 9	0	36 5	1	15 0	9	0	0	0	0	0	0	0	0	0	13	0
AURO	N/A		0	16	13 1	0	91	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0

a missing data; c data not available; b fail boundary

Table 3.4 Site-year Examination for 10 Sites with < 95% reasonable Data (shown in percentage of reasonable observations)

	Year										
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Site	Reasonable data										
	%										
REED	90	4	1	25	64	88	100	100	100	100	100
DURH	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	84
CLAY	N/A	78	56	65	72	99	100	100	100	100	100
WILL	N/A	N/A	60	0	57	100	100	100	100	100	100
HIGH	N/A	N/A	N/A	87	100	100	94	88	92	93	98
SALI	98	88	25	5	54	97	100	100	100	100	100
SILR	N/A	100	28	0	59	75	81	100	97	86	77
HAML	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	100	94	100
REID	89	52	3	0	59	98	100	100	100	94	96
AURO	N/A	96	64	75	100	100	100	98	100	100	100

Table 3.5 Summary of Site-year Examination for 10 Sites failing to have 95% reasonable data

No. of stations with reasonable observations < 95%	10
Total site-year included	84
Site-year with reasonable observation <95 %	37

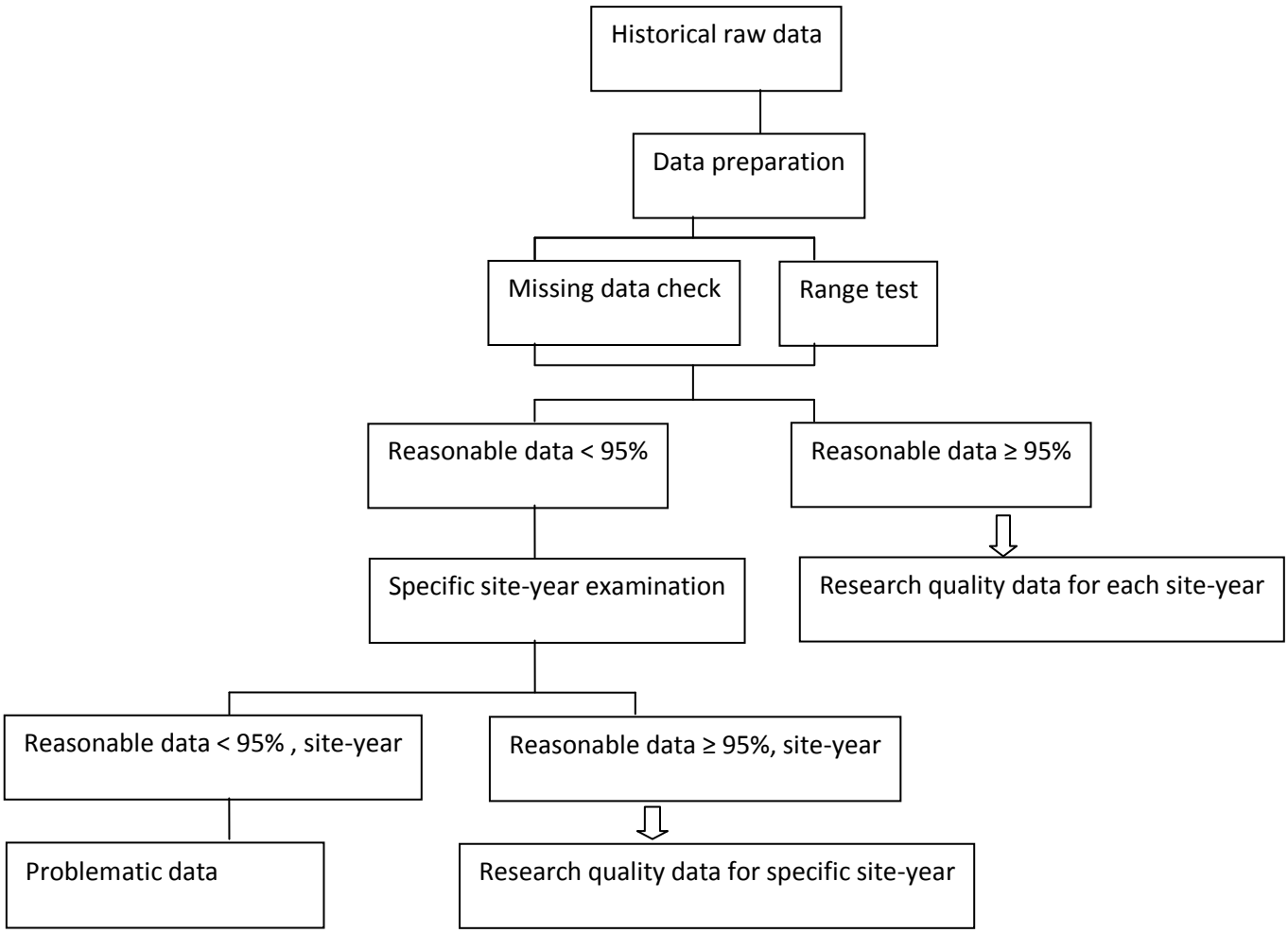

Figure 3.1 Flow Chart for Quality Assurance Procedures

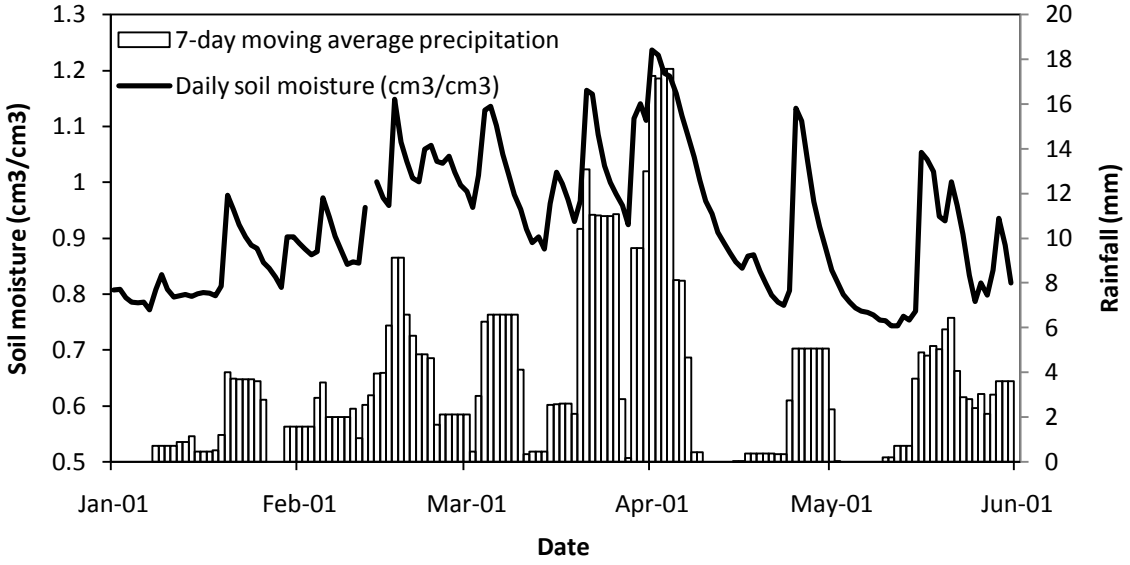

Figure 3.2 Time Series Sensed Daily Soil Moisture (with ECHO2 sensor) and Seven Day Average Precipitation at ECONet Site REED, January-June 2001.

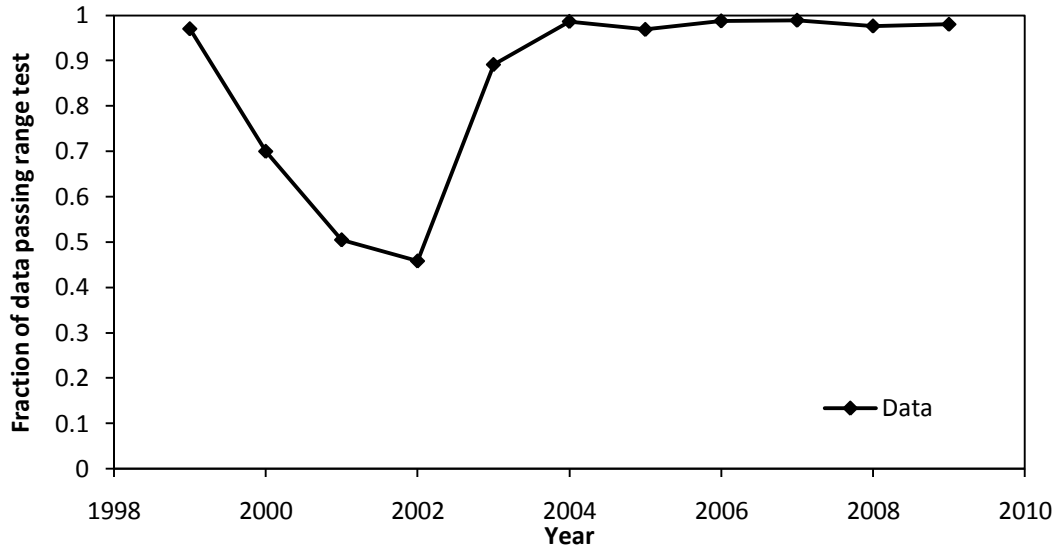

Figure 3.3 Observations Collected at 10 “problematic” ECONet Sites Passing the Range Test

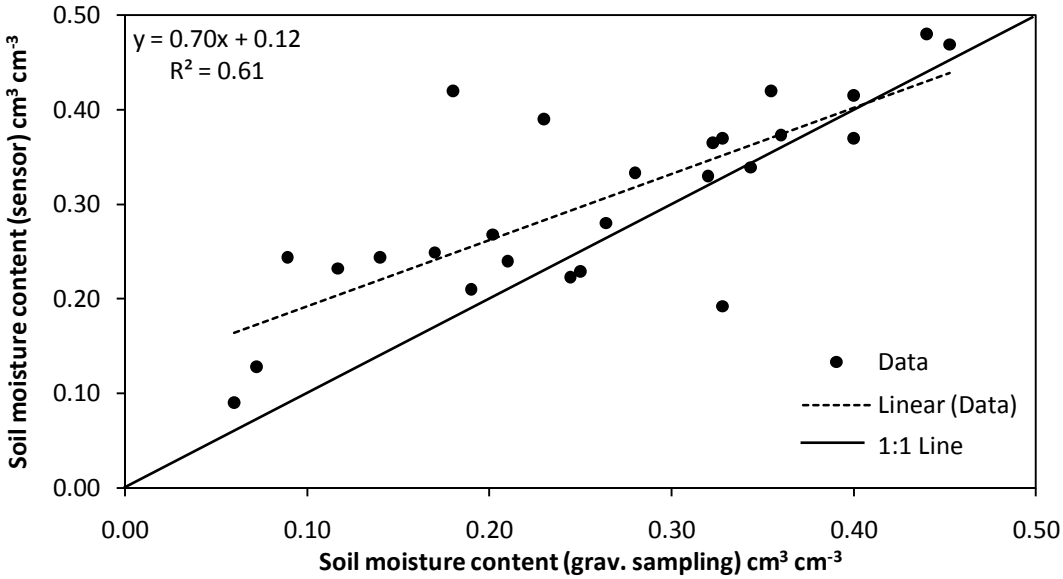

Figure 3.4 Water Content Measured with Field Samples vs. ECONet Water Contents. Points represent sampling at 26 different ECONet sites.

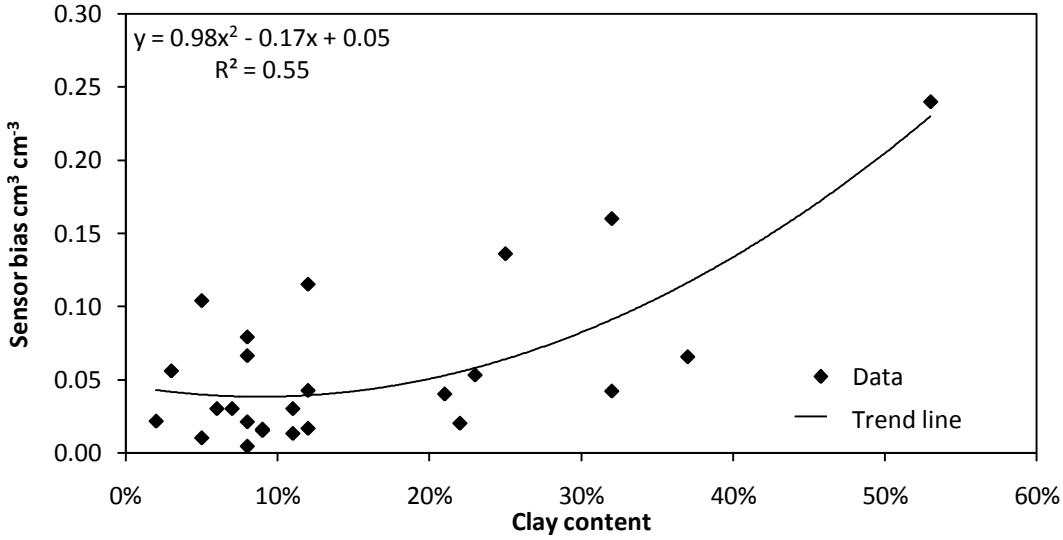

Figure 3.5 Correlation Between Clay Content and Overestimation of Sensor Readings, Sensor bias equals absolute difference between sensor measured and gravimetrically measured soil moisture content.

Chapter 4 Exploration of the Relationships of Soil Moisture to Soil Physical Properties

4.1 Introduction

Point observations of soil moisture in scattered ECONet stations may hold promise for creating regional soil moisture maps using geo-statistical methods, but the lack of density for these observations creates a challenge. One way to address this challenge is to use factors that influence soil moisture, mapped with spatial continuity or semi-continuity, to aid in interpolation. Soil moisture characteristics are influenced by soil properties, such as bulk density, texture, etc. (Cosby et al., 1984; Ghosh, 1980; Rawls et al., 1982). Thus, interpolating soil moisture conditions between sites likely requires knowledge of soil properties. However, high resolution sampling is not economically feasible for obtaining such information. An alternative way is utilize information contained in the SUURGO database, available through USDA NRCS. If relationships between known soil properties and soil moisture are significant, soil properties could be integrated into regional soil moisture map generation by, for example, co-kriging or kriging functions in GIS software (Stein et al., 1988). The basic question that must first be addressed is whether soil-map delineations are of value for explaining soil moisture patterns. So far little research has addressed this particular question.

Our intention in this chapter is to examine the possibility for developing regional soil moisture maps based on ECONet resources. Objectives were to 1) determine if there is significant variation between soil moisture content in groups categorized with taxonomic

soil-map delineations, 2) investigate the interrelationships among the soil physical properties which could influence soil moisture content, and 3) quantify the relationship between soil moisture content and soil physical parameters to determine which characteristics are most promising for use in soil moisture mapping. Our general approach was to use the soil information obtained in Chapter 2, together with the high quality soil moisture data periods identified in Chapter 3, to investigate the relationships of soil moisture content to the physical properties of soil. Our approach was also extended to use Soil Taxonomy. As pointed out by Smith and Forbes (1986) , the taxonomic category "soil family" was "intended to be useful for making major interpretations for agricultural and engineering purposes". Predictive research related to soil physical properties has been previously conducted based on family classification (Cosby et al., 1984; Heuscher et al., 2005). In this study, family-level and higher information was selected as classification criteria instead of soils series, since the later may be too detailed for practical purposes (Chapter 2).

4.2 Materials and Methods

4.2.1 Data

Soil samples used to generate the soil property dataset in this study were taken from 27 ECONet stations in the Piedmont and Coastal Plain regions of North Carolina (Chapter 2). At each station, intact soil cores were collected at the same depth as the ECONet soil moisture sensor (20 cm). For each site, the following data were available: 1) moisture retention determined at 10, 33, 66, 100, 500 and 1500kPa (hereafter P10, P33, P66, P100,

P500, P1500), 2) bulk density and air dried water content, 3) particle size distribution. Details on the methods used to collect these data are given in Chapter 2.

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. The average one-year precipitation across all sites was 98 cm, which was 25 cm lower than the 30-year normal (Figure A.1 in Appendix). 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 (Chapter 3), 21 stations provided a total of 7665 soil moisture 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. Statistical analysis was conducted to justify the separation of these intervals based on precipitation, PET, and soil moisture (described below).

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 4.1. 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.

4.2.2 Statistical Analysis for Seasonal Periods

Yearly and seasonal average soil moisture content at sampling sites was 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.

4.2.3 One-way Analysis of Variance

One-way analysis of variance (ANOVA) was performed for each taxonomic descriptor to determine if soil moisture content 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 soil moisture content 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 soil moisture variation. Further analysis was performed to determine if the variation in soil

moisture pattern could be better explained by the combination of two determined descriptors identified in the previous ANOVA test. For instance, results suggested soil moisture 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 soil moisture content attributed to each descriptor. Here, a combination of descriptor classes (Table 4.1) 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 soil moisture patterns in the studied area.

4.2.4 Principle Component Analysis

After ANOVA analysis, the results led to a question: could a descriptor or combination of descriptors account for most if not all the discernible patterns in soil moisture content variation? A principle component analysis (PCA) was used to assess overlaps in soil properties obtained from the sites in order to assess which information at a given site might be redundant. Since all the descriptors of classification were qualitative rather than numerical, we returned to the original dataset using measured physical parameters obtained from soil samples for this analysis. We needed to estimate the overlapping information about the soil physical parameters contained in the soil descriptors. For instance, one would expect that particle size distribution and wetness class are closely

related, and if a given parameter varied significantly over textural classes (e.g. clay and sand), it would be expected to vary also over wetness classes. Covariability of soil physical properties is expected to exist. It is quite possible that some physical parameters of soil, in linear or non-linear combination, are determinant to soil hydraulic properties. As an unsupervised method of multivariate statistics, PCA take into account the correlations among several variables that are simultaneously analyzed, thus allowing the extraction of better-summarized data. It achieves data reduction through orthogonal, uncorrelated, linear combinations of the original variables. The results could be weighted linear combinations of the hydraulic parameters defined as principle components (PCs). Previous to PCA, each variable was standard normalized to mean of zero and variance of one. The standard normalization was chosen to attribute an equal weight to each variable, since the variables have different natural scales. Kaiser-Meyer-Olkin (KMO) calculation and Bartlett's Test of Sphericity were performed to examine sampling adequacy. PCA was applied based on a correlation data matrix.

4.2.5 Multiple Linear Regression Model

The third stage of the analysis was an attempt to quantify the pattern of hydraulic properties of soil to provide a predictive relationship for soil moisture content. Forward stepwise (SPSS, 2000) multiple linear regression (MLR) analysis was performed using the means of daily soil moisture content 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 soil moisture content (in the sense of

the significance level for each parameter). In the preliminary test, 10 soil hydraulic 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.

4.2.6 Statistical Software

The ANOVA test and PCA were conducted with the Statistical Package for the Social Sciences (version 17 for Windows) (Nie et al., 1975). The MLR was conducted in Sigma Plot (Jandel Scientific, 2002).

4.3 Results and Discussion

4.3.1 Soil Moisture Pattern between Seasons

As shown in Table 4.2, daily precipitation, evapotranspiration and soil moisture are different between growing and non-growing season at the P=0.05 level. Most sampling sites are grass-covered. In North Carolina, the beginning of the grass-active period and dormancy occur in early May and late October, respectively. The emergence of vegetation coincides with the change in trend of precipitation from low to high with a background of an increasing temperature (Johnson et al., 2000). During the same period, there is an increase in average PET (5.51 compared to 10.91 mm). Although the precipitation was higher, enhanced evapotranspiration leads to a depletion of soil moisture compared to the non-growing season. These results are consistent with the general consensus that soil moisture is directly

influenced by rainfall and evapotranspiration (Eltahir, 1998; Priestley and Taylor, 1972). While these influences could not be detected in annual average data, it is clearly revealed by examination on seasonal variations. On the other hand, the investigations on seasonal soil moisture introduce influences other than soil properties for the interpolation of soil moisture behavior.

4.3.2 Analysis of Variance of Soil Moisture Content

Figure 4.1- Fig.4.3 and Table 4.3 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 4.1(number in parentheses). The height of each bar represents the F-ratio derived from the one-way ANOVA test for soil moisture content 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, soil moisture content varied (P=0.05) by single descriptors (wetness class and particle size) for each time interval (Table 4.3). 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. 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, it increases and differs largely between species in the growing season and thereby exerts different levels of control on retaining water in the soil (Zavaleta et al., 2003). Thus, the significance of soil properties for θ is lessened in the growing season.

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 yearly data). Because it provided the highest F ratio in all the cases, the largest difference for soil moisture behavior 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 soil moisture 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. The 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.

4.3.3 Principle Component Analysis

The soil physical parameters were generally linearly correlated; Table 4.4 is the correlation matrix, listing the correlation coefficients and significance level. Silt and PAW were eliminated from the correlations analysis because they are determined completely by the calculation of other measurements listed here. Bulk density and air dried water content were correlated somewhat less strongly or even not related to all the other variables. Bulk density was not related with other parameters, possibly because of its large variance originating from field sampling (Chapter 2). Data here indicated that bulk density increases with clay content, but not on a statistically significant level. The lack of a correlation between clay content on bulk density may explain why the literature on the relationship between clay and bulk density is not very conclusive. Williams (1970) found a negative relationship between bulk density and clay in arable soils and a positive relationship with soils under grass. Manrique and Jones (1991) concluded that the nature of the relationship between bulk density and clay content was different between soil orders: bulk density decreased with increasing clay content in Alfisols, Ultisols and Vertisols but was not influenced by clay content in Aridosols, Entisols, Inceptisols, Mollisols, Oxisols or Spodosols.Considering that most ECONet sites are covered by grass and their soils are highly varied, these prior observations are compatible with our observation of the lack of relationship between bulk density and clay content. 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). Air dried water content was

positiviely correlated with clay content, negatively correlated to sand content, and weakly correlated to the water content at -1500kPa, which is consistent with the common assumption that clay content increases the amount of water retained in soil. It 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). All the other prameters show fairly strong correlations, such as clay with P1500 (r=0.83); P33 with P66 (r=0.96). From Table 4.4, it is evident that all the variables were positively related expect for two exceptions. One is sand which was always negatively correlated with all the other parameters. Another expection was the negative correlation between bulk density and -10 kPa, which can be easily understood by the negative physical relationship between bulk density void space (macroporosity) for retaining water at low pressures.

The dataset yielded a KMO value of 0.778. Generally, KMO takes values between 0 and 1, with small values indicating that overall the variables have too little in common to warrant a PCA analysis. The value of 0.778 indicates that the degree of common variance among the 10 variables tested here is ranked "middling" and greater than the minimally accepted level of 0.7 (Pallant, 2004). Another indicator of the strength of the relationship among variables is Bartlett's test of sphericity (Pallant, 2004). It is used to test the null hypothesis that the variables in the population correlation matrix are uncorrelated. The observed significance level here was 0.000 which is small enough to reject the hypothesis. The result of KMO and Bartlett’s test of sphericity indicated the variables were suitable for a PCA.

In PCA, latent roots and vectors of the correlation matrix were extracted to reaveal clearer relations among the variables. The first three eigenvalues are listed in Table 4.5. The first principle component accounts for more than 59% of the variance, whereas the second and the third for only an additional 15% and 10%, respectively, which confirms the results of the above correlation analysis that all the variables are generally strongly correlated. In Table 4.6 , the configuration rotated by varimax of the first three principal components is reported with the correlation coefficients between the original variates and the principle components. The variables clay, sand, P33, P66, P100, P500, and P1500 appear closedly related, loading on the first principal components. The close correlation suggests soil texture may have a strong influence in determination of soil water retention characteristics. Bulk density and P10 are strongly correlated with the second principle component, but in opposed positions. Air-dried water content has the strongest association with the third principle component.

Score plots (Fig. 4.4) 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 their interelations through the cluster of points. If a variable is close to another, they will have high influence on each other. Conversely, if a variable is distant from another, the influence will be inverse. The projections onto the axes indicate their relative contributions for the corresponding components (Norušis, 1993). The score plot 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.4.4, it is noted that variables 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. Variable sand was distant from this cluster but negatively correlated ($P<0.05$) with all the variables in it. The strong negative correlation could be explained as sand is known as unfavorable for water storage. Bulk density and air dried water content are clearly separated from the cluster of points. They are considered as the two variables that account for the last two components, since no apparent correlation is found between them. As for physical meanings, bulk density (via its relationship to porosity) and air dried water content are representative of the maxium and minium limits of water content in the soil, respectively. Under field condition, soil moisture contents are not frequently at the maximum or minimum, thus the first PC might be considered as the most important function for soil moisture variation.

The results of PCA suggest that the different parameters, important in the first principle component, may essentially represents the same aspects in soil properties. For example, water contents under 1500kPa and 66kPa pressures are highly correlated (Table 4.4) and they could both be predicted by clay and sand content just as texturure depends on these variables. The different values for weight of each parameters in individual PCs indicates that a certain hydraulic property not only affects each parameter individually but is also affected by the dependence between parameters. The importance of PCA analysis will be further discussed in with the mutiple linear regression. To sum, PCA investigates the instrinsic connection between testing parameters but not their connection to soil moisture content.

Examining the dependence between parameters could improve study in the MLR by avoiding overlapping variables that would be included simutaneously.

4.3.4 Multiple Linear Regression Analysis

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 soil moisture content. The choice of MLR model here is intended to compare the importance of soil with other factors known to influence soil moisture content. We are concerned with exposing "robust" parameters in the data, but not the precision of the predictive equation.

The prelimary MLR model included 12 variables, precipitation, PET and 10 parameters representing measured soil physical properties (Table 4.7). After close examination of the importance for each variable in the initial MLR, it was reduced to its three most important variables with significant level at P = 0.10. After dropping the insignificant factors shown in the prelimary MLR model, the reduced MLR used to describe soil moisture (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 soil moisture. The P value for this model is <0.001 with an R^2 of 0.51.

Results shows a linear combination of independent variables PET (P = 0.002), P10 (P = 0.006), P1500 (P = 0.087) predicts soil moisture content. This suggests that soil moisture

content varied as a combined function of climate and soil properties. This is consistent with the findings by Robock et al. (1995) that soil moisture is controlled by interactions between atmospheric and land surface conditions and soil characteristics.

The 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 soil moisture from the fact that water is lost from soil by PET.

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 denied, although the variable "precipitation" is not significant as one of the three variables 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 soil moisture data. Soil moisture content could increase largely after a rainfall event, but the seasonal mean data used in the model smoothes the change following individual events.

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 4.6). However, as indicated by the correlation matrix P10 and P1500 are both highly dependent on clay and sand content

(P=0.01). Thus, the two parameters 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 soil moisture 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 soil moisture variation between stations on long-term basis. The finding that soil texture exerts control on soil moisture pattern is supported by much prior research with varied applications (Arya and Paris, 1981; Childs, 1969; Clapp and Hornberger, 1978). 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 of soil parameter 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).

4.4 Summary and Conclusions

In this chapter, our study focused on the relationship between soil properties and soil moisture content.. Qualitative descriptors from soil taxonomy were used to classify ECONet sites. Besides yearly data, seasonal data were also included since soil moisture conditions were different between growing and non-growing seasons. With descriptors from soil taxonomic family classification treated as one-way ANOVA factors, wetness class and particle size were significant categories for soil moisture variations (P=0.01 level) for both time periods. The influence from soil properties was greater in the non-growing season compared to the growing season, likely because in the non-growing season the vegetation influence was relatively negligible. Analysis simultaneously including the two significant factors only led to a slight change in F and P values, suggesting the information contained in particle size and wetness classification are probably correlated.

Returning to the original measured soil parameter dataset, high correlations were found between the 10 measured parameters. The PCA reduced the 10 parameters into three principle components that explained 85% of the variability with the data. We interpret the first component to represent soil water retaining function (closely related to soil texture), while the second and third components represent the upper boundary and lower boundary for soil moisture values under field conditions, respectively. There are parameters overlapping in each dimension judging from the component weights. Neither the weights of parameters, nor the correlations between parameters are the same in indivuial PCs.

Climate influences on soil moisture was included in MLR models. Even with precipitation and PET included, the significant influence of several soil properties was

clearly shown. The predictive equation was a linear combination of PET, P10 and P1500 that explained 51% of total variance in seasonal soil moisture. Precipitation was not highly significant in the model, likely because seasonal data were used. P10 and P1500 are not highly correlated in the principle component which is considered as the dimension most related to water retaining function. However, generally they are highly dependent to each other and both highly correlated to clay and sand content combined together as soil texture.

Results of this study suggest that it may be possible to use existing soil mapping delineations to develop regional soil moisture maps. In soil moisture interpolation between points observation, it would be advisable to distinguish major soil units rather than to treat the landscape as a whole with random observations points. Continued research is needed for integrating soil survey expertise into soil moisture interpolation. Variograms are highly desired as a quantitative analysis which relates spatial soil moisture variation to variation of soil physical properties. Results obtained here indicate that existing soil maps can be used for stratification purposes. However, as pointed by (Stein et al.(1988) , the variograms should be carried out on the basis of units containing at least 40 spatial points to ensure a reliable estimate. Thus, higher density of ECONet stations may be needed for developing soil moisture maps for North Carolina.

4.5 References

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Table 4.1 Site Descriptors and Classes for Each Descriptor Extracted from Family-level Classification. Descriptor classes are treated as categories in one-way ANOVA.

Descriptor	Classes
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), moderately 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)

The number in parentheses is the number of sampling sites in each classification. The classifications were available for all the sites expected for two sites designated with Udorthents. They are treated as “other” in every class. Only 21 stations with descriptors listed here were included in statistical analysis.

Table 4.2 Paired T tests on Seasonal Difference of Precipitation, PET and Soil Moisture Content. Data are daily records for corresponding parameters retrieved from ECONet stations. N=21. Different letters denote significant differences.

Season	Precipitation	PET	Soil moisture content
	mm	cm	cm^3cm^{-3}
Growing	3.11^a	10.97^a	0.26^a
Non-growing	2.26^b	5.51^b	0.31^b

Table 4.3 P-values from One-way ANOVA

	Sub order	Particle size	Wetness class	Particle size and wetness class
			P-value	
Year round	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

Table 4.4 Correlation Matrix (lower triangle) for Measured Physical Properties

	B.D	Clay	Sand	AD	- 10 kPa	- 33 kPa	- 66 kpa	- 100 kPa	- 500 kPa	- 1500 kPa
B.D	1.000									
Clay	0.047 ns	1.000								
Sand	-0.187 ns	-0.654***	1.000							
AD	0.018 ns	0.479***	-0.352**	1.000						
P10	-0.374**	0.536***	-0.498***	0.165 ns	1.000					
P33	0.240ns	0.674***	-0.705***	0.205 ns	0.502***	1.000				
P66	0.215 ns	0.645***	-0.724***	0.181 ns	0.467***	0.959***	1.000			
P100	0.465***	0.675***	-0.682***	0.287 ns	0.251 ns	0.797***	0.779***	1.000		
P500	0.280*	0.715***	-0.698***	0.048 ns	0.351**	0.728***	0.701***	0.820***	1.000	
P1500	0.263*	0.827***	-0.684***	0.223*	0.436**	0.834***	0.812***	0.852***	0.886***	1.000

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

Table 4.5 Eigenvalues of Correlation Matrix

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

Table 4.6 Correlations Between Original Variates and the First Three Principle Components. Values were muliplied by 100 and rounded to the nearest integer.

	Component		
	1	2	3
Variable	Component weights		
Bulk density	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

Table 4.7 MLR Results of PET, Precipitation and Soil Physical Properties on Soil Moisture Content. Overall MLR model: P value = 0.004, R2=0.51

Variable	Estimate	P-value
Intercept	0.08	0.57
PET	-0.03	0.02
Precipitation	-0.01	0.65
Porosity	-0.05	0.81
Clay	-0.13	0.59
Sand	-0.02	0.83
Air-dried water content	-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

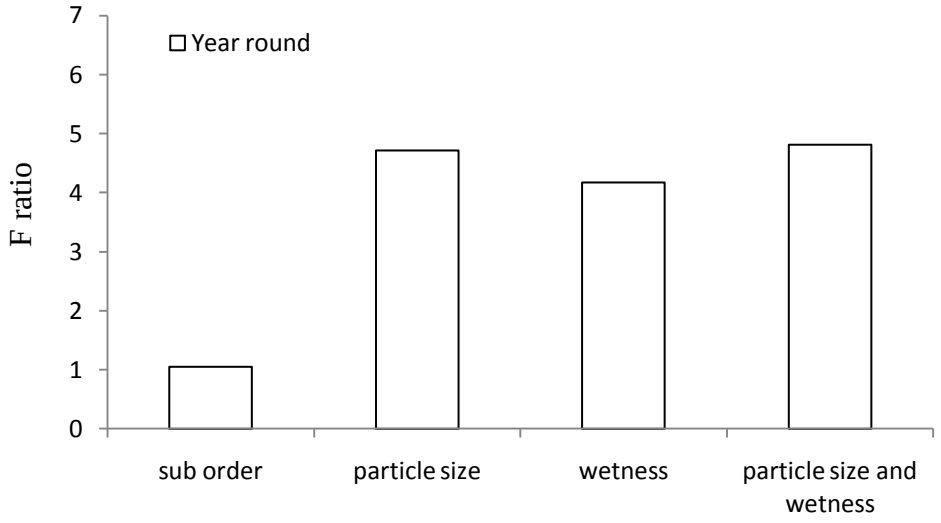


Figure 4.1 Values of the F ratio from One-way ANOVA with Yearly Data

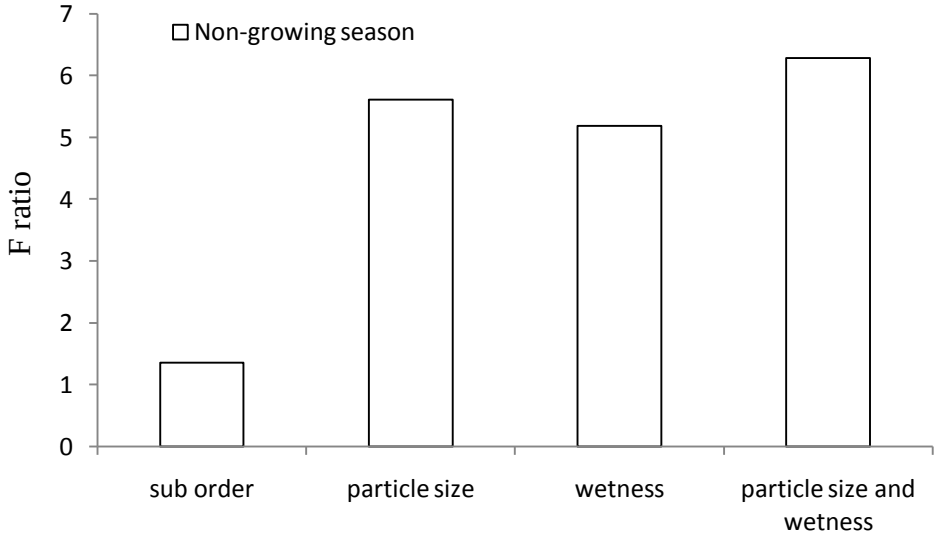


Figure 4.2 Values of the F ratio from One-way ANOVA with Non-growing season Data

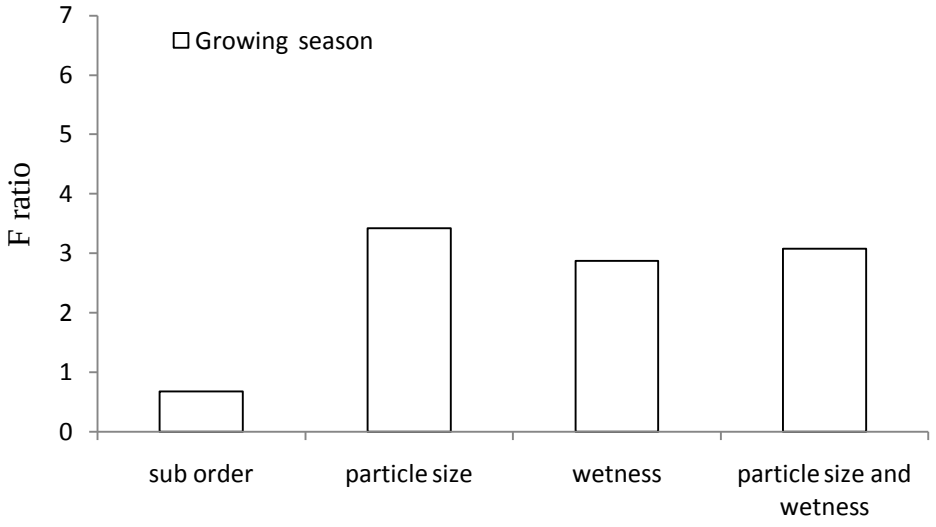
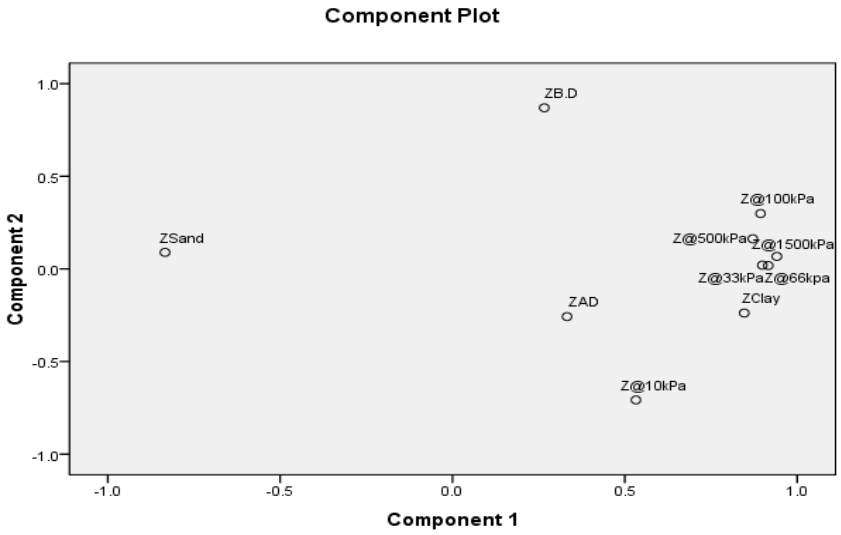


Figure 4.3 Values of the F ratio from One-way ANOVA with Growing-season Data



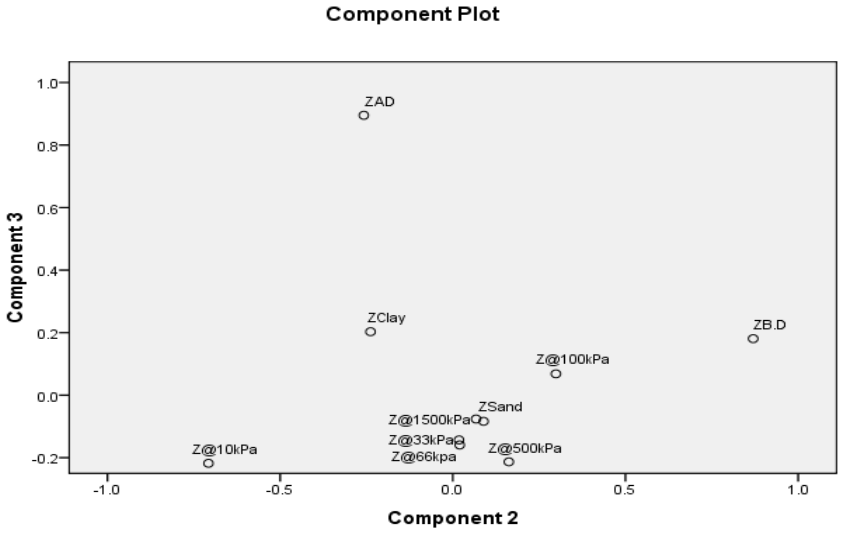


Figure 4.4 2-D Score Plots of the First Three Principle Components

Chapter 5 Summary and Thoughts for Future Study

5.1 Summary

In this study, a series of investigations related to soil moisture monitoring via the NC ECONet were performed. First, soil samples collected from 27 ECONet stations in the Piedmont and Coastal Plain were analyzed to generate a soil physical property dataset. Analysis of the dataset, with 11 physical parameters for each site, indicated that soil properties were highly variable. Particularly, properties which are considered to be closely related to soil hydraulic behavior exhibited strong locational differences. Soils from the 27 stations represented seven textural classifications, with porosities ranging from 0.36 to 0.58 $cm^3\ cm^{-3}$. When compared by physiographic region, five of 10 parameters exhibited significant differences between Piedmont and Coastal Plain sites.. These results imply highly diverse hydraulic behaviors amongst individual ECONet stations and between physiographic regions. The soil property dataset will be used to enhance ECONet metadata. We also propose that several new network products (i.e., plant available water and a saturation index) be developed based on the enhanced metadata.

Next, a quality assurance of historical soil moisture data documented in ECONet was conducted. The two major aspects considered in QA were missing data and observation range, with bounds set using measured soil properties. Among all 27 ECONet stations investigated, the percentage for station records per site passing QA examination differed, ranging from 67 to 100%. Only seven stations failed to pass QA at a rate > 95%. A large increase in the rate of data passing QA for these seven stations occurred in 2003 and after, suggesting the

superior performance of Theta Probe, installed at all sites after 2003, in soil moisture monitoring compared to the prior ECHO sensor. The individual site-year examinations provide a guide to obtaining viable data from problematic stations by avoiding site-years with problem data, instead of abandoning the entire dataset. Linear regression relating soil moisture content obtained from site sampling and the ECONet readings indicates an estimated standard error of 0.06 cm cm^{-3} for the Theta Probe. It was also noted that soil moisture appeared more likely to be overestimated in dry condition with a soil moisture value less than < 0.15 cm^3 cm^{-3}. We also observed a trend that sensor accuracy was lessened as clay content increased across sites. Based on these results, we recommend two approaches to maintain high quality data in ECONet soil moisture monitoring. First, routine site visits and prompt maintenance for each ECONet station are critical. Site sampling for soil moisture is highly recommended to be included during site visit. A second, valuable, though practically challenging approach is to develop specific calibration equations for individual sites. Soil-specific calibration should increase monitoring accuracy above the default 'universal' calibration.

Finally, knowledge of soil physical parameters also allowed us to investigate the relationship between soil properties and soil moisture content. With an ultimate goal of creating regional soil moisture maps from ECONet's point-based, on-site soil moisture monitoring network, our investigation focused on determining if soil survey information is of value to understand soil moisture differences between sites. Using seasonal soil moisture averages, results suggest soil moisture is likely to be influenced by two taxonomic classifications: wetness class and particle size. This suggests that existing soil mapping

delineations may provide information for soil moisture interpolation. Principle component analysis was used to assess overlaps in soil properties obtained from the ECONet sites in order to assess which information at a given site might be redundant for interpreting soil moisture behavior. Based on PCA, the 11 soil physical parameters were used to construct a three-component representation of the dataset. In the context of hydraulic properties, we interpreted the first component to represent soil water retaining function (closely related to soil texture), and the second and third components represent the upper boundary and lower boundary for soil moisture values under field conditions, respectively. Multiple linear regressions were used to derive quantitative expressions for the soil moisture content as a function of both climate and soil properties on a seasonal basis. The predictive equation was a linear combination of PET, P10 and P1500 that explained 51% of the total variance in seasonal soil moisture. Seasonal data adopted here lessened the influence of precipitation on soil moisture content. P10 and P1500 were not highly correlated in the first principle component, which we considered as the dimension most related to the water retaining function. However, generally these two parameters are analogous to the parameters clay and sand content, as revealed in PCA. This suggests soil texture (determined by clay and sand content) has the potential to be used for interpolating soil moisture content between individual stations, which was consistent with the analysis performed on taxonomic information (i.e. particle-size class).

5.2 Thoughts for Future Work

Besides PCA, an alternative way to study the correlation between soil physical parameters is cluster analysis. The PCA achieved dataset reduction by dividing soil physical

parameters into groups and creating new summarized dimensions. The challenge for PCA is that, we could only speculate on the context for each principle component. Cluster analysis could divide ECONet stations into groups based on the correlation between their soil physical parameters. The stations within the same clusters would have similar soil physical properties. An ANOVA test on soil moisture content could be conducted based on clusters, and if any significant difference is detected, we could draw a more confident conclusion that it is soil physical properties that affect soil moisture content. The reason we did not choose cluster in this study is that, a cluster-grouped classification (from preliminary hierarchical cluster) did not show any connection with existing soil survey classification (See Appendix). Although mean soil moisture content was different between clusters, the ANOVA test based on clusters did not have a P value as high as the ANOVA test based on soil taxonomic groups. Ideally, the combination of PCA and cluster may be the best way to investigate the soil physical property influence on soil moisture content, especially to identify the most important physical parameters.

The MLR model discussed here is not very predictive, only 51% variance was explained by the model. The seasonal data deployed here would not reflect the influence of rainfall events on soil moisture content. My suggestion would be to develop a model with data based on a shorter time interval (e.g. monthly data, even daily data). Alternative statistical technique would be included in the test for daily data, such as time series analysis. Another way to improve the productivity of the MLR would be to develop MLR models that consider of physiographic regions. Our study shows that soil physical properties exhibits differences (e.g. texture, saturated conductivity) in these two regions. A preliminary ANOVA

test revealed that soil moisture contents were significantly different between physiographic regions, while no significant differences were recognized in precipitation.

Results of this study suggest that it may be possible to use existing soil mapping delineations to develop regional soil moisture maps. However, for now there may be too little information to relate qualitative soil survey information to quantitative soil moisture content. Soil map delineation may be used to improve (co)kriging in soil moisture interpolation. Variograms are highly desired as a quantitative analysis which relates spatial soil moisture variation to variation of soil physical properties. The challenge is the number of points need for variograms is often more than 40. Thus, we may need to extend ECONet stations in order to develop soil moisture maps for North Carolina.

APPENDIX

Appendix A Supporting data

Table A.1 Full Name and Administrative Location of ECONet Stations Included the Study

Station	Name	City	County
AURO	Pamlico Aquaculture Field Lab	Aurora	Beaufort County
BUCK	Buckland Elementary	Buckland	Gates County
CAST	Horticultural Crops Res Stn	Castle Hayne	New Hanover County
CLA2	DAQ Clayton Profiler	Clayton	Johnston County
CLAY	Central Crops Research Station	Clayton	Johnston County
CLIN	Horticultural Crops Research Stn	Clinton	Sampson County
DURH	North Durham Water Reclamation Facility	Durham	Durham County
GOLD	Cherry Research Station	Goldsboro	Wayne County
HAML	Hamlet Tower	Hamlet	Richmond County
HIGH	UNCG - Lindale Farm Stn	High Point	Guilford County
JACK	Sandhills Research Station	Jackson Springs	Montgomery County
KINS	Cunningham Research Station	Kinston	Lenoir County
LAKE	Lake Wheeler Rd Field Lab	Raleigh	Wake County
LEWS	Peanut Belt Research Station	Lewiston	Bertie County
LILE	NC Electric Cooperative Anson Peaking Plant	Lilesville	Anson County
NCAT	NC A&T SU Research Farm	Greensboro	Guilford County
OXFO	Oxford Tobacco Research Stn	Oxford	Granville County
PLYM	Tidewater Research Station	Plymouth	Washington County
REED	Reedy Creek Field Laboratory	Raleigh	Wake County

Table A.1 Continued Full Name and Administrative Location of ECONet Stations Included the Study

Station	Name	City	County
REID	Upper Piedmont Research Stn	Reidsville	Rockingham County
ROCK	Upper Coastal Plain Res Stn	Rocky Mount	Edgecombe County
SALI	Piedmont Research Station	Salisbury	Rowan County
SILR	Siler City Airport	Siler City	Chatham County
TAYL	Taylorsville Tower	Taylorsville	Alexander County
WHIT	Border Belt Tobacco Res Stn	Whiteville	Columbus County
WILD	Williamsdale Field Lab	Wallace	Duplin County
WILL	Highway Patrol Comm. Station	Williamston	Martin County

Table A.2 Geographic Location of ECONet Stations Included in the Study

Station	Latitude	Longitude	Elevation	Climate Division Name
	degree		m	
AURO	35.36232	-76.7163	4	Central Coastal Plain
BUCK	36.46955	-76.7609	25	Northern Coastal Plain
CAST	34.32107	-77.9161	43	Southern Coastal Plain
CLA2	35.59158	-78.4589	250	Central Coastal Plain
CLAY	35.66979	-78.4926	350	Central Coastal Plain
CLIN	35.02218	-78.282	166	Southern Coastal Plain
DURH	36.02896	-78.8585	332	N/A
GOLD	35.37935	-78.0448	79	Central Coastal Plain
HAML	34.84207	-79.7384	336	Southern Piedmont
HIGH	35.99	-79.97	910	Northern Piedmont
JACK	35.18782	-79.6844	625	Southern Piedmont
KINS	35.30288	-77.5731	95	Central Coastal Plain
LAKE	35.72816	-78.6798	382	Central Piedmont
LEWS	36.1324	-77.1755	61	Northern Coastal Plain
LILE	34.97043	-79.9177	456	Southern Piedmont
NCAT	36.06733	-79.7345	792	Northern Piedmont
OXFO	36.30339	-78.6166	500	Northern Piedmont
PLYM	35.84887	-76.6506	20	Northern Coastal Plain
REED	35.80712	-78.7441	420	Central Piedmont

Table A.2 Continued Geographic Location of ECONet Stations Included in the Study

Station	Latitude	Longitude	Elevation	Climate Division Name
	degree		m	
REID	36.38152	-79.6998	858	Northern Piedmont
ROCK	35.89295	-77.68	88	Northern Coastal Plain
SALI	35.69744	-80.6219	703	Central Piedmont
SILR	35.7043056	-79.5042	614	Central Piedmont
TAYL	35.9139	-81.1909	1167	Central Piedmont
WHIT	34.41347	-78.7923	89	Southern Coastal Plain
WILD	34.7658	-78.1012	56	Southern Coastal Plain
WILL	35.83903	-77.0935	72	Northern Coastal Plain

Table A.3 Particle Size Distribution and Texture Classification at ECONet Stations

Station	clay	sand	silt	texture
	%	%	%	
AURO	11	48	41	sandy loam
BUCK	8	58	34	sandy loam
CAST	8	76	16	loamy sand
CLA2	11	75	14	sandy loam
CLAY	9	79	12	loamy sand
CLIN	8	68	24	sandy loam
DURH	21	59	20	sandy clay loam
GOLD	5	80	15	loamy sand
HAML	6	88	6	sand
HIGH	12	52	36	loam
JACK	3	90	7	sand
KINS	23	57	20	sandy clay loam
LAKE	7	80	13	loamy sand
LEWS	2	82	16	loamy sand
LILE	9	76	15	sandy loam
NCAT	17	37	46	loam
OXFO	53	24	23	clay
PLYM	22	46	32	loam
REED	32	52	16	sandy loam

Table A.3 Continued Particle Size Distribution and Texture Classification at ECONet Stations

Station	Clay	Sand	Silt	Texture
	%	%	%	%
REID	25	67	8	sandy clay loam
ROCK	12	60	28	sandy loam
SALI	12	43	45	loam
SILR	37	52	11	sandy clay
TAYL	32	64	4	sandy clay loam
WHIT	8	43	49	sandy loam
WILD	5	68	27	loamy sand
WILL	2	88	10	sand

Table A.4 Dataset of Soil Physical Properties at 27 ECONet Stations

Station	f	ρ_b	A.D	Ksat	P10	P33	P66	P100	P500	P1500
	cm^3/cm^3	g/cm^3	cm^3/cm^3	cm/hr	cm^3/cm^3					
AURO	0.39	1.61	0.01	3.20	0.36	0.33	0.30	0.19	0.11	0.09
BUCK	0.59	1.10	0.01	4.95	0.4	0.23	0.19	0.12	0.1	0.08
CAST	0.47	1.42	0.01	6.78	0.32	0.24	0.23	0.15	0.09	0.08
CLA2	0.44	1.48	0.03	5.13	0.31	0.26	0.24	0.20	0.10	0.07
CLAY	0.47	1.40	0.03	5.78	0.38	0.32	0.21	0.18	0.13	0.09
CLIN	0.36	1.69	0.01	7.60	0.36	0.19	0.15	0.14	0.13	0.07
DURH	0.40	1.59	0.03	8.95	0.34	0.32	0.26	0.27	0.16	0.13
GOLD	0.48	1.38	0.01	3.86	0.36	0.18	0.15	0.16	0.09	0.06
HAML	0.56	1.17	0.01	10.18	0.33	0.20	0.18	0.12	0.11	0.06
HIGH	0.41	1.56	0.02	3.48	0.35	0.34	0.33	0.26	0.16	0.10
JACK	0.56	1.17	0.02	11.40	0.29	0.16	0.14	0.07	0.06	0.04
KINS	0.40	1.59	0.02	3.20	0.39	0.38	0.38	0.27	0.19	0.15
LAKE	0.46	1.43	0.03	5.03	0.33	0.25	0.18	0.20	0.11	0.07
LEWS	0.57	1.13	0.02	2.01	0.45	0.14	0.12	0.12	0.06	0.04
LILE	0.45	1.47	0.02	8.03	0.38	0.21	0.14	0.14	0.13	0.08
NCAT	0.44	1.48	0.01	4.65	0.39	0.39	0.39	0.28	0.26	0.19
OXFO	0.53	1.25	0.07	6.63	0.48	0.36	0.35	0.24	0.18	0.16
PLYM	0.50	1.33	0.04	11.57	0.36	0.32	0.31	0.25	0.17	0.12
REED	0.47	1.40	0.02	5.93	0.40	0.34	0.27	0.27	0.21	0.15
REID	0.38	1.63	0.04	0.84	0.32	0.29	0.27	0.24	0.17	0.16

Table A.4 Continued Dataset of Soil Physical Properties at 27 ECONet Stations

Station	f	ρ_b	A.D	Ksat	P10	P33	P66	P100	P500	P1500
	cm^3/cm^3	g/cm^3	cm^3/cm^3	cm/hr	cm^3/cm^3					
ROCK	0.38	1.64	0.02	4.99	0.28	0.22	0.20	0.20	0.18	0.08
SALI	0.40	1.59	0.03	4.37	0.38	0.36	0.36	0.24	0.15	0.11
SILR	0.54	1.22	0.01	3.35	0.50	0.50	0.48	0.25	0.23	0.17
TAYL	0.43	1.51	0.01	0.48	0.36	0.35	0.33	0.28	0.24	0.18
WHIT	0.52	1.28	0.02	1.84	0.38	0.28	0.26	0.21	0.19	0.09
WILD	0.44	1.48	0.03	2.84	0.37	0.37	0.37	0.20	0.09	0.10
WILL	0.49	1.34	0.02	14.10	0.32	0.13	0.13	0.17	0.08	0.06

Table A.5 Seasonal Average Value of Soil Moisture Content, PET and Precipitation from ECONet Stations Records

Site	Season [a]	PET	Average daily θ	Precipitation
AURO	growing	4.04	0.28	2.29
BUCK	growing	4.20	0.37	2.54
CAST	growing	4.08	0.26	4.32
CLA2	growing	4.25	0.20	3.81
CLAY	growing	4.32	0.24	2.79
CLIN	growing	4.33	0.24	3.81
GOLD	growing	4.50	0.33	3.43
HAML	growing	4.78	0.12	4.57
HIGH	growing	4.01	0.27	2.03
JACK	growing	4.59	0.13	3.05
KINS	growing	4.49	0.19	3.05
LAKE	growing	4.50	0.21	2.79
LEWS	growing	4.23	0.26	2.79
LILE	growing	4.49	0.32	1.27
NCAT	growing	4.28	0.41	3.05
OXFO	growing	4.21	0.31	3.05
PLYM	growing	4.64	0.19	1.78
REED	growing	4.17	0.32	4.57
SILR	growing	4.43	0.32	4.57
WHIT	growing	4.19	0.27	3.81
WILL	growing	4.04	0.21	2.03

Table A.5 Continued Seasonal Average Value of Soil Moisture Content, PET and Precipitation from ECONet Stations Records

Site	Season [a]	PET	Average daily θ	Precipitation
AURO	non-growing	2.04	0.34	2.03
BUCK	non-growing	2.01	0.48	2.54
CAST	non-growing	2.17	0.32	1.52
CLA2	non-growing	2.00	0.24	3.05
CLAY	non-growing	2.23	0.34	2.03
CLIN	non-growing	2.24	0.27	2.29
GOLD	non-growing	2.30	0.36	2.29
HAML	non-growing	2.39	0.14	2.54
HIGH	non-growing	1.87	0.36	2.29
JACK	non-growing	2.35	0.14	2.29
KINS	non-growing	2.33	0.28	2.03
LAKE	non-growing	2.33	0.25	2.29
LEWS	non-growing	2.07	0.26	2.54
LILE	non-growing	2.34	0.40	1.78
NCAT	non-growing	2.16	0.42	2.29
OXFO	non-growing	2.05	0.42	2.29
PLYM	non-growing	2.39	0.23	2.03
REED	non-growing	2.13	0.39	3.05
SILR	non-growing	2.08	0.43	2.29
WHIT	non-growing	2.11	0.29	2.29
WILL	non-growing	1.92	0.25	1.78

a, Growing season from May, 2008 to October, 2008 and Non-growing season from November 2008 to April, 2009

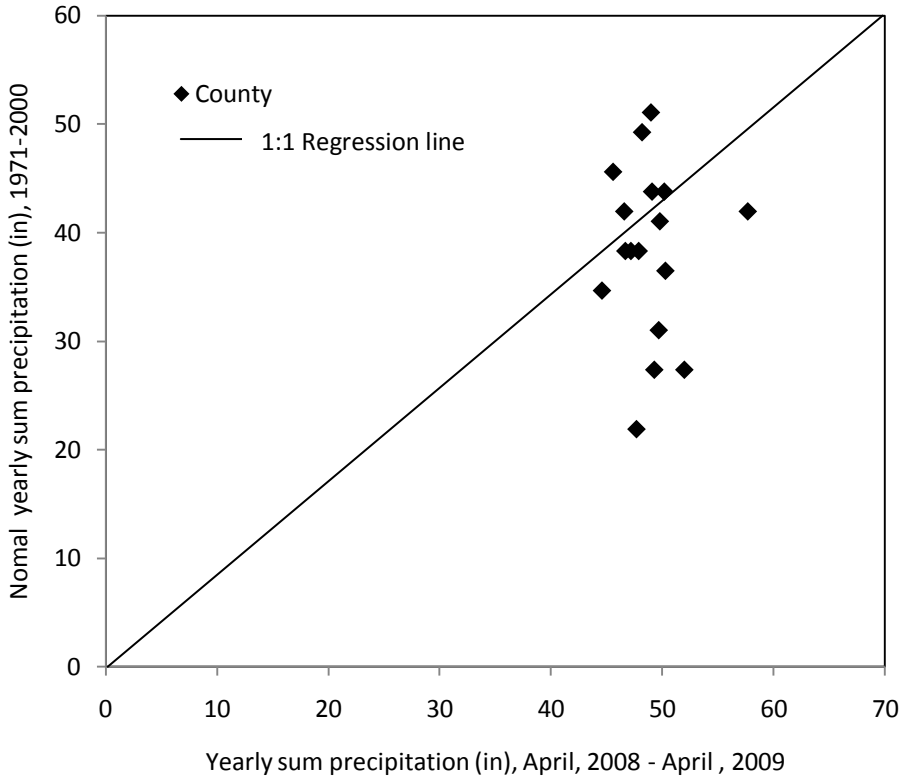


Figure A.1 Sum Precipitation in Tested Period Compared to 30 Years Normal

Appendix B Cluster Analysis

Station physical parameters (Table A.3 and Table A.4) were used in the cluster analysis to group ECONet stations according to their similarity in soil properties. We used agglomerative hierarchical clustering and Ward's minimum variance method (Ward, 1963). The method minimizes the difference within clusters while maximizing the differences between clusters. We chose Ward's method as it is less susceptible to chaining, where stations tend to be added to a cluster rather than forming a new group (SAS Institute, Inc,2003).Cluster membership and dendrogram resulted from cluster analysis was shown as Table B.1 and Figure. B.1. This cluster analysis was conducted with SPSS (Norusis, 1993). The reasons that we did not employ ECONet grouping by cluster analyses were:

1) There was no significant difference of soil moisture content between groups from cluster analysis as indicated by ANOVA test.
2) These groups have limited application compared to groups determined by soil taxonomy (see discussion in Chapter 4).

References:

SAS Institute, Inc., 2003. Statistical Analysis Software, version 9.1.3. SAS Institute Inc.,Cary, NC.

Ward, J.H., 1963. Hierarchical groupings to optimize an objective function. Journal of the American Statistical Association 58, 236 – 244.

Norusis, M. 1993. SPSS for Windows: advanced statistics SPSS Chicago, IL.

Table B.1 Cluster Membership of 27 ECONet Stations

Case	8 Clusters	7 Clusters	6 Clusters	5 Clusters	4 Clusters	3 Clusters	2 Clusters
1:AURO	1	1	1	1	1	1	1
2:BUCK	2	2	2	2	2	2	2
3:CAST	3	3	3	3	2	2	2
4:CLA2	4	4	3	3	2	2	2
5:CLAY	4	4	3	3	2	2	2
6:CLIN	3	3	3	3	2	2	2
7:DURH	5	1	1	1	1	1	1
8:GOLD	3	3	3	3	2	2	2
9:HAML	2	2	2	2	2	2	2
10:HIGH	1	1	1	1	1	1	1
11:JACK	2	2	2	2	2	2	2
12:KINS	6	5	4	4	3	3	1
13:LAKE	4	4	3	3	2	2	2
14:LEWS	2	2	2	2	2	2	2
15:LILE	3	3	3	3	2	2	2
16:NCAT	6	5	4	4	3	3	1
17:OXFO	7	6	5	5	4	3	1
18:PLYM	1	1	1	1	1	1	1
19:REED	6	5	4	4	3	3	1
20:REID	5	1	1	1	1	1	1
21:ROCK	4	4	3	3	2	2	2
22:SALI	1	1	1	1	1	1	1
23:SILR	8	7	6	4	3	3	1
24:TAYI	6	5	4	4	3	3	1
25:WHIT	1	1	1	1	1	1	1
26:WILD	1	1	1	1	1	1	1
27:WILL	3	3	3	3	2	2	2

```
                    Rescaled Distance Cluster Combine

 C A S E    0         5        10        15        20        25
Label  Num  +---------+---------+---------+---------+---------+

CLA2     4   -+
LAKE    13   -+
CLAY     5   -+-+
ROCK    21   -+ +---+
CLIN     6   -+ |   |
LILE    15   -+-+   |
GOLD     8   -+     +----------------------------------------+
WILL    27   -+     |                                        |
CAST     3   -+     |                                        |
HAML     9   -+-+   |                                        |
JACK    11   -+ +---+                                        |
BUCK     2   -+-+                                            |
LEWS    14   -+                                              |
DURH     7   -+-+                                            |
REID    20   -+ |                                            |
PLYM    18   -+-+---------+                                  |
WHIT    25   -+ |         |                                  |
HIGH    10   -+ |         |                                  |
SALI    22   -+ |         |                                  |
AURO     1   -+-+         |                                  |
WILD    26   -+           +----------------------------------+
REED    19   -+           |
TAYI    24   -+           |
KINS    12   -+---+       |
NCAT    16   -+   +-----+ |
SILR    23   -----+     +-+
OXFO    17   -----------+
```

Figure B.1 Hierarchical Cluster Analysis Dendrogram using Ward Method