

COMPLEX LANDSCAPE ANALYSIS FOR SATELLITE AND FIELD
ESTIMATIONS OF SOIL MOISTURE

by

MARIO A. GIRALDO

(Under the direction of Marguerite Madden)

ABSTRACT

Landscape assessment of soil moisture content is critical in understanding the hydrological cycle at the regional scale. In the hydrological cycle, soil moisture, is the amount of water present within the soil profile. Developing a global soil moisture observing system is of critical importance to the long term monitoring of the water cycle, in areas such as hydrology, climatology, ecology, agriculture, among others.

In this research, landscape complexity caused by soil and landuse classes and their relationships with the spatial and temporal variation of soil moisture and ground temperature are analyzed within areas equivalents to the pixel sizes of four environmental satellites. Under the principle that landscape fragments are spatial units in which biophysical factors interact, this research builds in the concept that the integration of remote sensing, hydrology, geostatistics, GIScience and landscape ecology is a valid methodological approach to explore the relationships between fragments and process expanding the inferential capabilities of remote sensing research in complex landscapes.

Throughout a GIS- remote sensing analysis of fragmentation I investigate the contribution of soil and landuse classes to landscape complexity as a way to understand the environmental factors influencing the soil moisture point readings of the *in situ* network at the Little River Watershed (LRW) south Georgia US. Also through a year

long field data collection, I established the spatial and temporal variation of soil moisture and ground temperature within and among adjacent homogeneous fields and five landuses (orchard, peanuts, cotton, grass and bare land) to the stations of the *in situ* network at the LRW.

The most important results include: 1. Criteria to define the appropriate pixel sizes of a satellite instrument to capture homogeneous expressions of soil moisture or ground temperature at the LRW. 2. Understanding the contribution to landscape and local complexity added by soil and landuse classes and their weight in point readings. 3. The assessment of soil moisture responds by different soils and land cover combinations. 4. The study of temporal stability of soil moisture in homogeneous fields matching the size of a Landsat TM pixel size. 5. The correlation between point readings and adjacent homogeneous fields under different landuses. 6. The assessment of temporal and spatial variation of soil moisture and ground temperature within and among homogeneous fields matching the size of a Landsat TM pixel size at the LRW.

Overall, this research contribute to satellite study of the water cycle by proposing a landscape ecology–hydrology approach to the problems of remote sensing of soil moisture and interpolation of soil moisture-soil temperature point reading within complex landscapes. This work contributes to the knowledge of the variation of biophysical variables for the remote sensing study of energy fluxes and the water cycle within complex landscapes.

INDEX WORDS: Soil moisture, remote sensing, landscape ecology, complexity, water

COMPLEX LANDSCAPE ANALYSIS FOR SATELLITE AND FIELD
ESTIMATIONS OF SOIL WATER CONTENT

by

MARIO ANDRES GIRALDO

Agricultural Engineer, Universidad de Caldas, Colombia, 1996

M.Sc., University of Georgia, 2003

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial
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MARIO ANDRES GIRALDO

Major Professor:	Marguerite Madden
Committee:	David Bosch Andrew J. Grundstein Thomas L. Mote Adrian W. Thomas

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
August 2007

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CHAPTER 1
INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

In the hydrological cycle, soil moisture is the amount of water present within the soil profile. Landscape assessment of soil moisture content is critical to understanding the hydrological cycle at the regional scale and in broad-scale studies of biophysical processes affected by global climate changes in temperature and precipitation. Therefore developing a global soil moisture observing system is of critical importance to the advancement of the knowledge of the water cycle in areas such hydrology, climatology, ecology, agriculture, and others (Njoku 2004) influencing global food, agriculture, and natural resources. Strong evidence supports the investigation of land-atmosphere water exchanges since soil moisture is believed to control important regional environmental conditions such summer precipitation over the US and other large mid-latitude continental regions (Bosch *et al.* 2005) and also it is essential in local processes such water resource management (Greiner, 1999), irrigation scheduling (Montesinos *et al.* 2001), crop production (Dardanelli *et al.* 2004), nutrient loss and landuse changes (Klinge *et al.* 2001), water chemical monitoring (Heathman *et al.* 2003), water transformations within the hydrological cycle (Satti and Jacobs 2004), and prediction of hydrological disasters such as floods and droughts (Park *et al.* 2004).

The use of satellite and field data to investigate soil moisture is a developing process challenged by the landscape complexity present in most terrestrial ecosystems. Landscapes are complex systems formed by spatial units in which biophysical factors fluctuate according to soil and landuse characteristics. Within a landscape patch or fragment, the combined precipitation, climate, vegetation cover, soil and terrain are responsible of the soil moisture at that location. If each of those variables presents uniform characteristics at the point reading location, that site becomes a good indicator of

the underlying process operating in a homogeneous portion of the landscape (Cosh *et al.* 2004). On the other hand, if point observations are taken from areas where two or more categories of the environmental factors converge, generalizations from that point reading become more challenging. In this research a multidisciplinary approach is used to expand the inferential capabilities of remote sensing data and point field readings to explore the relationships between spatial areas (fragments) and soil moisture (process) in a complex landscape.

At the Little River Watershed (LRW) in south Georgia, an *in situ* network of 29 ground stations was established in 2002 and 2003 by the Soil Moisture Experiment (SMEX) as a source of field point data for long-term hydrological studies in the agriculture landscape of the southeastern United States (figure 1.1a). Since its creation, researchers at the United States Department of Agriculture-Agriculture Research Service (USDA-ARS) have been interested in using the point readings of the stations to infer the soil moisture and environmental variables at the landscape scale in order to validate remote sensing data for environmental studies. Despite the abundant scientific literature showing progress in modeling soil moisture and understanding its controlling environmental factors at the point level (Hack-ten Broeke and Hegmans 1995, Heathman *et al.* 2003), landscape complexity challenges the generalization of point observations to broad heterogeneous areas (Kustas *et al.* 2003, Choi and Jacobs 2006).

Observations at the LRW reveal a complex landscape where environmental variables influencing soil moisture may change over small spatial areas (Cashion *et al.* 2004). In fact, the sites of the LRW network are located in an area greater than 2500 km² in a diversified landscape with a mix of land uses land covers (LULC), low elevation hills and a variety of soil types (Bosch *et al.* 2005), where the heterogeneity caused by spatial

variations of LULC and soil types has not yet been characterized (figure 1.1.b, c and d). Despite the fact that continuous readings are recorded from the network sites at the LRW, no research has investigated either the relationship between the point readings and the surrounding landscape, or the combination of environmental factors affecting soil moisture at the recording station. This knowledge is critical to advancing the understanding of underlying processes that regulate soil moisture before point data can be linked to the environmental conditions for an accurate interpolation to the landscape scale of the *in situ* soil moisture (Crow *et al.* 2005).

From the remote sensing perspective, previous research conducted by Bosch *et al.* (2005) in the LRW, and by Kustas *et al.* (2004), McCabe and Wood (2006) in other regions, suggest that landscape complexity is critical in selecting the appropriate remote sensing data since sensors with large pixel sizes may be unsuitable for characterizing local variations under highly heterogeneous landscapes (Kustas and Norman 2000, Anderson *et al.* 2004). Data validation through matching a pixel's reflectance value with a representative field point reading is desirable for linkage to a particular soil moisture response and minimizing uncertainty created by mixed LULC, soil or terrain characteristics (Merlin *et al.* 2006). The broad spectrum of pixel sizes among sensors commonly used for soil moisture analysis creates a need to investigate the size of the ground area that the point data can adequately represent, as well as the assessment of the homogeneity within different sample areas of different sizes centered at the point reading site location. Neither of these studies has been previously conducted at the LRW.



Figure 1.1. LRW: (a) reading station, (b) landscape fragments, (c) grazing area, (d) agriculture field

Previous studies of remote sensing of soil moisture have used surrogate variables to indirectly assess soil water status. Methodologies have been presented using variables that depend upon the soil and vegetation characteristics such as surface radiant temperature (TIR) (Park *et al.* 2004), microwave brightness temperature and combination of surface temperature and vegetation indexes (Carlson *et al.* 1995, Merlin *et al.* 2006). However, at the LRW no study has thus far evaluated the spatial variation of surface and radiant temperature in areas equivalent to the small footprints of satellite data, neither its correlation with soil moisture reading from the sites or with surrounding LULC fragments.

1.2. Background

Distributed surface soil moisture models that accurately portray the soil water status at the landscape scale are of paramount importance. Current models employ two general approaches: 1) the investigation of the partition of rainfall into infiltration and runoff (Schmugge *et al.* 2002) and; 2) the partition of the earth's surface energy into latent heat and sensible heat (Bastiaanssen *et al.* 1998). Unfortunately at present, measurements of distributed surface soil moisture over broad areas are limited. The use of remote sensing technology for landscape and regional scale monitoring of soil moisture is still in the developing stages and the majority of hydrologic monitoring is based on point data from ground based networks. With increased availability of remotely sensed image data from satellite and airborne platforms and wide distribution of digital data via internet clearinghouses, research efforts have been concentrated on finding appropriate ways to generalize field readings from point locations to larger areas and to optimize remote sensing technology for soil moisture quantification.

1.2.1. Point data interpolation. Three different methodologies have been traditionally used to study soil moisture using point data: hydrological modeling (Crow *et al.* 2005), direct interpolation using geostatistical analysis (Grayson and Western 1998), and indirect estimation from correlated environmental processes (Qiu *et al.* 2003). These three methods will be addressed separately.

a. Hydrological modeling.

In hydrological modeling, point data have been used to describe the process of water movement through the soil profile (infiltration) into the deepest layers of the ground (percolation). These processes are regulated by site specific characteristics such as vegetation cover, topography, soil layers, layers depth and water table, and by the hydraulic properties of the soil defined by soil variables such as soil texture as an expression of sand, silt and clay content; bulk density; saturated and unsaturated hydraulic conductivity; water release curve and matric pressure.

Water infiltration at point location is investigated using models based on Darcy's law and the Richard's equation (Short and Dawes 1995) that calculate water movement within a porous medium under transient saturated and unsaturated conditions based on the soil physical characteristics (Bornhoft 1994). Robust scientific literature is available describing different aspects of hydrological models such as behavior under different crop conditions (Carneiro da Silva and De Jong 1986), parameter selection (McGechan *et al.* 1997) and, laboratory and inferred data (Hack-ten Broeke and Hegmans 1996).

Determining values for the models' variables is possible through laboratory and field analysis. However this can become highly demanding in time, labor and cost. The infiltration model produced by the hydrological analysis is, therefore, highly site specific

in its explanatory properties and will rely on assumptions of homogeneity when used to describe areas from which soil data were not originally collected.

b. Interpolation using geostatistics

Finding the extent, size and shape of the ground area with homogeneous field conditions around the point data collection by a monitoring station has been a research problem addressed by geo-statistical analysis. Geostatistics are based on the principle that observations close to each other tend to be more similar than those that are farther apart (Tobler's law, Tobler 1970). A common technique used by these studies for assessing spatial variance is the variogram that relies on the analysis of the variation of the response of a point data set for a single variable referenced to its specific spatial location (Western *et al.* 1998). When a large number of points are available, the variogram will predict the extent of the field (range) for which similar conditions may be expected to occur.

In this way, point data are considered on the basis of their spatial location and the presence of ecological discontinuities such as terrain, soil and vegetation which will influence the explanation of the observed spatial trends. Under the best scenario, the observed variation within a point data set collected from a landscape with homogeneous terrain and vegetation cover may serve as an indicator of spatial variation of hydrological conditions and soil moisture response, but not of the factors causing such variation or the process underlying it (Western *et al.* 2004).

A different approach to the problem of spatial variation of point readings is addressed by temporal stability statistical theory in which the analyst seeks to understand how well a point measurement represents a moist field (Cosh *et al* 2004; Jacobs *et al*

2004). If intensive sampling is conducted in the field over a period of time, the mean of the field can be identified as well as the sites within the field that approach or diverge from that mean. In this way a site or sites that exhibit values with minimal deviation from the field mean can be considered as representative points of field conditions and therefore valid points for long term observations (Vachaud *et al.* 1985). Geostatistical analysis, therefore, summarizes the spatial variation of a variable to a single value or field mean as the representative indicator of the variable status without considering the spatial complexity. This has the limitation of oversimplifying the landscape since field means can be estimated for areas in the range of a few square meters to several square kilometers.

c. Correlation analysis.

The correlation between two or more environmental variables using linear and multilinear regression models is seen as an alternative approach to geo-statistical analysis since it relates soil moisture content to its environmental factors and may not be limited to the spatial area from which they were developed (Qiu *et al.* 2003). In this case, the use of surrogated and low cost, readily available ancillary information is an advantage allowing the prediction of soil moisture using simple environmental attributes (Broeke and Hegmans 1996). However, for complex landscapes, the validation of such models share the same logistic and economical constraints involved in the simultaneous collection of large amounts of field data for several environmental variables.

1.2.2. Remote sensing of soil moisture. Different approaches have been followed in the study of soil moisture using remote sensing data including: 1) dimensionality analysis of

multispectral data; 2) indirect estimates from surface temperature and vegetation; and 3) direct estimates from active longwave microwave. For example, Kauth and Thomas 1976 developed the tasseled cap transformation (TCT), using the Gram-Schmidt mathematical process that uses four Landsat multispectral scanner (MSS) bands in linear combination, obtaining four indices or dimensions called greenness, brightness, yellowness and nonsuch (Jackson 1983). The first two components, greenness and brightness, were essentially associated with the vegetation and soil components of the reflected spectrum and eventually, when compared, indicates the stage of development of an agriculture crop (Dave 1981). With a similar procedure using simulated data from the Landsat Thematic Mapper (TM), Crist and Cicone (1984) found that two components were similar to the greenness and brightness previously reported and at least one of the additional components, wetness, could be associated with soil characteristics, particularly soil moisture. Working with the wetness component, differences can be perceived in soil moisture status using the TCT, particularly when the soil approximates the wet limit or saturation (Musick and Pelletier 1988). Building on this research, when a multidimensional approach is followed, indices that better reflect the soil dynamic can be calculated and differences between dry and wet soils can be observed (Jackson 1983, Levitt *et al.* 1990). Also, using multispectral data, band ratios can be computed to infer soil moisture. In this case, ratios that combine a non- water absorption waveband with a waveband that overlaps the water absorption zone, such as TM bands 5 and 7, have showed statistical correlation with soil moisture (Levitt *et al.* 1990).

The combination of surface radiant temperature (T_o) and fractional vegetation cover is an indirect method of evaluating soil moisture (Li *et al.* 2004). Soil moisture content is strongly correlated with surface temperature because the latent heat (energy

storage in water when it evaporates) and sensible heat (heat transfer through conduction and convection from surface into the air) components of the energy balance at the surface level are affected by soil water content (Goward *et al.* 1985). Transpiration and evaporation increase as the soil water content rises. Under wet soil conditions, latent heat fluxes increase because the greater absorption of energy required in the evapotranspiration process decreases the sensible heat. Under dry soil conditions the inverse process occurs, because the radiative energy is not consumed in the evapotranspiration process and the sensible heat increases, causing (T_o) to rise (Vicente-serrano *et al.* 2004).

To estimate soil moisture under this approach, thermal bands from a multispectral sensor are converted to brightness temperatures and atmospherically corrected to account for the influence of the atmospheric water vapor (Price 1983.) A vegetation index, such as normalized difference vegetation index (NDVI), is used to account for changes in the vegetation cover and the effects of soil background in partially vegetated surface. A vegetation fractional cover (f_c) is computed using observations of minimum and maximum NDVI throughout the year (Ottle and Vidal-Madjar 1993). The relationship between (f_c) and (T_o) serves to create a dispersion diagram to classify the remote sensing image in areas in which variations in surface temperature are observed within areas of similar levels of vegetation cover (Carlson *et al.* 1990, Carlson *et al.* 1995, Vicente-Serrano *et al.* 2004).

A similar procedure has been used to disaggregating the information captured for coarse spatial resolution thermal data to infer characteristics at finer spatial resolution. In this case, the higher spatial resolution of the NDVI is used to disaggregate the coarser spatial resolution of the thermal pixel. The procedure is based on the selection of a set of

NDV pixels with similar characteristics to generate categories from smaller to larger vegetation cover that can be related to (T_R) variations using a least square regression (Kustas *et al.* 2003).

1.2.3. Landscape ecology. The extensive scientific literature in the field of soil moisture suggests that a combination of methodologies from different disciplines can contribute to solving the problem of soil moisture analysis at the landscape scale. The scientific disciplines of landscape ecology and hydrology share an interest in understanding environmental phenomena occurring at the landscape scale on the order of tens to thousands of km² in ground area. Since both of these disciplines have developed a robust set of techniques, current scientific literature suggests the potential of advancing the understanding of environmental process by integrating landscape ecology and hydrology (Janauer 2000). Indeed, a geographic information system (GIS) is an optimal geospatial tool for integrating components from different techniques for modeling purposes (Aspinall and Pearson 2000).

The field of landscape ecology is founded on the recognition of the strong linkage between spatial pattern and ecological processes and in understanding biophysical factors dependent on the spatial fragmentation of the landscape (Forman and Godron, 1986). Landscapes by definition are complex systems and understanding spatial pattern and the scales where patterns emerge are important steps towards comprehending their underlying processes. The description of complex systems is accomplished by decomposing them into their fundamental parts and interpreting their interactions (Hay *et al.* 2002).

The integration between remote sensing and landscape fragmentation has the

advantage of expanding the inferential capabilities of remote sensing research (Nagendra *et al.* 2004). Under an ecologic approach, processes are the product of the relationship between objects forming the structure of the landscape. Since landscape fragments/patches are the units of spatial resolution in which biophysical factors interact, the pixel oriented approach used in LULC and environmental analysis with remote sensing data has the disadvantage that pixels do not correspond with ecological units of spatial organization. Therefore to explore the relationships between pattern and process, an object oriented approach rather than a spectral or pixel oriented approach is required in the remote sensing image processing for biophysical analysis (Hay *et al.* 2002).

1.3 Objectives and research questions

The purpose of this dissertation is to study the landscape complexity at the LRW caused by the spatial variation of soil and LULC classes and its relationship with the problem of pixel size and soil moisture-soil temperature point reading interpolation within a complex landscape. Also, to investigate the spatial and temporal variation of soil moisture and ground temperature within areas equivalent to a pixel size of a Landsat TM image (i.e., 30 x 30 m) and its relationship with field based point readings.

Results of this research contribute to the study of remote sensing of soil moisture by proposing a landscape ecology–hydrology approach to the problem of pixel size and soil moisture-soil temperature point reading interpolation within complex landscapes. The findings of this work will contribute to the knowledge of the variation of soil moisture and ancillary variables within complex landscapes and its implications for the remote sensing of soil moisture.

This dissertation is organized into three manuscripts. In the first manuscript

(chapter 2) it is hypothesized that by characterizing the spatial complexity of the LRW landscape in terms of LULC and soil type it is possible to define the extent of areas with homogeneous conditions for the study of soil moisture with remote sensors and point data. It is hypothesized, also, that the point readings from the *in situ* sites are centroids of homogeneous areas, albeit irregular in shape, of the landscape and therefore can be used to infer conditions for larger areas matching the spatial extent of ground areas imaged by pixels of remote sensing data.

The research questions on this chapter are:

- What is the contribution of soil and LULC variability and their combined effect to the complexity of the LRW landscape?
- How does the complexity of the LRW landscape changes over four different spatial areas (i.e., 30, 90, 250 and 1000 m)?
- What are the most dominant and frequent soil types and vegetation covers at the LRW and what is their variation over different spatial areas?
- What is the most appropriate spatial resolution of remote sensing data for soil moisture applications at the LRW based in soil and vegetation variations?
- What are the most distinctive physical characteristics of the dominant soil types at the LRW, and what is their effect in the soil moisture response?

The results reported in chapter 2 contribute to the understanding of the spatial variability of the soil moisture at the LRW to the hydrological modeling of soil moisture and to the remote sensing data validation under complex landscapes. Also, it has a methodological contribution to soil moisture studies by integrating tools from landscape ecology, geographic information science (GIScience), remote sensing, geometric cartography and hydrological modeling.

The next two manuscripts of this dissertation, chapter 3 and 4, evaluate the hypotheses that there is a strong correlation between soil moisture (chapter 3), ground and infrared temperature (chapter 4) from the *in situ* sites and adjacent homogeneous fields and, therefore, those sites are good indicators of the local landscape conditions. These chapters also hypothesize, that adjacent fields to the sites present different responses in soil moisture, ground and infrared temperature that can be attributed to LULC characteristics.

The research questions in chapter 3 are:

- What is the spatial and temporal variation of soil moisture in 30 by 30 m homogeneous fields adjacent to the sites?
- What is the temporal stability of soil moisture within a 30 by 30 m field?
- What is the correlation of readings collected in two consecutive days from 30 m fields?
- Are the variations in soil moisture site specific?
- If there is infield variation in soil moisture, can directional effects be observed within the sampled location?
- What is the variation of soil moisture among different LULCs (i.e., grass, orchard, peanuts, cotton and bare-soil)?
- Is there a correlation between soil moisture from different LULCs and the average soil moisture at an adjacent 30 m field?

The research questions on chapter 4 are:

- What is the spatial and temporal variation of ground and infrared temperature in 30 by 30 m homogeneous fields adjacent to the stations?
- Are the variations in ground and infrared temperature site specific?

- What is the correlation between ground and infrared temperature and soil moisture in 30 m fields adjacent to the stations?
- What is the variation of ground and infrared temperature among different LULCs?
- What is the correlation between temperature and soil moisture in different LULC?
- How do the readings from the *in situ* stations compare with readings from adjacent fields collected with hand carried devices?

The results of these two manuscripts contribute to understanding the spatial variation at the LRW of soil moisture, ground and infrared temperature within areas that match a pixel size of a Landsat TM image, thus assessing the relationship between readings from stations and adjacent homogeneous fields. Furthermore, these manuscripts provide information about the spatial and temporal variation of those variables within and among homogeneous fields and between those fields and other LULCs.

1.4 Research summary

This dissertation investigates the problem of using soil moisture and temperature ground point data for regional and remote sensing studies of soil moisture in complex landscapes. Under the principle that landscape fragments are spatial units in which biophysical factors interact, this research builds on the concept that the integration of remote sensing, hydrology, geostatistics, GIScience and landscape ecology is a valid methodological approach to explore the relationships between fragments and process expanding the inferential capabilities of remote sensing research (Nagendra *et al.* 2004). In this way, this research is a contribution to the call of the International Hydrological Program IHP-V, to close the gap between ecology and hydrology by integrating tools and concepts from both disciplines as a methodological alternative to understand the hydrological

cycle in different ecosystems (Janauer 2000).

In this research throughout a GIS-remote sensing analysis of fragmentation, I investigate the contribution of soil and LULC classes to landscape complexity as a way to understand the environmental factors influencing the soil moisture point readings of the *in situ* network at the LRW. Also, through a year long field data collection, I established the spatial and temporal variation of soil moisture and ground temperature within adjacent homogeneous fields and LULCs to the stations of the *in situ* network at the LRW. The most important results include:

- Criteria to define the most appropriate pixel sizes of a remote sensing instrument required to capture homogeneous soil moisture or ground temperature at the LRW.
- Considerations for using the stations of the *in situ* network as centroids of remote sensors of different pixel sizes.
- Defining the contribution to landscape and local complexity by soil and LULC classes and their weight influencing in the point reading measurement.
- The study of the variation of physical properties of soils belonging to similar or close adjacent textural classes.
- The assessment of soil moisture responses by different soils.
- The study of temporal stability of soil moisture in homogeneous fields matching the size of a Landsat TM or ETM+ pixel size.
- The correlation between point readings and adjacent homogeneous fields under different LULCs.
- The assessment of temporal and spatial variation of soil moisture and ground temperature within and among homogeneous fields matching the size of a Landsat TM or ETM+ pixel size at the LRW.

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CHAPTER 2

LANDSCAPE ECOLOGY ANALYSIS OF A COMPLEX LANDSCAPE FOR FIELD
AND REMOTE SENSING OF SOIL MOISTURE¹

Giraldo, M., Madden, M., Grundstein, A., and Bosch, D. To be submitted to the *Journal of Hydrology*

Abstract

This research investigates the landscape complexity within a network of soil moisture stations at the Little River watershed (LRW) in south Georgia, USA and its implications for the validation of remote sensed soil moisture data. The environmental variables soil and landuse land cover (LULC) influence the spatial distribution of soil moisture and therefore, the aggregated spectral reflectance for unit ground equal to the pixel size of a remote sensor. Using Object Based Image Analysis (OBIA), Voroni/Thiessen polygons, point distance analysis and landscape metrics, the spatial complexity and within pixel heterogeneity caused by soil and landuse land cover (LULC) variation are analyzed within four different spatial areas (1000, 250, 90 and 30 m) around the stations of the LRW network. The spatial areas were selected considering the pixel sizes of satellite image data commonly used in remote sensing of soil moisture. The second part of this research uses a mono-dimensional hydrological model, FASST (Fast All Season Strength model, US Army Corps of Engineer), to evaluate the variability in the water infiltration process among the five most representative soils at the LRW landscape under similar landuse and climatic conditions. The results show that fragmentation caused by LULC is 14% greater than that caused by soil types and when both variables were considered together, 5 times more landscape fragments were found than for a single variable alone. Distance analysis showed that pixel centered at the LRW soil moisture stations with spatial resolution larger than 160 m (LULC) and 120 m (soil type) are unsuitable to capture homogeneous conditions of soil and LULC, while remote sensors with spatial resolutions less than 100 m (LULC) and 10 m (soil) can capture homogeneous conditions around most of the reading stations. Only a few combinations of soil type/LULC such Tifton/forest, dominated the study area despite the high landscape fragmentation. High variation in the water infiltration process was found within the five soils even between those belonging to similar textural classes. This research demonstrated that 1) landscape complexity in terms of soil and LULC should be considered first to select appropriate remote sensors in soil moisture studies; 2) at the LRW complex landscape ground stations are more useful in validating fine resolution than coarse resolution remote sensing data; 3) under similar LULC, surface soil moisture varies at short distances according to soil diversity; and 4) soils within similar textural may present variations in water infiltration, suggesting a need for integrating soil data and hydrological modeling to the validation process of remote sensing imagery.

This research contributes to the field of remote sensing of soil moisture by: 1) Assessing the landscape complexity that influence a regional representation of soil moisture conditions using field data; 2) defining the more appropriate scale of remote sensing data for soil moisture applications in the LRW complex landscape; and 3) evaluating the spatial heterogeneity that influence soil moisture point readings at different units of spatial resolution.

Key words: Landscape metrics, Object Based Image Analysis OBIA, soil moisture, remote sensing, point data, LULC, soil diversity.

2.1. Introduction

In the water cycle, soil moisture controls both the water flow between the atmosphere and the ground and the distribution of water within the soil profile. Remote sensing data is seen as a promissory approach to evaluate soil moisture behaviors in different types of landscapes and at different sampling areas providing in a single look a regional description of the water redistribution at different temporal and spatial resolutions (McCabe and Wood 2006). There are two critical research points in advancing the study of soil moisture using remote sensing data: 1) defining the appropriate pixel size that matches the spatial complexity of the landscape under study and; 2) defining the area on the ground that can be represented by field data collected at a single point location.

The different options of remote sensing data available to study soil moisture include pixel sizes ranging from less than 1 m² to more than 1 km², thus creating a need to find the appropriate pixel size that accurately represents the soil moisture conditions for a given landscape. Soil moisture is a spatially distribute variable influenced by the individual and combined behavior of environmental variables such as precipitation, vegetation cover, soil and topography. This behavior may change over different spatial sampling areas according to variations in the landscape and the ecosystem characteristics.

At the regional level, the spatial variation of each variable involved in the soil moisture expression, as well as their combined effects, define the level of landscape complexity and, therefore, the minimum area in which homogeneous conditions can be observed. As the level of landscape complexity increases, remote sensing instruments with coarse spatial resolution summarize in a single pixel mixed expressions of the environmental variables involved in the soil moisture expression, decreasing their

potential for accurate descriptions of the water process at the local scale (Merlin *et al.* 2006).

The second critical question in the remote sensing of soil moisture involves an understanding of the area on the ground that data from a single field sampling point can represent. Point data collected on the ground have been used to establish soil moisture on different landscapes and different environmental conditions (Crow *et al.* 2005). The problem inherent in the sample design of this field data collection is the determination of the minimum spatial area for which a point reading is an adequate representation of soil moisture conditions. Traditional soil moisture studies analyze the distribution of soil moisture behavior using geostatistical techniques in which the spatial location of the point data determines the characteristics of their environmental behavior (Western and Blöschl 1999, Choi and Jacobs 2006). Interpolation analyses are based on the principle of Tobler's law that samples collected from proximal locations tend to have more similar behavior than those collected from distant locations (Tobler 1970). Distance analysis of point data neighbors that are similar in nature can be used to indicate the ground extent in which a landscape presents homogeneous characteristics and approximate the scale in which similar environmental conditions exist (Mohanty and Skaggs 2001, Starks *et al.* 2006). This approach has proven useful when little information is available on the environmental conditions of the soil moisture response. However, since the number of sample points and the intensity of the sampling procedure must be increased according to the degree of landscape complexity, logistic and economical constraints of field data collection may prevent an adequate number of simultaneous samples and an accurate description of the study area conditions (Cosh *et al.* 2005).

Landscapes by definition are complex systems and their description is accomplished by decomposing them into their fundamental parts and interpreting their interactions. Since landscape fragments are the units of spatial resolution in which biophysical factors interact, a pixel oriented approach used in LULC analysis has the disadvantage that the pixel as the remote sensor data unit does not correspond with ecological units of spatial organization (Hay *et al.* 2002, Burnett and Blaschke 2003). Therefore, to explore the relationships between pattern and process, this research uses an object based image analysis (OBIA) approach rather than a pixel oriented approach for the remote sensing image processing. Previous studies have reported the advantage of OBIA approaches in disclosing landscape complexity in rural landscapes (Chmiel 2006, Ozdarici and Turker 2006)

In this research, we investigate the appropriate pixel size that matches the spatial complexity of a complex landscape at the same time that we evaluate the spatial extent of the field that a point data in such a landscape can represent. By integrating spatial analysis techniques derived from geometry cartography, landscape ecology and hydrology, we study landscape complexity and fragmentation, as well as we define the minimum area of homogeneous soil moisture conditions at the Little River Watershed (LRW) near Tifton, Georgia, USA.

Preexisting geospatial data sets of soil and vegetation classes are used to characterize landscape complexity while a hydrological model is used to characterize soil moisture variations among landscape units. In our approach, the variation between neighboring field point data is no longer linked to their spatial separation, but to the vegetation, soil characteristics and environmental conditions associated with a particular point sample in the field. It is hypothesized that soil moisture behaviors can be assigned

to areas with similar environmental conditions regardless of their spatial proximity and eliminate the need for a large number of field samples and intense sampling procedures.

In the first section of the research, the complexity of the study area is analyzed by evaluating the spatial variation of soil and vegetation types over four ground areas approaching the spatial resolution of remote sensing data frequently reported in soil moisture studies. We estimate the minimum area in which homogeneous soil moisture conditions can be found, determining the weight and composition of those homogeneous areas within the landscape. The objectives are to define the most appropriate pixel size of a remote sensing instrument to conduct soil moisture analysis in the study area, to define the heterogeneity of four spatial areas and to find the dominant soil/LULC characteristics within those areas. In the second section of the research, we use field data from an *in situ* hydrological network at the LRW operated by the United States Department of Agriculture-Agriculture Research Service (USDA-ARS), to evaluate the variation in water retention among the dominant soil types present at the study area. The objective is to test variation in soil moisture response among the dominant soil types at the LRW.

This research contributes to the study of remote sensing of soil moisture by bringing methodologies from geometric cartography, landscape ecology and hydrologic modeling to remote sensing, to approach the problem of pixel size and soil moisture assessment within complex landscapes. The benefits of integrating methods and techniques from the disciplines of hydrology and ecology already has been suggested (Janauer 2000), therefore, this research is a contribution to an innovative and multidisciplinary approach to the study of the water cycle in complex and diverse ecosystems.

2.2. Methodology

2.2.1 Study area.

The Little River Watershed LRW in the South Atlantic coastal plain of the United States, near Tifton, Georgia extends over 334 km² of relatively flat terrain characterized by broad floodplains with poorly defined stream channels and gently sloping uplands varying from 1 to 5%. The typical soil for the area is sandy loam with a sandy surface horizon and heavier textured subsoil. This type of soil presents low water holding capacities, with fast superficial drainage. The annual average precipitation is approximately 120 cm. Rainfall is the combination of convective and frontal precipitation that can produce intense thunderstorms. While summers are long, hot and humid, winters are short and mild. The landscape is composed of a diversity of land covers including forest, cropland, pasture, residential areas and wetlands. Animal production is combined with agricultural activities yielding year-round production of vegetables and row crops (Bosch *et al.* 2004, Cashion *et al.* 2005).

An *in situ* network of 27 stations equipped with soil moisture Stevens-Vitel Hydra-probes (Stevens Water Monitoring Systems, Inc.) was established in 2002 within the LRW (figure 2.1) as one of the sites for the 2003 USDA-NASA soil moisture experiment, (SMEX 2003) (<http://hydrolab.arsusda.gov/smex03/SMEX03v5.pdf>). Since then, continuous records have been collected and used in hydrological studies (Bosch *et al* 2004) and in remote sensing data validation for soil moisture applications (Cashion *et al* 2005). The devices are randomly distributed at the LRW recording ground temperature and soil moisture information at three soil depths 5.08, 20.32 and 30.48 cm every 30 minutes. Hydra-probes measure a dielectric constant for the soil and convert it to

volumetric soil moisture based upon a factory provided calibration equation (Campbell, 1990, Gaskin and Miller 1996).

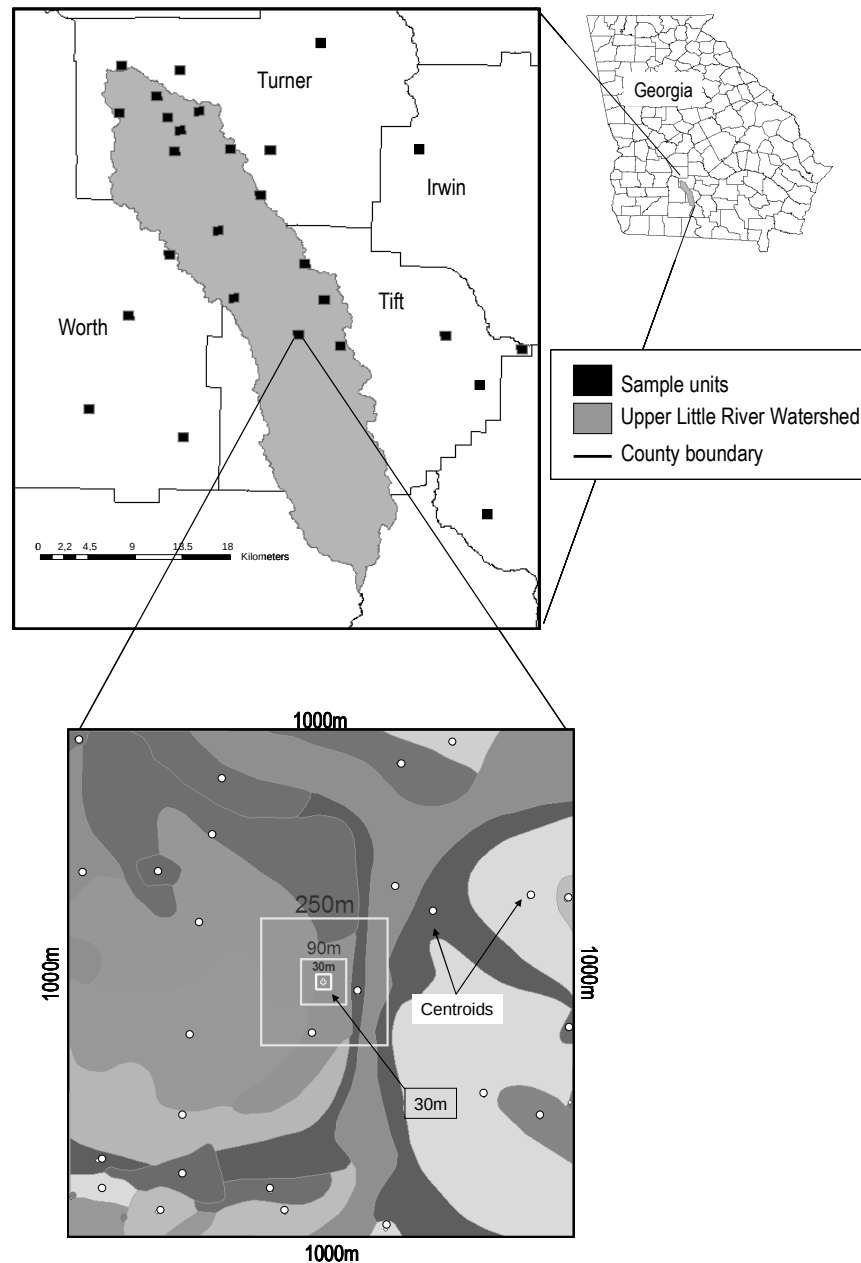


Figure 2.1. a. Location of the Little River Watershed and sampling sites. Sites shown at their approximate geographic location. b. 1000 m, 250 m, 90 m and 30 m concentric sample areas and centroids of soil polygons.

2.2.2 Landscape complexity analysis.

a. Sampling

Sampling areas were centered on the point locations of the Hydra-probe reading stations. Five different sample sizes including: Thiessen (Voronoi) polygons and four square concentric areas of 1000, 250, 90 and 30 m side were used to evaluate the spatial variation of the soil types and LULC. In the field of geometry cartography, Thiessen polygons are geometric constructs used to divide a study region into areas according to relative spatial locations of points within a point set. Each point location is the centroid of a polygon that is formed by lines drawn equidistant to the location of a neighboring point data. Under this configuration, the number of sides of each polygon increases according to the number of proximal neighbors surrounding the point data, and the total area of the polygon decreases, when the distances between neighbor points is short (figure 2.2).

Using the spatial location of the Hydra-probe sites as centroids, Thiessen polygons were automatically generated dividing the study area into 29 different units. Since Thiessen polygons follow a procedure that relies on the spatial distribution of the Hydra-probe stations, each polygon size is an indicator of the extension of the ecological area that each Hydra-probe reading station is serving. In addition to this tessellation of the landscape, four concentric square areas of 1000, 250, 90 and 30 m size centered at the point location of the Hydra-probe stations were defined within each Thiessen polygon as areas of ecological sampling (see figure 2.1b). These four sampling areas allow us to analyze landscape variation through a range of spatial sampling areas that match most of the satellite remote sensing data available and reported in soil moisture studies. From the 29 Hydra-probe sites, a sample of 8 sites forming a North-South transect were selected to conduct the landscape and hydrological analysis (figure 2.2).

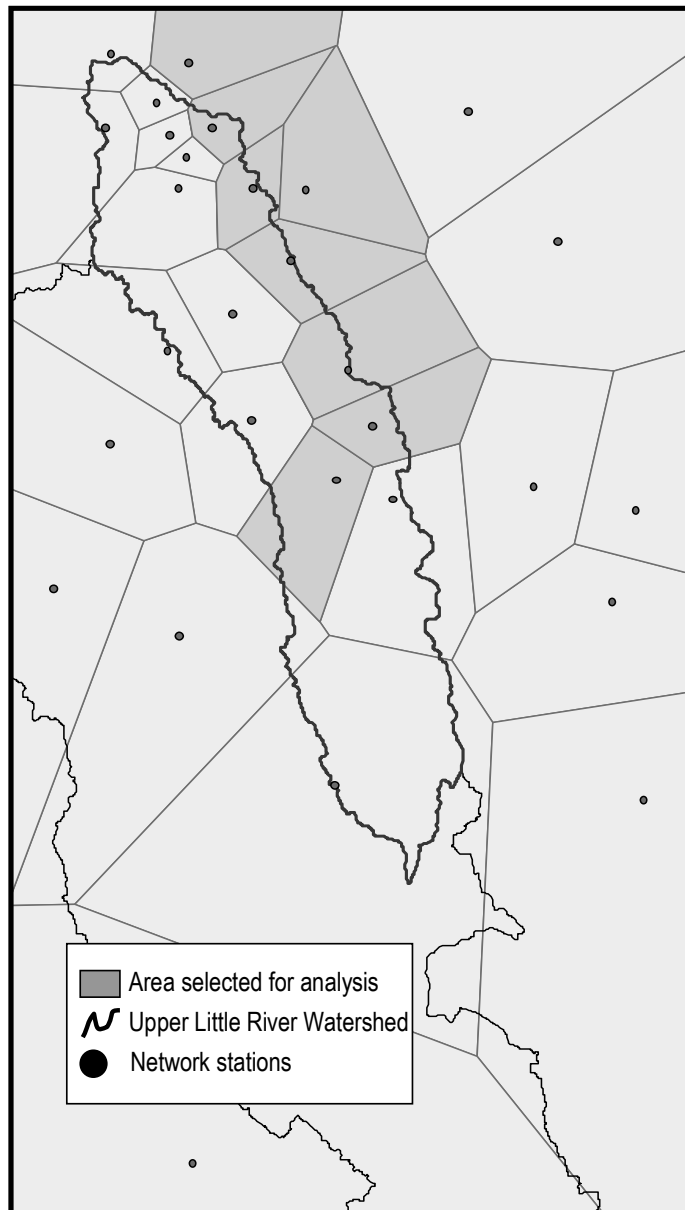


Figure 2.2. Thiessen polygons from Hydra-probe sites and eight selected (shaded) for landscape analysis.

b. Data sources and processing

Vector files from the USDA-National Resource Conservation Service (USDA-NRCS) Soil Survey Geographic Database (SSURGO) (<http://www.ncgc.nrcs.usda.gov/products/datasets/ssurgo/>) were used to construct a regional soil type classification for the study area. Three individual vector files for Worth, Tift and Turner counties were mosaiced and subset to the extent of the study area. Mosaics of 1:12,000-scale, true color digital aerial photographs from 2005 (geo-referenced and geometrically corrected) were obtained from the USDA-Aerial Photography Field Office (USDA-APFO) National Agricultural Inventory Project (<http://datagateway.nrcs.usda.gov/>), and used to generate a LULC classification of the study area. SSURGO metadata reports that the soil types are accurate within areas of 2 acres (0.8 ha).

Landscapes by definition are complex systems and their description is accomplished by decomposing them into their fundamental parts and interpreting their interactions. Since landscape fragments are the units of spatial resolution in which biophysical factors interact, a pixel oriented approach used in LULC analysis has the disadvantage that the pixel as the remote sensor data unit does not correspond with ecological units of spatial organization (Hay *et al.* 2002). Therefore, to explore the relationships between pattern and process, an object oriented approach rather than a pixel oriented approach was selected for the remote sensing image classification.

Object based image analysis (OBIA) is the identification of landscape objects or features based on their contextual characteristics (e.g., texture, shape, size and proximity) (Corcoran and Winstanley 2006). We use OBIA based software, *Definiens Professional 5.0* (formerly *Definiens e-cognition*) to produce a segmentation and preliminary LULC

classification of the study area. The initial step in the classification procedure segmented the image into different spatial units according to parameters of spectral composition, shape and size. Intense experimentation with several combinations of the segmentation parameters was required in order to obtain accurate segments of the different units of LULC. A threshold of 200 pixels (800 m^2) was selected to delimit the minimum fragment size since it guarantees that spatial units of $30 \times 30 \text{ m}$ or more will be included. We followed a bottom-up image analysis that gave preference to interpretation elements such as position, size and association in the classification process (King 2002). Manual on-screen image classification followed the segmentation process, selecting segments representing typical units for each of the LULC classes by visual inspection using the aerial photographs as reference for LULC. The classification process generated a vector file with the classes, urban, roads, agriculture fields (identify four agriculture subclasses) forest, grassland, orchard, wetland and water. A field inspection to identify polygons with questionable LULC was conducted within the 1000 m areas and the misclassified polygons were marked and recoded to guarantee 100% accuracy within the sampling units.

c. Analysis

After the image classification was completed, a GIS analysis was performed for the four different areas of landscape units (i.e., 1000, 250, 90, and 30 m) at each of the eight selected sites, to assess soil/LULC combinations and the soil and landuse composition (figure 2.3 a and b).

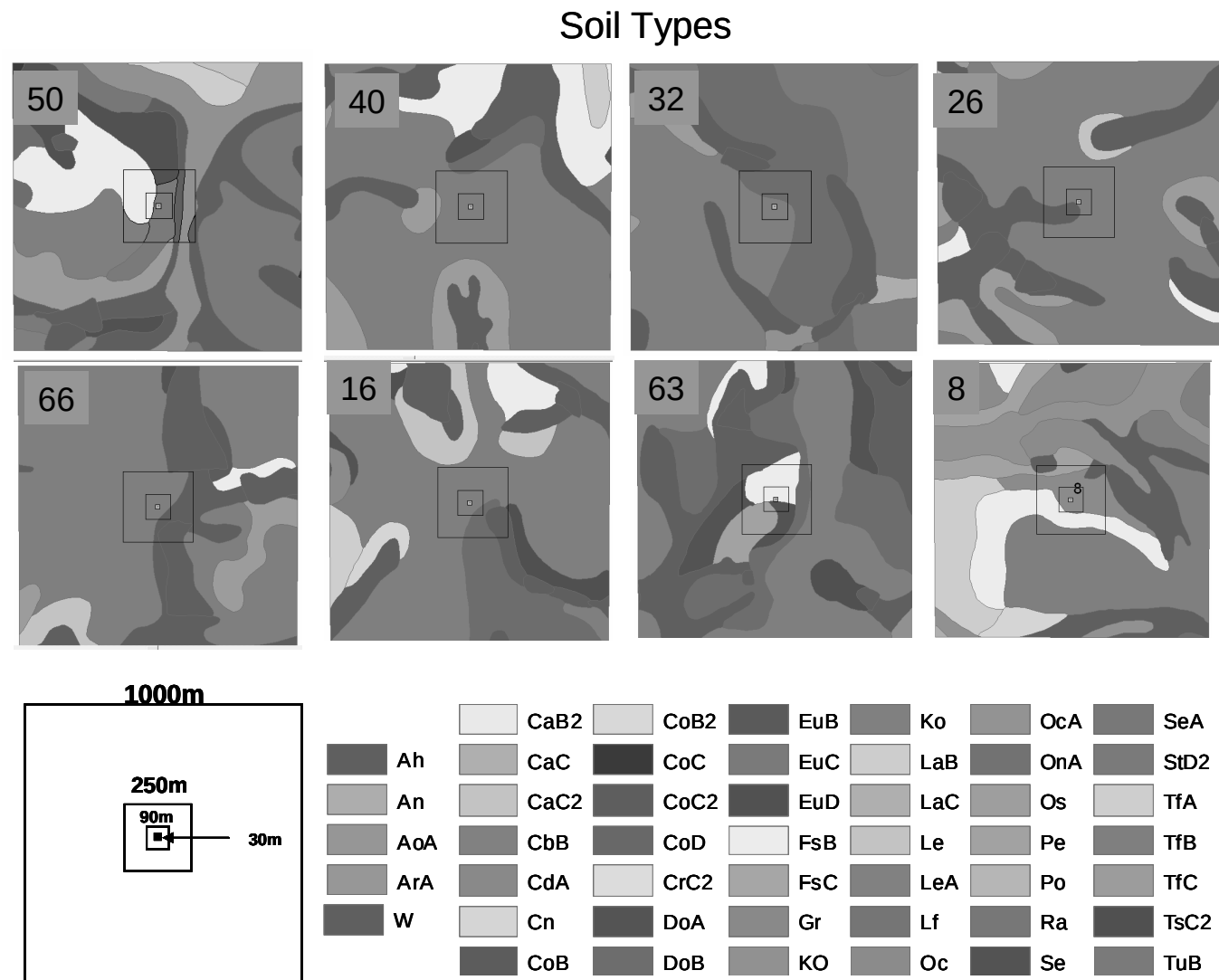


Figure 2.3 (a) Soil types for eight Hydra-probe sites within three concentric sampling areas

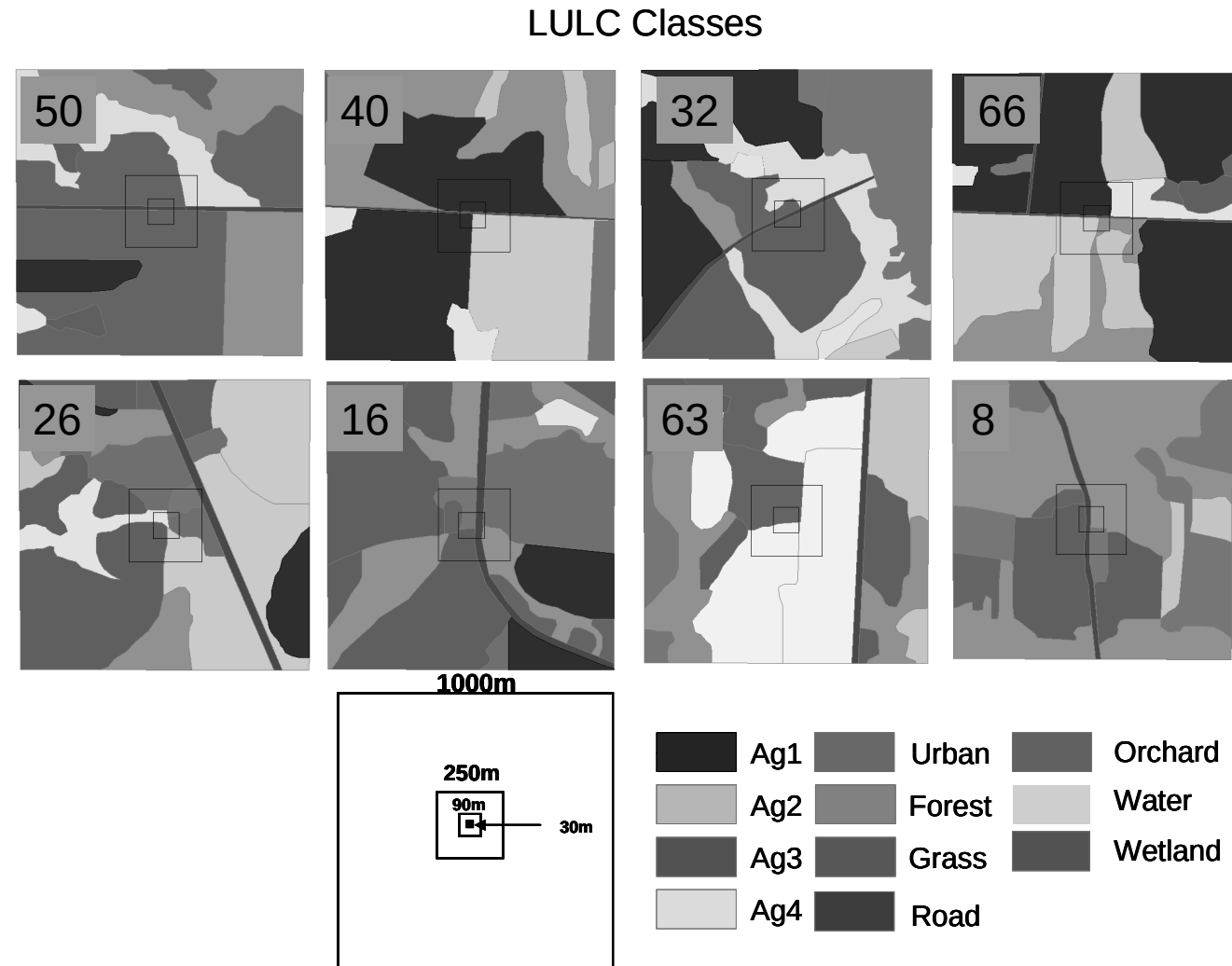


Figure 2.3 (b) Landuse/land cover (LULC) for eight Hydra-probe stations within three concentric sampling areas

The ecological variables of soil and landuse were compared in this analysis using the landscape metrics of number of fragments, minimum and maximum fragment size and perimeter-area relationship that has been recommended by previous works (Li *et al.* 2005).

The ratio perimeter/area serves as an indicator of patch shape in which large ratios indicate elongated fragments while lower ratios indicate rounded fragments (MacGarigal *et al.* 2002). In addition to the landscape fragment analyses, two different distance analysis were performed: 1) distance between the Hydra-probe site and the centroids of each one of the fragments present within the sampling unit of 1000 m radius, and 2) distance between the Hydra-probe site and the edge of the closest soil/LULC fragment. The distances were computed using the spatial analysis function of *ArcGIS 9.1*. In this research, distance analysis serves as an indicator of the geographic extent of the homogeneous area surrounding the Hydra-probe site. This analysis also characterizes the LULC and soil type that is influencing the Hydra-probe readings.

The landscape parameter “dominance”, as the LULC/soil type that covers the largest landscape area and “frequency”, as the LULC/soil type with the largest number of fragments were obtained using the software *FRAGSTATS* (MacGarigal *et al.* 2002). The fragmentation analysis was conducted using the software packages *Definiens Professional 5.0*, *ArcGIS 9.1* and *FRAGSTATS*. Descriptive statistics and analysis of variance (ANOVA) were performed to assess the landscape variation of the two variables and their combined effect between sites and among the four sampling areas per site. The difference between sites is used as an indicator of the variation of the variables at the landscape scale, while the difference among sampling units is an expression of scale variation within a common location.

The results of this analysis allow us to understand the landscape complexity within the four different sampling areas of the study, thus suggesting the appropriate spatial resolution of remote sensing data that is optimal for soil moisture experiments in this landscape. Also from this analysis, we define the dominant soil and vegetation types and the most predominant combination of LULC/soil within the landscape and within the vicinity of each Hydra-probe *in situ* stations. The ecological effect of the soil and vegetation combinations on the variation of the soil moisture behavior among the Hydra-probe sites is then assessed in the next stage of this research by modeling the water distribution within the soil profile for the soil types dominating the study area.

2.2.3 Hydrological analysis. The effect of combined soil and LULC on the soil moisture behavior at the LRW was evaluated using the Fast All-seasons Soil STrength model (FASST), a one-dimensional model developed by the Cold Regions Research and Engineering Laboratory of the US Army Corps of Engineers (Frankenstein and Koenig, 2004). The soil moisture component of FASST runs in a distributed mode producing estimates of soil moisture content for mono or multi-layer soil profiles for each ecological area according to their soil, land cover and topography attributes. Its fundamental operations are the calculation of an energy and water budget that estimates, among other variables, the heat flow and soil moisture using meteorological and ground data. To estimate soil moisture conditions, FASST requires a meteorological data file, soil properties file and a third file containing site specific conditions such as surface characteristics, vegetation cover, moisture and temperature initial conditions and soil vertical profile.

In this research, the meteorological data for the study region was obtained from USDA weather stations within the area of the Hydra-probe network at the LRW. For an accurate estimation of soil characteristics, FASST requires a robust set of meteorological data including values for air pressure, temperature and humidity, wind speed and direction, precipitation, cloudiness, solar and infrared radiation. The physical parameters for the soil were obtained initially from the attributes provided by the SSURGO data set. The infiltration parameters for the saturated and unsaturated hydraulic conductivity and the van Genuchten water retention parameters were estimated using ROSSETA, a program developed by the U.S Salinity Lab (USSL)(Schaap, 1999).

In the estimation of the soil parameters, ROSSETA accepts three types of inputs: 1) textural classes; 2) percentage of sand silt and clay (SSC); and 3) SSC and bulk density. In this research we used the SSC provided by the SSURGO data set as basis for the parameter estimation. The results of the estimation were compared to the USDA unsaturated soil hydraulic properties database (UNSODA), within which laboratory values for other soils with similar textural characteristics are reported. The variables saturated water content (θ_s), residual water content (θ_r), the coefficient (α) and exponent (n) of the van Genuchten water retention function, the matching point at saturation (K_o) and saturated Hydraulic conductivity (K_s), where used to assess the hydraulic variability among soil types.

The sensitivity of the FASST model to variations in precipitation and in the hydraulic and water retention parameters was tested using combinations of soil and vegetation classes under different precipitation regimes. Furthermore, individual files containing physical and hydraulic characteristics for the five most representative soils were prepared and the soil moisture behaviors were estimated using an identical

vegetation cover. Likewise, an identical set of meteorological conditions was used to guarantee that the modeling conditions were identical and that the variations in soil moisture behavior are the consequence of variations in the soils physical parameters.

In addition to soil and vegetation cover, the environmental factors of rain fall and topography are among the principal factors affecting the soil moisture characteristics. An analysis of precipitation for the LRW at eight time periods during 2005-2006 showed that when a rainfall event occurs, the eight study sites received similar precipitation amounts and, therefore, can be considered under similar precipitation regimens (Giraldo *et al.* 2007). Topography at the LRW also is relatively flat with slopes in the range of 1 to 5% over the whole study area. The eight sites selected in this study were uniform in slope and within the sampling units slope was mostly less than 1% variation. Nevertheless, we acknowledge that for a generalization of the results at the landscape scale, topographic variations should be considered within the model simulation.

2.3. Results

2.3.1. Distance analysis and homogeneous conditions

Distance analysis between the Hydra-probe sites and the edges and centroids of the closest polygons indicates the likelihood that other soils and landuses affect the soil moisture behavior at the reading site in addition to the conditions in which the *in situ* station is located. The analysis showed a minimum distance to the edge of a different soil type fragment as low as 8 m with an average distance of 35 m. Considering the distance to a different LULC polygon edge, sites 16 and 63 were the only sites with more than 5 m of distance, while the remaining sites were between 1.5 and 4 m range. The minimum distance between a Hydra-probe station and the centroid of a soil fragment can be as low

as 13 m (site 63) and as large as 238 m (site 66) and to a LULC fragment centroid can be as low as 7 m (site 40) and as large as 268 m (site 63).

These results indicate that in the scenario of a remote sensing data validation using a pixel by pixel approach with a pixel centered at the Hydra-probe site, the pixel resolution to resolve a homogeneous area surrounding the Hydra-probe site should be less than 10 m under LULC and around 30 m under soil type considerations. In general, in order of proximity, road, low urban grass and agriculture were the closest LULCs to the *in situ* sites location and, therefore, the most influential to the soil moisture behavior measured by the Hydra- probe station.

A factor analysis of the ANOVA, comparing the variation of distance between the different landuses and soils was used to identify variation in the spatial complexity within the 1000 m size area. Significance differences at the 0.05% probability level were found only for the distances to the nearest landuses and not to the soil types surrounding the site indicating that soil composition changes from site to site (site specific) without an specific predominance of a particular soil type that influences the soil moisture behavior around the station sites.

The size of the LULC/soil fragments within a 1000 m sampling unit serves to indicate the minimum and maximum homogeneous areas that can be found within such area, and therefore, approximates the spatial resolution of the remote sensor instrument that can better capture the spatial complexity of the landscape without sub-pixel mixing. The results show (table 2.1) high variation among sites for the minimum and maximum suitable remote sensor spatial resolution. The highest rank for the maximum (14.3 – 63.6 ha) and minimum (10 - 1060 m²) fragment size was found for the variable soil. In general, remote sensors with spatial resolutions larger than 160 m (LULC) and 120 m

(soil type) are unsuitable to capture homogeneous areas at any of the locations study in this analysis while remote sensing data with spatial resolutions of less than 100 m (LULC) and 10 m (soil) will be more successful to capture landscape homogeneous conditions.

Table 2.1 Maximum and minimum fragment size within 1000 x 1000 m* areas.

Site	LULC	maximum/ha**	LULC	minimum/ha	Soil	maximum/ha	Soil	minimum/ha
8	Forest	23.13	Grass	0.96	TfB	27.79	LaC	0.106
16	Ag	19.68	Grass	0.62	TfB	53.08	Ah	0.007
26	Ag	19.75	Grass	0.68	TfB	63.67	TfC	0.081
32	Low Urban	18.66	Road	0.75	TfB	31.64	Ah	0.001
40	Ag	23.80	Road	0.71	TfB	57.31	Se	0.089
50	Grass	30.66	Road	0.61	EuC	14.37	TfC	0.006
63	Ag	16.83	Ag	0.74	TfB	34.95	LaC	0.009
66	Ag	16.26	Road	0.45	TfB	46.40	Ah	0.078

* km²: 1000000 m²

**ha: hectare 10000 m²

2.3.2. Analysis of soil heterogeneity

a. Thiessen polygons

The 29 automatically generated Thiessen polygons defined an area of 4316. 5 km² with a total perimeter of 1371.6 km. The polygons of the eight selected sites represent 11% of the area (475.6 km²) and 20% of the perimeter (263.3 km). The areas covered by the eight polygons were in the range between 28.5 (site 32) and 87.2 km² (site 66) (table 2.2). There was no difference in the shape of the Thiessen polygons as measured by the perimeter/area ratio between the eight study sites. A more detailed analysis of the individual perimeter/area ratios is required to draw particular conclusions about the functional ecological effect of such fragments.

Table 2.2. Descriptive statistics for the eight sampled Thiessen polygons

Site	Area km ² (Ta)	Perimeter km	Perimeter/Area
8	69.95	35.07	0.05
16	77.21	43.60	0.06
26	55.02	30.79	0.06
32	28.48	15.52	0.05
40	38.11	22.34	0.06
50	66.13	36.76	0.06
63	52.96	30.74	0.06
66	87.22	45.91	0.05
Total	475.08	263.38	0.06

b. Soil complexity analysis

A total of 6520 soil fragments belonging to 48 different soils were detected within the eight selected sites. The ratio between total area (Ta) and number of fragments (n), showed variation in the level of fragmentation within the study area with site 8 and site 63 as the most and least fragmented respectively (table 2.3). The analysis showed that the soil with the highest dominance is not necessarily the one with the highest frequency (table 2.3). In fact, soil Tifton-B (TfB) was observed as the dominant soil with the largest percentage area for all the eight Thiessen polygons analyzed. On the other hand, the most frequent soil type within the study area is Alapaha (Ah) since this soil has the largest number of fragments for all the eight sites. Fragments covered by water (W) showed the second largest number of fragments for most of the study areas except for site 50. Compared with other soil types, TfB presents the largest fragment size for all the sites with exception of site 50 in which Kinston-Onsler (KO) is the largest. However, the percentage of area covered by TfB varies from site to site, ranging between 21.7% (site 50) and 43% (site 26). This broad range indicates that there is variation in the spatial distribution of soil types between the sites and suggests that other soils, such as Ah and Fuquay (FsB) have an important role in the environmental conditions of the study areas especially in sites 50 and 63 (figure 2.4).

Table 2.3. Dominance and frequency of soil types at the landscape scale.

Site	Thiessen total area (Ta)km ²	Total No of soil fragments (n _s)	Ratio Area/fragments (Ta/ n _s) km ²	Dominant soil type	Dominant soil type total area km ²	% from Thiessen area
8	69.95	772	0.090	TfB	28.13	40
16	77.21	1188	0.065	TfB	27.79	36
26	55.02	776	0.071	TfB	23.68	43
32	28.47	359	0.080	TfB	11.31	40
40	38.10	473	0.081	TfB	12.57	33
50	66.13	990	0.067	TfB	14.35	22
63	52.96	866	0.061	TfB	15.13	29
66	87.21	1096	0.080	TfB	32.77	38
Total		6520				

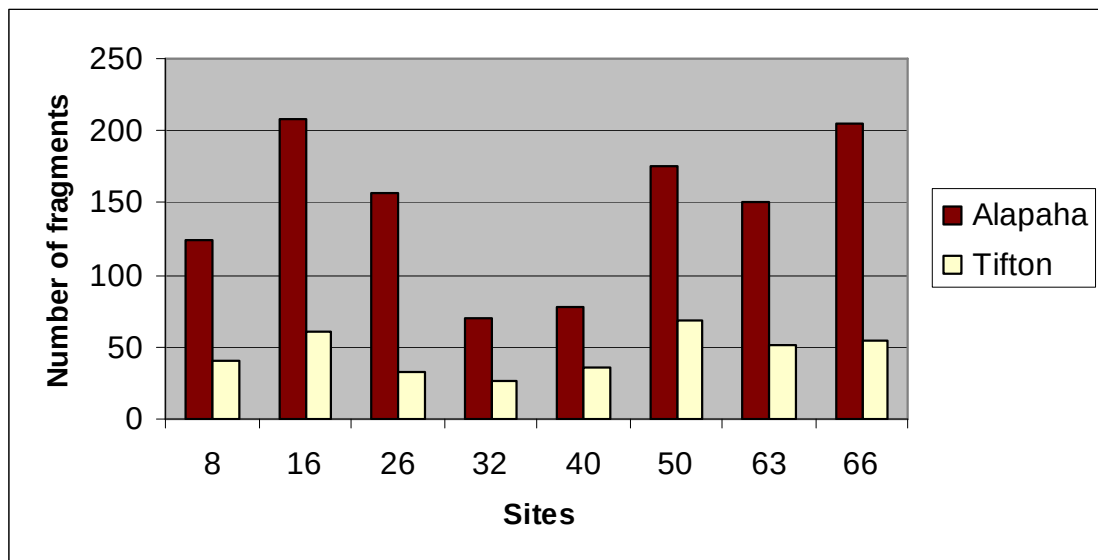


Figure 2.4. Comparison between the most frequent (Alapaha) and the dominant (Tifton B) soil types among the eight study sites.

c. Soil complexity and scale

The analysis of dominance and frequency of soil types in three different sampling areas showed (table 2.4) that the variation in the dominant soil type is site specific across sampling areas. For example, soil type TfB dominates in five of the sites in all three

spatial areas. On the other hand, in site 50, a different soil type dominates at each of the three spatial extents, while in sites 8 and 63, TfB dominates at 1000 m resolution and Ocilla (Oc) and FsB dominate at the 250 and 90 m sampling site sizes. These results coincide with the observations of Lin *et al.* 2005 showing that majority of the variability for single soil properties can be found at the local scale suggesting the importance of considering short-range effects when analyzing soil properties.

At the smaller sampling size, the values of frequency followed a similar trend to that observed at the Thiessen polygon level with soil types Ah and W showing the highest values of frequency. On the other hand several other soil types such as FsB, Oc, StD2 and EuC proved to be important for some areas of the landscape especially at the lowers sampling areas of the study. This tendency of a few soil types being dominate also was observed at the 90 m sampling size with exceptions of specific sites (8, 50 and 63). High values of frequency and diversity of soil types are important when considering the ecological functions of the soil within the landscape, since high diversity of soil types at the local scale has been found to have strong relationship with habitat heterogeneity (Ibanez *et al.* 2005). Therefore, local soil frequency and dominance indicates spatial variations in the ecological processes in which soil is involved.

It is possible to conclude from this analysis, that high frequency of soil types is present at the local scale at the LRW with variations that are site specific. Despite the diversity of the landscape in soil types, only few soils have the highest impact in the environmental conditions. This impact of a few soils is caused by either a single soil occupying a large area or by having a high number of fragments scattered around the study area.

Table 2.4. Dominance and frequency of soil types at three different spatial areas.

	90m				250m				1000m			
Site	Most frequent soil type*	n _s	Dominant soil type	% of area	Most frequent soil type**	n _s	Dominant soil type	% of area	Most frequent soil type	n _s	Dominant soil type	% of area
8	Shared	2	Oc	94	Shared	6	Oc	45	Oc	21	TfB	28
16	Shared	2	TfB	90	Shared	4	TfB	74	Ah	27	TfB	54
26	Shared	2	TfB	76	Shared	2	TfB	87	Ah	22	TfB	64
32	Shared	2	TfB	81	Shared	3	TfB	50	Ah	19	TfB	34
40	TfB	1	TfB	100	Shared	2	TfB	99	Ah	18	TfB	59
50	Shared	2	StD2	70	Ah	8	FsB	30	EuC	29	EuC	20
63	Shared	3	FsB	61	Shared	7	FsB	37	W-Se-Ah	23	TfB	35
66	Shared	2	TfB	87	Shared	5	TfB	67	W	14	TfB	69

n_s : number of fragments

* indicates two or more soil types with one fragment each

** indicates three or more soil types with one fragment each

2.3.3. Analysis of LULC heterogeneity

a. LULC complexity analysis

A high level of patch segmentation resulted from the object based classification of the air photos within the LRW study area totaling 7514 fragments, classified within 11 LULC categories. The landscape level of fragmentation is not site specific since the values for the ratios of total area to number of fragments (Ta/n_L) are similar for all sites in the range of 5.5-6.9 ha (table 2.5). The level of dominance of a single LULC class within a site (37%-50%) was considerably higher than that observed for the soil types (21% - 40%). When considering eleven classes, forest is the LULC class dominant for the eight sites. However when the agriculture classes are lumped together, this class appears dominant in three out of eight sites (table 2.5).

Table 2.5. Dominance and frequency of landuses at the landscape scale.

Site	Thiessen total area Km ² (Ta)	Total No of LULC fragments (n _L)	Ratio Ta/n _L Km ²	Dominant Land use	Dominant LULC total area (Km ²)	% from Thiessen area
8	69.95	1080	0.064	Forest	27.08	39
16	77.21	1318	0.058	Agriculture	33.44	43
26	55.02	865	0.063	Agriculture	27.34	50
32	28.47	495	0.057	Forest	10.46	37
40	38.10	683	0.055	Forest	14.42	38
50	66.13	967	0.068	Forest	29.28	44
63	52.96	845	0.062	Forest	24.46	46
66	87.21	1260	0.069	Agriculture	38.38	44
Total		7514				

Table 2.6. landuses ranked according to greatest percentage of fragments.

	First		Second		Third	
Site	Land use	% from total	Land use	% from total	Land use	% from total
8	Forest	31	Urban	17	Ag4	10
16	Forest	25	Ag2	13	Urban	12
26	Forest	26	Ag4	20	Ag1	13
32	Forest	26	Urban	17	Ag4	12
40	Forest	29	Urban	19	Grass	12
50	Forest	32	Ag1	15	Grass	14
63	Forest	33	Ag1	13	Urban	11
66	Forest	25	Grass	14	Ag4	14

In addition to forest, the landuses with the highest frequency for all sites were agriculture, urban and grass. Overall, the combination of three landuses account for more than 50% of the total number of fragments in all the sites although their combination was different among the sites (table 2.6),. The presence among the most frequent classes of the urban class is particularly important when assessing the hydrological characteristics of the study area since impermeable surfaces associated with urban landuse differ in their surface temperature and hydrological behavior from vegetation covers. In this analysis, the urban class shows a site specific effect since it was the second most frequent in three of the sites (8, 32 and 40) and the third most frequent in two more (16 and 63).

b. LULC complexity and sampling unit size

The dominance of the LULC classes across the different sampling areas showed site specific results since half of the sites have the same dominant LULC at all three of the sampling areas studied, while the other half showed different combinations of LULC over all the sampling areas (table 2.7). In this way, agriculture dominates across sampling areas in three sites (26, 40 and 66), while grass dominates only for site 50. Unlike the trend observed for soil diversity, in this analysis the dominant LULC coincide with the most frequent LULC at the three different spatial sampling areas (table 2.7).

At the level of the smallest spatial areas (90 and 250 m) LULC have average highest patch frequency than the soil types. In fact, LULC average frequency ranged between 4 and 5.7 fragments, while soil types ranged between 2 and 4.6 fragments (table 2.4 and 2.7). Similar results were found with the largest sampled areas such as 1000 m and Thiessen polygons in which for each site the number of LULC fragments was greater than the number of different soil type fragments (tables 2.3, 2.5 and 2.7).

These results suggest that when considering environmental variables individually, vegetation covers is the environmental variable that incorporates more of the complexity due to fragmentation within this landscape. The high diversity of the landscape in vegetation covers even in small areas suggests that remote sensors that can discriminate smaller areas are more likely to capture the complexity of diverse LULC. For remote sensing applications of soil moisture, these results indicate that sensors that can discriminate among the different vegetation covers are likely to have more success in assessing the vegetation component of the soil moisture response.

Table 2.7. Dominance and frequency of LULC at three different spatial areas.

Site	90m				250m				1000m			
	n _L	Most frequent land use	Dominant land use	% of Area	n _L	Most frequent land use	Dominant land use	% of area	n _L	Most frequent land use	Dominant land use	% of Area
8	4	Shared*	Forest	46.2	7	Forest	Forest	37.5	16	Urban	Urban	19.2
16	6	Shared**	Urban	33.6	8	Forest	Forest	39.3	21	Forest	Agriculture	47.8
26	5	Agriculture	Agriculture	44.4	8	Agriculture	Agriculture	46.4	20	Agriculture	Agriculture	64.8
32	4	Grass	Grass	38.1	4	Grass	Grass	49.0	17	Agriculture	Agriculture	43.7
40	4	Agriculture	Agriculture	92.1	5	Agriculture	Agriculture	96.9	13	Agriculture	Agriculture	59.9
50	3	Grass	Grass	84.8	5	Grass	Grass	94.4	14	Grass	Grass	63.3
63	2	Shared*	Grass	61.1	3	Agriculture	Agriculture	60.1	19	Agriculture	Agriculture	53.6
66	5	Agriculture	Agriculture	69.3	6	Agriculture	Agriculture	57.1	17	Agriculture	Agriculture	69.5

* two different landuses in the study area

** six different landuses in the study area

2.3.4. Complexity analysis of combined soil and vegetation cover

The high level of landscape fragmentation previously discussed in the analysis of soil and LULC increased when the two variables were considered together (table 2.8). When both of these variables are combined, a total of 38,716 landscape patches were found within the eight study areas. The eight sites showed a similar trend in the ratio of *Total area* to *number of fragments* (Ta/n_c), suggesting that the level of landscape fragmentation is not site specific, although the composition of its diversity may be. This result is consistent with what was previously discussed for the individual analyze of LULC and soils.

For this analysis of combined LULC/soil types, some of the LULC classes were grouped together into more general classes to facilitate the analysis of landuse-soil combinations. Four agriculture classes were grouped in a new class named AllAg; also, forest and orchard classes were clumped in the class AllTree, while roads and urban areas formed the class AllUrb. The remaining landuses were kept as single classes.

When analyzing the three most dominant LULC/soil combinations ranked by order of area covered (table 2.8), there were no differences among sites for the first and second dominant combinations AllAg-TfB and AllTree-Ah respectively. These two combinations differed not just in the LULC but also in soil type. For the third dominant LULC/soil combination with the exception of site 32 all the sites have the same LULC (AllTree) and differences were found among the soil types. Despite the fact that the same combination (AllAg-TfB) being ranked first for all the sites, important differences (in the range of 12.5 and 31.1 %) were found in the percentage of area that it covered. This is particularly important in sites 40, 50 and 63 where the difference in second dominant combination (AllTree –Ah) is less than 6%, suggesting a possible shared dominance between different landuses and soil types.

The in-site number of combinations for the eight sites showed an average of 23 soil types interacting with a single LULC group. The maximum combination of soil types (35) with a single LULC was observed in site 16 for the LULC groups AllTree and Allurban.

In summary, this analysis of combined LULC/soil types shows that under a scenario where two environmental variables are analyzed together, the level of landscape complexity is substantially greater than that observed when individual variables are considered separately. Although the level of fragmentation between the sites appears to be similar, site specific differences were found in the dominance of LULC-soil type combinations and in the diversity of such combinations.

For the remote sensing analysis of soil moisture in this landscape, these results suggest that extrapolation of point sample measurements of soil moisture to near by locations of soil moisture conditions based only on the analysis of vegetation cover can produce errors since the combination of LULC and soil types may add complexity to the soil moisture behavior. On the other hand, since the dominant combination represents in average 21% of study area and not more than 31%, the identification of dominant combinations and their soil moisture behavior is suggested as the first step to produce a distribute representation of soil moisture under a complex landscape. Furthermore, the high average ratio soil type/LULC (25:1) implies that at each site important variation of the soil moisture conditions can be found even within similar landuses. In this way, in the next session a detailed characterization of the variations in the water infiltration process produced by the dominant and most frequent soils under similar climatic characteristics will serve to assess the differences that in soil moisture behavior can be expected in fields with similar LULC.

Table 2.8. Sites frequency in combinations of land use- soil types and three dominant combinations ranked.

				First		Second		Third	
Site	Thiessen total area Km ² (Ta)	Total No of combined fragments (n _C)	Ratio Ta/ n _C Km ²	LULC-soil type combination	% from Thiessen area	LULC-soil type combination	% from Thiessen area	LULC-soil type combination	% from Thiessen area
8	69.95	5223	0.013	AllAgr-TfB	24.0	AllTree-Ah	8.9	AllTree-KO	8.2
16	77.21	6672	0.011	AllAgr-TfB	24.6	AllTree-Ah	10.0	AllTree-KO	6.0
26	55.02	4546	0.012	AllAgr-TfB	31.1	AllTree-Ah	9.4	AllTree-KO	5.1
32	28.47	2183	0.013	AllAgr-TfB	20.2	AllTree-Ah	9.8	AllUrb-TfB	7.1
40	38.10	3167	0.012	AllAgr-TfB	13.4	AllTree-Ah	10.4	AllTree-TfB	9.0
50	66.13	5670	0.012	AllAgr-TfB	12.5	AllTree-Ah	9.9	AllTree-KO	6.9
63	52.96	4835	0.011	AllAgr-TfB	16.4	AllTree-Ah	10.3	AllTree-TfB	5.6
66	87.21	6420	0.014	AllAgr-TfB	27.2	AllTree-Ah	9.7	AllTree-KO	5.3
Total		38716							

2.3.5. Hydrological assessment of soil variation. Soil types Alapaha (Ah), Fuquay (FsB), Ocilla (Oc), SunSweet (StD2) and Tifton (TfB) were responsible for the highest frequency and dominance within the study area. Therefore, we compare these soils in their physical and hydraulic characteristics to assess their variability in the soil moisture behavior at the local scale.

The analysis of the SSURGO database shows that with the exception of StD2, the soil types found at the LRW are under the same USDA class, loamy sand, with similar percentages of salt, silt and clay, as well as bulk density (table 2.9). Soil type, StD2 is the only soil with silt characteristics differing in the textural components from the other units and classified under the USDA texture class sandy loam. Among the loamy units, differences were found in the depth of the first two layers for which TfB presents a shadow first layer (<10 cm), that is different from a little deeper layer (<24 cm) for Ah, FsB and Oc. Soil Oc has the deepest second layer of the four loamy units reaching down to 70 cm depth. In contrast with the loamy units, StD2 present two shallow upper layers that combined with its clayed texture may cause differences in the short and long term infiltration process.

The percentage of clay, silt and sand from the SSURGO data set were processed through the ROSETTA V1.0 program to estimate the Hydraulic parameters of the five soil types (table 2.10). Slight differences were found among the five soils for the saturated water content (θ_s) and residual water content (θ_r). More important differences were found between StD2 and the four loamy soils for the coefficient (α) and exponent (n) of the van Genuchten water retention function, and for the matching point at saturation (K_o). FsB and TfB present similar saturated Hydraulic conductivity (K_s), while Oc and StD2 showed the minimum and maximum values of the five soil types for

this variable (table 2.10).

Table 2.9. Physical properties of the most frequent and dominant soil types

Soil name	Alapaha	Fuquay	Ocilla	SunSweet	Tifton
Soil symbol	Ah	FsB	Oc	StD2	TfB
%Sand	83.8	84.9	83.8	66.6	85.3
%Silt	9.2	9.1	9.2	23.4	9.2
%Clay	7	6	7	10	5.5
Bulk density g/cc	1.5	1.65	1.55	1.4	1.5
Depth 1 st layer	0-28	0-26	0-24	0-4	0-10
Depth 2 nd layer	28-46	26-31	24-72	4-14	10-15
USCS soil class 1 st layer	Loamy Sand IS	Loamy Sand IS	Loamy Sand IS	Sandy Loam sL	Loamy Sand IS
USCS soil class 2 nd layer	Sandy Clay SC	Sandy Clay SC	Sandy Clay CL SC	Clay or Sandy Clay CL SL	Sandy Loam SC SM

Table 2.10. ROSSETA estimates of Hydraulic properties

Soil name	Alapaha	Fuquay	Ocilla	SunSweet	Tifton
Soil symbol	Ah	FsB	Oc	StD2	TfB
θ_r cm ³ /cm ³	0.0484	0.0477	0.0476	0.0438	0.0472
θ_s cm ³ /cm ³	0.3912	0.39	0.3765	0.4	0.3892
Alog(1/cm)	-1.4466	-1.4389	-1.4411	-1.54	-1.4341
(α)	0.035751	0.0364	0.036207	0.02884	0.036804
N log10	0.2935	0.3152	0.2912	0.1667	0.3244
N or (n)	1.9656	2.0663	1.9552	1.4679	2.11057
Ks log(cm/day)	2.2026	2.2734	2.1366	1.8027	2.3027
Ks cm/sec	1.84e-3	2.17e-3	1.59e-3	7.35e-4	2.32e-3
Ko log10	1.4321	1.4501	1.421	1.2402	1.4602
L No Units	-0.8366	-0.8326	-0.8682	-0.8703	-0.8323

2.3.6. Fast All-season Soil Strenght FASST

The effect of the physical and Hydraulic characteristics in the water budget and in the soil moisture of the five soil types were evaluated using the one-dimensional state of the ground model FASST. The five soils were tested using the same set of meteorological data and under no vegetation cover. The model was initialized with identical soil moisture and ground temperatures for all the five soils, as well as, individual soil files with the differences described for the soil layers, and the physical and Hydraulic

parameters of each soil type. The meteorological data present three precipitation events on Julian days 261, 265 and 271.

At the ground surface level (0- <5 cm layer), it was found that three loamy soils (Ah, FsB and TfB) present a similar trend in soil moisture responses with variations of less than 2% of soil moisture content between them (figure 2.5). Soil StD2 showed a soil moisture pattern different from the loamy soils characterized by greater water content and longer soil moisture conditions after precipitation events. This is caused by the clayed conditions of the soil that makes the process of water movement into the soil profile slower than under more sandy conditions (loamy soils). At this soil layer, soil Oc showed the lowest soil moisture contents of the five soils with 5% of soil moisture difference when compared with the loamy soils. In fact, since water infiltrates faster into its deepest first sandy layers soil Oc, presented the lowest values of soil moisture content for all the depths analyzed. In general, FsB and Ah presented the smallest temporal variations in soil moisture and the most similar behavior in the water movement through the soil profile. Some differences among the loamy soils appear after 5 cm depth, where soil TfB presents around 2.5% less water content than FsB and Ah. This effect is caused by the changes in soil conditions on first two layers of TfB with a faster infiltration process occurring after 10 cm depth. At this soil depth, StD2 appears as the driest soil until around day 265 when the water provided by the first precipitation event infiltrates reaches this layer. This characteristic of clayed soil has important implications for investigations of soil moisture conditions using remote sensing since despite high moisture values registered at the surface level and recorded by the sensor, very different conditions will be present in deepest layers of the soil that can be inferred only by the integration of mapped soil distributions with the remote sensing analysis.

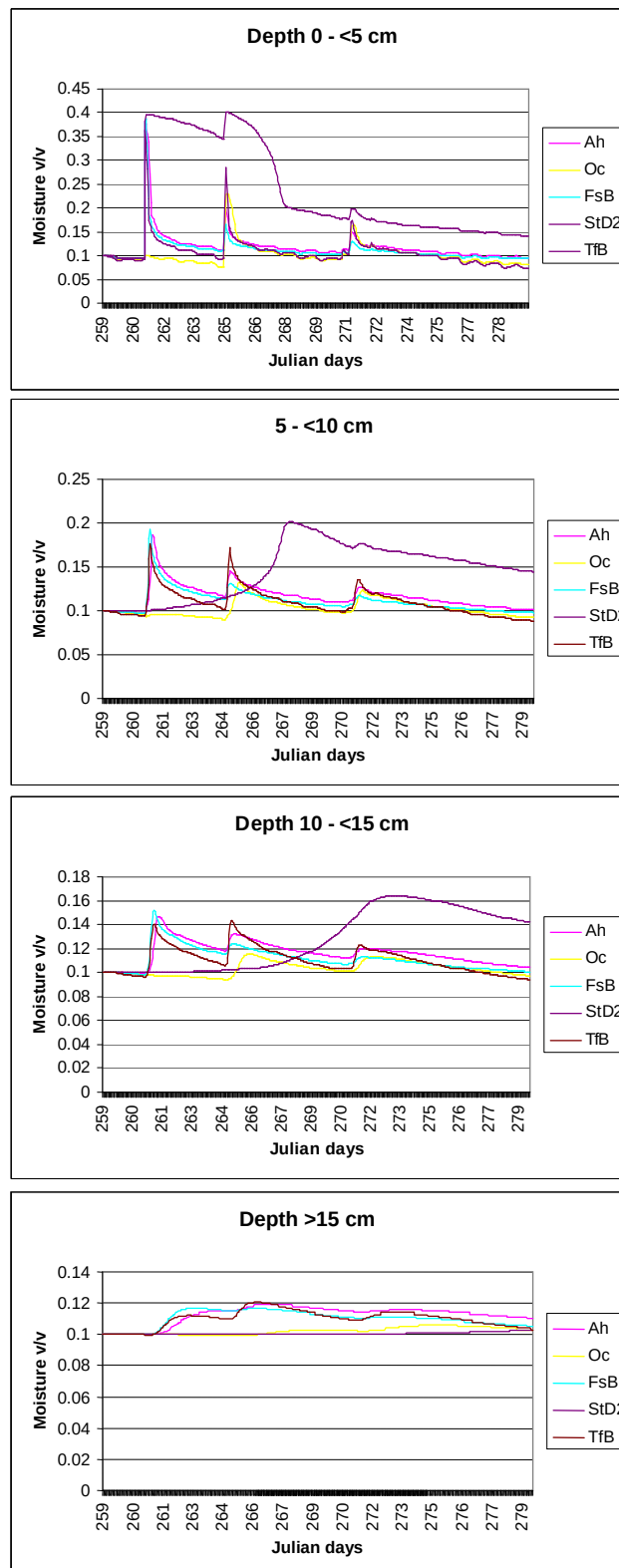


Figure 2.5. Soil moisture response from five soil types at three different depths.

2.4. Discussion and Conclusions

The results of this research suggest that the LULC and soil types at the Little River Watershed make this landscape very fragmented and complex. The heterogeneity observed in the landscape is not the same everywhere and rather site specific with important variations among sites in the composition and combinations of the dominant elements. Despite this heterogeneity, a few soil types and LULC classes can be identified as the most characteristic of the landscape and, therefore, useful for the hydrological assessment of soil moisture characteristics. The impact of the typical LRW soil types is caused either because a single soil type occupies a large area or because it has a high number of fragments scatter around the study area. This tendency was observed to be independent of the spatial area but with some exceptions that are site specific.

Not one of the analyzed eight Hydra-probe stations is located in an area in which a single combination of land use-soil type makes up a 30 m square area. This result indicates that in addition to the LULC where the site is located, other LULC are expected to influence the soil moisture behavior at the site location with greater effects over the Hydra-probe readings, especially when shorter distances between adjacent fragments and the station point location are observed (table 2.11). This is particularly important for the scenario of a remote sensing data validation using a pixel by pixel approach with a pixel centered at the Hydra-probe site, since in our research, at least two different LULC and two soil types are found within the 30 x 30 m area surrounding the Hydra-probe station. The presence of the classes urban and road is particularly important when assessing the hydrological characteristics and soil moisture of the sites because impermeable surfaces associated with urban landuse create a different soil moisture behavior than areas under vegetation cover.

The lack of statistical differences in distance between sites and soil types indicates that the soil composition around the sites is diverse and, therefore, the soil types that influence the soil moisture behavior change from site to site. In this way, a detailed characterization of areas surrounding the Hydra-probe stations sites and in the classes forming the AllAg and AllTree group may serve to understand the soil moisture behavior within such fields and its relationship with the Hydra-probe sites. On the other hand, the high diversity of localized LULC in the small sampling spatial areas (e.g. 90 m) suggests that instruments that can discriminate smaller features on the ground are more likely to capture the individual LULC complexity and better predict the soil moisture behavior.

The high soil types LULC ratio observed (23:1) suggest a landscape in which variations of the soil moisture conditions can be found even within similar LULC with short distance intervals (less than 160 m). For the remote sensing analysis of soil moisture in this landscape these results suggest that techniques to estimate soil moisture based on vegetation cover may present errors due to assumptions of homogeneity this can be addressed by the incorporation of ancillary soil information to the process of soil moisture estimation. In this regard, the work of Chen *et al.* 2004 suggests methodological approaches for the remote sensing discrimination of soil heterogeneity that can be useful when sampling agriculture areas in the off-cropping season. In a similar way, errors also can be avoided when interpolating ground point data to unknown areas by incorporating ecological criteria based on the variability of the environmental variables that affect soil moisture. This should be conducted in addition to the geo-statistical analysis based on spatial distance alone.

Despite the complexity of the LRW landscape, two LULC/soil combinations AllAg-TfB and Alltree-Ah were found to contribute with at least 21% of study area. In

this way, the identification and analysis of the dominant and most frequent LULC/soil type combination is suggested as an important first step in the process of producing a distributed soil moisture representation at the landscape scale.

The benefit of OBIA approach rather than a pixel-based approach in studying spatial heterogeneity has been demonstrated since soil moisture processes can be linked directly to the areas of unique spatial organization rather than arbitrary pixel ground areas in landscapes of high complexity.

Table 2.11. LULC and soil types for Hydra-probe sites and their nearest fragment

Site	Hydra-probe soil type	Nearest soil type	Hydra-probe LULC	Nearest LULC
8	Oc	FsB	low urban	road, grass, agriculture, forest
16	TfB	DoB	low urban	agriculture, road
26	Ah	TfB	wetland	agriculture, forest
32	TfB	DoB	grass	road, orchard, agriculture,
40	TfB	TfC - DoB	agriculture	road
50	StD2	FsB	grass	road, grass
63	FsB	Se, Pe	grass	agriculture
66	TfB	Ah	agriculture	road, wetland, agriculture

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CHAPTER 3

SOIL MOISTURE VARIATION AND LANDSCAPE HETEROGENEITY FOR
REMOTE SENSING APPLICATIONS IN SOUTH GEORGIA, USA¹

¹ Giraldo, M., Madden, M., Bosch, D., Usery, L and Kvien, C. To be submitted to the *Journal of Hydrology*

Abstract

Accurate long term study of the environmental cycles and the calibration of remote sensing data using the *in situ* network of soil moisture stations operated by the USDA-ARS-SEWRL near Tifton, Georgia rely on understanding the relationships between the point field data and the surrounding landscape. Under an object oriented approach that recognize landscape fragments/patches as the landscape spatial units of organization, this research investigates the spatial and temporal variation of soil moisture (SM) conditions in eight 30 m by 30 m homogeneous fields matching the pixel size of a Landsat Thematic Mapper (TM) or Enhanced Thematic Mapper plus (ETM+) image and adjacent to eight stations of the *in situ* network. We also study the effect of five different landuses/land cover (LULC) (grass, orchard, peanuts, cotton and bare-soil) in the temporal and spatial variation of soil moisture. On eight occasions throughout 2005 and January 2006 we collected soil moisture field data establishing comparisons within and among eight homogeneous fields. Consistently throughout time, analysis of variance (ANOVA) showed high variation in the soil moisture behavior among the small fields and high homogeneity in the soil moisture behavior within them. A precipitation analysis for the eight sampling dates throughout the year 2005 showed similar rainfall conditions for the eight studying locations and, therefore, soil moisture variations among locations are explained by local conditions. Temporal stability geostatistical analysis showed that soil moisture presents high temporal stability within the small fields at all the locations and that a single point reading location can be used to monitor soil moisture status for the field within a maximum 3% volume/volume (v/v) of soil moisture variation. However, only five of the eight soil moisture stations correlated with the average of their adjacent homogeneous field. Similarly, t-statistic analysis showed that soil moisture status in the upper soil layer changes within 24 h. We found statistic differences in the soil moisture between the different LULC and also statistic differences between them and the adjacent fields. Considering the heterogeneity of the broader landscape, these results confirms that an object oriented approach rather than a pixel oriented approach of remote sensing data will contribute to identify soil moisture variations under heterogeneous landscapes. Also, that the *in situ* network will serve better in remote sensing studies in which sensors with fine spatial resolution are evaluated. This study is a first step towards identifying landscape units (patches) with homogeneous soil moisture behavior that can be monitored using the single point reading of the network stations. It is recommended to extend this study to other areas of the watershed to increase the understanding of the relationships between the soil moisture stations and the surrounding landscape for improving the use of remote sensing to model soil moisture behavior.

Key words: spatio-temporal analysis, soil moisture, remote sensing, scale, point data, LULC.

3.1. Introduction

The combination of environmental variables such as soils types, vegetation covers, topography and climatic conditions creates, within the landscape, spatially distributed patterns of soil moisture varying over different scales of space and time (Qiu *et al.* 2003, Anderson *et al.* 2004). As a consequence, soil moisture is not a random phenomenon, but a spatially organized one in which the spatial variability of its response varies according to the size of the sampled areas and the characteristics of the environmental variables that produces it (Western and Blöchl, 1999).

Defining the geographic extent of a moist field that is represented by a point sample as measured by a typical monitoring system has been a critical topic of investigation that is needed to advance the process of retrieving and validating soil moisture estimates from remote sensors. Under field conditions with homogeneous soil texture, vegetation cover and hill slope, studies demonstrate that single point measurements can accurately represent the average soil moisture of an entire agriculture field and, therefore, be useful under certain spatial ranges to calibrate the soil moisture estimates from remote sensing instruments (Western and Blöchl 1999, Jacobs *et al.* 2004). However, in spatially heterogeneous landscapes, high spatial and temporal variation in soil moisture behavior is created by the combination of precipitation, landuse-land cover (LULC), soil type and topography that change over distances of less than a few hundreds of meters (Grayson and Western 1998, Pauwels *et al.* 2001).

In the heterogeneous agricultural landscape within the Little River Watershed (LRW) in south Georgia, an *in situ* network of 27 ground stations was established in 2002 and 2003 as a source of ground-based point data to validate remote sensing analyses of soil moisture, soil temperature and climate and for long term hydrological studies in the

southeastern United States (Bosch *et al.* 2005). This watershed is composed of a variety of soil types ranging from the fine sandy loamy conditions in the floodplain to the heavy textured and most eroded uplands, forming a diverse landscape with a mix of landuses. Agricultural fields with different crops are interwoven with pastures, natural and planted forest and orchard parcels of different size, shape and extent. Vegetation covering the soil in annual and seasonal row crops also changes through the cropping season from bare soil to full vegetated conditions.

In highly fragmented and diverse landscapes, the uncertainty of the soil moisture estimates from remote sensors is likely to increase by using sensors with coarse spatial resolution. Under coarse spatial resolution, the ground area of the pixel value is larger than the landscape fragment sizes for soil, LULC and topography, thus, the pixel reflectance value in the image will comprise a mix of different soil moisture behaviors. In the context of the USDA-NASA Soil Moisture Experiment 2003 (SMEX03), temporal stability geostatistical analysis demonstrated that each one of the *in situ* devices at the LRW produces reliable information of the soil moisture conditions showing that data collected by each location is also stable throughout time (Bosch *et al.* 2005). When using satellite remote sensing data from the Tropical Rainfall Measurement Mission Microwave Imager (TRIMM) and the Moderate Resolution Image Spectro Radiometer (MODIS), the works of Cashion *et al.* (2005) showed that at the LRW, remote sensors with coarse spatial resolution in the magnitude of several square kilometers produce inaccurate estimates of the soil moisture conditions.

They suggested that satellite remote sensing data with smaller effective field of view (EFOV) less than a square km could better capture the spatial heterogeneity of the landscape at the LRW and, therefore, improve estimations of the soil moisture behavior.

As a result of these observations, instruments with small EFOV (less than 30 m) such as the multispectral scanners of the Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+), the radar sensors on RADARSAT and the thermal infrared sensors in Advanced Spectral Thermal Emissions Radiometer (ASTER) and Advanced Land Imager (ALI) are expected to better capture the landscape environmental complexity, and more accurately analyze local field conditions.

The general objective of this research is to investigate within the heterogeneous LRW landscape, the spatial variation of ground-based soil moisture point data collected from small fields matching in area the ground resolution of small EFOV remote sensors. Our hypothesis is despite the heterogeneity of the LRW at the landscape scale, it is possible to find temporally and spatially homogeneous soil moisture behaviors within small fields of 30 x 30 m at different landscape locations. Also, within those fields and, as a consequence of homogeneous soil moisture conditions, a single point measurement can be used to represent the soil moisture behavior of the entire field. Another hypothesis is that homogeneous soil moisture conditions can be identified within small field regardless of their LULC and that each LULC has a characteristic soil moisture behavior that is different from the others. In this case, the objective is to evaluate the soil moisture variation within five dominant LULCs in the LRW landscape.

As a contribution to the continually advancing field of remote sensing of soil moisture, our results increase field knowledge that led to a better interpretation of the results of the soil moisture experiment SMEX03. During an intense field campaign in the Summer of 2003, field soil moisture and meteorological data were collected with the purpose of validating satellite remote sensing data from sensors such as the Advanced Very High Resolution Radiometer (AVHRR), Advanced Microwave Scanner Radiometer

(AMSR) and the Advanced Synthetic Aperture Radar (ASAR), among others (Bidlish *et al.* 2003, Bosch *et al.* 2005, Cashion *et al.* 2005). This research also offers an opportunity to increase field knowledge of soil moisture behavior in heterogeneous landscapes towards linking fine spatial resolution data with ground measurements for broad scale estimations of soil moisture.

3.2. Methodology

3.2.1. Study area. The fields evaluated in this study are located at the northeastern portion of the 334 km² Little River experimental watershed in the South Atlantic coastal plain of the United States, near Tifton, Georgia (figure 3.1). The watershed has relatively flat topography characterized by broad floodplains with poorly defined stream channels and gently sloping uplands varying from 1 to 5%. The typical soil for the area is sandy loam with a sandy surface horizon and heavier textured subsoil. This type of soil presents low water holding capacities, with a fast superficial drainage. The annual average precipitation is approximately 1200 mm. Rainfall is unevenly distributed through the year with short-duration rains during the winter and high-intensity thunderstorms during the summer. While summers are long, hot and humid, winters are short and mild. The landscape is composed of a diversity of LULC including forest, cropland, pasture, residential areas and wetlands. Animal production is combined with agricultural activities yielding year-round production of vegetables and row crops (Bosch *et al.* 2004, Cashion *et al.* 2005).

The *in situ* network of soil moisture measurement devices at the LRW is composed of 27 stations equipped with Stevens-Vitel Hydra-probes (Stevens Water Monitoring Systems Inc.) recording soil moisture information at three soil depths at 30

minute intervals (2, 8 and 12 inches) along with ground temperature every 30 minutes. Hydra-probes measure a dielectric constant for the soil and convert it to volumetric soil moisture based upon a factory provided calibration equation (Campbell 1990, Gaskin and Miller 1996). The network was established in 2002 as one of the sites for the SMEX03 (<http://hydrolab.arsusda.gov/smex03/SMEX03v5.pdf>) and since then continuous records have been used in hydrological studies (Bosch *et al* 2004) and in remote sensing analysis (Cashion *et al* 2005).

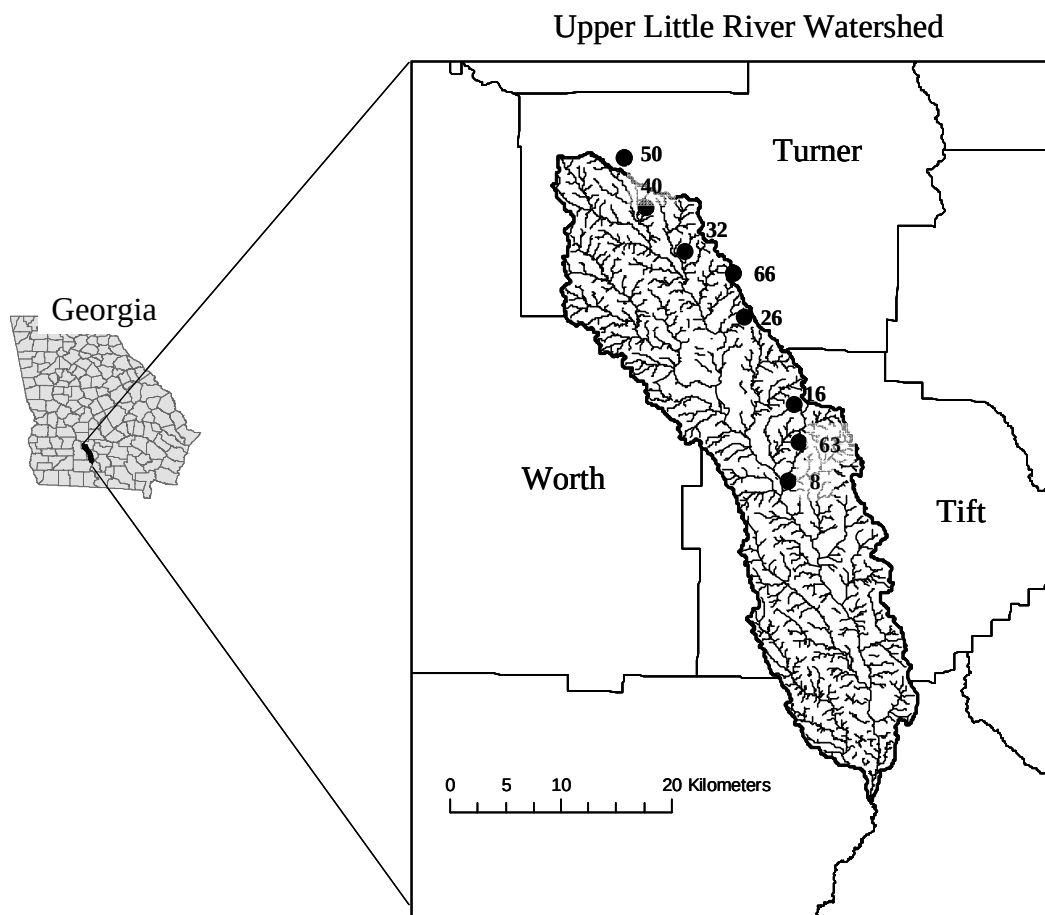


Figure 3.1. Location of the Little River Watershed in southeastern Georgia US and the sampling locations. The location of the sites is approximate to their true geographic location.

3.2.2. *In situ* field data collection. A sample of eight fields associated with the *in situ* soil moisture monitoring stations were selected for this research considering the logistical and practical constraints of access and completing field measurements within the same day (table 3.1). Within each of the sampling fields, soil moisture was measured using a portable Theta capacitance probe (Dynamax, Inc., ML2X Theta probe) that measures dielectric conductivity similar to the Hydra-probe explained above. The accuracy and reliability of this equipment in obtaining soil moisture point data were demonstrated by Jacobs *et al.* (2003) and Bosch *et al.* (2005), among others.

Table 3.1. Location, soil information and annual precipitation for the study sites

Site	Y Coordinate	X Coordinate	Elevation (m)	Land cover	Soil name	Total PPT 2005 (cm)
8				Grass	Ocilla	150.2
16	3494245.16	256307.44	123	Grass	Tifton	150.2
26	3502328.72	252215.12	115	Row crop	Alapaha	147.7
32	3507196.64	249514.28	123	Grass	Tifton	140.5
40	3511504.48	246611.08	134	Row crop	Tifton	141.0
50	3516116.84	244911.43	113	Grass	Sunsweet	151.3
63	3490204.59	258057.01	110	Grass	Fuquay	132.4
66				Bare soil	Tifton	138.0

Three different soil moisture data sets were collected during eight field campaigns throughout 2005 and January 2006. The first data set consists of soil moisture field data collected randomly within eight 30 by 30 m fields, each one of them associated with a Hydra-probe soil moisture-weather station. The Hydra-probe stations studied were: sites 8, 16, 26, 32, 40, 50, 63 and 66 (figure 3.1). For each field, 10 to 20 readings were collected on four different dates: March 11, March 28, April 12 and May 24 of 2005.

The second data set was created with soil moisture samples collected from the same fields, but following a systematic sampling process in which the location of each reading was known and kept constant for each one of the four sampling dates. Each

reading was taken at 3 m intervals in four directions from the Hydra-probe station collecting a total of 20 samples per field. An ideal configuration of the sampling procedure is presented on figure 3.2., with four perpendicular directions, however adjustments in the directions were made in some locations to avoid landscape variations and to preserve field homogeneity. At some locations, fewer than four directions were evaluated considering obstacles such as roads or channels. With the purpose of testing the temporal stability of the soil moisture reading, the samples were taken twice on two consecutive days: November 30 and December 1 of 2005, and January 13 and January 14 of 2006.

The third soil moisture data set was collected from five fields from the LULC grass, orchard, bare land and agriculture. The agriculture landuse was represented by two fields one with peanuts and one with cotton. From each landuse, eight to ten soil moisture readings, were collected at 3 m intervals following a 25-30 m transect, in which each sampling location was recorded and revisited four different times in November-December 2005 and January 2006, as mentioned above. The starting point for the transect was established immediately outside the perimeter of the 30 by 30 m field surrounding the Hydra-probe soil moisture stations. The grass, orchard, bare land and agriculture transects were associated by their close distance with the Hydra-probes sites: 50, 32, 66 and 40, respectively.

Ground temperature at 10 cm depth and surface temperature at 1 m above the surface also were measured simultaneously at each one of the soil moisture reading locations and for each one of the three data sets previously described. The analysis of the temperature data set and its relationship with soil moisture readings is presented in chapter 4 of this dissertation. Precipitation records for each site were obtained from rain

gages at the Hydra-probe stations, extracted for a 12-day period at intervals of 5 minutes and aggregated by day for each one of the sampling dates.

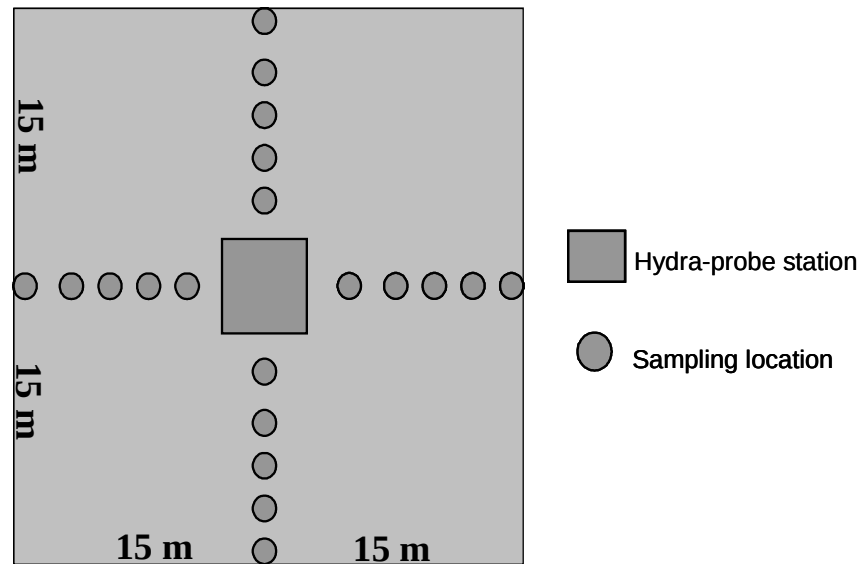


Figure 3.2. Ideal soil moisture field sampling at 3 m intervals within a 30 x 30 m area.

3.2.3. Statistical Analysis. Time stability analysis, one way analysis of variance (ANOVA), Tukey and Tamhane *post hoc* analysis, Pearson's correlation coefficient, General linear model, and t-test were used to analyze the field data. Time stability analysis requires calculating the mean of the volumetric soil moisture content of different places within the field. This average value is defined as the field mean. Using the field mean, Vachaud *et al.* (1985) present the mean relative difference and the variance of the relative difference as the standard test for time-stable point assessments. Mean relative difference is an indicator of the bias of a sample from the mean. The variance is an indicator of the precision of that reading. As an overall estimation of the time stability of a site within a field, the RMSE of mean relative difference combines both metrics. Therefore, places exhibiting a low RMSE are the most time stable within the studied field

(Jacobs *et al.* 2004). The advantages of these tests have been discussed in the works of Grayson and Western (1998), and Mohanty and Skaggs (2001).

The purpose of the mean relative difference is to measure, through time, how a particular site compares to the average of the field, indicating if the site is wetter or drier than the field mean. If the mean relative difference for a site is close to zero, that particular point-site can accurately estimate the mean of the field. Grayson and Western (1998) and Cosh *et al* (2004) formulated the mean relative difference as:

$$\bar{\delta}_i = \frac{1}{t} \sum_{j=1}^t \frac{S_{i,j} - \bar{S}_j}{\bar{S}_j}$$

where S_{ij} is the j th sample at the i th site of n sites within the field, and $\bar{S}_j$, the field mean is the computed average among all sites for a given date and time $j(j=1$ to $t)$.

The variance of the relative difference characterizes the precision of the point measurement Jacobs *et al.* (2004) formulated the variance of mean relative difference as:

$$\sigma(\delta)_{i,j}^2 = \frac{1}{n_t - 1} \sum_{t=1}^{n_t} \left(\frac{\theta_{i,j,t} - \bar{\theta}_{j,t}}{\bar{\theta}_{j,t}} - \bar{\delta}_{i,j} \right)^2$$

In addition to these tests, the Person's coefficient of correlation (Cosh *et al.* 2004) is presented as a complementary test to determine site time stability. The Pearson's correlation coefficient is defined by Cangelosi *et al.* (1976) as an abstract measure of the degree of relationship between two variables. This coefficient corresponds to the square

root of the coefficient of determination that considers the proportion of variation in one population-variable that is explained by the values of another population-variable. The Pearson's coefficient of correlation will compute the correlation of the soil moisture pattern between two days. Highly correlated patterns have values close to (1) uncorrelated patterns have values close to (0) and inversely correlated patterns have values close to (-1).

ANOVA is a statistical test that compares variation within the individual samples of a group, as well as the variation between groups from a sampling process. In this analysis an F value is generated and a statistical significance for the difference between and within groups can be established at the probability level of 0.05, 0.01 or less. In this research, ANOVA analyses were performed to compare the soil moisture behavior among the eight moist fields and to find fields that are similar in soil moisture behavior. A general linear model with factor analysis is a modification of the ANOVA test that divides the sources of variation within the groups by associated factors. This analysis was used to find directional effects within the moist fields.

In all the instances where statistical significance was found, a *post hoc* test was performed to detect the groups for which the difference shows significance. The Levenne homogeneity test was performed to decide which *post hoc* analysis to choose. When homogeneous variance within the groups was detected, a Tukey test was applied and Tukey groups of similar behavior were formed. In the scenarios in which the variance was not homogeneous, the Tamhane *post hoc* test was used.

A general two-paired t- test was computed to establish the significance of the difference between the soil moisture patterns from two simultaneous dates. This test will be described in more detail within the results section below.

3.3. Results

3.3.1. Soil moisture variation between and within fields

a. Precipitation analysis

The number of rainfall events for the 12-day period ranged between 3 and 6. The minimum average precipitation in a rain event was less than 2.5 cm observed previous to May 24 and the maximum was 10 cm previous to March 28. Under these precipitation conditions, the field work included at least one dry condition on May 24, one wet condition on March 28 and two intermediate conditions on the sampling days April 11 and March 11 (table 3.2 and figure 3.3). In general, the four dates of systematic sampling (November-December, and January 2006) were conducted under drier conditions than the previous sampling in early 2005, excepting the May reading (the driest one).

The precipitation records for a 12-day period prior to field soil moisture data collection showed that during rainfall events all the sites received simultaneous precipitation with small variations among them. The ANOVA of the precipitation events supported this observation with no significance difference at 0.01 probability level among locations for any of the 12-day periods before field data collections. This indicates that the water supply was homogeneous for all the sites prior the field data collections and, therefore, the differences in moisture conditions on the ground can be considered as the result of intrinsic environmental conditions acting within the field and mostly independent of water supply.

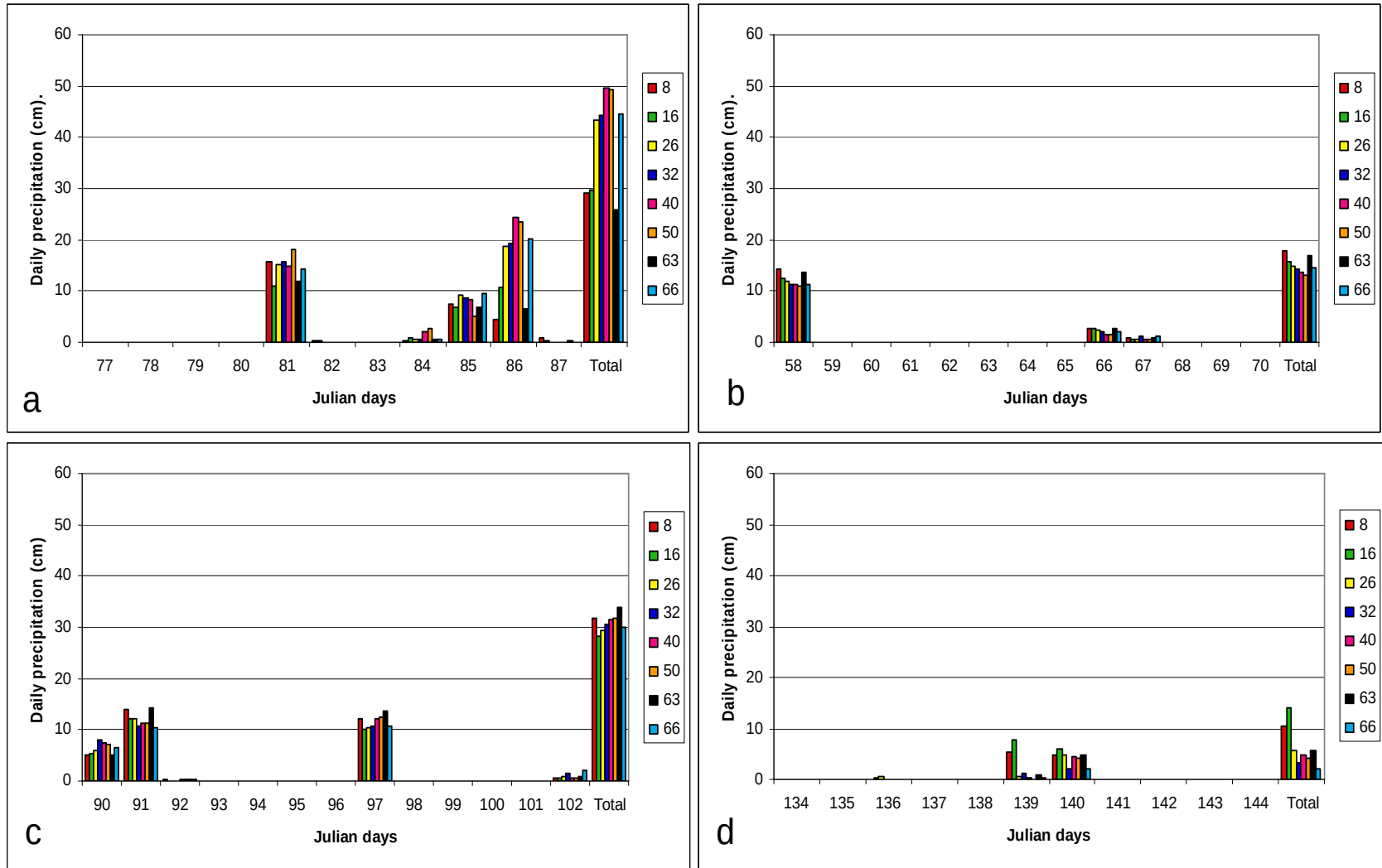


Figure 3.3. Actual precipitation at the sampling sites for the field data collections dates of March 11 (a), March 28 (b), April 12 (c), May 24 (d), and November – December (e) of 2005, and January of 2006 (f).

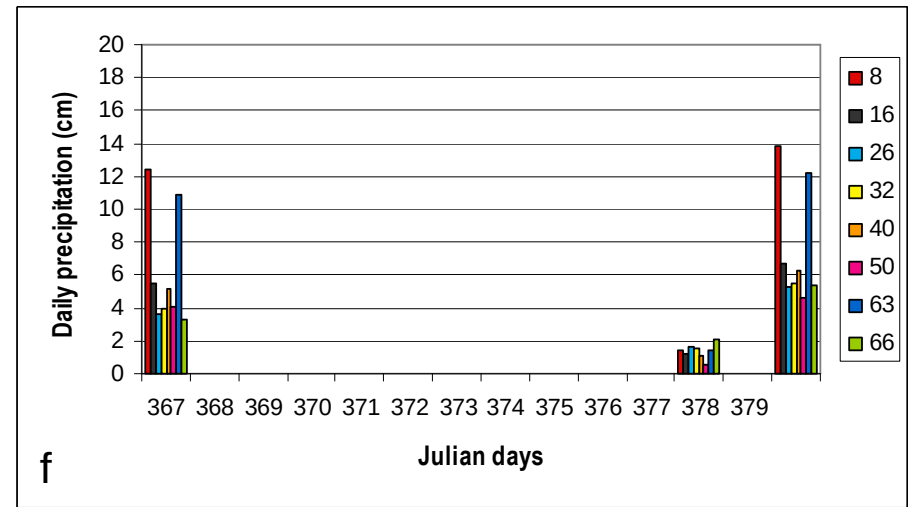
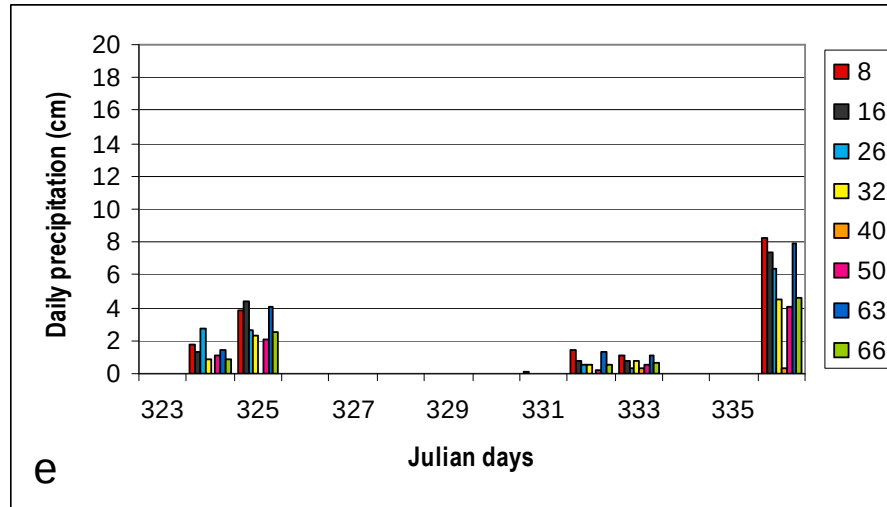


Figure 3.3. (Continued) Actual precipitation at the sampling sites for the field data collections dates of March 11 (a), March 28 (b), April 12 (c), May 24 (d), and November – December (e) of 2005, and January of 2006 (f).

Table 3.2. Summary of 12 day precipitation records previous to field data collection

Sampling date	Average total PPT/site in (cm)	Max. total PPT/site in (cm)	Min. total PPT/site in (cm)	No rain events	Average No of rain events
March 11, 2005	5.9 (15.1)	7.05 (17.9)	5.19 (13.2)	4	1.4
March 28, 2005	15.5 (39.4)	19.5 (49.5)	10.23 (25.9)	6	2.6
April 11, 2005	12.1 (30.9)	13.3 (33.8)	11.1 (28.2)	5	2.4
May 24, 2005	2.4 (6.3)	5.52 (14.0)	0.87 (2.2)	6	0.5
December 01, 2005	5.4 (13.8)	8.28 (21.0)	0.36 (0.9)	6	1.0
January 14, 2006	2.9 (7.5)	5.44 (13.8)	1.82 (4.6)	3	0.9

b. Soil moisture descriptive statistics

The mean volumetric soil moisture and the infield variation recorded for eight locations at each of the eight field data collection dates are presented in figure 3.4. In general, the periods of maximum and minimum soil moisture values correspond to the periods of maximum and minimum cumulative precipitation. The driest and wettest conditions match the cumulative precipitation values observed during a 12-day period before the sampling. Closer inspection of these data reveals site differences in soil moisture that are not explained by precipitation trends. The soil moisture records shown site 8 with the highest values of volumetric soil moisture while site 40 has the lowest values of volumetric soil moisture for most of the sampling dates. When compared with the precipitation record, site 8 presented the highest cumulative precipitation only for three of the sampling dates, while sites 63, 16 and 50 have greatest precipitation inputs for the five others dates. On the other hand, the lowest soil moisture values were found at sites 32 and 40 where the precipitation records shows site 40 with rainfall above the average for two of the sampling dates and less than 1.25 cm (0.5 inches) of rain below the average for three of the sampling dates.

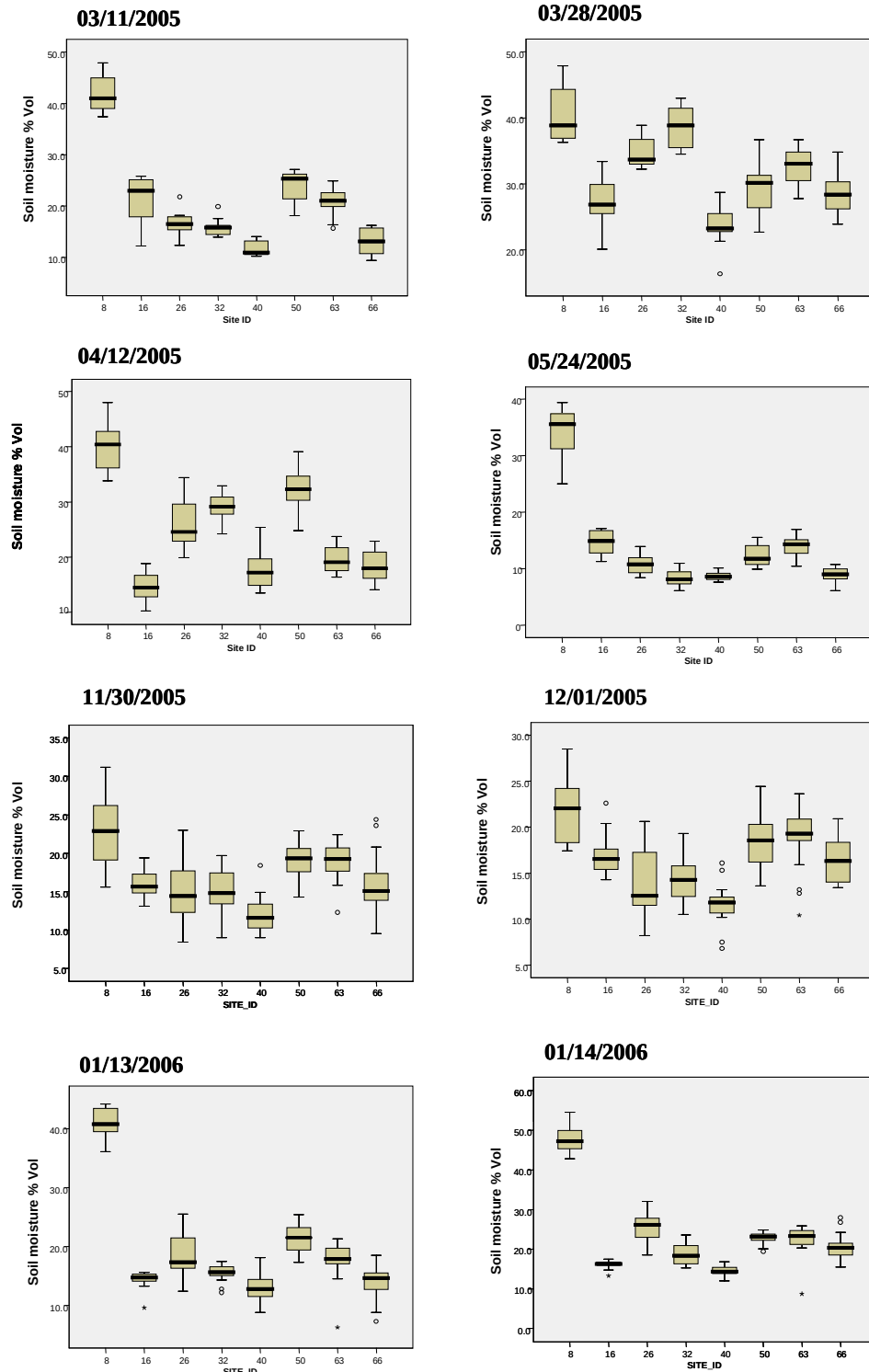


Figure 3.4. Soil moisture descriptive statistics for eight data collection locations. (Values in the (y) axis were automatically generated to fit the data).

Likewise, site 32 had higher precipitation than the average. These observations support the hypothesis that within eight sampling fields, soil moisture has a site specific behavior caused by intrinsic environmental variables beyond precipitation acting at the local scale. The descriptive statistics showed the standard deviation for the soil moisture in the range of 0.7 and 4.8% with an average of 2.8% when considering all the data sets together. The sites with higher soil moisture values such as site 8 and 16 presented greater standard deviation in each one of the different sample dates as did the sites with lower soil moisture. In the research of Anderson *et al.* (2004), high standard deviations were associated with soils approaching either the wet or the dry limits. As with total soil moisture, this research demonstrated that variation among fields for each of the field data collections days is not completely explained by precipitation alone.

c. Analysis of variance (ANOVA) of soil moisture

The difference between soil moisture conditions at each site for the different reading dates was explored using a one way ANOVA. This analysis uses two sets of variation to perform a comparison between the fields. The variation *within groups* accounts for the differences among all the sample points collected within a field on a given date. The variation among groups compares the overall variation among the fields for a given date. The statistical significance of the analysis is set at the probability level of 0.05 or 0.01.

The ANOVA for the eight fields showed statistical differences in soil moisture for all the sampling dates with significance below the 0.01 probability level. A large ratio in the range of 33.1 and 237.9 in the mean squares *between groups* and *within groups* (F value), confirms the variation in soil moisture behavior among the fields suggested by the

descriptive statistics. The low values for the *within groups* mean square score showed by the ANOVA analyses indicate low soil moisture variation within a given field, suggesting a homogeneous behavior of the soil moisture within the 30 by 30 m field.

The Tukey *post hoc* test was used to explore in more detail the variability among groups shown to be significant different by the ANOVA. The Tukey test conducts a multiple comparison among the fields, creating groups with similar responses for the studied variable significant at the probability level of 0.05. Table 3.3 summarizes the Tukey groups formed in one by one comparisons between sites. The number of times a pair of fields is placed together indicates the strength of the similarity between fields. In this case the strongest relationships were found between pairs 26-32, 32-66 and 50-63 which were grouped together six times, while the weakest relationships were found between pairs 8-29, 8-40, 8-66 and 40-50. Site 8 was found with the most unique soil moisture behavior, while site 66 presented a high level of similarity with other sites.

The similarity between soil moisture conditions at sites 26 and 32 can be explained by the precipitation record and the soil type since both sites received similar amounts of rainfall with less than 2.5 cm of difference for all the sampling dates and both sites belong to the Tifton soil series thus sharing similar soil characteristics.

Table 3.3. Tukey groups of similar soil moisture conditions.

Sites	8	16	26	32	40	50	63	66	Total
8		1	0	1	0	2	2	0	6
16	1		2	2	4	5	4	5	23
26	0	2		6	3	3	4	4	22
32	1	2	6		5	1	2	6	23
40	0	4	3	5		0	1	4	17
50	2	5	3	1	0		6	3	20
63	2	4	4	2	1	6		5	24
66	0	5	4	6	4	3	5		27
Total	6	23	22	23	17	20	24	27	0

The vegetation cover at site 32 is a short grass, while site 26 is located at the edge of an agriculture field in which hay is cut for cattle consumption. Similarities between sites 16 and 50 are not explained by the precipitation record since the difference in cumulative rain is more than 10 and even 18 cm of rain. These soils also differ in soil type since 16 is in the Tifton series while site 50 is in the Sunsweet series. However, their vegetation cover is similar since a homogeneous grass is present in both of them. These sites also are exposed to transit of agriculture equipment that may influence the soil physical characteristics.

After the cropping season is over, the area of site 40 previously planted with peanuts remains bared and without vegetation cover. This condition is similar to site 66 in which an important number of point samples were taken from the bare soil section of the field. The association between site 40 and 66 is related to a lesser degree with the cumulative precipitation since there are differences of only 2.5 and 5 cm of cumulative rain between them for the dates in which soil moisture was similar. Moreover, other sites that were not grouped with them have similar rainfall in a range of less than 2.5 cm of precipitation difference.

As previously mentioned, the most dissimilar sites were sites 40 and 50, and 50 and 32. To a lesser degree, low association was found between sites 16 and 32 in a total of six of the sampling dates. Compared with the precipitation input, the differences of cumulative rain were less than 2.5 cm in four occasions in the case of sites 40 and 50, and on three occasions for the differences between sites 50 and 32. For the pair 50 and 32, there were two occasions with high differences in cumulative rain and two occasions with very close total rain, indicating once again the secondary influence of precipitation in the

between fields variation.

d. Soil moisture time stability

The purpose of the parameter mean relative difference is to measure how a particular sampling location compares to the average soil moisture of the 30 by 30 m field, indicating if the sampling location is wetter or drier than the field mean. This analysis serves also as an indicator of the infield variation of surface soil moisture. In this regard, the results for the November-December field data collections showed field 26 with the highest range on mean difference with values between -36% and 39%, while the sites 16 and 50 showed the lowest variation with ranges between -12 and 19%, and -19 and 16%, respectively. For the January field data collections, the mean relative difference in variation decreased for all the fields when compared with the November-December, although site 26 was still the highest one (-19 and 26%). Field 8 showed the lowest variation with a range between -4 and 4% of mean relative difference (figure 3.5d).

When analyzing the two samples together (November-December and January), the mean difference (figure 3.5c) showed a high level of homogeneity within each of the sampled fields. The highest average of mean relative difference was 2.6% in site 66, followed by sites 8, 16 and 26 with values of 2.1, 1.2 and 1.0%, respectively. For all the other sites, the mean relative difference was below 0.1% of the field mean and even as low as <0.04% on sites 40 and 50, showing these two fields as the most homogeneous ones. Since the mean differences approached zero, these results indicate that the sampling points within the fields are very close to each field mean and, therefore, can accurately estimate the surface soil moisture behavior of the entire 30 by 30 m field.

Our results show a high level of infield homogeneity that contrast with the results of similar research performed in larger fields. For instance, the works of Bosch *et al.* (2005) in the Little River Watershed showed that at the landscape scale, measures made with a hand carried Theta probe can represent the field mean by only 3 to 12% of the mean relative difference. The highest range of readings that over and under estimating the field mean were observed on site 66 (-26% and 30%) and site 16 (-30% and 29%) and the lowest ranges were observed in sites 40 and 50 (-11% and 13%).

The work of Jacobs *et al.* (2003) showed variability in the range of 4 and 24% of the mean relative difference in agriculture fields of 800 m, explained as variations in the hill slope position, and by heavy textured soils conditions with high percentage of clay. In our research, by selecting small landscape fragments, the in-field heterogeneity caused by topographic differences was minimized since similar slope conditions applied to all the sampling points. This observation is important for future works comparing soil moisture behaviors, since by selecting small landscape fragments, heterogeneity among locations can be maximized for topographic variables.

On the other hand, Cosh *et al.* (2004) showed that uneven distribution of precipitation plays an important role in the soil moisture behavior of the point samples. Assuming similar soil conditions in large fields and unevenly distributed precipitation events over space, when compared with the mean of the field, dry points will receive less precipitation while wet points will be the ones with highest amounts of rain-fall. When the study is conducted over short periods of time the distribution of rain-fall is especially critical, since the results will show points of temporal instability that over or under estimate the field mean.

Differences in LULC and their spatial distribution is a characteristic that may produce variations in the mean relative difference between the fields. In the case of site 66, portions of the field are part of an bare land with an un even vegetation cover mix of short grasses and weeds and eventually bushes that were mowed during some reading dates. In the field at site 16, some of the areas were affected by the transit of agriculture equipment, not only affecting the growth of the tall grass cover but also the compaction of the soil and the infiltration of water into the ground. These details in LULC may explain the range in the time stability showed by some of the point readings of these fields.

Alternatively, the stability in fields 50 and 40 can be explained by their relatively homogeneous land cover. Field 50 forms part of a large pasture and the entire field is covered by the same type of grass, while field 40 is part of a mechanized agriculture field and changes in vegetation cover through the growing season similarly affect all the sampling points. This homogeneous characteristic of vegetation cover, in addition to the homogeneity in precipitation, slope and soil physical properties, may contribute to the high stability of the soil moisture recorded at these two sites.

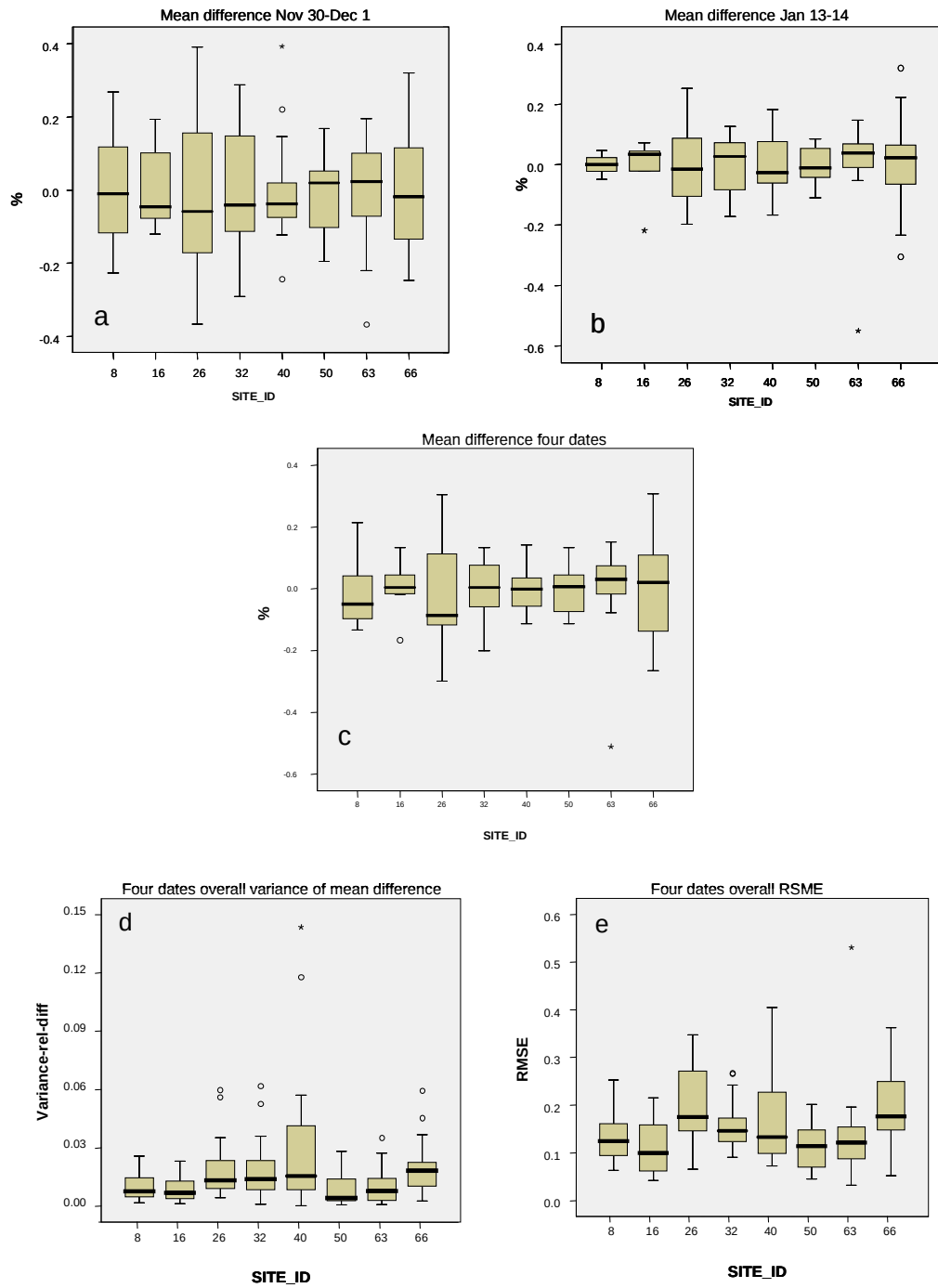


Figure 3.5. Mean relative difference in SM between pairs of simultaneous data (a and b) and overall difference from four field data collections together (c). Four dates of overall variance of mean difference (d) and root mean square error (e).

e. Pearson's correlation coefficient

The Pearson's correlation coefficient was computed to evaluate if all the infield locations experience similar soil moisture variations within a short time lag, in this case one day of difference. The results for the Pearson's correlation coefficient (table 3.4) show clear differences among the sites, since the coefficients were significant in both sets of field data collections only for the samples collected from sites 26, 32 and 63 at the probability level greater than 0.05. Site 63 showed a stable correlation around 70% for both set of readings, while sites 26 and 32 decreased their correlation levels from 71 and 67% for the first set to 60 and 62% for the second set, respectively. On the other hand, site 50 was the only site in which the Pearson's correlation coefficient was not significant at the probability level of 0.05 or higher for both set of readings.

In general, the significance level for the computed correlations was higher for the set of field data collected in November-December than for the set on January. In this regard, the rain-fall in the late afternoon of January 13 may help to explain the differences in the trends of the two sets of data. While in the November-December set water from precipitation had at least two days to enter and distribute into the soil profile, on January 14 this process was just at its earliest stages, showing an apparent uneven distribution along the sites.

The Pearson's correlation coefficient is an indicator of the spatial stability of the soil moisture point data. Low coefficients with low significance levels indicate that the process is unstable in space and for the time lag in which data were collected. However, since the average standard deviation for the point data and the mean relative difference

for those five locations are small, point data from them can be used to infer infield conditions within the ranges of standard deviation and mean relative difference.

Table 3.4. Pearson's correlations of soil moisture paired samples

Site	Nov 30 and Dec 01, 2005			Jan13 and Jan14, 2006		
	N	Correlation	Sig.	N	Correlation	Sig.
8				12	0.449	0.143
16	14	0.434	.121	9	0.699	0.036
26	20	0.710	.000	20	0.598	0.005
32	20	0.671	.001	20	0.618	0.004
40	15	0.549	.034	16	0.307	0.248
50	18	0.324	.189	18	0.252	0.314
63	20	0.707	.000	15	0.697	0.004
66	19	0.564	.012	17	-0.103	0.695

f. Two samples t-test

A two samples paired test was computed to evaluate the variation in average soil moisture values from one day to the next (table 3.5). This analysis serves as an indicator of the difference between fields on the time required to produce infield soil moisture variation. The results for the November-December set of records showed no significant statistical difference at the 0.05 probability level for any of the fields. The maximum mean difference between two records for a field was less than 1.2%. For the January records, all the fields show statistical difference at the 0.01 probability level, with a maximum mean difference between two records of 6.8%.

The difference between both sets of field data can be explained by the precipitation regimens previous to and during the field data collections. For the November-December collections, the fields were in the process of drying out since rain occurred 24 h previous to the data collection. This rain was the last in a series of three

consecutive raining days contributing more than 2.5 cm of water to the sites, with exception of sites 40 and 50 with less than 2.5 cm. On the January field data collection date, the fields were in the process of wetting since no precipitation occurred in a period of 10 days previous to the field data collection until the evening of January 13. On this evening, 0.5 to 2 cm of rain was recorded for all the sites producing different soil moisture conditions on January 14, less than 18h after the January 13 field collection.

Table 3.5. Two sample t-test of soil moisture paired samples

November 30-December 1, 2005						
	Mean	Std. Deviation	Std. Error Mean	t	df	Sig (2 tailed)
8						
16	1.10	2.24	.60	1.845	13	.088
26	-1.27	2.89	.64	-1.968	19	.064
32	-.94	2.22	.49	-1.889	19	.074
40	-.56	2.36	.60	-.930	14	.368
50	-.66	2.95	.69	-.956	17	.352
63	-.13	2.38	.53	-.253	19	.803
66	.48	3.21	.73	.664	18	.515
January 13 and 14, 2006						
8	-6.71	3.12	.90	-7.439	11	.000
16	-1.93	1.33	.44	-4.335	8	.002
26	-6.81	3.32	.74	-9.160	19	.000
32	-3.12	1.93	.43	-7.233	19	.000
40	-1.85	2.30	.57	-3.216	15	.006
50	-1.57	2.46	.58	-2.710	17	.015
63	-4.68	3.07	.79	-5.909	14	.000
66	-6.76	2.21	.53	-12.575	16	.000

The statistically significant difference found by the paired t-test comparing the January data collections may indicate that after a precipitation event the process of water infiltration into the soil profile and the time required to produce infield soil moisture variation may take less than 24 h for all the locations investigated. The lack of statistical difference for the November-December field data may indicate a fast process of drying out at the upper layer of the soil (0 - 10 cm) and a very low water holding capacity of the

soil at all the eight locations. About 24 h appears to be sufficient for a water infiltration process to occur to the deepest layers of the soil.

g. Directional effects within fields

In this analysis, soil moisture point measurements were grouped according to the direction in which the reading was taken. A minimum of two and a maximum of five directions were considered for each site. The directions were coded using the number of the site followed by the position of each point sample in the sequence of readings. Figure 3.6 shows for each site the behavior of the mean volumetric soil moisture distribution for each direction at each sampling date. The descriptive statistics for this analysis shows that for sites 8, 16, 26, 32, 63 and, 66 at the directions 82, 161, 261, 324, 632 and 664 the soil moisture mean was highest than the others on the same field in at less three of four reading dates. Also, site 50 was the only field in which the directions have a random behavior with no characteristic trend.

Using a general linear model with factorial components, the statistical significance of the directional trends observed in the soil moisture within the fields was analyzed. The factorial ANOVA shows that for sites 8, 16 and 63, there is no significant difference at the probability level of 0.05 for the mean soil moisture values among directions for any of the four reading dates. Site 26 was the only site in which statistical difference was found in at least three of the four reading dates. The *post hoc* Tamhane test showed direction 261 statistically different from the other three directions considered for this site. These point readings are located close to an access road on which there is frequent transit of agriculture equipment that may have altered the soil physical characteristics in terms of structure and compactness.

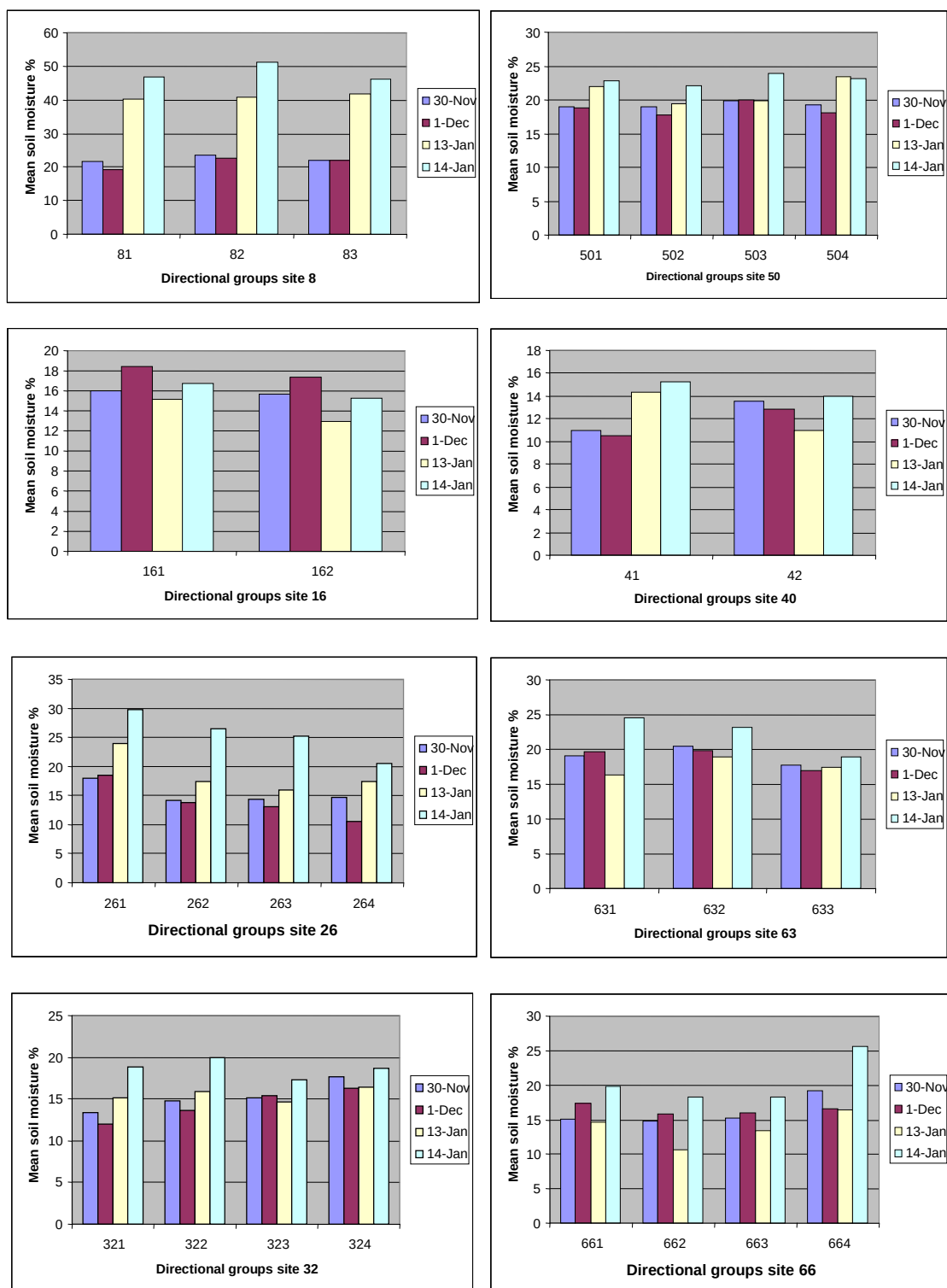


Figure 3.6. Mean volumetric soil moisture for directional groups analyzed at each site for four dates of readings.

In site 66, soil moisture in directions 662 and 664 were statistically different from each other in two of the four reading dates. 664 corresponds to a portion of the field covered by a mixed vegetation that is 60 cm tall and periodically mowed to the ground, while direction 662 is in the open portion of the field with almost no vegetation cover present during the sampling dates. Site 32, as well as site 50, 40 and 63, presented the most stable and uniform characteristics of vegetation cover.

3.3.2. Statistical analysis for transects of five different landuses.

a. Descriptive statistics

Table 3.6 shows the descriptive statistics for four different dates of soil moisture field data collected on 25-30 m long transects associated with five different landuses. The results shows the transect orchard and grass have the wettest conditions, while the transects through agriculture fields, peanuts and cotton, were the driest. The areas under agricultural activity showed the lowest standard deviations with average values around 1%, while the transect grass presented the highest standard deviations with values between 1.8 and 2.6%. The transect studied at the bare land field exhibits an intermediate behavior, tending to group with the wettest landuses rather than with the driest LULC.

b. Soil moisture variation between landuses

The ANOVA between the soil moisture values observed for the five 25-30 m LULC transects showed significant statistical differences for all the four dates at 0.01 probability level. This is an indicator of high variability existing between the soil moisture response among the five transects. On the other hand, very low variation was found between the

sampling points within a landuse, indicated by the lowest scores of the mean square within groups. The highest differences between landuses were found in the field data collection conducted in January with scores almost twice as high as from the November-December data collection.

A Tukey-Tamhane analysis of means was used to explore, in more detail, the variability between groups showed by the ANOVA (table 3.7). The LULC transect to transect comparison showed transects from agriculture fields, peanuts and cotton, as the most similar landuses with not statistical difference among them for any of the four reading dates. Also, these transects had the greatest differences with orchard, grass and bare land showing statistical differences on all the sampling dates. Orchard and bare land showed similarity for three of the reading dates, while orchard and grass for only two of the reading dates. Soil moisture field data from grass and orchard were consistently higher than in agriculture and bare land fields during the November-December reading. For the January field data collection grass and orchard still presented the highest soil moisture content although with more than 3% of average volumetric soil moisture among them. On the January 14th sampling, orchard and bare land had 1.8% of average soil moisture difference between them.

c. One-Sample t-Test

A one sample t-test was performed to compare the relationship between the average soil moisture within a transect with the mean soil moisture obtained from the closest 30 by 30 m sampled field. In this analysis, the test value for t-test corresponds with the average soil moisture of the field for a given date.

Table 3.6. Descriptive statistics for volumetric (%) soil moisture in transects associated with five landuses.

	N	Mean	Std.	Std.	95% Confidence Interval for Mean		Minimum	Maximum
			Deviation	error	Lower Bound	Upper Bound		
11/30/2005								
Orchard	8	16.8	2.09	.7401	15.075	18.575	14.5	21.3
Cotton	7	13.8	1.65	.6248	12.300	15.357	11.3	15.8
Peanut	8	13.6	1.00	.3546	12.812	14.488	12.0	14.6
Grass	10	19.1	2.18	.6905	17.558	20.682	16.1	22.7
Bare land	8	16.1	1.68	.5973	14.738	17.562	14.3	19.3
12/01/2005								
Orchard	8	16.2	1.65	.5858	14.852	17.623	14.0	18.4
Cotton	7	12.7	1.11	.4217	11.754	13.818	11.8	15.0
Peanut	8	11.4	1.32	.4671	10.345	12.555	9.0	12.8
Grass	10	17.9	2.21	.7013	16.344	19.516	13.6	21.3
Bare land	8	16.4	2.17	.7704	14.616	18.259	12.4	18.9
01/13/2006								
Orchard	8	17.7	2.49	.8805	15.643	19.807	15.2	22.0
Cotton	8	14.2	1.37	.4864	13.137	15.438	11.7	15.9
Peanut	8	13.2	.83	.2958	12.538	13.937	11.9	14.5
Grass	8	21.5	2.58	.9149	19.374	23.701	17.7	24.7
Bare land	8	10.1	2.06	.7317	8.370	11.830	8.1	14.4
01/14/2006								
Orchard	8	19.1	.91	.3224	18.338	19.862	18.0	20.9
Cotton	8	14.5	.87	.3087	13.845	15.305	13.4	15.6
Peanut	8	14.5	1.16	.4131	13.586	15.539	13.1	16.6
Grass	8	23.0	1.79	.6336	21.564	24.561	19.4	24.8
Bare land	8	17.2	1.48	.5258	16.007	18.493	14.7	18.9

Table 3.7. Tukey groups of similar soil moisture conditions.

Transects	Grass	Peanut	Cotton	Orchard	Bare soil	Total
Grass		0	0	2	1	3
Peanut	0		4	0	0	4
Cotton	0	4		0	0	4
Orchard	2	0	0		3	5
Bare soil	1	0	0	3		4
Total	3	4	4	5	4	

This analysis consistently showed no significant difference between transects of grass and its corresponding 30 by 30 m adjacent field. Peanut transects were not different in three reading dates, while bare land was different on only two reading dates. On the other hand, cotton and orchard showed significance differences with their adjacent fields

for three of the four soil moisture readings. This analysis indicates that regardless of the spatial proximity between two homogeneous fields, LULC is a factor affecting the soil moisture behavior between them. This is an important observation suggesting that the point readings from the stations of the *in situ* network cannot be interpolated to near by locations exclusively under criteria of proximity. LULC is an element that contributes to the landscape complexity and as it was demonstrated in this research, to the spatial and temporal variation of soil moisture at the local scale.

3.4. Discussion and Conclusions

Soil moisture is a spatially organized variable that behaves according to the spatial and temporal variation of precipitation, topography, soil characteristics, LULC and climate. Increasing variations of such variables will produce a complex scenario of soil moisture behaviors that will challenge the attempts of producing a distributed representation of soil moisture at the landscape scale. In this research, by selecting 30 by 30 m fields, landscape complexity was minimized at the local scale and homogeneous spatial and temporal soil moisture conditions were identified at all of the eight study locations confirming the research hypotheses.

The analysis of precipitation showed that the eight selected locations received similar rainfall amounts during the 12 days previous to the eight data collections, therefore, soil moisture variations among fields were not the consequence of rainfall variations and the soil moisture behavior was expressed according to the site specific dynamics of water into the soil profile. Likewise, as a consequence of the small area covered by each field, the topographic variations in slope steepness and even to a certain

degree soil physical properties were minimized within the field boundaries.

ANOVA and *post hoc* analysis show high differences in soil moisture conditions among the fields, but also similarities among pairs of locations despite their spatial separation. Similarities among pairs of locations can be attributed to a similar LULC, soil type or both. On the other hand, using temporal stability analysis, the analysis demonstrated that within the homogeneous 30 by 30 m field a single point reading location can be used to infer average field conditions with less than 3% v/v soil moisture variation between infield readings. However, the lack of significance in the Pearson's correlation coefficient for most of the eight fields suggests that using a single point location to estimate field conditions may produce errors when short time lags (less than a day) are considered. In this regard, portions of the fields affected by external factors (i.e., human activities) should be avoided since they present different soil moisture conditions.

The two pair t-test showed that all the eight locations that were analyzed experiment soil moisture variations at the upper soil layer (0 - 10 cm) in less than 24 hours, indicating a fast process of water movement into the soil profile. This observation should be further investigated since it may indicate that soil moisture conditions in the upper soil layer do not necessary correspond with soil water contents at the deepest layers, and therefore, to establish hydrological conditions or water status in this landscape using remote sensing data alone may not be sufficient.

The analysis of soil moisture conditions within five LULC transects confirmed the hypothesis that homogeneity in soil moisture can be found in small areas regardless of their LULC. Also that similarities and differences in the soil moisture behavior can be found among different LULC that can not be explained completely by the type of

vegetation cover. This result serves a first step in the process of identifying the origins of individual soil moisture dynamics that acting at the local scale can be associated with particular portions of a complex and diverse landscape towards an appropriate long term evaluations of soil moisture behaviors at the regional scale.

In this context, continuing with the studies of small fields around each one of the Hydra-probe *in-situ* stations will help to assess the characteristics of the field that each reading station is representing in the landscape. In this approach, each reading station can be an indicator of a particular combination of precipitation, LULC, soil and topography that operating at the local scale has several replicates through the landscape. Combining groups of similar soil moisture behavior is expected to produces an accurate representation of the soil moisture dynamics at the landscape scale.

The methodology of using small fields as landscape units of soil moisture conditions is in agreement with landscape ecology theory in which complex systems are described by decomposing them into their fundamental parts (fragments) and interpreting their interactions (Hay *et al.* 2002). Homogeneous fields are, in our case, areas of spatial organization within the landscape in which a soil moisture behavior can be identified. Since landscape fragments are the units of spatial resolution in which biophysical factors interact, the pixel oriented approach used in LULC and environmental analysis with remote sensing data has the disadvantage that pixels do not correspond with ecological units of spatial organization. Therefore, for further research of soil moisture using remote sensing data, we consider that an object oriented approach that considers the sizes and composition of landscape units rather than a spectral or pixel oriented approach is required in the remote sensing image processing.

Under an object oriented approach and using the technical capabilities of geographic information systems, the integration of small field behaviors with environmental conditions will reduce the amount of uncertainty associated with regional representations of soil moisture based merely on geostatistics and mathematical formulations. On the other hand, the small field approach offers an alternative to avoid the mismatching between ground point field data and satellite pixels since it transforms ground point field data into ground unit areas. This transformation allows the direct linking of ground field data with the unit areas of a remote sensor, providing a better assessment of the soil moisture data retrieved by different satellite and aircraft sensors.

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CHAPTER 4

GROUND AND SURFACE TEMPERATURES VARIABILITY IN COMPLEX
LANDSCAPES FOR REMOTE SENSING OF SOIL MOISTURE¹

¹ Giraldo, M., Madden, M., Bosch, D., Usery, L and Kvien, C. To be submitted to the *Journal of Hydrology*

Abstract

An *in situ* network of stations operated by the US Department of Agriculture-Agriculture Research Service at Tifton, Georgia (USDA-ARS-SEWRL) was established at the Little River Watershed (LRW) near Tifton Georgia US for the long term study of biophysical cycles. The relationships between soil moisture and ground temperature point readings measured by the stations and the surrounding landscape have not been quantified yet and the knowledge about this relationship is required to inform an accurate interpolation of the *in situ* readings and to produce distributed representations of soil moisture and energy balances to the landscape scale. Since the LRW shows landscape heterogeneity at small spatial areas and since remote sensing image data units (pixels) shows mixed signatures when pixels are larger than the landscape spatial units where the processes occur, this research propose and object oriented approach to investigate process variability within to landscape spatial units (patches/fragments). Eight landscape fragments (fields) of 30 m by 30 m matching the pixel size of a Landsat Thematic Mapper (TM) image and adjacent to the stations were selected to investigate 1) relationships between soil moisture (SM), ground (GT) and infrared temperatures (IRT); 2) spatial and temporal variation of GT and IRT within the fields and within landuses: grass, orchard, peanuts, cotton and bare-soil; and 3) the relationship between the point reading of the stations and readings collected from the landscape fragments. Analysis of variance (ANOVA) showed high seasonal independent variation in the GT and IRT behavior between the eight fragments as well as, site specific, in-field homogeneity at each of the eight fragments. We found statistic differences in the GT and IRT between the different landuses as well as high correlations between GT and IRT regardless of the landuse. Also we found high correlations between the stations readings and the adjacent field average value. High standard deviations found within the fields for the variable IRT, suggest that when a single point reading for this variable is selected for the validation of either remote sensing data or water- energy models, errors may occur. The results confirm the hypothesis that 30 m fields can be used as landscape spatial units for soil moisture and ground temperature studies, demonstrating the advantage of using an object oriented approach that account for local expressions of environmental process decreasing the errors and uncertainties of estimating sub-pixel values. To replicate this study in other areas of the network will produce a better understanding of this complex landscape and the spatial area represented by point readings of the stations.

4.1. Introduction

Ground and infrared temperatures (GT and IRT) are critical parameters needed to indirectly estimate indirectly from remote sensing data energy fluxes and soil moisture for the hydrological cycle from the soil and the vegetated layers of the landscape. Using thermal infrared remote sensing data to estimate energy fluxes in the soil-atmosphere interface offers several advantages over ground data collection, including the production of comprehensive data for large areas, the reduction of costly logistical and labor intense ground surveys and decreased errors associated with large, individual, non simultaneous point data readings.

Monitoring evapotranspiration and soil moisture using parameters estimated from remote sensing data is a developing process, with progress made in the construction of developing energy flux models (Norman *et al.* 1995), spatially discriminating the soil and vegetated components of the image spectral spectrum (Carlson *et al.* 1990, Schmugge *et al.* 2002) and linking vegetation indices and radiometric surface temperatures (Kustas *et al.* 2003). In the process of testing the models and validating remote sensing data, accurate ground point data are required (Prince 1983, Li *et al.* 1999, Schmugge *et al.* 2002). The importance of point data has been demonstrated by recent research in which ground readings are used in the validation of spectral reflectance measurements from Landsat satellites for water content of agriculture fields (Jackson *et al.* 2004); in validating surface temperatures extracted from Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper plus (ETM+) (Li *et al.* 2004); and in modeling energy fluxes from aircraft data over agriculture fields (Kustas *et al.* 2004).

Since models are formulated and later validated using ground data measured from relatively homogeneous areas, the accuracy of the estimates can be compromised when the ground area corresponding to an image pixel combines spectral information from different land-covers (Kustas and Norman 2000). Energy fluxes in the soil-atmosphere interface do not exhibit a linear behavior in the scaling process (Bresnahan and Miller 1997). Therefore, assessing the extension of the field for which a point reading can be used as a valid predictor of local conditions is a critical task, especially when the validation process is attempted over heterogeneous landscapes (Chen *et al.* 2005).

Under a pixel oriented approach, the validation of landuse and environmental analysis of remote sensing data has the disadvantage that pixels do not correspond with landscape, ecological units of spatial organization (landscape fragments). In complex landscapes the relatively coarse spatial resolution of the thermal infrared band from satellites such as AVHRR (greater than 1 km) and GOES (4 km), compresses thermal emittance information corresponding to mixed areas within a single digital value, while remote sensors such as ASTER and Landsat with finer spatial resolution (less than 120 m) will more adequately measure the thermal nature of smaller and more homogeneous ground areas (Li *et al.* 2004).

Landscapes, by definition, are complex systems made up of land cover units (i.e. patches or fragments) in which biophysical factors such as soil moisture and evapotranspiration interact. Decomposing complex systems into their fundamental parts is a logic step towards comprehending their underlying processes (Hay *et al.* 2002). It also implies shifting approaches in using remote sensing data from a pixel oriented to object oriented methodologies that recognize the landscape units of spatial organization.

This alternative has the potential to expand the inferential capabilities of remote sensing research by integrating remote sensing and landscape fragmentation assessment as a methodological tools to explore the relationships between pattern and process (Nagendra *et al.* 2004).

At the Little River Watershed (LRW) in southeastern Georgia (USA) a network of *in situ* soil moisture devices has been established to produce continuous point readings of environmental variables such as soil temperature, precipitation, and soil water content to be used for the long term study of hydrological and ecological cycles. In the 2003 version of the USDA-NASA soil moisture experiment (SMEX03) the potential of this network to validate ecological variables estimated from different airborne and satellite remote sensing platforms was demonstrated opening the possibility for a regionalized assessment of soil moisture conditions for which the reliability of the network will be critical (Bosch *et al.* 2005).

However, observations at the LRW suggest a complex landscape where environmental variables may change over small spatial areas (Cashion *et al.* 2005). In fact, the LRW is a diversified landscape with a mix of landuses, low elevation hills and a variety of soil types where the influence of the landscape variation in the point reading, has not yet been quantified. Despite the fact that continuous readings are recorded from the network sites at the LRW, no research has investigated the relationship between the ground temperature point readings at the stations compared with readings recorded at the surrounding landscape to test the accuracy of interpolation of the *in situ* readings to the landscape scale. Also, linking point data to the surrounding environmental conditions is critical knowledge for understanding the underling factors that regulate biophysical

processes such as soil moisture and surface energy fluxes (Crow *et al.* 2005). This research builds on the results of Bosch *et al.* (2005) as a next step in understanding the reliability of the *in situ* network at the LRW for long term studies and the validation of remote sensing estimates.

Based in landscape ecology theory that recognizes landscape patches (fragments) as areas in which environmental processes occur, the objective of this research is to evaluate the spatial and temporal variability of surface and ground temperature within landscape fragments equivalent to a pixel size of a Landsat TM image surrounding the stations of the LRW network. We assess if temperature readings from the network stations represent local homogeneous areas and different landuses of the adjacent landscape and, therefore, if the stations' data can be used in modeling energy fluxes at the scale of landscape objects (patches/fragments). Our final objective is to investigate if correlations can be found between the variables soil moisture ground and surface temperature collected from the stations, the homogeneous fields and landuses, as a way to understand the relationships of these variables in soil moisture and energy fluxes within a complex landscape.

Our results are a first step towards understanding the underling behavior of ecological conditions that influence ground and surface temperature across the LRW complex landscape with significant implications for scaling up the point data from the soil moisture network stations and their use in modeling energy flux of ecological cycles and remote sensing data validation. This research also offers an alternative to the traditional pixel oriented methodologies of data validation by suggesting an object

oriented approach in which the biophysical process are studied in homogeneous fragments as individual constituents of the landscape complexity.

4.2. Methods

4.2.1. Study area

The eight Hydra-probe stations considered for this study were selected with a criterion of easy accessibility, diverse landscape, short travel time between them and short distance from a main road to permit ground measurements to be collected for all stations in one day. These sites form a transect that crosses the east portion of the LRW from north to south and they are surrounded by a variety of land covers in a typical rural landscape with grazing, orchard, pine plantations, and row crop areas near the cities of Arabi, Chula, and Tifton which is located southward of the transect. The annual precipitation for 2005 at the eight study sites ranged from 151.3 to 132.4 cm, with an average of 143.9 cm (table 4.1). Rainfall is evenly distributed throughout the year, with frequent short-duration high-intensity thunderstorms in the summer.

Overall, the area has a relatively flat topography characterized by broad flood plains with poorly defined stream channels and gently sloping uplands varying from 1 to 5%. Soils at the eight sites are primarily loamy sands with four sites comprised the soil type Tifton (TfB) (table 4.1) characterized by deep, well drained, moderately slowly permeable soils that formed in loamy marine sediments. These soils are on nearly level to gently sloping uplands and have slopes that range from 0 to 8%. The soil at site 50 is a Sunsweet (StD2), which is a well drained, moderately slowly permeable soil on uplands and slopes from 2 to 25%. Soil at site 63 is a Fuquay, FsB, characteristic of the upper

coastal plain, deep to very deep well drained soil, typically under row crop agriculture (USDA 2004).

Table 4.1. Location, soil information and annual precipitation for the study sites. Coordinates are in UTM, WGS84.

Site	Y Coordinate	X Coordinate	Elevation (m)	Land cover	Soil name	Soil symbol	Total PPT 2005 (cm)
8				Grass	Ocilla	Oc	150.2
16	3494245.16	256307.44	123	Grass	Tifton	TfB	150.2
26	3502328.72	252215.12	115	Row crop	Alapaha	Ah	147.7
32	3507196.64	249514.28	123	Grass	Tifton	TfB	140.5
40	3511504.48	246611.08	134	Row crop	Tifton	TfB	141.0
50	3516116.84	244911.43	113	Grass	Sunsweet	StD2	151.3
63	3490204.59	258057.01	110	Grass	Fuquay	FsB	132.4
66				Bare soil	Tifton	TfB	138.0

The Hydra-probe stations are part of the *in situ* network at the LRW composed of 27 stations with Stevens-Vitel Hydra-probes (Stevens Water Monitoring Systems, Inc.) recording ground temperature and soil moisture information at three soil depths 5.08, 20.32 and 30.48 cm (2, 8 and 12 inches) at 30 minute intervals. Details about the soil moisture instruments at the stations and the relationships between dielectric constant and volumetric soil moisture can be found in Gaskin and Miller (1996) and also in Campbell, (1990). A full description of the Hydra-probe network also can be found in the documents of the USDA Soil Moisture Experiment 2003 (<http://hydrolab.arsusda.gov/smex03/SMEX03v5.pdf>) and in the paper of Bosch *et al.* (2005).

4.2.2. Data collection. A sample of eight stations from the LRW *in situ* soil moisture network were selected for this research considering the logistic and practical constraints of getting to all eight location and taking readings at the moment of maximum insolation

of the day in the time interval between 10:00 am and 3:00 pm. The Hydra-probe sites are summarized in table 4.1 and their location in the study area can be observed in figure 3.1. Two different data-sets were collected during eight field campaigns through the year 2005 and January 2006. The first data set consisted of 10 to 20 readings collected from a 30 by 30 m field defined around the area where a Hydra-probe station was located. The second data set was created with readings from five 30 m transects demarcated within fields under the landuses: grass, orchard, bare land and agriculture. Two fields from the agriculture landuse were sampled, one with peanuts and one with cotton. From each landuse, 8 to 10 readings were collected at 3 m intervals in an area distant from the parcel borders. The fields of grass, orchard, bare land and agriculture were selected by their proximity to the stations: 50, 32, 66 and 40, respectively. Sampling was conducted throughout the year with the purpose of testing seasonal effects within and among locations. The sampling dates were: March 11, March 28, April 12, May 24, November 30, and December 1 of 2005; and January 13 and January 14 of 2006. Total daily precipitation was obtained from the precipitation records of each site for a 12-day period previous to the sampling date. Soil moisture, ground and surface temperature were measured simultaneously at each one of the locations for each one of the data set mentioned. Ground temperature (GT) at one depth at 0-10 cm was measured using a digital thermometer (TPD32 Omega Engineering, Inc.) while surface temperature (IRT) was recorded approximately 1 m above the surface using an infrared thermometer (OS643 Omega Engineering, Inc.). Soil moisture (SM) was recorded using a Theta capacitance probe ML2X Theta probe (Dynamax, Inc.) that measures dielectric conductivity similarly to the Hydra-probe devices of the *in situ* network.

4.2.3. Statistical analysis. One way analysis of variance (ANOVA) is a statistical test that compares variation within the individual samples of a group, as well as the variation between groups from a sampling process. In this analysis, an F value is generated and a statistical significance for the difference between and within groups was established at the probability level of 0.05, 0.01 or less. ANOVA analyses were performed to compare the variation within fields and among fields for the variables GT and IRT. Descriptive statistics such the mean and the standard deviation also were generated for the variables GT and IRT at each site and for each one of the reading dates.

In all the ANOVAs where statistical significance was found, a Tukey/Tamhane *post hoc* test was performed to detect the groups for which the difference was significance. Previous to the *post hoc* analysis, a Levenne homogeneity test was performed to evaluate homogeneity of variance. When homogeneous variance within the groups was detected, a *post hoc* Tukey test was applied and Tukey groups of similar behavior were formed. In the scenarios in which the variance was not homogeneous the Tamhane *post hoc* test was used.

Pearson's correlation coefficient also was used to evaluate the level of association between the variables GT, IRT and SM. The Pearson's correlation coefficient is defined by Cangelosi *et al.* (1976) as an abstract measure of the degree of the relationship between two variables. This coefficient corresponds to the square root of the coefficient of determination that considers the proportion of variation in one population-variable that is explained by the values of the other population-variable. Highly correlated patterns

have values close to (1), uncorrelated patterns have values close to (0) and inversely correlated patterns have values close to (-1).

4.3. Results

4.3.1. Analysis of Precipitation and Soil Moisture. Ground and surface temperature are strongly correlated with soil moisture content since the latent heat and sensible heat components of the energy balance at the surface level are affected by soil water contents (Goward *et al.* 1985). Transpiration and evaporation increase as the soil water content rises. Under wet soil conditions, latent heat fluxes increase because the greater absorption of water in the evapotranspiration process decreasing the sensible heat. Under dry soil conditions, the inverse process occurs since the radiative energy is not consumed in the evapotranspiration process and the sensible heat increases, risen (T_o) (Vicente-serrano *et al.* 2004). Considering this, the analysis of precipitation is needed to understand the water status of the ground when the samples were collected. A description of the precipitation for a 12-day period previous to the temperature sampling is provided in Chapter 3 of this dissertation. That analysis showed that during rainfall events all the sites sampled in this study received simultaneous precipitation, although in different amounts. The field work included at least one dry condition on May 24, one wet condition on March 28 and two intermediate conditions on the sampling days of April 11 and March 11.

The ANOVA of precipitation showed no significant differences between sites in the amount of water supplied by precipitation previous to each one of the sampling collections.

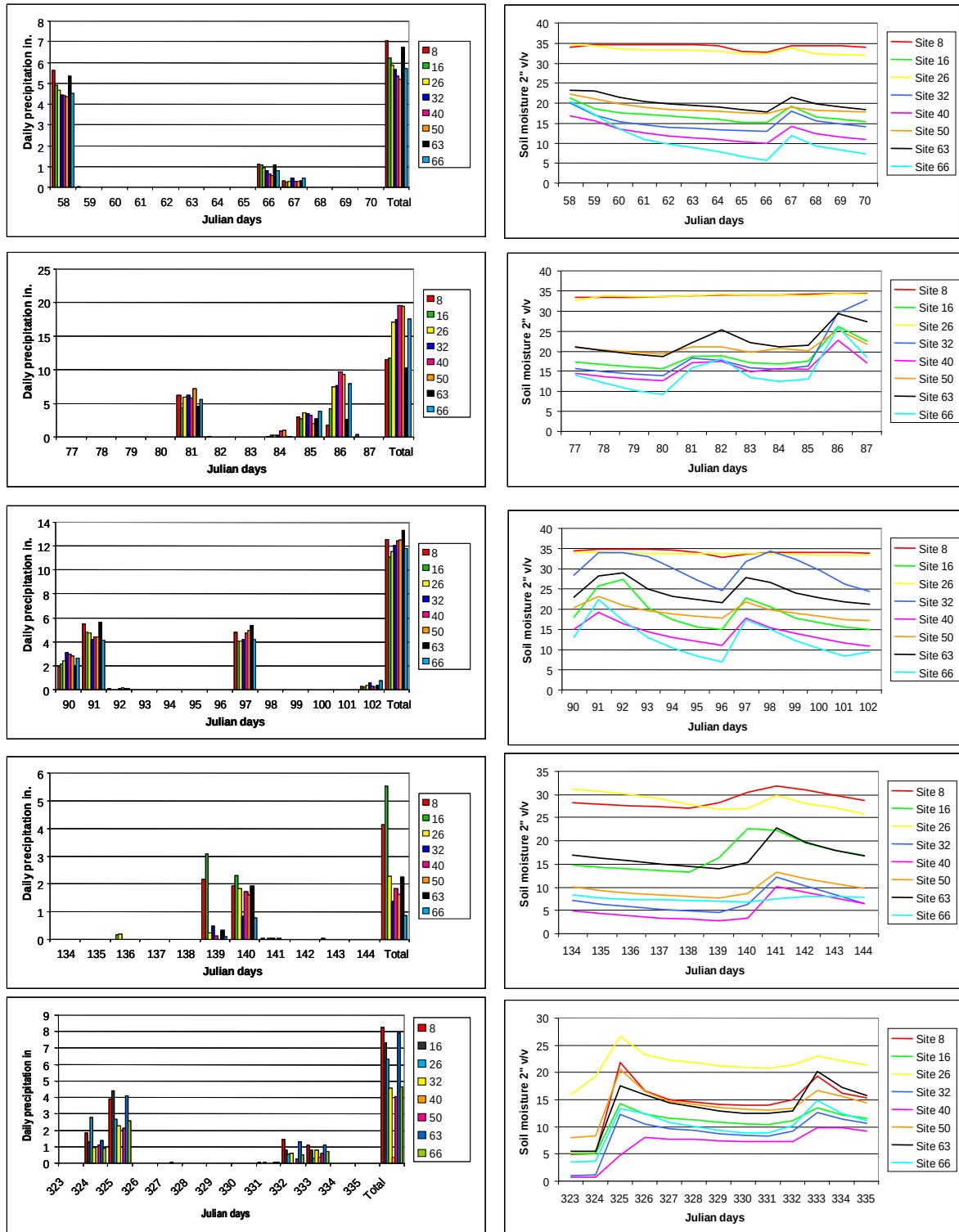


Figure 4.1. Daily precipitation (left) and 2in (5.08cm) soil moisture (right) recorded by the Hydra-probe reading stations for the eight sampling dates.

Also, all of the stations presented an overall similar pattern of soil moisture content at 5.08 cm (2 in) depth, with similar peaks during the days of rainfall and lowest values during the dry days (figure 4.1). Important differences can be observed in the absolute values of soil water content among the stations in the 12-day period before sampling, regardless of the sampling date. This is an indicator of site specific differences in soil moisture behavior among the sites that is independent of water supply and suggests the influence of other environmental conditions at the local level other than precipitation.

4.3.2. IRT and GT field readings. Descriptive statistics for the variables GT and IRT collected from the fields around the stations are presented using two levels of aggregation: 1) at the watershed level and 2) at the site level.

a. Descriptive statistics of aggregated IRT and GT

At the watershed level of aggregation, there are no apparent differences in the average values of GT and IRT (figure 4.2). The average temperature for the series of eight readings showed close values between both variables with a maximum average difference of 6.7°C (12°F) during the summer reading (Julian day 144) and a minimum average difference of -0.2°C (-0.4°F) for the late fall readings (Julian days 334 and 335).

However, GT consistently showed the lowest average standard deviation for the eight readings with a range of values between 1.1 and 2.2°C (2 and 4°F), while the IRT range was between 2 and 4.4°C (3.6 and 8°F) (figure 4.2). This indicates a level of stability in the ground temperature and a more unstable behavior in the readings at the surface level. The largest average standard deviation for IRT was observed in the late fall reading (Julian day 334) while for the GT the maximum average standard deviation was found in

the mid spring (Julian day 144).

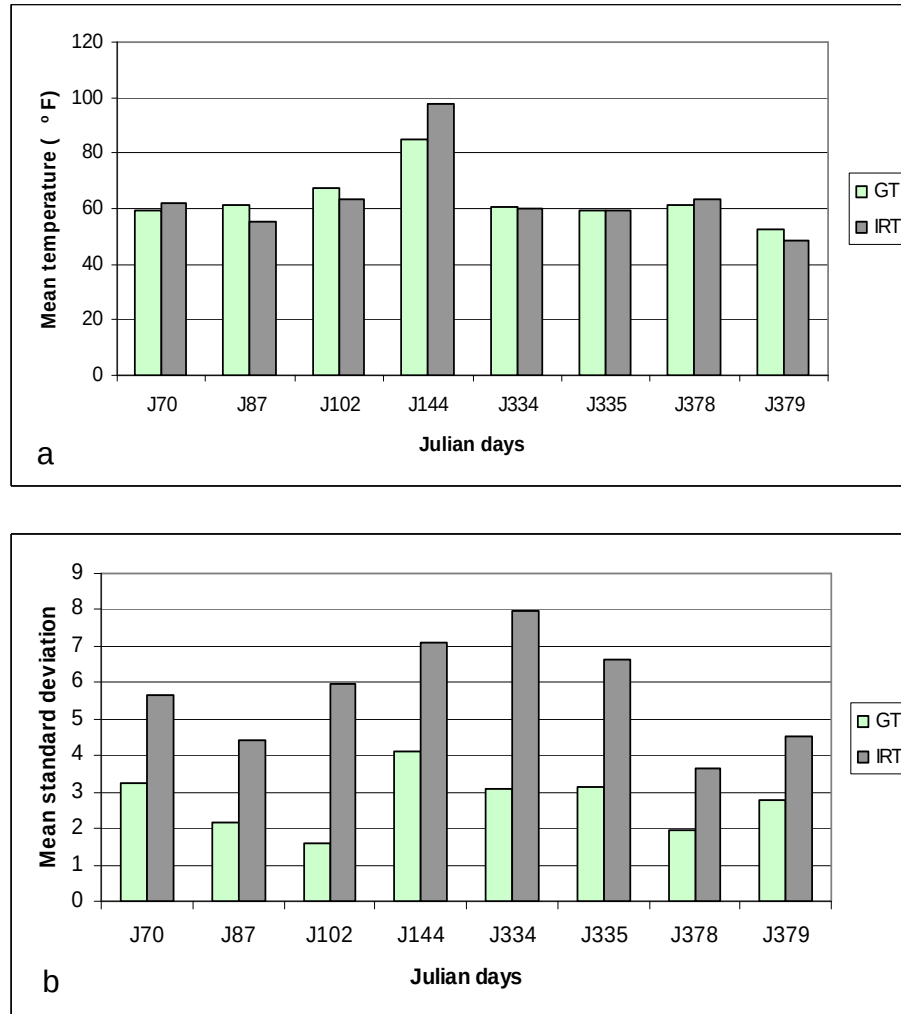


Figure 4.2. Average temperature (a) and standard deviation (b) of IRT and GT aggregated by sampling date for the entire LRW.

When aggregating the values at the site level, greatest differences were found between the GT and IRT in particular fields. This is in agreement with the observation of a site specific effect demonstrated by the 5.08 cm (2 in) soil moisture record. For instance, fields at station 26 and 63 showed average values of GT greater than IRT,

while, sites 32 and 66 have an opposite behavior (figure 4.3). GT showed the highest values with a maximum difference of 1.7°C (3°F) in site 63 and a minimum of 0.15°C (0.26°F) in site 8, while IRT has a maximum difference of 2.7°C (5°F) on site 32 and a minimum of 0.1°C (0.15°F) at site 16 (figure 4.3).

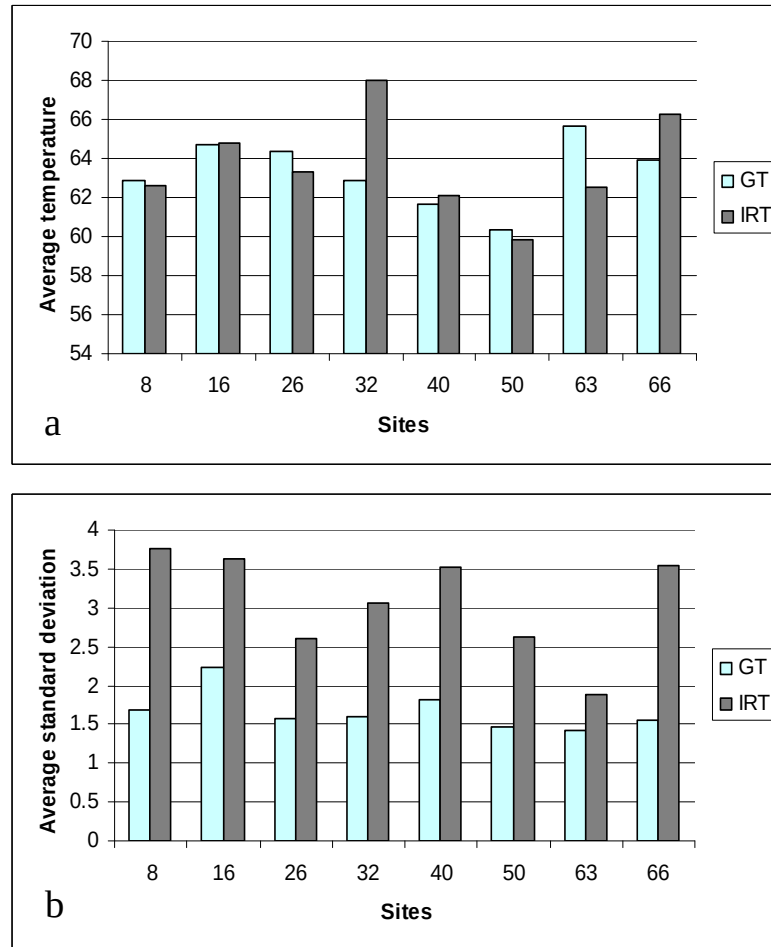


Figure 4.3. Average (a) and standard deviation (b) of GT and IRT at each site across all sample dates units are on Fahrenheit degrees.

Once again, GT showed smaller average standard deviation than IRT for all the fields analyzed varying in the range of 1°C or less while for IRT was in the range of 1 and 2°C . Field associated with sites 50 presented the lowest average temperatures for both

variables, sites 16 presented the highest GT and site 63 the highest IRT. Overall, GT showed less variation in a given location or in a particular sampling time than the IRT readings. The data analysis suggests site specific differences in the values for both variables that are independent of water supply in the form of precipitation and, therefore, should be analyzed in the context of other environmental factors acting at the local scale.

b. Field GT and IRT:

Figures 4.4 and 4.5 show the temporal analysis of average GT and IRT at the field level through the 8 reading collections. The highest range of GT among fields was observed on May 24, 2005 with a range of values between 25 and 32 °C, while the lowest range was found in the April 12 readings with only 1 °C of difference. For IRT the highest range was found on November 30, 2005 with 12 °C of difference while 5.5 °C was found as the lowest range on January 13, 2006. When compared with GT, IRT showed higher ranges of values for a single set of readings.

The average standard deviation for GT for the eight fields showed overall values under 1.4 °C through the eight reading dates with the lowest values observed on March 28, 2005 April 12, 2005 and January 13, 2006. This general trend presented some clear exceptions for some sites for a given date such as site 8 and site 63. In addition to those dates January 14, 2006 also presented low average standard deviations for the IRT variable. Although the general trend showed an upper threshold of 2 °C standard deviation, the readings on May 24, November 30 and December 1, 2005 were generally above this limit in almost all the sites (figure 4.4 and 4.5).

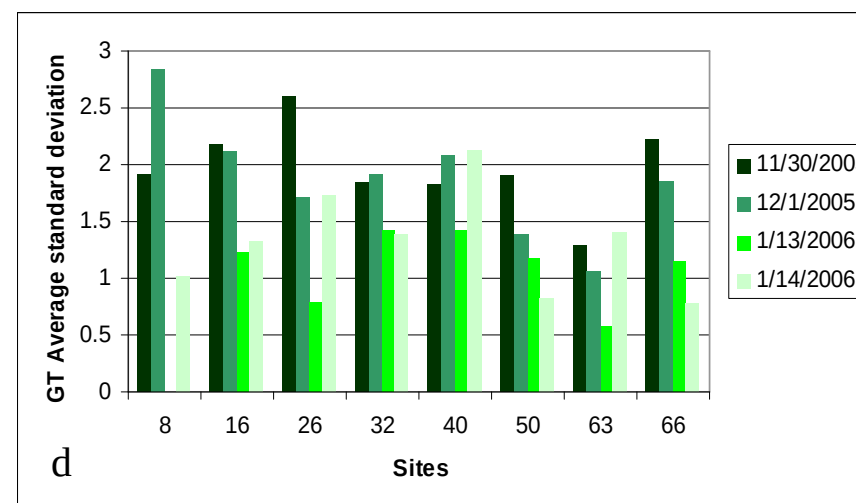
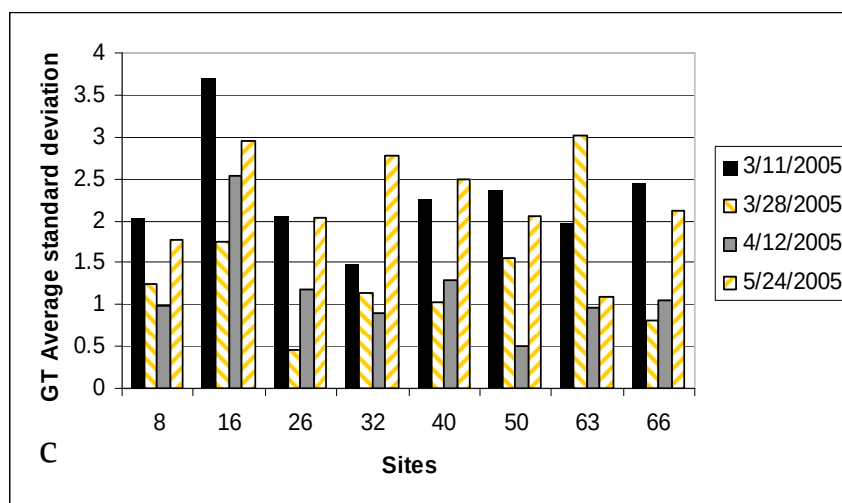
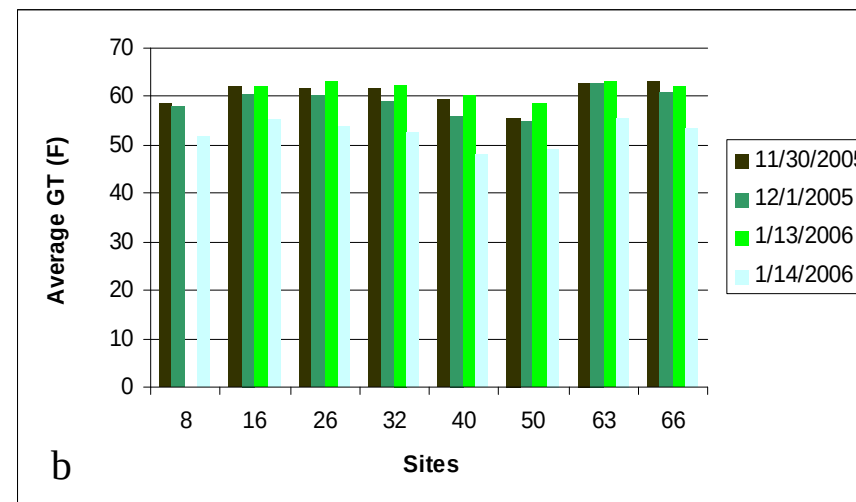
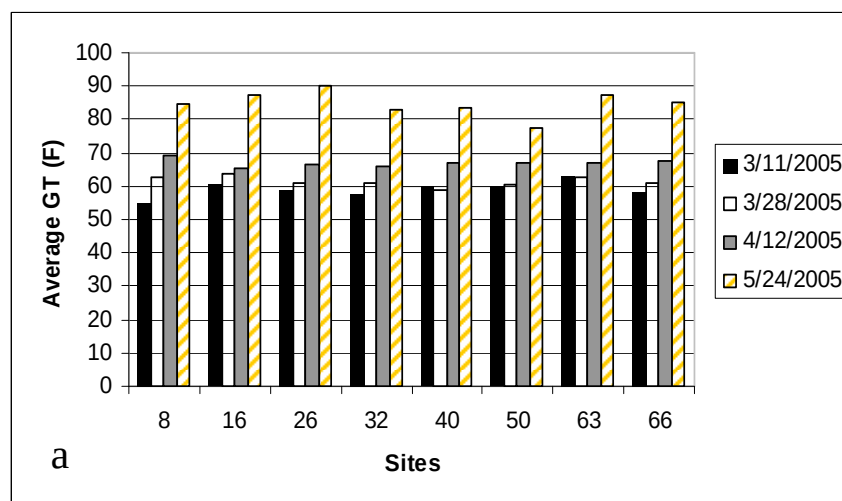


Figure 4.4. Average GT (a and b) and standard deviation (c and d) for eight dates of field data collection.

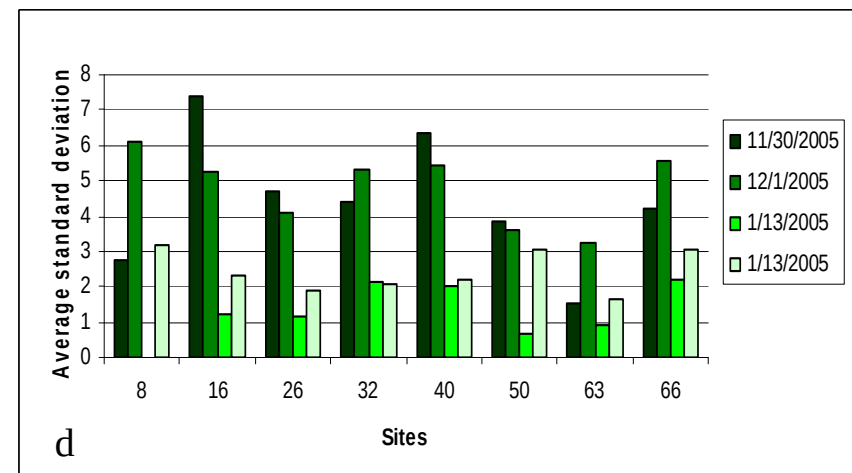
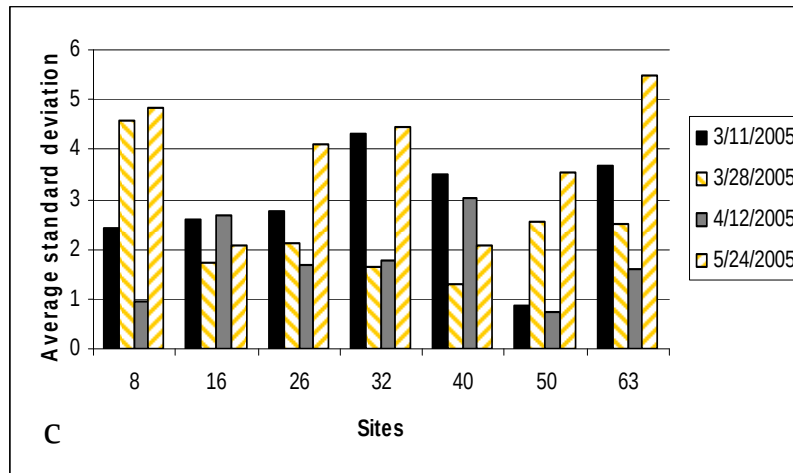
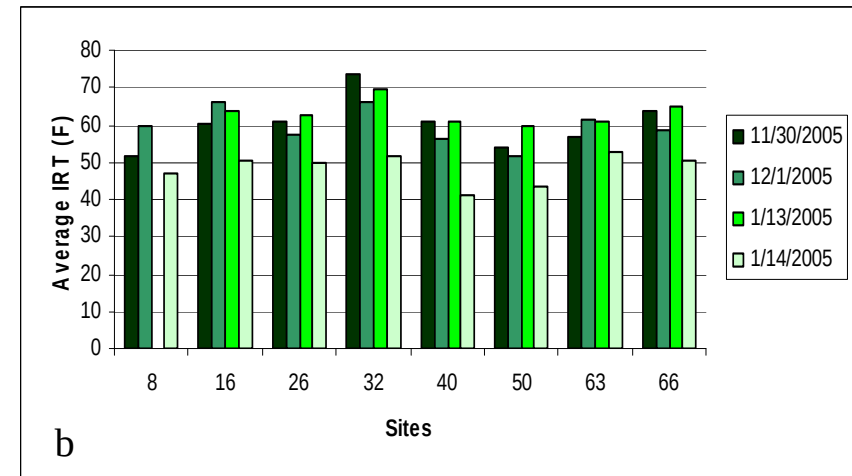
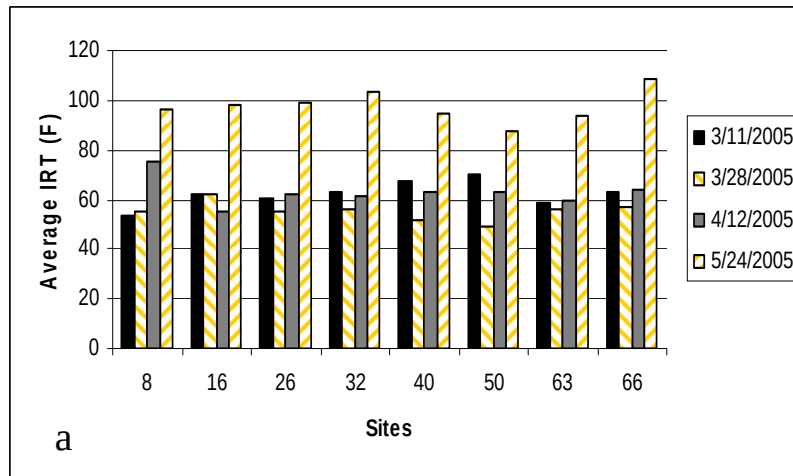


Figure 4.5. Average IRT (a and b) and standard deviation (c and d) for eight reading collections.

4.3.3. Analysis of variance ANOVA

A one way ANOVA was conducted for each sampling dates to evaluate if statistical differences were present among the fields for the variables GT and IRT. The results of this analysis showed statistical difference for both variables at the probability level of 0.01 in all the field data collections (table 4.2 and table 4.4). The difference between sites is represented in the ANOVA by the mean square value *between groups*, while the variation within each site is represented by the mean square value in the *within group* category.

a. ANOVA analysis of GT at eight small fields

The maximum and minimum limits of the range of observations correspond respectively to the readings on May 24, 2005 with the highest average GT and the reading on April 12, 2005 with the lowest value. Since both limits of the range were found on two different times in the spring season and since the remaining values within the range do not appear to be linked to a particular time of the year, it is reasonable to affirm that there is no seasonal effect on GT variations among sites.

The analysis of the mean square values in the *within groups* category of the ANOVA showed relatively small values in all the eight data collections. The range of values for this analysis was between 1.3 and 5.5 registering the lowest limit on January 13 and the highest limit on March 11, 2005 respectively. These low values indicate relatively small local variation of GT within a field around a Hydra-probe reading station through the year. Since the ANOVA analysis showed statistical difference within the small fields for the GT variable, the Tukey *post hoc* analysis serves to identify groups of sites that have similar behavior on a given reading date. Sites sharing the same Tukey

group have no statistical difference in their means for a given variable.

Table 4.2. Analysis of variance of GT for small fields in eight field data collections

Ground temperature						
		Sum of Squares	df	Mean Square	F	Sig.
03-11	Between Groups	359.490	7	51.356	9.319	.000
	Within Groups	325.137	59	5.511		
	Total	684.627	66			
03-28	Between Groups	221.358	7	31.623	12.775	.000
	Within Groups	215.363	87	2.475		
	Total	436.721	94			
04-12	Between Groups	137.764	7	19.681	13.148	.000
	Within Groups	181.119	121	1.497		
	Total	318.884	128			
05-24	Between Groups	1446.426	7	206.632	43.431	.000
	Within Groups	528.110	111	4.758		
	Total	1974.536	118			

Ground temperature						
		Sum of Squares	df	Mean Square	F	Sig.
11-30	Between Groups	811.072	7	115.867	28.910	.000
	Within Groups	545.066	136	4.008		
	Total	1356.139	143			
12-01	Between Groups	911.935	7	130.276	35.623	.000
	Within Groups	497.365	136	3.657		
	Total	1409.300	143			
01-13	Between Groups	298.177	6	49.696	37.948	.000
	Within Groups	141.434	108	1.310		
	Total	439.612	114			
01-14	Between Groups	733.731	7	104.819	52.888	.000
	Within Groups	235.846	119	1.982		
	Total	969.578	126			

In table 4.3, the number of times that a pair of fields is grouped together is indicated by the number within the matrix. The most dissimilar small fields present the lowest grouping number while the most similar fields will show the highest grouping number. Since eight are the total number of readings performed, this is the highest possible

number in which two sites can be grouped together. The total number of Tukey groups that a site has is an indicator of similarity (high total number) and dissimilarity (low total number) with the other sites and, therefore, a measure of the spatial heterogeneity of the responses.

Table 4.3. Tukey groups of significance difference between sites for GT at the 0.01 probability level. Numbers indicate number of times both small fields were found grouped together.

Sites	8	16	26	32	40	50	63	66	Total
8		1	1	5	3	0	1	5	16
16	1		5	4	1	0	4	3	18
26	1	5		6	2	2	3	5	24
32	5	4	6		3	3	3	4	28
40	3	1	2	3		5	2	3	19
50	0	0	2	3	5		2	1	13
63	1	4	3	3	2	2		4	19
66	5	3	5	4	3	1	4		25
Total	16	18	24	28	19	13	19	25	

The Tukey analysis showed the field around site 50 as the most dissimilar for the variable GT with only 13 groups. Only site 40 showed high similarity with this site since they shared the same group a total of 5 times (62.5%). On the other hand, the small field at site 32 presented the greatest similarities with other fields for this variable with a total of 28 groups, followed by site 26 with 24 groups. These two groups showed the most similar behavior since they were grouped together in 6 (75%) occasions, while sites 8 and 50, and 16 and 50 showed the most dissimilar behavior since they did not share a similar group for any of the 8 readings of this experiment.

b. ANOVA analysis of IRT at eight small fields

The analysis of variance for the variable IRT showed the readings on November 30 with the maximum difference between sites since high values of mean square *between groups* were found. The minimum difference between sites was found on March 28 corresponding to the lowest values for the mean square *between groups* (table 4.4). The results of the analysis showed that high and low values of mean square *between groups* are not necessarily associated with a particular season, suggesting the lack of seasonal effects on the behavior of the sites. This observation also applies to the mean square difference observed *within groups* in which readings collected from two continuous dates present the maximum and minimum values for the set of observations. In the case of IRT, the range of differences within the groups is greater than those observed for the GT analysis, confirming that at the small field level IRT present a less homogeneous behavior with a high in-field variation.

Comparing the ANOVA results for IRT with the results for GT presented in section 2.1 shows that the reading dates for which lowest and highest values were found are different, this suggests a different set of ecological variables influencing the specific response of both variables. Tukey groups of similar mean IRT showed the field at site 50 also is the most dissimilar one for the IRT with 10 groups, while site 26 is the most representative site with a total of 31 similarity groups (table 4.5). Coinciding with the results observed for GT, a strong relationship between site 50 and 40 was observed, sharing a total of 5 groups (62.5%), while a weak relationship exists between groups 8 and 50, and 16 and 50 for which no groups were shared in this study.

Table 4.4. Analysis of variance of IRT for small fields in eight field data collections

IRT/Surface temperature						
		Sum of Squares	Df	Mean Square	F	Sig.
03-11-2005	Between Groups	1539.447	7	219.921	22.115	.000
	Within Groups	586.732	59	9.945		
	Total	2126.179	66			
03-28-2005	Between Groups	1249.264	7	178.466	26.030	.000
	Within Groups	596.483	87	6.856		
	Total	1845.747	94			
04-12-2005	Between Groups	3937.694	7	562.528	108.676	.000
	Within Groups	626.321	121	5.176		
	Total	4564.016	128			
05-24-2005	Between Groups	4184.867	7	597.838	37.484	.000
	Within Groups	1770.364	111	15.949		
	Total	5955.231	118			

IRT/Surface temperature						
		Sum of Squares	Df	Mean Square	F	Sig.
11-30-2005	Between Groups	6246.775	7	892.396	43.272	.000
	Within Groups	2804.712	136	20.623		
	Total	9051.486	143			
12-01-2005	Between Groups	3024.892	7	432.127	18.178	.000
	Within Groups	3233.047	136	23.772		
	Total	6257.939	143			
01-13-2006	Between Groups	1230.531	6	205.089	78.274	.000
	Within Groups	282.975	108	2.620		
	Total	1513.506	114			
01-14-2006	Between Groups	1870.899	7	267.271	44.290	.000
	Within Groups	718.120	119	6.035		
	Total	2589.020	126			

When ordering the sites by the total number of groups they share, it is possible to observe the sites at the extreme portion of the watershed (50 and 8) with the lowest values while the sites located at the center have the highest values. This observation also applies for the groups of the variable GT in which 50 and 8 were the fields with the lowest number of shared groups.

Table 4.5 Tukey groups of significance difference between sites for IRT at the 0.01 probability level

Sites	8	16	26	32	40	50	63	66	Total
8		1	3	1	3	0	3	2	13
16	1		4	3	1	0	3	3	15
26	3	4		5	5	2	6	6	31
32	1	3	5		2	1	4	3	19
40	3	1	5	2		5	2	3	21
50	0	0	2	1	5		1	1	10
63	3	3	6	4	2	1		4	23
66	2	3	6	3	3	1	4		22
Total	13	15	31	19	21	10	23	22	

Overall, no seasonal effect was found in the spatial variation of GT or IRT within and among sites. The eight sampled fields presented greater homogeneity for the variable GT than for the variable IRT, although no statistical differences were found in the point data within the 30 by 30 m area for any of the two variables. The statistical differences found among sites are similar for both variables and suggest site specific effects on the variable responses. Some sites were identified as presenting a more unique response while others are very similar, indicating spatial diversity in the GT and IRT behavior.

4.3.4. IRT, GT and soil moisture correlation coefficients. Pearson's correlation coefficients were calculated for the variables GT, IRT and soil moisture (SM) recorded from the 30 by 30 m fields and aggregated under two schemes: by reading date and by site. In the data aggregated by date, positive correlations between GT and IRT were statistically significant at the probability level of 0.01 for all the sampling dates. Between

these, variables the correlation coefficient ranged between 0.28 and 0.75. The correlation with SM was statistically significant only for half of the sampling dates for both GT and IRT. For those dates, there was a negative correlation with SM and GT and IRT, with the exception of the reading on April 11, 2005 (Julian day 102) (table 4.6). These observations suggest a close relationship between GT and IRT and more variation in the relationship between GT/RT and SM.

The correlation analysis performed between variables at the site level (table 4.7) showed high positive correlation between GT and IRT that was significant at the probability level of 0.01. The level of association for these variables ranged between 0.807 for site 50 and 0.982 for the site 26. On the other hand, a negative correlation was found for SM and GT and IRT (significant at the probability level of 0.01) for all the sites, except for site 16 in which the correlation was significant at the 0.05 probability level between IRT and SM.

Although these results are in agreement with those reported by other studies in terms of negative correlations found between SM and GT while positive correlations were found between GT and IRT (Carlson *et al.* 1990, Carlson *et al.* 1995, Goward *et al.* 1985), we found that the strength of these correlations are affected by local conditions especially in the relationships between GT and SM and IRT and SM. These effect was most notorious between IRT and SM in which the differences between sites were found in the range between -0.36 and -0.83.

Table 4.6. Pearson's correlation coefficients for IRT, GT and soil moisture (SM) aggregated by sampling date. Values with ** and * show correlations with statistical significance at the 0.01 and 0.05 probability level, respectively.

Date	variable	GT-IRT	GT-SM	IRT-SM
3/11/2005	GT	0.340 (**)	-0.365(**)	-0.529(**)
3/28/2005	GT	0.543 (**)	0.163	-0.044
4/11/2005	GT	0.585 (**)	0.328(**)	0.673(**)
5/24/2005	GT	0.285 (**)	0.014	-0.199(*)
11/30/2005	GT	0.446 (**)	-0.246(**)	-0.331(**)
12/01/2005	GT	0.449 (**)	0.003	0.002
1/13/2006	GT	0.314 (**)	-0.246(**)	-0.204(*)
1/14/2006	GT	0.754 (**)	0.06	0.011

Table 4.7 Pearson's correlation coefficients for IRT, GT and SM aggregated by fields. Values with ** and * are correlations with statistical significance at the 0.01 and 0.05 probability level, respectively.

Site	Correlations		
	GT-IRT	GT-SM	IRT-SM
8	.960(**)	-.573(**)	-.572(**)
16	.917(**)	-.513(**)	-.361(*)
26	.982(**)	-.752(**)	-.824(**)
32	.919(**)	-.635(**)	-.831(**)
40	.915(**)	-.715(**)	-.824(**)
50	.807(**)	-.628(**)	-.788(**)
63	.971(**)	-.724(**)	-.689(**)
66	.939(**)	-.649(**)	-.727(**)

4.3.5. Ground and infrared temperature variation for different landuse transects.

ANOVA analysis for GT and IRT showed significant difference between landuses at the probability level of 0.01 for both variables. Higher values *between groups* implies different behavior between the landuses while the differences *within groups* implies a higher variation in the individual response within a given landuse. The differences *between groups* and *within group* were greater for the values of IRT than for GT (table

4.8) suggesting a more stable behavior of GT than IRT within a given landuse. These properties are important when selecting either GT or IRT to characterize environmental conditions of the landscape.

The Tukey groups of similarity showed that while grass and peanuts demonstrated the most similar behaviors for IRT and GT, the landuses grass and bare soil have a lesser similar behavior for both variables. The two agriculture landuses studied here, peanuts and cotton showed similar GT and IRT values and a loose association with other vegetated landuses. In this way cotton showed a low association with the landuse grass for the variable IRT since they shared only a single similar group. On the other hand, the perennial landuse orchard did not show a particular trend that differentiates it from others vegetated landuses such as cotton or grass for both variables. Orchard was only clearly differentiated, although it was clear its differentiated from the non-vegetated landuse, bare soil, for the variable GT.

Table 4.8. Analysis of variance of GT and IRT for landuse at the LRW

Variable	Variation source	Sum of Squares	Df	Mean Square	F	Sig.
GT Nov30	Between Groups	759.851	4	189.963	2.866	.037
	Within Groups	2386.439	36	66.290		
	Total	3146.290	40			
GT Dec01	Between Groups	212.226	4	53.056	21.726	.000
	Within Groups	87.913	36	2.442		
	Total	300.139	40			
GT Jan13	Between Groups	179.896	4	44.974	35.919	.000
	Within Groups	43.824	35	1.252		
	Total	223.720	39			
GT Jan14	Between Groups	211.862	4	52.965	79.982	.000
	Within Groups	23.178	35	.662		
	Total					

Table 4.8 (Continued). Analysis of variance of GT and IRT for landuse at the LRW

Variable	Variation source	Sum of Squares	Df	Mean Square	F	Sig.
IRT Nov30	Between Groups	455.798	4	113.950	6.440	.001
	Within Groups	636.958	36	17.693		
	Total	1092.756	40			
IRT Dec01	Between Groups	346.375	4	86.594	4.694	.004
	Within Groups	664.064	36	18.446		
	Total	1010.439	40			
IRT Jan13	Between Groups	233.250	4	58.313	32.220	.000
	Within Groups	63.344	35	1.810		
	Total	296.594	39			
IRT Jan14	Between Groups	607.631	4	151.908	41.614	.000
	Within Groups	127.765	35	3.650		
	Total	735.396	39			

Table 4.9 Tukey groups of similar GT and IRT at the 0.05 probability level.

Ground temperature						
Transects	Grass	Peanut	Cotton	Orchard	Bare soil	Total
Grass		4	3	2	0	9
Peanut	4		3	2	0	9
Cotton	3	3		3	1	10
Orchard	2	2	3		1	8
Bare soil	0	0	1	1		2
Total	9	9	10	8	2	
Surface temperature						
Transects	Grass	Peanut	Cotton	Orchard	Bare soil	Total
Grass		4	1	2	0	7
Peanut	4		3	2	2	11
Cotton	1	3		2	3	9
Orchard	2	2	2		2	8
Bare soil	0	2	3	2		7
Total	7	11	9	8	7	

4.3.6. Pearson's correlations between soil water and soil temperature in different landuse transects.

A positive linear association was found between IRT and GT for each one of the landuses studied here. This positive association was stable through the four reading dates for

which data were collected (figure 4.6). A less clear correlation was found between the temperature variables and SM for the landuses studied here (table 4.10). Significant negative correlations at the 0.01 probability level were found between SM and temperature only for bare soil and a negative correlation at the 0.05 significant level was found between SM and GT in the landuse cotton. The results found in this section show that landuse has an important influence in the relationship between GT - IRT and SM. Peanuts and bare soil that present a low vegetation cover and exposed soil negatively affects SM-GT relationship, while landuses such a grass, orchard or cotton had no significant effect on such relationship.

Table 4.10 Pearson's correlation coefficients for IRT, GT and soil moisture (SM) for different landuses. Values with ** and * are correlations with statistical significance at the 0.01 and 0.05 probability level, respectively.

Transect	Correlations		
	GT-IRT	GT-SM	IRT-SM
Bare soil	.919(**)	-.559(**)	-.592(**)
Cotton	.952(**)	-.117	-.092
Peanut	.827(**)	-.371(*)	-.347
Orchard	.560(**)	-.330	.081
Grass	.839(**)	-.213	-.102

4.3.7. Comparison between Hydra-probe and Tetra probe field readings

Data from the Hydra-probe *in situ* stations was validated comparing them with field data collected with hand carried devices from a 30 m adjacent field. In general, the readings for 5cm ground temperature for the eight stations agree with the average GT and IRT of the readings obtained from the 30 m adjacent field with a range of variation between <1 and 3.8 °C.

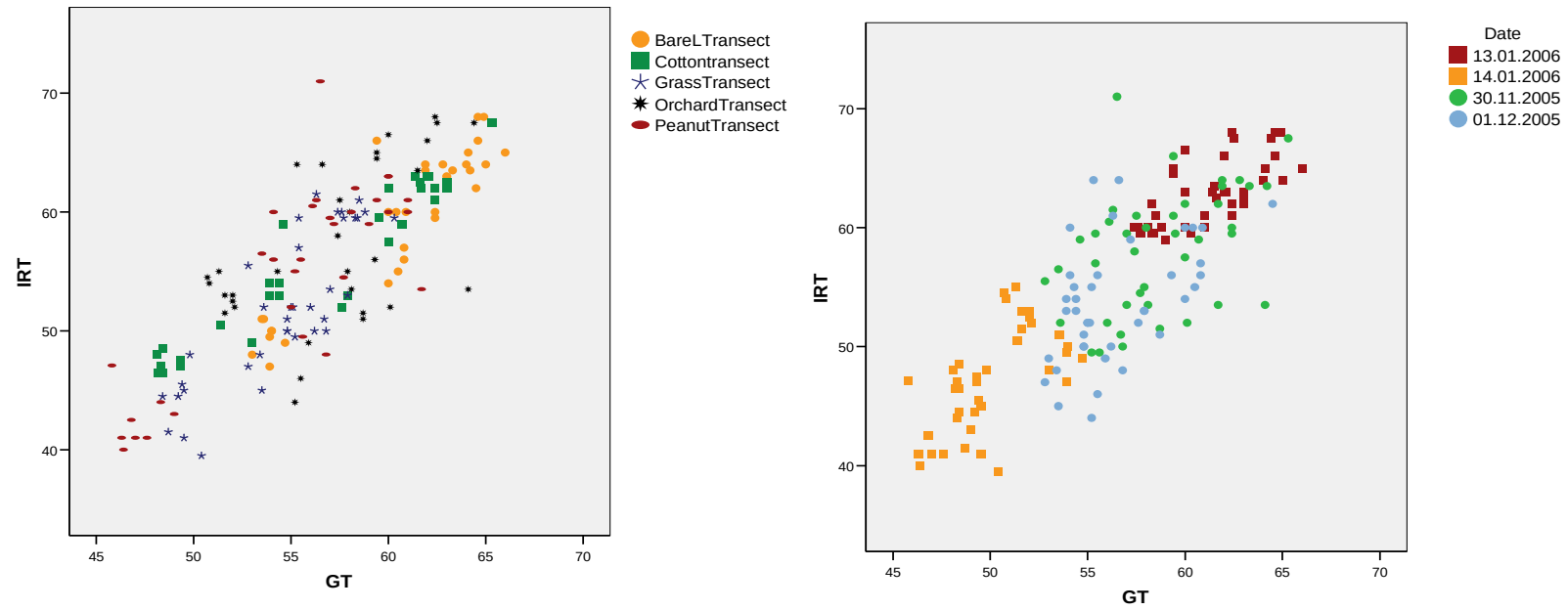


Figure 4.6. Relationship between GT and IRT for five landuse transects (a) and four reading dates (b).

Seasonal or site specific effects were not observed influencing this agreement. On the other hand, only five of the stations' readings at 5 cm depth agree with the field average recorded with the hand carried equipment for the variable SM. Two of the stations (26 and 66) tended to overestimate field conditions while station 50 tended to underestimate them with not appreciable seasonal effect in these variation. In both cases of under and over-estimating field SM behaviors, the causes can be diverse including variation in the water table, equipment calibration or human errors suggesting the need to conduct a separate study that address this variation (figure 4.7). Also, considering the long term goal for the Hydra-probe stations, the results of this analysis suggest the need to replicate the field validation on the remaining stations of the network to find if variations also occur in other stations and explore their suitable explanations.

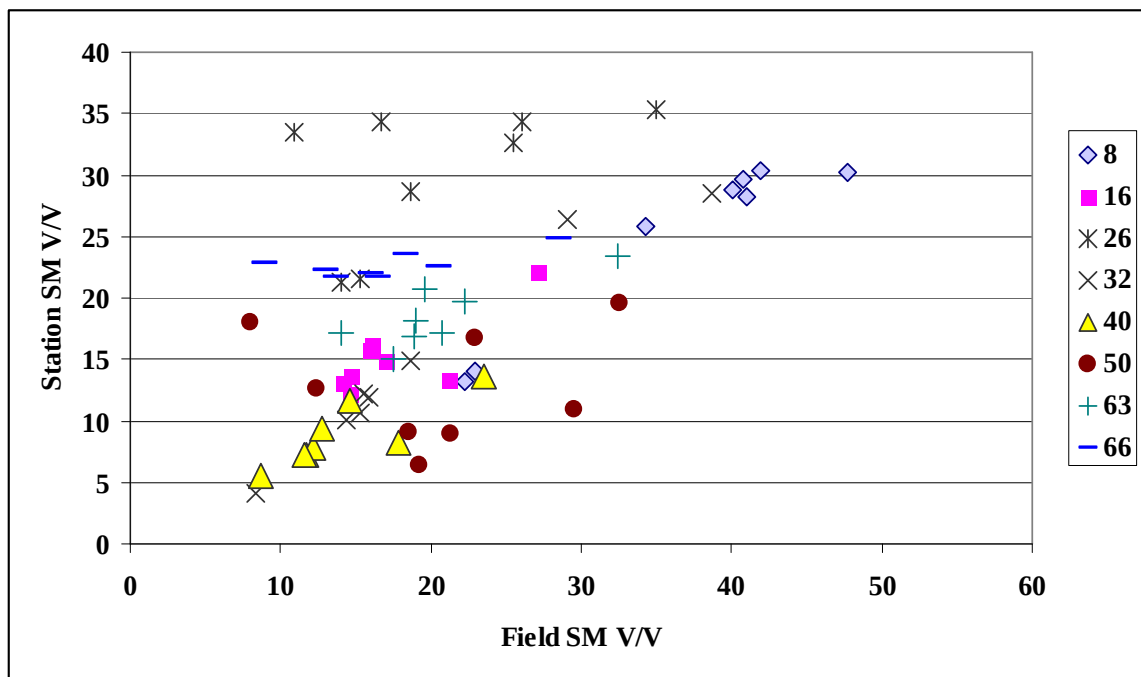


Figure 4.7. Relationship between readings from Hydra-probe stations and hand carried devices for the variables SM, IRT and GT.

4.4. Discussion and Conclusions

Landscape fragments are spatial units with unique combinations of physical characteristics such as landuse-land cover, soil and terrain. Within a landscape fragments biophysical processes are expected to have similar behavior. With increasing landscape complexity, fragments tend to be smaller in size and a higher diversity of combined environmental conditions even under similar land covers (Chapter 2 of this dissertation). This variability presents a challenge to routine monitoring of soil moisture in a spatially distributed manner. At the LRW, this research showed that within 30 x 30 m landscape fragments is possible to find high spatial homogeneity in the GT and IRT response independent of seasonal variation. For that reason, a 30 x 30 m field size is an appropriate landscape spatial unit to study energy fluxes under this complex landscape condition.

The greater standard deviations of the IRT compared with the GT indicates that regardless of seasonal variation or vegetation cover, there is a level of uncertainty in the assessment of IRT, even within small spatial areas. Rapid changes in local conditions such as atmospheric state, canopy resistance to transpiration, cloud cover or wind speed are mentioned as its possible causes (Goward *et al.* 1985). This variability may cause errors when point field measurements are used for the ground validation of remote sensing data, or when indirect estimations of soil moisture conditions are calculated using radiometric surface temperature (T_R) from satellite thermal data (Carlson *et al.* 1990, Kustas *et al.* 2004). However, the variability can be decreased by collecting more than one reading for a single point location, since their average values will better reflect the conditions at that point location.

The statistical differences among fields for GT and IRT were found to be: 1) seasonally independent; 2) associated with the *in situ* characteristics of the landscape fragments; and 3) only partially explained by landuse conditions. In this case, fields under similar land covers (see table 4.1) presented both similar (fields 26 and 40) and different (fields 8 and 50) behavior. In the same way, the study of variation among landuse transects showed strong differences only between the bare soil and the vegetated transects and only small differences with weak trends within the vegetated transects, in spite of their different vegetation type (grass, orchard, low crops). These observations suggest that other factors in addition to vegetation cover strongly influence the SM response and its correlation with GT and IRT supporting the hypothesis that in studying soil moisture conditions, vegetation cover is not sufficient to define a homogeneous landscape fragment.

In this regard, under a landscape approach, a broader concept of fragment should be considered that incorporates, in addition to vegetation cover, variables such as soil, topography and climate when defining the limits of the landscape fragment. Methodologies that consider the indirect estimation of soil moisture conditions based on vegetation component and surface temperature (Kustas *et al.* 2004), can benefit from an approach that incorporates ancillary information from soil and topographic characteristics since their estimates can be improved while accounting for the loss of infield variability. The work of Chen *et al.* (2005), suggest that ground water hydrology is an important modifier of the soil moisture and evapotranspiration around a point data source. Therefore, knowledge about the local soil physical properties influencing water movement can increase the accuracy of estimates.

The wide range of values for the correlation between SM and temperature among the eight fields suggest that a site specific approach is recommended to decrease the errors of using these correlations to estimate biophysical values at the local level. The importance of having a site specific approach was also supported by the analysis of the variability of the 5.08 cm (2 in) SM among the stations, in which under similar precipitation regimes, each location presented different absolute values and response time.

Overall, under complex landscapes, a pixel oriented approach to study biophysical process pose difficulties to the interpretation of mixed signatures and inferring accurate environmental parameters if pixels are larger than the landscape spatial units in which the processes occurs. Since the LRW is a complex landscape in which heterogeneity is present within small spatial areas, this research suggested the advantage of using an object oriented approach that accounts for local expressions of environmental processes and decreasing the errors and uncertainties of estimating sub-pixel values. As a general strategy to incorporate landscape analysis within environmental remote sensing, future research should consider methodologies in which landscape fragments extracted from high spatial resolution remote sensing data are associated with biophysical processes using the quantitative methods of landscape ecology metrics as a way to link landscape pattern to process while considering the limitations of complexity within ecosystem analysis.

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CHAPTER 5
SUMMARY AND CONCLUSIONS

5.1 Overview

Soil moisture investigations using satellite and field data is a developing process, challenged by the landscape complexity of most terrestrial ecosystems. Landscapes are complex systems formed by mosaics of individual spatial units conceptualized as fragments where biophysical factors fluctuate according to unique combinations of soil and land use land cover (LULC) characteristics. This research uses a multidisciplinary approach (i.e., Object oriented image analysis-OBIAS, Landscape ecology analysis, GIS spatial analysis, cartographic geometry and hydrological modeling) to explore the relationships between landscape fragments and soil moisture processes in complex landscapes. The research purpose was twofold, first to define landscape-based spatial criteria to use satellite data in direct and indirect assessment of soil moisture. The second purpose was to study spatial and temporal variation of single point readings for soil moisture and ground temperature that can be used to infer soil moisture conditions for larger fields and different land uses. The study area was the complex landscape at the Little River watershed (LRW) near Tifton GA US. The analysis includes GIS spatial analysis, LULC analysis, landscape fragmentation analysis, landscape metrics, soil diversity studies (using ROSETTA software and UNSODA database), infiltration modeling using the mono dimensional model FASST, and statistical analysis such as Analysis of variance, Tukey *post hoc* analysis, temporal stability analysis, Pearson's correlation coefficient, t-test and a generalized linear model.

Under present conditions of global climate change, this dissertation is timely and important considering the need to advance knowledge for using both ground and satellite readings to monitor biophysical variables concretely related to the water cycle and energy

fluxes. Also, the methods and results presented here are of interest to the broad scientific community considering that complexity is common to most terrestrial landscapes worldwide. This study is a landscape-based assessment of spatial variation of soil moisture offering a multidisciplinary approach with important contributions to the recurrent problem of linking landscape structure with biophysical process. The landscape-based approach is attractive in its application of data from current and new generations of environmental satellites since it provides economy of time and resources by using ready available data for exploratory studies of spatial variation. This dissertation also contributes to the knowledge of the relationship between point readings from the Little River Watershed (LRW) soil moisture and meteorological stations and the surrounding landscape with a proven methodology that can be replicated to investigate similar questions in the remaining stations or other landscapes.

5.2 Summary

5.2.1. Landscape ecology approach to soil moisture estimates

The landscape spatial complexity at the LRW was investigated using Object oriented image analysis (OBIAS), spatial analysis, cartographic geometry and hydrological modeling. Point distance analysis and landscape metrics were calculated within four different areas of spatial resolution matching the pixel sizes of satellite data commonly used on remote sensing analysis. The distance analysis between the stations location and the centroids of the landscape fragments showed that remote sensors with spatial resolution greater than 120-160 m are unsuitable to capture homogeneous conditions of soil and LULC under the LRW, while remote sensors with spatial resolutions of 10m or

less can capture homogeneous conditions in most of the study area. This is an important result when using remote sensing data to study biophysical variables in the LRW. On the other hand, none of the eight field reading station analyzed can truly be considered representatively a centroid of a 30 m homogeneous field for extrapolating the point measuring data from the station to an area equivalent to a 30 by 30 m pixel. Indeed, the overall arrangement of soil types and landuse around the stations varies from site to site. This indicates that the soil moisture and ground temperature recorded at these stations can be used to infer conditions in areas with similar soil type-landuse combination, although these areas may not be adjacent to the reading station.

This observation contests assumptions of previous studies that consider soil moisture as a spatially distributed variable exhibiting spatial autocorrelation where adjacent areas tend to have similar soil moisture behavior while distant areas tend to have different soil moisture. Of special interest is the presence of impermeable surfaces in most of the 30 m fields around the stations. Impervious surfaces greatly affect hydrological processes and energy fluxes thus influencing pixel values recorded by remote sensors and cause errors when the stations are used as a centroid pixel value in a pixel to pixel data validation.

Previous observations at the LRW suggested the importance of understanding a complex landscape where environmental variables affecting soil moisture may change over small spatial areas. It has been hypothesized that a landscape complexity is produced mainly by land cover variations. This research demonstrated that landscape fragmentation caused by landuse at the LRW is 14% greater than that fragmentation caused by soil types. When both variables were considered together, landscape fragments were 5.1-5.5

times more common than for either variable evaluated on its own.

Previous studies mainly rely solely on vegetation cover to indirectly estimate soil moisture. However, this analysis of landscape fragmentation, which includes two variables demonstrates the importance of considering soil characteristics ground heterogeneity analysis since variation in soil conditions modify the soil moisture response. Soil physical analysis using the ROSSETA program and the UNSODA data set as well as, hydrological modeling conducted under similar landuse conditions of the five most dominant soils in this study using the model FASST indicates important differences in observed water retention despite similarities in some of the soils' physical properties. These observations suggest that for future studies, incorporating a parameter that accounts for the soil variability may add precision to soil moisture estimates by avoiding oversimplification of the landscape conditions.

Moreover, the study of soil type-landuse revealed that only some LULC such forest, agriculture and low urban and some soil types such Tifton and Alapaha and their combinations dominated the study area despite the high landscape fragmentation. It is logical to suggest that considering these combinations within modeling and prediction processes of water redistribution will offer a bi-variable grouping criterion for remote sensing pixel values. These combinations will decrease soil moisture estimation errors caused by overlooking site specific conditions.

5.2.2. Point readings and 30 m field SM variability

A year long field data collection over eight different landscape fragments with homogeneous LULC conditions and adjacent to the stations of the Hydra-probe field

network was used to investigate the in-field and among fields spatial and temporal variation of soil moisture and ground temperature point data. One-way analysis of variance (ANOVA) and *post hoc* Tukey analysis served to demonstrate variations and site specific characteristics in soil moisture and ground temperature among fields. When variations within 30 m fields are analyzed, low spatial and seasonally independent soil moisture and ground temperature variations are observed. This confirms the hypothesis that processes in this complex landscape can be analyzed by considering 30 m fields as appropriate landscape sampling units. Temporal stability analysis such the mean relative difference supports this affirmation since in 30 m fields, a mean of the field can be identified within a maximum 3% v/v (volume/volume) soil moisture variation within infield readings. Infield homogeneity of soil moisture analyzed through temporal stability analysis, Pearson's correlation coefficient and paired t-test suggests that a single point within such fields can be used as an indicator of field conditions regardless of the season. In this regard, a generalized multi linear analysis of the ANOVA showed directional effects in some of the fields in areas in which human actions cause special soil moisture conditions.

On the other hand, similarities in the soil moisture and ground temperature behavior can be observed among fields despite the fact they are located several kilometers, apart while other fields present behaviors that clearly differentiate them from one another. These conditions were associated with either similar dominant LULC, soil type or both at the station location.

In a separate analysis, field data collected in four occasions from transects over the five LULC landscape fragments: peanuts, cotton, grass, orchard and bare land, served

to demonstrate the variation among fields caused by land cover and not necessarily by land use and the infield homogeneity regardless of the LULC in soil moisture and ground temperature. Also from this analysis was possible to demonstrate that proximity between point readings is not enough to produce similar soil moisture and ground temperature values, since t-test among homogeneous fields with different LULC and adjacent to each other showed significant differences for both variables.

Finally, the variable infra-red temperature showed high spatial variability within 30 m fields indicating that potential errors can exist when a single point reading is used as source of data validation for water- energy models.

5.2.3. GT – IRT and SM relationships

In terms of the relationship between soil moisture (SM), ground temperature (GT) and infrared temperature (IRT), this research demonstrated the advantage of using an object-oriented approach that considers homogeneous landscape fragments as study units.

ANOVA and *post hoc* Tukey analysis serve to demonstrate seasonal independent high variation in the GT and IRT behavior between eight different fragments as well as, site specific, in field homogeneity within each of the fragments. Statistically significant differences were found in GT and IRT between the different land uses. At the same time, high correlations between GT and IRT regardless of the land use were observed. The correlation analysis confirms observations of previous studies of high correlation between SM and GT, although in this study the correlation was found to be site specific since high differences in the correlation coefficients were observed among sites. The readings for GT from the eight Hydra-probe stations agree with the readings collected with hand

carried devices for 30 m adjacent fields. For SM only five of the stations' readings agree. In fact, two of the stations tend to overestimate field conditions while one station tends to underestimate them. This suggests a need for future studies that will verify the sources of such variation and its presence in other stations within the network.

5.3 Conclusions

In summary, in the first manuscript I assessed the level of complexity at the LRW finding the contribution to the spatial complexity by different combinations of soil types and LULC. I also determined the effects of this complexity in the selection, according to their spatial resolution, of satellite data to study soil moisture. Spatial resolutions larger than 160 m will always produce sub-pixel heterogeneity, while spatial resolution below 10m will better prevent mixed signals. Under a landscape object-oriented approach, I analyzed the spatial composition of soil and landuse on areas around eight stations of an *in situ* network demonstrating that soil type variation should be considered when assessing soil moisture distribution. The landscape based approach demonstrated that under highly fragmented landscape conditions, assumptions of spatial autocorrelation should be avoided since soil moisture response will depend on the combination of both soil and LULC characteristics changing over short distances.

In the second and third manuscripts, a year-long field data collection served to demonstrate that homogeneous areas equivalent to the pixel size of a Landsat TM or ETM+ image have similar soil moisture and ground temperature conditions and, therefore, a single point reading can be used as an indicator of variable status for that area. The opposite was found for the variable infra red temperature, where a single point

reading may be unsuitable for accurate area estimations in validation studies considering its high infield spatial variation. The previously cited correlation between ground temperature and soil moisture was confirmed here. Site specific behavior suggests that regression models using both variables are reliable only when applied to the site where the data were obtained. Agreement was found for ground and infrared temperature between the readings from all the stations of the *in situ* network and the adjacent fields. This was also true for soil moisture but only for in five stations, suggesting that a more detailed analysis of the entire network is needed to explain the reasons of such disagreement. Finally, the analysis of soil moisture, ground and infrared temperatures within five landuses demonstrates low variability within the landuses fragments and important difference among them. More observations are needed to conclude about the causes behind differences or similarities between the landuses.

Overall, this research contributes to satellite studies of the water cycle by proposing a landscape ecology (e.g. object oriented) approach to the problems of point reading interpolation and remote sensing of soil moisture-soil temperature within complex landscapes. This work contributes to the knowledge of the variation of biophysical variables for the remote sensing study of energy fluxes and the water cycle within complex landscapes.

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