The dynamics of active layer soil moisture over Canadian Arctic tundra in Trail Valley Creek, NT, observed in-situ and with remote sensing

by

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ABSTRACT

The dynamics of active layer soil moisture over Canadian Arctic tundra in Trail Valley Creek, NT, observed in-situ and with remote sensing

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SAR remote sensing offers a technology potentially capable of capturing information about soil moisture at high spatial and temporal resolutions. This method has been shown to be effective in lower latitude environments however there has been a lack of investigation in arctic environments, particularly in organic permafrost soils. A preliminary analysis was performed at Trail Valley Creek, Northwest Territories, where an investigation of the statistical spatial variability of soil moisture and processes controlling soil moisture was completed. Both of these are key steps required for modeling soil moisture retrievals from satellites. Second, an assessment of the sensitivity of RADARSAT-2 backscatter to surface soil moisture conditions was completed to examine whether SAR can provide a much needed method to map soil moisture across the arctic. Results showed a strong relationship between backscatter and soil moisture ($R^2=0.688$) and demonstrate the potential for SAR soil moisture retrieval in arctic ecosystems.
ACKNOWLEDGEMENTS

I’d like to start by expressing my gratitude to my advisor Dr. Aaron Berg for all of his support and guidance throughout all stages of completing this thesis. I’d also like to show my appreciation to Dr. Philip Marsh, my committee member, for providing his very helpful expertise and support. Without both Aaron and Phil, I would not have not been able to obtain the prestigious awards that I did, and I am deeply appreciative for the effort they put into helping me get them. Thank you to Justin Adams for all of his ideas and expertise and for introducing me to the world of remote sensing ground truthing while we tried to survive in the tundra. Thanks to everyone else who braved the many environmental hazards of the Arctic tundra to help with my field collection, including Elizabeth Wrona, Mark Russell, Cuyler Onclin, Karoline Wischnewski, and Manuel Helbig.

Special thanks to all of the support staff in the Geography department for all of their help that allowed me to receive scholarships, prepare for the field, and ease logistical matters. Thanks to all of my friends, office-mates, and geography friends for pulling me from my work and keeping me sane during grad school. Thanks to Allan Merchant for not only providing me with excellent suggestions for improving my thesis, but also for putting up with all my ups and downs throughout this process. To my parents, thanks for always encouraging me to be my best and supporting me no matter what I choose to do.
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Chapter 1: Introduction

1.1. Introduction

The climate of the Canadian Arctic has undergone drastic changes in recent years, with 1983-2012 observed to be the warmest 30 year period in the last 1400 years according to Alexander et al. (2013). This warming has resulted in observed changes to many components of the arctic environment including precipitation (AMAP, 2012), evaporation (Walsh et al., 2005), permafrost degradation (Marsh et al., 2002), runoff (St. Jacques and Sauchyn, 2009), biogeochemical cycling (Grosse et al., 2011), and vegetation growth (Lantz et al., 2012). These changes can affect carbon inputs to the atmosphere, hydroelectric generation, and infrastructure built on permafrost (Nelson et al., 2001). In the remote north where monitoring stations are sparse, these variables are often difficult to measure. As a result they are often poorly understood, which can lead to a high degree of uncertainty when predicting environmental changes. This area is also expected to continue to warm greatly in the coming decades, and to be one of the most vulnerable to climate change impacts in the world.

Soil moisture impacts many of the environmental processes that are affected by climate change. Soil moisture imparts control on permafrost thaw by controlling the thermal conductivity and thus heat transfer to the frost table (Endrizzi et al., 2011). Vegetation growth is also controlled in part by soil moisture, with soil moisture representing the pool of available water for plant growth (Schwinning and Sala, 2004). Biogeochemical cycles (Porporato et al., 2003), and surface energy fluxes that control precipitation and evaporation (Koster and Mahanama, 2012) are also controlled in part by soil moisture. Consequently, soil moisture data can provide models with initial conditions necessary to monitor and predict changes to these processes more
accurately. These processes are important to accurately monitor and predict in order to effectively manage arctic ecosystems in the face of climate change. Of utmost importance is permafrost degradation. Permafrost underlies much of the Arctic and is defined as soil, sediment, or rock that remains at or below 0°C for two or more consecutive years (AMAP, 2012). Permafrost extent has decreased and active layer (the upper layer of permafrost that thaws seasonally with changes in temperature) depth has increased in response to temperature increases in the arctic within the past two to three decades (AMAP, 2012). It is important to enhance our understanding of permafrost degradation, as it will affect carbon input to the atmosphere, vegetation shifts, runoff, hydroelectric generation, transportation, and infrastructure built on permafrost. Better understanding the dynamics of soil moisture can help with our understanding of permafrost dynamics. This research investigates a method to gather large scale soil moisture measurements in the arctic in order to enhance this understanding.

Knowledge of soil moisture in this region is limited by its remote location. Ground measurements are very time consuming and expensive, and are typically observable at relatively small spatial scales. Remote sensing techniques allow for large scale observations of soil moisture in remote locations. Backscatter from active RADAR (Radio Detection and Ranging) satellites has been found to be a function of soil moisture in lower latitudes (Merzouki et al., 2011; Ulaby, 1974; Ulaby et al., 1996). However, less is understood about RADAR sensitivity to soil moisture in the western arctic tundra. The arctic tundra is much different than the lower latitude environments where most RADAR sensitivity analysis has been focused on, due to the large presence of organic soil and unusual degree of surface roughness caused by underlying permafrost in the tundra. Therefore, further investigation of the use of this technique in the Canadian Western Arctic tundra is required.
Backscatter models are often used to relate surface soil moisture to backscatter values from satellites. These models use the statistical characteristics (e.g. variability, distribution, homogeneity) of soil moisture measured in situ to facilitate prediction of soil moisture values from backscatter values. Additionally, RADAR satellite data average soil moisture over 10’s of metres, masking the true heterogeneity of soil moisture below the resolution of the satellite (Famiglietti et al., 1999). Therefore, an understanding of this heterogeneity is required to better evaluate satellite performance. Lack of understanding of the spatial structure of soil moisture can lead to inaccurate representation of the variable for model validation. Consequently, variability of soil moisture in an area must first be understood to ensure that measurements accurately capture the true nature of the variability. Accurate validation also requires the proper design of ground measurements to ensure that they represent the true statistical characteristics of the soil moisture in that environment. This requires a good understanding of soil moisture spatial statistical characteristics. For these reasons, satellite and model validation requires a realistic representation of soil moisture variability. Soil moisture spatial variability in organic permafrost soils of the Western Canadian Arctic tundra has been under investigated. This must first be investigated a priori to satellite validation and calibration for soil moisture retrieval.

1.2. Research Aim and Objectives

The few climate and soil moisture observations in the arctic tundra, as well as the limited investigation of SAR soil moisture retrieval in this area leads to the following research question: What are the controlling processes on active layer soil moisture spatial variability in the Western Canadian Arctic tundra and how effective is SAR remote sensing for measuring this property in permafrost environments? Based on the above research question, this research will address two main objectives:
1. Provide a fundamental characterization of the statistical properties of soil moisture at the field scale in the arctic tundra. This is further divided into three sub-objectives: a) characterize the statistical nature of soil moisture spatial variability; b) determine the land surface characteristics that control soil moisture in this environment; and c) determine the scales at which soil moisture varies with the use of variogram analysis. These three sub-objectives will lead to more representative soil moisture data to compare with satellite derived measurements of soil moisture for validation by determining the most representative scale at which to measure soil moisture. They will also provide data to improve models that derive soil moisture from SAR backscatter.

2. Evaluate and model the sensitivity of C-band RADARSAT-2 SAR data to active layer soil moisture over organic permafrost soils of the arctic tundra. This objective is divided into three sub-objectives: a) evaluate the sensitivity of RADARSAT-2 data to soil moisture within two measurement depths; b) extrapolate this sensitivity to model soil moisture across the landscape; and c) evaluate the dominant land surface controls on spatial soil moisture variability modeled from RADARSAT-2 retrievals.

1.3. Thesis outline

This thesis contains three subsequent chapters addressing the above objectives. Chapter 2 addresses the first objective of the thesis and its sub-objectives: characterizing the statistical nature of, and controlling processes on, soil moisture spatial variability. This manuscript includes a brief literature review of soil moisture spatial characteristics, the methods carried out in the research, the results, and a discussion of the results and their overall relevance. Chapter 3 addresses the second objective, and sub-objectives, of the thesis: to assess the sensitivity of RADARSAT-2 SAR data to soil moisture conditions in the arctic tundra. This chapter is further
broken down to a brief literature review of SAR soil moisture retrieval, methods, and the results with discussion of their relevance. Chapter 4 concludes with a summary of the major findings of the thesis, including some suggestions for future research.
Chapter 2: A statistical characterization and investigation of the controlling processes on soil moisture variability over organic permafrost soils of the Western Canadian Arctic tundra

Abstract

Knowledge of the spatial variability of soil moisture over Arctic regions is required to better understand the hydrology, climate, and biogeochemistry of the arctic. However, the measurement of soil moisture over organic permafrost soils of the arctic tundra is challenging due to its inaccessibility, and as a result the characterization of soil moisture spatial variability is poorly understood in this environment. For this research, seven plots (42 m by 42 m; and 630 m by 630 m) were established at Trail Valley Creek, Northwest Territories, where soil moisture in the top 5 cm and 20 cm was measured on five separate dates in September of 2013, and July and August of 2014. To evaluate the controlling processes on soil moisture variability, additional measurements at each point included depth to frost table, microtopography type, and shrub presence. Statistical, geostatistical, and correlation analyses were completed for each plot on each sampling date. Soil moisture was generally found to be highly variable and often spatially independent. Patterns of variability were controlled by depth to frost table, microtopography, the presence of shrubs, and topography. The controlling processes varied between plots and ultimately depended on the topography of the plot, which drove changes to the amount and depth of standing water within the inter-hummocks, and the depth to frost table, driving changes to surface characteristics. It is anticipated that these results will facilitate retrieval of active layer soil moisture measurements in organic permafrost soils of the arctic tundra over large areas from remote satellites. These measurements will be useful for understanding and modeling
environmental processes including permafrost thaw patterns, vegetation shifts, and nutrient cycling.

2.1. Introduction

Soil moisture is critical to understand as it has been shown to impart control on several environmental processes including active layer thaw (Endrizzi et al., 2011), precipitation and evaporation (Koster and Mahanama, 2012), runoff (Dunne and Black, 1970), vegetation growth (Schwinning and Sala, 2004) and changes to biogeochemical cycling (Porporato et al., 2003). These variables are often difficult to measure in the remote north where monitoring stations are sparse. As a result they are often poorly understood, which can lead to a high degree of uncertainty when predicting dynamic responses of these processes under the impact of climate change. Large scale measurement of soil moisture can advance the measurement and understanding of these processes. Recent advances in the field of remote sensing provide a means of estimating soil moisture at fine spatial and temporal scales. Validation of satellite model derived soil moisture values requires accurate in situ field measurements of soil moisture and its variability before remote sensing can be used operationally for monitoring purposes. Additionally, the understanding of soil moisture variability can facilitate modeling of several environmental processes that depend on soil moisture.

Numerous studies have investigated the spatial variability of soil moisture in lower latitude environments for mainly agricultural applications (Brocca et al., 2007; Crow et al., 2012; Famiglietti et al., 2008, 1999; Western and Blöschl, 1999; Wilson et al., 2003). These studies have facilitated validation of satellites for soil moisture acquisition in mineral soils in these lower latitude environments by improving scaling techniques to compare ground data with
satellite data. However, the scaling techniques developed in these environments may not be applicable to arctic environments as the surface characteristics are much different, with different processes driving variability in soil moisture.

For example, Trail Valley Creek (TVC) is underlain by continuous permafrost, where frost heave and cryoturbation of the permafrost produce mineral (clay and silt) earth hummocks, creating a type of microscale change in topography, called mineral earth hummocks. Refer to Mackay (1980) for a more detailed description of the formation of these hummocks. These hummocks have diameters between 0.4 to 1 m, raising approximately 0.1 to 0.4 m above the surrounding inter-hummock surface area (Quinton and Marsh, 1999). These hummocks have a mineral surface or a thin (0 to 10 cm) layer of vegetation or organic material (peat), while the inter-hummock areas contain peat, up to 50 cm in thickness (Quinton and Marsh, 1999). Peat has a much higher infiltration capacity, lower bulk density, higher porosity, and higher hydraulic conductivity than mineral soil, resulting in the inter-hummock areas being the dominant drainage pathways with higher moisture contents (Quinton and Marsh, 1999). This difference in soil properties and moisture content results in differences in vegetation between hummocks and inter-hummocks, with hummocks often supporting a thin layer of lichen, and inter-hummocks supporting sedges and small vascular plants with an underlying moss cover (Quinton et al., 2000). The presence of permafrost, limited storage in the active layer, and microtopography lead to typically high and variable soil moisture conditions in the organic permafrost soils of the arctic tundra (Meade et al., 1999). The main hydrologic controls of summer soil moisture in this environment are known to be meltwater and rainfall infiltration as inputs, and evaporation as the main output (Woo and Marsh, 1990). However, due to its remote location, limited studies have
investigated soil moisture spatial structure at the field scale in arctic landscapes or in organic soils (Chapin et al., 2000).

Engstrom et al. (2005) investigated spatial and temporal controls on soil moisture variability in a coastal Arctic plain in Alaska. They found that soil moisture in areas characterized by high centred polygons and troughs was spatially controlled by variability in microtopography, and at the larger watershed scales (10 to 100 m$^2$) changes in basin topography was the main control, with lower areas being wetter than higher areas. Petrone et al. (2004) investigated a harvested peatland in Quebec, and found ecosystem scale (1 to 10 m$^2$) soil moisture spatial variability to be strongly correlated to vegetation cover and microtopography, and larger, watershed scale soil moisture to be correlated to basin topography. Anctil et al. (2002) also investigated soil moisture variability in a peatland in Quebec and found similar ranges as mineral soil, suggesting that the controls could be similar there. There are few studies that have observed soil moisture spatial variability at the field scale in the Canadian Western Arctic. There is a need for a method to robustly estimate soil moisture mean and variability in organic permafrost soils of the arctic tundra, as methods for lower latitudes are not applicable due to the vastly different soil and environment characteristics.

The objective of this chapter is to characterize active layer soil moisture spatial variability in organic permafrost soils of the Canadian Western Arctic tundra. This will be met with three objectives; 1) characterize the statistical nature of soil moisture spatial variability; 2) determine the role of land surface characteristics on controlling soil moisture spatial variability, including microtopography type, frost table depth, shrub presence, and topographic indicators; and 3) use variogram analysis to determine the scales at which soil moisture varies. It is suspected that
strong dominance of organic soil and the presence of permafrost will cause the spatial variability of soil moisture in this environment to behave much differently than in mineral soils.

2.2. Research Methods

2.2.1. Study area

Research was conducted at Trail Valley Creek (TVC), a watershed located approximately 50 km northeast of Inuvik, Northwest Territories (Figure 2.1). The catchment lies within the continuous permafrost zone and is mostly open tundra. Dominant vegetation includes grasses, lichens, and mosses (Pohl et al., 2005) with patches of small shrubs and trees. The landscape is characterized by hummocky terrain described in section 2.1 (Figure 2.2), where mineral earth hummocks cover approximately 50% of the ground surface (Quinton and Marsh, 1999). Gently rolling hills dominate the landscape, with the basin having a mean slope of 3° (Pohl et al., 2005). Research took place within two previously established study sites (Marsh et al., 2002); 1) TVC Upper plateau (TUP), a flat, upland site with very few shrubs; and 2) TVC Main meteorological site (TMM), located in Siksik Creek, a tributary of TVC. The area around TMM contains a few more small shrubs than TUP and small variations in local topography. Field work took place in September 2013 at TUP, and in July and August of 2014 at TMM.
Figure 2.1: Location of the Trail Valley Creek watershed (red outline) within Canada.

Figure 2.2: Cross-sectional view of mineral hummocks and organic inter-hummocks within the study plots.
Upper plateau study plots were TUP Coarse, 396900 m$^2$ (70 m resolution) and nested within it was TUP Fine, 3600 m$^2$ (10 m resolution) in area (Figure 2.3). Five study plots were established at TMM (Figure 2.4), to balance a secondary objective (not discussed in this study) of validating soil moisture stations surrounding the COSMOS sensor at this site. They are named TMM1, TMM2, TMM3, TMM4, and TMM5, based on sequential distance away from the sensor. Each of these TMM plots consists of a grid of points 42 m by 42 m, with 7 m spacing, for a total of 49 points in each plot. The vegetation in these plots consists of mostly mosses, lichens, sedge, and small patches of low shrubs [$Betula glandulosa$ (dwarf birch) and $Salix arctica$ (arctic willow)] with a maximum height of approximately 50 cm. Table 2.1 summarizes the main characteristics of the plots. TMM1 and TMM2 were a mix of both mineral hummocks and organic soil and had visible standing water in the inter-hummocks. These two plots had the greatest density of shrubs. TMM3 and TMM4 both had even deeper standing water within the inter-hummocks, with a thicker layer of organic soil overlying mineral hummocks. These plots lay in areas of topographical convergence, where lateral flow is directed to, evident in the Landsat image of the plots (Figure 2.4b). They were dominated with sedge clumps, and had a lower density of shrubs. TMM5 was on a slope, in an area of divergence (a higher area where lateral flow is directed away from), and contained a larger density of shrubs, and large mineral hummocks with a thinner layer of organic soil overlying them. TUP Coarse covered a larger area, and was relatively flat, with some areas dominated by moss and lichen, and others with patches of small shrubs. TUP Fine had fewer shrubs, a dominance of sedge clumps, and low relief topography.
Figure 2.3: TUP study plots over: a) a digital elevation model of the site; b) a true colour composite of Landsat Thematic Mapper of study site.

Figure 2.4: TMM study plots over a) a digital elevation model of the site; b) a true colour composite of Landsat Thematic Mapper of study site.
Table 2.1: Characteristics of each study plot and dates measurements were taken. Values in brackets are standard deviations.

<table>
<thead>
<tr>
<th>Study Plot</th>
<th>Size and Spacing</th>
<th>Dates Soil Moisture Measured</th>
<th>Dates depth to frost table measured</th>
<th>July mean depth to frost table (cm)</th>
<th>August mean depth to frost table (m)</th>
<th>Mean slope (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMM1</td>
<td>42m x 42m x 7m</td>
<td>Jul 24, 26, 28; Aug 25, 2014</td>
<td>Jul 28; Aug 25, 2014</td>
<td>66.8 (18.0)</td>
<td>75.6 (21.3)</td>
<td>2.6 (1.2)</td>
</tr>
<tr>
<td>TMM2</td>
<td>42m x 42m x 7m</td>
<td>Jul 24, 26, 27; Aug 25, 2014</td>
<td>July 27; Aug 25, 2014</td>
<td>61.4 (14.4)</td>
<td>68.8 (17.4)</td>
<td>3.4 (1.24)</td>
</tr>
<tr>
<td>TMM3</td>
<td>42m x 42m x 7m</td>
<td>Jul 24, 26, 27, 2014</td>
<td>Jul 27, 2014</td>
<td>36.6 (9.9)</td>
<td>N/A</td>
<td>3.2 (1.2)</td>
</tr>
<tr>
<td>TMM4</td>
<td>42m x 42m x 7m</td>
<td>Jul 24, 26, 27, 2014</td>
<td>Jul 27, 2014</td>
<td>40.3 (11.5)</td>
<td>N/A</td>
<td>2.6 (1.3)</td>
</tr>
<tr>
<td>TMM5</td>
<td>42m x 42m x 7m</td>
<td>Jul 24, 26, 29; Aug 25, 2014</td>
<td>Jul 29; Aug 25, 2014</td>
<td>49.6 (14.5)</td>
<td>52.5 (14.7)</td>
<td>7.7 (1.9)</td>
</tr>
<tr>
<td>TUP Fine</td>
<td>70m x 70m x 10m</td>
<td>Sept 11, 2013</td>
<td>Sept 11, 2013</td>
<td>N/A</td>
<td>40.3 (13.3)</td>
<td>1.6 (0.8)</td>
</tr>
<tr>
<td>TUP Coarse</td>
<td>60m x 60m x 70m</td>
<td>Sept 11, 2013</td>
<td>Sept 11, 2013</td>
<td>N/A</td>
<td>49.59 (14.16)</td>
<td>2.51 (1.31)</td>
</tr>
</tbody>
</table>

2.2.2. Field Methods

Systematic sampling along a grid of transects was used to gain an understanding of surface soil moisture variability at the field scale. At each point, three 5 cm soil moisture measurements (volumetric water content) were taken within 25 cm of the coordinate with a Steven’s Hydra Soil Moisture Sensor, which integrates the soil moisture in the top 5 cm. This sensor sends out an electromagnetic wave of 50 MHz frequency, and measures the returning signal which is dependent on the electric permittivity, and thus dielectric, of the medium (Seyfried et al., 2005). From this dielectric value, volumetric water content can be estimated as the dielectric is directly proportional to the moisture content in the soil between the measurement tines. Three measurements were taken to reduce micro scale moisture variation.

At the same location three 20 cm soil moisture measurements integrated throughout the top 20 cm of the soil were taken with a FieldScout TDR 300 Soil Moisture Meter. TDR involves
insertion of electrodes (a steel or brass rod) into the soil to determine the dielectric constant of the soil. The probe sends out an electromagnetic wave to determine the propagation time of the wave, which is directly related to the dielectric constant, and can be related to the volumetric water content of the soil (Noborio, 2001).

Soil sample cores were also obtained at randomly selected points across the TMM plots from which a volumetric soil moisture estimate was obtained to complete site-specific calibration of the moisture probes. Forty-five samples were taken from the top 6 cm to calibrate the Hydra probe, and thirty from the top 20 cm to calibrate the FieldScout TDR probe. Care was taken to obtain a mixture of both mineral and organic samples. These samples were sealed and weighed within five days of returning from the site (camping at the site delayed weighing of the samples). The soil cores were then oven dried at 70°C for ~72 hours to determine dry mass. From these values, volumetric water content was found and compared to the field measurements. The Hydra probe was calibrated using a linear regression between the field measured real dielectric constant and the volumetric water content determined from the 6 cm cores, with an RMSE of 0.0548 m³m⁻³ (Figure 2.5a). The FieldScout was calibrated using an exponential regression model fitted between field measured volumetric water content and the volumetric water content determined from the 20 cm cores, with an RMSE of 0.0519 m³m⁻³ (Figure 2.5b). An exponential model was used due to the FieldScout estimating high volumetric water contents relatively poorly. These relationships provided equations for calibration of each probe, both of which were applied to the raw field measured soil moisture data prior to analysis to obtain measurements of calibrated soil moisture.
Figure 2.5: Calibration curves for the: a) Steven’s Hydra Soil Moisture Sensor (5 cm); and b) FieldScout TDR 300 Soil Moisture Meter (20 cm).

To address objective 2, the following surface features were measured or recorded at each grid point. These included: 1) microtopography type [hummock (area of higher local elevation) or inter-hummock (area of lower local elevation)], visually determined; 2) the depth to the frost table, which is defined as the distance from the top of the soil surface to the top of the ice saturated, impermeable upper surface of the soil, measured with a graduated steel rod that was able to clearly identify the top of the frozen layer; and 3) the presence or absence of small shrubs (Betula glandulosa or Salix arctica) within 25 cm of the grid point (the presence of shrubs was not recorded at TUP).

The TUP study plots were sampled once on September 11, 2013, as sampling frequency was constrained by limited access to the site. All TMM study plots were sampled repeatedly to capture variability in both dry and wet conditions. All measurements in each study plot were completed within 90 minutes. Table 2.1 outlines the dates that measurements were taken at each
site and plot. Note that a precipitation event began halfway through sampling on July 27th, so measurements were taken in subsequent days at the remaining plots.

2.2.3. Statistical Analysis

2.2.3.1. Statistical Characteristics

For each plot and day, the three 5 cm soil moisture measurements taken at each point in the grid were averaged to obtain one value for each point in the grid. The same procedure was carried out for the three 20 cm soil moisture measurements. The data was analysed for statistical moments [mean, median, standard deviation (SD), coefficient of variation (CV) skewness, kurtosis, normality] for each depth of measurement, for each plot and date [e.g. Brocca et al. (2007) and Wilson et al. (2003)]. A Shapiro-Wilk test was completed to test for normality. Spearman’s rank correlation coefficient, or Spearman’s rho, was used to determine the strength of the statistical association between 5 and 20 cm soil moisture to explain some shared variance between the two depths of measurement. This test was used because many of the soil moisture samples were not normally distributed, demonstrating need for a non-parametric test.

2.2.3.2. Role of land surface characteristics in controlling soil moisture variation observed at two sample depths

An assessment of the physical processes controlling soil moisture was done to determine which mechanisms control soil moisture spatial variability and how they differ between plots. The Mann-Whitney U test was used to determine the control of microtopography on soil moisture by differentiating soil moisture between hummocks and inter-hummocks. This non-parametric test was used due to the observed non-normality of the soil moisture data. The same
test was used to test the significance of shrub presence on soil moisture by separating points with shrubs, and without shrubs.

Spearman’s rho was used to determine the strength of the statistical association between: 1) soil moisture and frost table depth; and 2) soil moisture and topographic indicators. Three topographic indicators were used in this study: slope, specific contributing area, and wetness index. A LiDAR DEM of Trail Valley Creek (Marsh et al., 2010) with a resolution of 2 m was used for the derivation of these topographic indicators. Slope, a measure of surface inclination (rate of maximum change in elevation values), was found in degrees using the original DEM in ArcGIS following Burrough and McDonell (1998). Specific Contributing Area (SCA) represents the upslope contributing area to each cell. The FD8 algorithm (Freeman, 1991) was used to calculate SCA, as the FD8 algorithm is a multiple flow direction method where areas of flow divergence can be identified. Calculation of the SCA was completed in Whitebox GAT (Lindsay, 2014). Finally, topographic wetness index (WI) values were extracted from the DEM using Whitebox GAT (Lindsay, 2014). This value provides a measure on the susceptibility of a pixel to be saturated based on topographic characteristics. Following Beven and Kirkby (1979), the Whitebox GAT tool utilizes the following equation to calculate WI:

\[ WI = \ln \left( \frac{A_S}{\tan \beta} \right) \]  

(2.1)

where \(A_S\) is the SCA (Freeman, 1991), and \(\beta\) is the slope in degrees (Horn, 1981). The value of each topographic indicator was found for each point in the plots, and the strength of association between these values and soil moisture values was assessed using Spearman’s rho.
A geostatistical analysis of the soil moisture data was conducted utilizing variograms to assess the scale at which soil moisture varies in each plot over each date. Spatial autocorrelation is a measure of the similarities between closely spaced measurements. Soil moisture is typically thought to be spatially autocorrelated (Western and Blöschl, 1999). Variogram analysis is valuable in soil moisture statistical analysis as it provides insight into the scale at which soil moisture is naturally variable, and is described in detail by Western et al. (2004). Briefly, a variogram is a plot of the variance between points as a function of their separation distance. The shape of the variogram demonstrates that there is some degree of spatial autocorrelation if it reaches a sill (levels out horizontally). The sill represents the spatial variance of two distantly separated points. The distance at which it levels out is known as the range, the distance at which soil moisture variability no longer increases with separation distance. The nugget is equal to the y-intercept. A large nugget indicates variation due to measurement error, or a spatial control causing variation at a scale smaller than the sampling interval (Webster and Oliver, 2007). These values of the nugget, sill, and range are estimated by fitting a variogram model to the sample variogram. The ratio of the nugget effect to the total semivariance (nugget:sill) provides a measure of the degree of spatial autocorrelation (Petrone et al., 2004). If the ratio is less than 25%, the nugget effect is small enough that the data is strongly spatially dependant. If it is between 25% and 75% it is moderately spatially dependent, and above 75% indicates no autocorrelation. The degree of autocorrelation was determined based on the nugget:sill method. Some variograms did not reach a sill. This suggests that the data is autocorrelated, caused by variation at a scale larger than the sampling spacing (Western et al., 2004).
Variograms were plotted for soil moisture on each day in each plot, for each depth, and used to assess the degree of autocorrelation within each plot. This provided insight into which physical processes control soil moisture in each plot.

2.3. Results

2.3.1. Statistical Characteristics

Tables 2.2 and 2.3 show the descriptive statistics for 5 and 20 cm soil moisture, respectively. July 24th was relatively dry, while the remaining days had higher mean and median soil moisture values. All plots demonstrated reasonably large ranges and CVs of soil moisture, with the 5 cm demonstrating more variability than 20 cm. TMM3 and TMM4 had the highest variability. At the 5 cm depth, the soil moisture was normally distributed in 55% of the plots, and at the 20 cm depth was normally distributed in 71% of the plots. The likelihood of 5 cm samples exhibiting normality varied with location. The plots TMM1, TMM2, and TMM5 were typically normally distributed whereas the TMM3, TMM4, and TUP plots were not. The plots that were not normally distributed were generally skewed to the right (positively skewed) as demonstrated by their skewness values. The 20 cm soil moisture distributions were found to have normal distributions in most plots except when very wet. Similar to the 5 cm measurements, plots that were not normally distributed were skewed to the right.
Table 2.2: Descriptive statistics for 5 cm soil moisture. *Shapiro-Wilk test statistic, W. Bold values indicate that the sample is normal at a 95% confidence interval.

<table>
<thead>
<tr>
<th>Plot</th>
<th>Date</th>
<th>n</th>
<th>Mean (%)</th>
<th>Median (%)</th>
<th>SD (%)</th>
<th>C.V.</th>
<th>Range</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>S-W test*</th>
</tr>
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<tbody>
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<td>TMM1</td>
<td>July 24</td>
<td>49</td>
<td>37.5</td>
<td>32.1</td>
<td>15.6</td>
<td>0.42</td>
<td>52.4</td>
<td>0.47</td>
<td>-1.08</td>
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<tr>
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<tr>
<td></td>
<td>July 28</td>
<td>49</td>
<td>50.3</td>
<td>50.9</td>
<td>13.2</td>
<td>0.26</td>
<td>56.8</td>
<td>-0.18</td>
<td>-0.55</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>49</td>
<td>63.5</td>
<td>64.6</td>
<td>10.7</td>
<td>0.17</td>
<td>43.6</td>
<td>-0.46</td>
<td>-0.48</td>
<td>0.96</td>
</tr>
<tr>
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<td>21.5</td>
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<td>0.45</td>
<td>50.4</td>
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<td>76.2</td>
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Table 2.3: Descriptive statistics for 20 cm soil moisture. *Shapiro-Wilk test statistic, W. Bold values indicate that the sample is normal at a 95% confidence interval.

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<th>Plot</th>
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<th>Mean (%)</th>
<th>Median (%)</th>
<th>SD (%)</th>
<th>C.V.</th>
<th>Range</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>S-W test*</th>
</tr>
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<td>37.8</td>
<td>6.2</td>
<td>0.17</td>
<td>28.7</td>
<td>-0.32</td>
<td>-0.10</td>
<td>0.98</td>
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<td>44.6</td>
<td>6.4</td>
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<td>6.0</td>
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<td>25.8</td>
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<td>-0.35</td>
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<td>31.0</td>
<td>7.5</td>
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<td>34.6</td>
<td>0.19</td>
<td>-0.42</td>
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<td>37.4</td>
<td>10.6</td>
<td>0.29</td>
<td>40.2</td>
<td>-0.18</td>
<td>-0.89</td>
<td>0.97</td>
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<td>36.9</td>
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<td>39.8</td>
<td>16.4</td>
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<td>2.02</td>
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<tr>
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<td>TMM5</td>
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<td>22.0</td>
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<td>0.26</td>
<td>27.5</td>
<td>0.59</td>
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<td>7.9</td>
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<tr>
<td></td>
<td>July 29</td>
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<td>28.6</td>
<td>6.8</td>
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<td>37.7</td>
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<td>TUP Fine</td>
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<td>0.32</td>
<td>56.0</td>
<td>0.54</td>
<td>-0.18</td>
<td>0.97</td>
</tr>
</tbody>
</table>
The relationship between mean and variability of soil moisture has application for the modeling and estimation of soil moisture from satellite observations, as it allows estimation of soil moisture variability over an area, given the mean. The relationship between the CV and the mean water content over both measurement depths can be seen in Figure 2.6. Overall, the larger CVs at the 5 cm depth were seen at low moisture contents, whereas trends varied with plot in the 20 cm depth. TMM3 and TMM4 had the highest 5 cm CVs and the CV increased with mean, contrasting with the other plots which either increased slightly, or decreased, with mean.

**Figure 2.6:** Mean vs. CV of soil moisture at each plot for each day for a) 5 cm soil moisture, and b) 20 cm soil moisture.

The strength of association between 5 and 20 cm soil moisture measurements was assessed with Spearman’s rho, for each plot and date. All rho’s were significant with the exception of TMM1 on July 28. Spearman’s rho values ranged from 0.40 to 0.81, demonstrating shared variance between the two depths of measured soil moisture. TMM4 demonstrated the strongest association between the two measurement depths, whereas TMM1, TMM2, and TMM5 demonstrated the weakest.
2.3.2. *Role of land surface characteristics in controlling soil moisture variation observed at two sample depths*

Microtopography imparted control on soil moisture in most plots. Inter-hummocks generally maintained significantly higher mean soil moisture values than hummocks, shown in Figure 2.7. This was observed over both depths of measurement. Overall, inter-hummocks were significantly wetter than hummocks in 45% (5 cm) and 59% (20 cm) of the plots, which is expected due to the higher hydraulic conductivity of peat in inter-hummocks driving lateral flow into these areas (Quinton and Marsh, 1999) giving inter-hummocks higher moisture contents. However, inter-hummocks in TMM1 were wetter only on days when the mean soil moisture was higher. TMM2 and TMM5 soil moisture did not significantly differ between microtopography types, whereas TMM3, TMM4, and both TUP plots consistently had strong control from microtopography.
Frost table depth was generally positively associated with soil moisture (Table 2.4) in both hummocks and hollows, where higher soil moisture values corresponded with deeper frost table depths. This observed relationship is likely due to higher moisture content enhancing the thermal conductivity of the soil, allowing more heat energy penetration to thaw the frost table (Hayashi et al., 2007; Wright et al., 2009). Stronger rho values were observed with the 5 cm soil moisture measurements. The highest rho values between frost table depth and soil moisture were observed in TMM1 (5cm), TMM2 (both depths), and TMM4 (both depths). Since microtopography was also observed to influence soil moisture significantly, the difference between frost table depth measured in hummocks and inter-hummocks was also assessed in each
plot using a Mann-Whitney U test. Hummocks had significantly deeper frost tables than inter-hummocks in TMM2, TMM5, TUP Fine, and TUP Coarse (p-values=0.002, $1 \times 10^{-6}$, 0.0008, and $1 \times 10^{-8}$ respectively, however, no significant difference was observed in TMM1, TMM3, or TMM4. When all TMM plot data was assessed together, hummocks had significantly deeper frost tables than inter-hummocks (p-value=0.02). Since there was an observed relationship between microtopography and frost table depth, this collinearity needed to be removed to isolate control from frost table depth on soil moisture. Soil moisture in hummocks and inter-hummocks was sub-divided, and a Mann-Whitney U test was used to determine whether the relationship between frost table depth and soil moisture differed between microtopography types. The results are seen in Table 2.4 and show that soil moisture was more commonly associated with frost table depth in hummocks, particularly in TMM1, TMM2, and TUP Fine. Frost table depth was significantly associated to both hummocks and inter-hummocks in TMM4, with inter-hummocks demonstrating a stronger association at both depths.
Table 2.4: Spearman’s rho values for soil moisture and frost table depth. Bold values are significant at a 95% confidence interval.

<table>
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<tr>
<th>Site</th>
<th>Date</th>
<th>5 cm Soil Moisture</th>
<th>20 cm Soil Moisture</th>
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<tr>
<td></td>
<td></td>
<td>All Points</td>
<td>Hummocks</td>
</tr>
<tr>
<td>TMM1</td>
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<td>0.45</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.43</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>July 28</td>
<td>0.52</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>-0.01</td>
<td>-0.11</td>
</tr>
<tr>
<td>TMM2</td>
<td>July 24</td>
<td>0.62</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.56</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.58</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>0.32</td>
<td>0.57</td>
</tr>
<tr>
<td>TMM3</td>
<td>July 24</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.19</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.23</td>
<td>0.29</td>
</tr>
<tr>
<td>TMM4</td>
<td>July 24</td>
<td>0.29</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.38</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.46</td>
<td>0.62</td>
</tr>
<tr>
<td>TMM5</td>
<td>July 24</td>
<td>0.33</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.45</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>July 29</td>
<td>0.27</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>0.14</td>
<td>0.21</td>
</tr>
<tr>
<td>TUP Fine</td>
<td>Sept 11 2013</td>
<td>0.14</td>
<td>0.40</td>
</tr>
<tr>
<td>TUP Coarse</td>
<td>Sept 11 2013</td>
<td>0.01</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Figure 2.8 shows the dissimilarities between mean soil moisture measured at points that contained small shrubs within 25 cm of the point, and those without shrubs. In general, points with shrubs present had significantly lower soil moisture values than points with no shrubs present, likely due to moisture uptake by plant roots, and the roots creating tunnels within the soil, consequently increasing hydraulic conductivity. Points with shrubs present were significantly drier in 61% (5 cm) and only 40% (20 cm) of the plots, but were never significantly wetter than points with no shrubs. The significance was more pronounced in TMM1, TMM2, and TMM5.
Figure 2.8: Mean soil moisture values in areas with shrubs and areas without shrubs for a) 5 cm, and b) 20 cm depths, for each plot and date. * indicates significantly wetter at a 95% confidence interval from the Mann-Whitney U Test.

There were some statistically significant Spearman’s rho values observed between soil moisture and topographic indices (Table 2.5). Slope was significantly negatively associated with soil moisture in 10% (5 cm) and 12% (20 cm) of the plots. SCA was significantly positively associated with 5 cm soil moisture in 10%, and 20 cm soil moisture in 29%, of the plots. Finally, WI was significantly positively associated soil moisture in 5%, and 35% of the plots for 5 cm and 20 cm depths, respectively. All of these relationships are in the anticipated direction, as soil moisture is expected to be greatest in areas with lowest drainage or: small slopes, large specific contributing area, and large wetness indices.
Table 2.5: Spearman’s rho values for 5 and 20 cm soil moisture and topographic indicators: slope, specific contributing area (SCA), and wetness index (WI). Bold values are significant at a 95% confidence interval.

<table>
<thead>
<tr>
<th>Site</th>
<th>Date</th>
<th>Slope 5 cm Soil Moisture</th>
<th>SCA 5 cm Soil Moisture</th>
<th>Slope 20 cm Soil Moisture</th>
<th>SCA 20 cm Soil Moisture</th>
<th>WI 5 cm Soil Moisture</th>
<th>WI 20 cm Soil Moisture</th>
</tr>
</thead>
<tbody>
<tr>
<td>TMM1</td>
<td>July 24</td>
<td>-0.03</td>
<td>0.08</td>
<td>-0.17</td>
<td>0.12</td>
<td>0.09</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
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<td>-0.13</td>
<td>0.12</td>
<td>-0.35</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>July 28</td>
<td>-0.19</td>
<td>-0.08</td>
<td>-0.29</td>
<td>0.06</td>
<td>-0.11</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>-0.37</td>
<td>N/A</td>
<td>0.15</td>
<td>N/A</td>
<td>0.05</td>
<td>N/A</td>
</tr>
<tr>
<td>TMM2</td>
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<td>0.17</td>
<td>0.31</td>
<td>-0.15</td>
<td>0.37</td>
<td>0.14</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.01</td>
<td>0.26</td>
<td>-0.14</td>
<td>0.22</td>
<td>0.21</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.08</td>
<td>0.33</td>
<td>-0.12</td>
<td>0.13</td>
<td>0.23</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>-0.32</td>
<td>N/A</td>
<td>0.27</td>
<td>N/A</td>
<td>0.34</td>
<td>N/A</td>
</tr>
<tr>
<td>TMM3</td>
<td>July 24</td>
<td>0.08</td>
<td>0.05</td>
<td>0.16</td>
<td>0.35</td>
<td>0.10</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.13</td>
<td>0.18</td>
<td>0.19</td>
<td>0.37</td>
<td>0.24</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.08</td>
<td>0.13</td>
<td>0.11</td>
<td>0.45</td>
<td>0.19</td>
<td>0.54</td>
</tr>
<tr>
<td>TMM4</td>
<td>July 24</td>
<td>0.12</td>
<td>0.15</td>
<td>0.08</td>
<td>0.20</td>
<td>0.12</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
<td>0.07</td>
<td>0.15</td>
<td>0.01</td>
<td>0.25</td>
<td>0.13</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>July 27</td>
<td>0.01</td>
<td>-0.04</td>
<td>0.19</td>
<td>0.31</td>
<td>0.20</td>
<td>0.34</td>
</tr>
<tr>
<td>TMM5</td>
<td>July 24</td>
<td>0.27</td>
<td>0.26</td>
<td>0.05</td>
<td>0.70</td>
<td>0.12</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>July 26</td>
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<td>0.06</td>
<td>-0.06</td>
<td>0.11</td>
<td>-0.06</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>July 29</td>
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<td>0.13</td>
<td>-0.08</td>
<td>0.01</td>
<td>0.11</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>Aug 25</td>
<td>-0.14</td>
<td>N/A</td>
<td>0.11</td>
<td>N/A</td>
<td>0.02</td>
<td>N/A</td>
</tr>
<tr>
<td>TUP Fine</td>
<td>Sept 11</td>
<td>-0.14</td>
<td>0.07</td>
<td>-0.02</td>
<td>0.23</td>
<td>-0.16</td>
<td>-0.03</td>
</tr>
<tr>
<td>TUP Coarse</td>
<td>Sept 11</td>
<td>0.08</td>
<td>-0.07</td>
<td>0.22</td>
<td>0.01</td>
<td>0.17</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

2.3.3. Geostatistical analysis

Figures 2.9-2.11 show the variograms from this study, for which the details of derivation are described in section 2.2.3.3. Exponential models are commonly used to approximate soil moisture variograms (Anctil et al., 2002; Western and Blöschl, 1999; Western et al., 2004). However, spherical models were found to improve approximation of the data in this study, which was also observed at the field scale by Nyberg (1996) and Joshi and Mohanty (2010). TMM3, TMM4, and both TUP plots consistently had very large nugget effects, whereas TMM1, TMM2,
and TMM5 demonstrated some degree of spatial autocorrelation and smaller nugget effects, primarily when the mean soil moisture was relatively high.

All TMM1 variograms reached a sill, and any lack of autocorrelation was confirmed with a large nugget effect (nugget:sill >75%). TMM1 exhibited spatial autocorrelation in both depths of measurement on days when the mean soil moisture was higher: On July 26th, 5 cm and 20 cm soil moisture were moderately autocorrelated, with ranges of 42 m, and 16 m, respectively; On July 28, 20 cm soil moisture was moderately autocorrelated, with a range of 16 m; On August 25th, the day with the highest mean soil moisture, 5 cm soil moisture was strongly autocorrelated with a range of 12 m. TMM2 demonstrated very similar trends, with soil moisture demonstrating autocorrelation on days with high mean soil moisture: on August 25th, 5cm soil moisture was strongly autocorrelated with a range of 23 m; and on July 26th and 27th, 20 cm soil moisture was moderately autocorrelated with ranges of 29 and 30 m respectively. TMM5, with the exception of July 26th, never reached a sill. On July 26th, 5 cm soil moisture was moderately spatially autocorrelated; with a range of 17 m. TMM3, TMM4, and both TUP plots consistently had very large nugget effects, demonstrating variability at a scale smaller than the sampling distance, or never reached a sill, demonstrating variability at a scale larger than the sampling distance.
Figure 2.9: Variograms for 5 cm soil moisture at a) TMM1, b) TMM2, c) TMM3, d) TMM4, e) TMM5.
Figure 2.10: Variograms of 20 cm soil moisture at a) TMM1, b) TMM2, c) TMM3, d) TMM4, e) TMM5.
2.4. Discussion

2.4.1. Statistical Characteristics

Large CV and range values demonstrated that soil moisture is quite variable in this environment, exceeding what is typically seen in previous soil moisture studies carried out over mineral soils (Brocca et al., 2007). Brocca et al. (2007) summarized 22 soil moisture variability studies and found soil moisture to often be normally distributed, including one study conducted in organic soils (Anctil et al., 2002). Famiglietti et al. (1999) found soil moisture to be normally distributed in mid-ranges of mean moisture content, but positively skewed under dry conditions and negatively skewed under moist conditions. There are not enough sample dates in this study to conclude how soil moisture distribution varies over time with changing moisture conditions; however in general, the 20 cm soil moisture is similar to findings in mineral soil in that it is often normal (71% of cases), whereas the 5 cm soil moisture is not normally distributed (55% of cases) as often as many studies in mineral soils.

Figure 2.11: Variograms of 5 and 20 cm soil moisture at a) TUP fine; and b) TUP Coarse.
Many soil moisture variability studies have found the CV of soil moisture to decrease with mean (Brocca et al., 2012; Famiglietti et al., 2008, 1999). Here we observed that trend overall at the 5 cm depth, however not in plots TMM3 and TMM4. At the 20 cm depth, CV was highest and lowest at the higher mean soil moistures, with the trend varying between plots. Famiglietti et al. (2008) found that at the field scale (less than 100 m), mean and variability were unrelated, which may be the case here. It is possible that at this small scale, soil moisture is more random, than would be expected if a much larger scale (one that compared with more regional topographical variations) was examined.

The technique of measuring soil moisture in 5 and 20 cm depth integrates measurement over the observation length of the tines, so some shared variance and statistically significant correlation is expected between the two depths of observed soil moisture (similar to Wilson et al., 2003). TMM1, TMM2, and TMM5 had a thinner organic layer overlying the mineral earth hummock, providing a hydrological disconnection between the top 5 and 20 cm of soil, and explains the slightly lower rho values in these plots. Contrarily, TMM4 had fewer mineral mounds and a deeper organic layer, with the strongest observed rho between 5 cm and 20 cm. The fact that all plots demonstrate an association between 5 and 20 cm soil moisture has large implications on northern hydrology, as most hydrological processes and models are concerned with moisture in the deeper vadose zone as opposed to the 5 cm surface moisture, however many remotely sensed measurements of the soil water content are restricted to the near surface.

### 2.4.2. Overall land surface controls on soil moisture variability

Overall, soil moisture was observed to be highly variable, often non-normally distributed and spatially independent. This is attributed to physical processes shown here to impact soil
moisture including frost table depth, microtopography, and the presence of shrubs. These variables are also quite variable at very fine scales. It was consistently observed that TMM3, TMM4, and both TUP plots displayed different statistical characteristics than the other three plots as they demonstrated: the largest CVs; non-normality; and the highest range of CV that did not decrease linearly with mean. These plots also had the largest control from microtopography, where inter-hummocks demonstrated significantly higher moisture contents than hummocks. Quinton & Marsh, (1999) determined inter-hummocks to be the dominant drainage pathways in this watershed as a result of much higher hydraulic conductivity in peat soil. This would likely enhance the wetness and surface moisture of inter-hummock areas when the frost table is sufficiently close to the surface to constrain the saturated flow to the near surface. TMM3, TMM4, and both TUP plots all lie in areas of convergence and had the shallowest frost table depths (Table 2.1), with the most standing water in the inter-hummocks (visually observed). It is likely that the increased standing water increased surface soil moisture in inter-hummocks, and enhanced overall variability in these sites.

In contrast, TMM1, TMM2, and TMM5 demonstrated different spatial statistical characteristics. Autocorrelation occurred in these plots when they were very wet. TMM2 and TMM5 had no sill on days with no autocorrelation, suggesting that landscape controls on soil moisture patterns occur at a scale larger than the sampling distance. Larger scale variations in topography likely dominate the soil moisture pattern in this area as TMM2 and TMM5 have the highest mean slopes (Table 2.1).

Soil moisture variability was also related to shrub presence and frost table depth, which could also influence statistical properties in all plots. Points with lower moisture contents were generally found in points with shrubs present. Shrub roots absorb moisture from the soil leaving
the areas around them drier. Their roots may also increase preferential pathways for water flow, increasing porosity and consequently decreasing water holding capacity. Over sites where the frost table depth was significantly correlated to soil moisture, a deeper frost table corresponded to higher soil moisture. This observed relationship is likely due to higher moisture contents enhancing the thermal conductivity of the soil, allowing more heat energy penetration to melt the frost table (Hayashi et al., 2007; Wright et al., 2009). Frost table depth was deeper in hummocks than inter-hummocks due to greater insulation properties of peat in inter-hummocks limiting heat energy propagation to the frost table (Mackay, 1981; Quinton and March, 1995).

The difference in statistical characteristics between plots separated by only a few 10s of meters demonstrates the high degree of variability of soil moisture in this environment. When observed, ranges were between 12 to 42 m. It would be beneficial for future studies to investigate soil moisture with spacings similar to these ranges, over a larger extent, to capture variability at the larger scale controlled by topography. Sampling spacing should also be less than 70 m since the TUP coarse plot had sampling spacing too large to capture any variability caused by topography. Additionally, the amount and depth of standing water should be considered a key component for understanding soil moisture in this environment, as the controlling processes on soil moisture vary significantly with this, and should be measured in future studies.

2.5. Conclusion

Organic permafrost soils of the arctic tundra differ from mineral soil by sustaining much higher and more variable soil moisture, non-normality, as well as seldom exhibiting significant autocorrelation, than what has been observed in previous studies carried out over mineral soils (e.g. Brocca et al., 2007). Here we have shown that surface soil moisture variability is not only
controlled by different processes (organic soil mixed with mineral, frost table depth, microtopography) at the field scale compared to mineral soils, but that these controls also vary between plots that are only 10’s of meters away from each other. It is suggested that measurement sampling spacing be adapted in future research to ensure that variability caused by topography is captured. This research is essential to provide a foundation for modeling soil moisture in this environment and will help to develop models that will allow for more accurate soil moisture measurements over the arctic tundra from satellites. This is important for providing northern researchers with large scale soil moisture measurements for implementation into hydrological and climatic models to improve prediction of several hydrologic and climatic processes in Canada’s north.
Chapter 3: Evaluating the sensitivity of C-band RADARSAT-2 SAR data to active layer soil moisture over Arctic Tundra in Trail Valley Creek, NT.

Abstract

Measurement of soil moisture over the arctic tundra is challenging for a number of reasons including the high degree of variability of soil moisture, upscaling and downscaling challenges, and difficulties related to inaccessibility. As a result, it is important that new remote sensing techniques are developed. Earth observation satellites utilizing active C-band microwaves have been found to be sensitive to surface soil moisture (top 5 cm) in mineral soils; however less is understood about their sensitivity to soil moisture in the tundra, particularly in organic soils underlain by continual permafrost with an unusual degree of surface roughness and high spatial variability at small scales. The objectives of this research are to assess the sensitivity of RADARSAT-2 backscatter to surface soil moisture in typical arctic tundra, to model surface soil moisture using RADARSAT-2 backscatter, and to evaluate the degree to which landscape controls correlate to modeled soil moisture. For this research, five plots (42 m x 42 m) were established at Trail Valley Creek, Northwest Territories, where soil moisture measurements in the top 5 cm and 20 cm were sampled every 7 m, coincident to two RADARSAT-2 overpasses (θ = 24°) in July of 2014. Linear backscatter values (σ°_{HH}, σ°_{HV}, σ°_{VV}, σ°_{HH/VV}, σ°_{HV/HH}) extracted from the July 24th and 27th SAR images were compared to field measured soil moisture at each sampling depth using linear regression. The cross-polarization ratio (σ°_{HV/HH}) was found to demonstrate the strongest relationship with field measured soil moisture in the top 5 cm (R^2=0.688), with significant relationships with 20 cm soil moisture also observed. Soil moisture was modeled over a select area of the watershed using the linear regression equation developed, with an RMSE of 4.27%. Modeled soil moisture weakly to moderately correlated to landscape
variables across the watershed, demonstrating that topography has a control on soil moisture in this environment. These results provide new insight into the interaction of SAR microwaves with peat soils underlain by permafrost.

3.1. Introduction

Soil moisture is important to understand in arctic environments as it imparts control on key environmental processes including, but not limited to: active layer thickness (Endrizzi et al., 2011), water availability for plant growth (Schwinning and Sala, 2004), surface energy fluxes that control precipitation and evaporation (Koster and Mahanama, 2012), and biogeochemical cycles (Porporato et al., 2003). Climate change is altering trends in these processes including changes in hydrology, permafrost thaw, vegetation shifts, carbon inputs to the atmosphere, and affecting infrastructure built on permafrost (Nelson et al., 2001; Walsh et al., 2005). However, these trends are poorly understood due to lack of observations in the arctic. Large scale measurements of soil moisture could enhance modeling, understanding, and predicting changes to these processes. Microwave remote sensing can potentially provide an excellent, non-destructive way of retrieving soil moisture measurements over very high spatial and temporal resolutions, impossible to do with ground measurements.

Synthetic aperture RADAR (SAR) is a form of active microwave remote sensing that has demonstrated sensitivity to surface soil properties, including soil moisture (Moran et al., 2000; Ulaby et al., 1996). SAR is advantageous to other satellite retrievals of soil moisture (e.g. passive microwave) due to its high spatial resolution. SAR backscatter has been shown to directly correlate to the soil dielectric constant (Moran et al., 2000), which is strongly related to the volumetric water content of the soil.
RADARSAT-2 is a SAR satellite that has operation modes with very high spatial resolution (1 m to 100 m), which give it potential to provide very detailed information about soil moisture spatial variability at the field scale (10s of metres). RADARSAT-2 has a C-band sensor (5.6 cm wavelength), which has been shown in mineral soils to have a sensitivity to the soil dielectric properties particularly for images taken at lower incidence angles (< 30°), which is the angle between the RADAR illumination and the normal to the ground surface (e.g. Adams et al., 2013). This is due to lower angles being closer to perpendicular to the ground surface, producing less volume and multiple scatter from vegetation and surface roughness. This makes SAR scenes acquired from low incidence angles advantageous to acquire information about surface soil moisture. RADARSAT-2 has other advantages as it has a quad-polarization mode from which both horizontally (H) and vertically (V) polarized wave signals are sent and received. HH, VV, HV, and VH are used to name different responses, or linear backscatter channels, where the first letter denotes the polarization of the transmitted signal, and the second letter denotes the polarization of the received signal. A reciprocity property of the RADAR scattering results in HV and VH being identical (Ulaby et al., 1996), therefore only one is often reported in results.

Studies have shown SAR soil moisture retrieval to be fairly effective for soil moisture retrieval in environments with mineral soils and modest amounts of vegetation, namely in agricultural studies where the effects of surface roughness and vegetation have been explored (e.g. McNairn et al., 2012; Moran et al., 2000; Rahman et al., 2008; Thoma et al., 2008). However, limited research has been conducted to assess its applicability in the arctic tundra (Kane et al., 1996; Meade et al., 1999; Wall et al., 2010), which has different surface properties due to the presence of organic soil and permafrost that causes hummocky terrain. Vegetation and nonuniform surface roughness complicate the retrieval of soil moisture from SAR satellites.
Therefore, the absence of large vegetation in the arctic tundra makes SAR a promising way of measuring soil moisture in this environment. Additionally, Toyra et al., (2001) demonstrated that the RADARSAT signal can penetrate through grasses and sedges in a wetland environment, similar to the surface vegetation found at TVC.

A few studies have been conducted to assess how the SAR signal interacts with permafrost underlain peat soils, listed in Table 3.1. Studies such as Kane et al. (1996) and Meade et al. (1999) which were conducted over organic soil overlying glacial till in Alaska, and demonstrated weak to moderate relationships between SAR (ERS-1 and 2, VV) and soil moisture. In contrast, Bourgeau-Chavez et al. (2007) and Kasischke et al. (2009, 2007) found strong relationships between soil moisture and VV backscatter from ERS-1 and 2 in an Alaskan boreal peatland. Jacome et al. (2013) also found strong relationships between RADARSAT-2 backscatter and soil moisture in a boreal peatland, particularly with the cross-polarization ratio (HV/HH). These examples support the investigation of SAR soil moisture retrieval in organic soils; however more investigation is required in a wider variety of environments to make SAR soil moisture retrieval in the north operational. Therefore, there is a need to further our understanding of how SAR signals interact with organic soils of the arctic tundra. The objectives of this research are to: 1) assess the sensitivity of RADARSAT-2 backscatter to surface soil moisture in organic soils of the arctic tundra; 2) extrapolate the sensitivity to model RADARSAT-2 retrievals for meaningful surface soil moisture patterns across the watershed with an empirical regression modeling approach; and 3) evaluate the dominant landscape controls on the spatial soil moisture patterns observed from RADARSAT-2.
Table 3.1: Review of literature with a focus on SAR soil moisture retrieval over organic and/or arctic environments. The ranges in $r$ and $r^2$ values are due to multiple cases being examined in each study (e.g. wet and dry days, different incidence angles, burned and unburned sites).

<table>
<thead>
<tr>
<th>Study</th>
<th>Location (soil type)</th>
<th>Satellite (linear backscatter channel)</th>
<th>Observed Relationship between backscatter and soil moisture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kane et al. (1996)</td>
<td>Brooks Range, Alaska (organic over glacial till)</td>
<td>ERS-1 (VV)</td>
<td>$r^2=0.49-0.53$</td>
</tr>
<tr>
<td>Meade et al. (1999)</td>
<td>Brooks Range, Alaska (organic and glacial till)</td>
<td>ERS-1 and 2 (VV)</td>
<td>$r^2=0.03-0.36$</td>
</tr>
<tr>
<td>Bourgeau-Chavez et al. (2007)</td>
<td>Delta Junction region, Alaska (boreal peatland)</td>
<td>ERS-2 (VV)</td>
<td>$r^2=0.59-0.82$</td>
</tr>
<tr>
<td>Kasischke et al. (2007)</td>
<td>Delta Junction region, Alaska (boreal peatland)</td>
<td>ERS-1 and 2 (VV)</td>
<td>$r^2=0.59-0.82$</td>
</tr>
<tr>
<td>Sass and Creed (2008)</td>
<td>Utikima River drainage basin, Alberta (boreal peatland)</td>
<td>ERS-1 and 2 (VV)</td>
<td>$r^2=0.45$</td>
</tr>
<tr>
<td>Kasischke et al. (2009)</td>
<td>Tanana River floodplain, Alaska (boreal peatland-herbaceous vegetation cover)</td>
<td>ERS-2 (VV)</td>
<td>$r=0.74$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>No relationship in forested wetland site</td>
</tr>
<tr>
<td>Wall et al. (2010)</td>
<td>Cape Bounty, Nunavut (High arctic - polar desert and grass-sedge communities)</td>
<td>RADARSAT-1 (HH)</td>
<td>$r^2=0.003-0.413$</td>
</tr>
<tr>
<td>Jacome et al. (2013)</td>
<td>Le Grande basin, Quebec (boreal peatland)</td>
<td>RADARSAT-2 HH HV VV HV/HH</td>
<td>$r^2=0.06-0.51$ $r^2=0.05-0.78$ $r^2=0.02-0.46$ $r^2=0.06-0.8$</td>
</tr>
</tbody>
</table>

3.2. Research Methods

3.2.1. Study Area

This research was undertaken within a small area of the Trail Valley Creek (TVC) watershed, located approximately 50 km northeast of Inuvik, Northwest Territories. The area is underlain by continuous permafrost, and dominated by hummocky terrain, described in section
2.1. Field-scale measurements were taken at a site described as the TVC Main Meteorological (TMM) site, in the Siksik Creek watershed, a tributary of TVC. Vegetation includes patches of low shrubs [Betula glandulosa (dwarf birch) and Salix arctica (arctic willow)] with a maximum height of approximately 50 cm, mosses, lichens, and sedge. The research site is located north of the Boreal tree line, therefore lacks tall vegetation, and has topography characterized by low to moderate relief, providing a suitable study site for a RADAR sensitivity study.

3.2.2. Field Methods

Five measurement grids were established at the study site (Figure 3.1), all 42 m by 42 m with 7 m spacing, for a total of 49 points in each grid. At each point on the grid, three 5 cm volumetric water content measurements were taken within 25 cm of the 49 grid points with a Steven’s Hydra Soil Moisture Sensor, which integrates the soil moisture in the top 5 cm. At the same location three 20 cm soil moisture measurements integrated throughout the top 20 cm of the soil were taken with a FieldScout TDR 300 Soil Moisture Meter. These measurements were taken coincident (within 6 hours) with RADARSAT-2 acquisitions on July 24th and 27th (Table 3.2). A heavy precipitation event began halfway through sampling on July 27th, and consequently only three of the grids were sampled (MM2, MM3, and MM4). Soil cores were acquired to conduct site-specific calibrations of both soil moisture sensors. Forty-five samples from a mix of both mineral and organic surface soils were taken from the top 6 cm to calibrate the Hydra soil moisture sensor, and thirty samples from the top 20 cm were taken to calibrate the FieldScout TDR probe. Each sample was sealed and later oven dried at 70°C for ~72 hours to determine its true volumetric water content. A linear regression equation was used to approximate the relationship between the true volumetric water content and the real dielectric of the Hydra probe resulting in a probe calibration with an RMSE of 0.0548 m³ m⁻³. The FieldScout was calibrated
using an exponential regression model fitted between field measured volumetric water content and the volumetric water content determined from the 20 cm cores, with an RMSE of 0.0519 m$^3$m$^{-3}$. These calibration equations were applied to the sensor data to obtain calibrated soil moisture values prior to data analysis.

Figure 3.1: Map of measurement plot points and outlines, overlaid on a digital elevation model of TMM.
### Table 3.2: RADARSAT-2 image acquisition details.

<table>
<thead>
<tr>
<th>Date (2014)</th>
<th>Beam Mode (Incidence angle)</th>
<th>Orbital Pass</th>
<th>Acquisition Time (MT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>July 10</td>
<td>FQ2 (21°)</td>
<td>Ascending</td>
<td>18:54</td>
</tr>
<tr>
<td>July 24</td>
<td>FQ5 (24°)</td>
<td>Descending</td>
<td>8:52</td>
</tr>
<tr>
<td>July 27</td>
<td>FQ5 (24°)</td>
<td>Ascending</td>
<td>18:58</td>
</tr>
<tr>
<td>Aug 3</td>
<td>FQ2 (21°)</td>
<td>Ascending</td>
<td>18:54</td>
</tr>
<tr>
<td>Aug 10</td>
<td>FQ2 (21°)</td>
<td>Descending</td>
<td>8:17</td>
</tr>
<tr>
<td>Aug 17</td>
<td>FQ5 (24°)</td>
<td>Descending</td>
<td>8:52</td>
</tr>
<tr>
<td>Aug 20</td>
<td>FQ5 (24°)</td>
<td>Ascending</td>
<td>18:58</td>
</tr>
</tbody>
</table>

#### 3.2.3. RADAR Image Processing

A total of seven RADARSAT-2 scenes were acquired over TVC throughout the summer of 2014, the details for which are in Table 3.2. Low incidence angles were used as the SAR signal has been found to be less influenced by the effects of surface roughness and vegetation, and more so by soil moisture (Baghdadi et al., 2002). Each fully polarimetric (HH + HV +VV) scene was captured in find-quad (FQ) beam mode. The remotely sensed RADARSAT-2 data was processed with the RADARSAT-2 Toolkit for Monitoring Soil Moisture (Array Systems Computing Inc.). The multi-polarisation pre-processing tool was used to extract the $\sigma_{\text{HH}}$, $\sigma_{\text{HV}}$, and $\sigma_{\text{VV}}$ linear intensity backscatter channels. Briefly, three main steps were applied: radiometric calibration, speckle filter, and terrain correction. Radiometric calibration to $\sigma^0$ was completed to allow for quantitative analysis of the data. Next, a box car (mean) 5×5 speckle filter was applied to correct for speckle and noise, which inherently degrade the quality of SAR images. This assigns each pixel (12 m × 12 m) with the mean of the surrounding pixels in a 5×5 pixel area. Lastly, terrain correction using a digital elevation model (DEM) of TVC was used to produce an orthorectified product, which used the Range Doppler orthorectification method (Small and Schubert, 2008). From this, linear intensity channels $\sigma_{\text{HH}}$, $\sigma_{\text{HV}}$, and $\sigma_{\text{VV}}$ were
extracted, and calculation of the co- and cross-polarization ratios was completed ($\sigma_{HH/VV}^0$, $\sigma_{HV/HH}^0$, respectively).

### 3.2.4. Statistical Analysis

#### 3.2.4.1. Sensitivity analysis and model development

A mean value of 5 cm soil moisture for each grid point was determined from the three 5 cm soil moisture measurements taken at each grid point on both July 24th and 27th. Following this, a mean value for 5 cm soil moisture was determined for each of the five larger grids for both July 24th and 27th. This methodology was repeated for the 20 cm soil moisture measurements. Additionally, the mean of the linear backscatter values ($\sigma_{HH}^0$, $\sigma_{HV}^0$, $\sigma_{VV}^0$, $\sigma_{HH/VV}^0$, $\sigma_{HV/HH}^0$) within the grid outlines were found for each grid on July 24th and 27th. These were compared to the field measured mean values of soil moisture at both depths with a linear regression analysis to assess the sensitivity of the linear backscatter channels to soil moisture conditions.

The linear backscatter channel that was found to have the strongest relationship to field measured soil moisture conditions (as reported in section 3.3.1 - $\sigma_{HV/HH}^0$) was used to model near surface soil moisture. The equation from the linear regression model between $\sigma_{HV/HH}^0$ and field soil moisture values was inverted and applied to the given backscatter values from both July 24th and 27th. The means within each grid outline were compared to the mean observed soil moisture values to assess the performance of the model, as was done by Mcnairn et al. (2012). The root mean square error (RMSE) was used to quantify the model performance:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(M_i - O_i)^2}{N}}$$  \hspace{1cm} (3.1)
where $N$ is the number of data samples, $M_i$ is the modeled soil moisture value at point $i$, and $O_i$ is the observed soil moisture at point $i$. A low RMSE indicates a good agreement between observed and modeled soil moisture and therefore indicates strong model performance.

The empirical model equation was then applied to each pixel of each of the seven RADARSAT-2 images (Table 3.2) to produce maps of modeled soil moisture across a 1×1.75 km area of the watershed, within which lies the TMM study site. The temporal mean of the soil moisture estimates determined from $\sigma^2_{HV/HH}$ from all seven images was determined to highlight areas with high temporal persistence in either high or low moisture contents. This temporal mean will be referred to as modeled soil moisture in the subsequent analysis.

3.2.4.2. Dominant landscape factors which may control soil moisture

The modeled soil moisture was then compared to landscape variables to determine the dominant controls on soil moisture in this environment. The modeled soil moisture maps were resampled to 50 m to further minimize speckle noise. The modeled soil moisture was compared to the following landscape variables (as described below): wetness index, slope, solar radiation, canopy height, and snow persistence; also scaled to a 50 m spatial resolution. Maps of all of the variables over the landscape can be seen in Figure 3.2.
With the exception of snow persistence, each landscape variable was extracted from a LiDAR scan of the site, flown in 2004, the details of which can be found in Marsh et al. (2010). It was assumed that the topography of the site has not changed substantially in the 10 years since the scan was acquired, and that changes in vegetation are minimal for the purposes of this study.

Figure 3.2: Maps of landscape variables used to compare with soil moisture across a 1 × 1.75 km area of TVC.
Briefly, a DEM with a spatial resolution of 2 m was determined from ground returns from the LiDAR scan, from which slope, wetness index, and solar radiation were determined.

Slope (slope steepness in degrees) was extracted using ArcGIS following Burrough and McDonell (1998) and is a measure of surface inclination. Wetness index values, a measure of the susceptibility of a pixel to be saturated based on its slope and specific contributing area, were extracted using Whitebox GAT (Lindsay, 2014). The tool utilizes the following equation to calculate wetness index, following Beven and Kirkby (1979):

\[
Wetness\ Index = \ln \left( \frac{A_s}{\tan \beta} \right)
\]  

(3.2)

where \(A_s\) is the specific contributing area, calculated using the FD8 algorithm (Freeman, 1991), and \(\beta\) is the slope in degrees following Horn (1981).

Solar radiation was extracted with ArcGIS, as a total amount of clear sky, incoming solar insolation over the study period (July 10 to August 20, 2014) per unit area (2×2 m pixel) following the model developed by Fu and Rich (2002). This model utilizes the latitude (to determine solar declination and position) and surface topography (slope and aspect, the angle of the slope) to predict solar radiation received at the surface.

Canopy height was extracted from the LiDAR scan of the site, details of which can be found in Marsh et al. (2010). Briefly this method subtracts the maximum laser pulse returns from the ground returns (the DEM) to the scanner to determine canopy height.

Snow persistence was determined from six optical images of snow cover over the melt season of 2008. The images were reclassified as either 0 (no snow) or 1 (snow) based on a visually determined threshold of the blue band from the optical image. The six images were then
averaged to obtain a measurement of snow persistence through the melt season for each pixel, ranging from 0 (never had snow cover) to 1 (had snow cover in all images). It is assumed that there will be a relationship in snow persistence from year to year.

These variables were first compared to the modeled soil moisture using Pearson’s r correlation as an exploratory analysis to determine the strength and direction of the correlations. Additionally, a geographically weighted regression (GWR) analysis was undertaken to assess the spatial regression between the landscape variables and modeled soil moisture and to determine which predictor variable had the strongest relationship with soil moisture. GWR is a local form of regression analysis, and is advantageous to use for spatial data instead of a global model such as ordinary least squares regression, as it accounts for autocorrelation in the data which is observed here. GWR calculates the local $r^2$ within an optimized bandwidth for each data point, which allows for $r^2$ between variables to vary across space. Additional information on GWR can be found in Fotheringham et al. (2002). In GWR, the Akaike information criterion (AIC) value is used to compare models. Thus, the AIC was used to determine which predictor variables were the strongest. Also an important value in GWR is the conditional number. If the conditional number of the analysis is greater than 30, results should not be trusted due to multicollinearity between the predictor variables. This conditional number was observed for each analysis to determine the reliability of the results.
3.3. Results and Discussion

3.3.1. Sensitivity of RADARSAT-2 data to soil moisture conditions

The linear backscatter variables extracted from the RADARSAT-2 imagery were found to be linearly dependent on field measurements of soil moisture at both sampling depths (Table 3.3). The backscatter channels demonstrated weak to strong relationships with soil moisture in both depths of measurement, with slightly stronger relationships observed with the 5 cm soil moisture. \( \sigma_{\text{HH}} \) and \( \sigma_{\text{HV/HH}} \) exhibited the strongest sensitivity to 5 cm soil moisture. In both cases, as soil moisture increased, backscatter also increased (Figure 3.3). Jacome et al. (2013) and Merchant (2014) also found \( \sigma_{\text{HV/HH}} \) to be the most sensitive backscatter channel to surface soil moisture in a peatland environment.

Table 3.3: \( r^2 \) of linear regression between backscatter values and field measured soil moisture. Bold values are significant at a 95% confidence interval.

<table>
<thead>
<tr>
<th>Field Soil Moisture: Depth</th>
<th>( \sigma_{\text{HH}} )</th>
<th>( \sigma_{\text{VV}} )</th>
<th>( \sigma_{\text{HV}} )</th>
<th>( \sigma_{\text{HV/HH}} )</th>
<th>( \sigma_{\text{HH/VV}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 cm</td>
<td>0.654</td>
<td>0.124</td>
<td>0.020</td>
<td>0.688</td>
<td>0.440</td>
</tr>
<tr>
<td>20 cm</td>
<td>0.400</td>
<td>0.003</td>
<td>0.138</td>
<td>0.530</td>
<td>0.623</td>
</tr>
</tbody>
</table>
Figure 3.3: Linear regression relationships between mean 5 cm field measured soil moisture and a) mean $\sigma^0_{HH}$ backscatter, and b) mean $\sigma^0_{HV/HH}$ backscatter. Note that mean soil moisture was obtained for each of the five grids on July 24, but for only 3 of the grids on July 27.

There were also some significant correlations between backscatter channels (the cross- and co- polarization ratios) and 20 cm soil moisture. Bourgeau-Chavez et al. (2007) also found the SAR signal to be sensitive to both 6 and 12 cm soil moisture, and note that in an environment dominated with peat, the RADAR wave could penetrate deeper into the very light and porous peat, when the surface is very dry. Ulaby (1982) argues that the sensing depth of C-band RADAR is deeper than 5 cm for very dry soils, due to low dielectric properties. It is likely that when the peat is dry, the sensing depth is deeper since the SAR signal can penetrate through the porous peat. However, it is difficult to determine whether the SAR signal is sensing moisture in the top 20 cm given the multicollinearity between 5 and 20 cm soil moisture. The 20 cm measurement integrates moisture over 20 cm that includes the top 5 cm, and these two depths are often correlated (refer to Chapter 2) and suggest that we can also infer soil moisture in the top 20 cm given the strong correlation between the two.
3.3.2. Modeling soil moisture

The sensitivity of RADARSAT-2 to surface soil moisture was extracted to estimate soil moisture. The relationship between 5 cm soil moisture and $\sigma_{HV/HH}$ was the strongest and consequently was used for the remainder of the study. The line of best fit equation from the linear regression in the previous section was inverted to obtain a simple empirical model equation to calculate soil moisture given $\sigma_{HV/HH}$ values:

$$\text{Soil moisture (\%) = 51.47} \sigma_{HV/HH} - 51.96$$  \hspace{1cm} (3.3)

These modeled values were then compared to the measured values on July 24th and 27th to assess the fit of the model. The model yielded an RMSE of 4.27%, a relatively low RMSE which suggests that SAR can be used to model soil moisture over this region. Figure 3.4 demonstrates that for many plots, the model can roughly estimate the median field soil moisture. However the derived soil map fails to capture the large variability observed in the field as the model consistently produces smaller ranges and interquartile ranges. This is likely due to the differing support sizes [the area or volume integrated by each sample (Western and Blöschl, 1999)] of each measurement technique. The SAR imagery takes an average over an area the size of the speckle filter (60 m), masking variability caused by controlling landscape features such as hummocks and inter-hummocks that occur at much smaller scales. Contrarily, the validation data obtained with a hand-held moisture probe results in a much higher number of measurements and given the sampling area is less than 100 cm$^3$, this technique was able to capture this smaller scale variability and thus yield much larger ranges.
Figure 3.4: Boxplot of measured 5 cm soil moisture and modeled soil moisture. Within each boxplot, the horizontal black line represents the median, the box is the range between the 1\textsuperscript{st} and 3\textsuperscript{rd} quartile, the whiskers are the maximum and minimum values (excluding outliers), and outliers are the dots outside of the range of the whiskers.

The temporal mean of the modeled soil moisture across the landscape can be seen in Figure 3.5. Dry and wet patterns in soil moisture can be observed in the modeled soil moisture that will be compared to topographical variables (Figure 3.2), in the discussion below.
3.3.3. Dominant landscape factors which may control soil moisture

The modeled soil moisture patterns demonstrate some correlation to the landscape variables (Table 3.4), with the strongest relationship being observed with wetness index. All relationships were significant at a 95% confidence interval due to a very large sample size.

Table 3.4: Pearson’s r values between modeled soil moisture and landscape variables.

<table>
<thead>
<tr>
<th>Pearson’s r</th>
<th>Wetness Index</th>
<th>Slope</th>
<th>Solar Radiation</th>
<th>Canopy Height</th>
<th>Snow Persistence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modeled Soil Moisture</td>
<td>0.364</td>
<td>-0.319</td>
<td>-0.097</td>
<td>0.194</td>
<td>0.311</td>
</tr>
</tbody>
</table>
With respect to the wetness index, we would expect a positive correlation to soil moisture, where areas expected to be more saturated based on topography have higher moisture contents. Similar to relative elevation this is observed in the SAR derived soil moisture with an r of 0.364. Slope was expected to be negatively correlated to soil moisture, where areas with a greater slope would likely have better drainage and therefore a drier surface. This expectation was also observed in the spatial patterns of mean soil moisture with a correlation of -0.319.

With respect to radiation, we expected a negative relationship, where areas that receive more solar radiation are drier due to higher evaporation rates. This relationship was not observed in our spatial maps with a correlation of -0.097. Endrizzi et al. (2011) found surface soil moisture spatial variability in Siksik Creek to be more connected to subsurface flow patterns linked to water table height and topography rather than radiative controls, including slope and aspect. Additionally, Carey and Woo (2001) found that in a sub-arctic mountain site, north-facing slopes (areas with lower radiation) had greater surface moisture (also observed here) due to shallow thaw depths.

Canopy height was expected to have a positive relationship with soil moisture, where areas with larger vegetation have higher soil moisture, as areas near streams, where we would expect soil moisture to be greater, often have greater canopy heights (Marsh et al., 2010). This positive relationship was observed here with a spatial correlation of 0.194. However, backscatter is attenuated by tall vegetation, so areas with larger canopy height likely influence the backscatter more than soil moisture, as the distance the radar wave must travel through the canopy increases with canopy height, increasing the amount of attenuation (Toyra et al., 2001). Considering this, the satellite may be detecting vegetation in the form of trees or tall shrubs and not soil moisture, in areas where this type of vegetation is present. In this case, we see that
increased canopy height corresponded to increased $\sigma_{HV/HH}^o$ backscatter, which corresponds well with other studies that have found that $\sigma_{HV}^o$ corresponds well with canopy height in boreal peatlands (e.g. Merchant, 2014; Pulliainen et al., 1994). Snow persistence was expected to positively correlate to soil moisture, where areas that had snow for a longer amount of time theoretically receive less sunlight or had a deeper snowpack, which would cause higher soil moisture contents following the melt season. This relationship was observed with an $r$ of 0.311.

GWR was used to further our understanding of which variables best predict soil moisture across the landscape, the results of which can be seen in Table 3.5. All conditional numbers were less than 30 indicating that the results are reliable. Wetness index and snow persistence had the lowest AIC values, indicating that these variables are the best predictors of soil moisture with $r^2$ of 0.407 and 0.428, respectively. Solar radiation and canopy height had the highest AIC values, indicating that they are less valuable predictor variables. When all variables were used to predict soil moisture, the model was not as strong with an $r^2$ of 0.294 and AIC of 4692, indicating that one or more of the predictor variables should not be used. These GWR results agree with the Pearson’s $r$ results where wetness index, snow persistence, and slope have stronger relationships, and canopy height and solar radiation have weaker relationships with soil moisture.

**Table 3.5:** Adjusted $r^2$ and akaike information criterion values from GWR between predictor variables and modeled soil moisture.

<table>
<thead>
<tr>
<th>Geographically Weighted Regression</th>
<th>Wetness Index</th>
<th>Slope</th>
<th>Solar Radiation</th>
<th>Canopy Height</th>
<th>Snow Persistence</th>
<th>All Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>0.407</td>
<td>0.411</td>
<td>0.292</td>
<td>0.401</td>
<td>0.428</td>
<td>0.294</td>
</tr>
<tr>
<td>AIC</td>
<td>4607</td>
<td>4616</td>
<td>4629</td>
<td>4617</td>
<td>4604</td>
<td>4692</td>
</tr>
</tbody>
</table>
While some relationships are weak, they do offer some insight into which landscape variables have dominant effects on soil moisture. Topography (e.g. wetness index) and snow persistence had more of an effect than canopy height; however none of the relationships are very strong, suggesting that the soil moisture model can likely be improved with the development of a radar backscatter model which considers surface characteristics and soil moisture statistical characteristics.

Wall et al. (2010) found backscatter from RADARSAT-1 to be much more sensitive to soil moisture on dry days in the high arctic. Ulaby et al. (1986) suggest that when the volumetric moisture content reaches above ~35%, the RADAR signal becomes insensitive to soil moisture. This is due to specular reflection of the RADAR microwaves. In this study, most of the field means were below 35%, however it is likely that this was not the case over the larger area used to assess the correlation between the modeled soil moisture and landscape indices. There are likely areas that are very saturated, where the satellite signal may not be sensitive to soil moisture, for example Kasischke et al. (2009) found backscatter from ERS to be strongly negatively correlated to water table height when the water table was above 6 cm. There are also patches of tall vegetation that attenuate the backscatter, making it insensitive to soil moisture in those areas.

3.4. Conclusion

This research demonstrated that the SAR signal from RADARSAT-2 is correlated to surface soil moisture in organic soils of the arctic tundra. This shows the potential to monitor surface soil moisture with SAR over the arctic tundra. Furthermore, the signal showed moderate to strong relationships with both 5 cm ($R^2=0.688$) and 20 cm ($R^2=0.623$) soil moisture, and that
the RADAR wave may penetrate deeper in this porous, organic soil. We created a simple empirical regression model from the observed sensitivity which statistically significantly correlated to various landscape controls over the watershed, especially topography (and particularly when this is expressed as wetness index). The cross-polarization ratio was found to be the best linear backscatter variable to model soil moisture over this environment. It is anticipated that the results here will be useful not only for RADARSAT-2 retrievals, but also for retrievals from the recently launched Soil Moisture Active Passive (SMAP) mission and also the planned RADARSAT constellation mission (2018), both of which will increase monitoring frequency over Canada’s north. Once there is a robust way of gathering large scale soil moisture information at high spatial and temporal resolutions, these measurements will be very useful to enhance hydrological modeling of the north, particularly for permafrost degradation, biogeochemical cycling, surface-atmosphere interactions, and vegetation shifts.
Chapter 4: Summary and Conclusions

This thesis addressed two main research objectives which are necessary to develop models that retrieve surface soil moisture information from SAR satellites in organic soils of the arctic tundra. First, an investigation of the statistical characteristics of soil moisture and the controls on soil moisture in this environment was completed. It was found that field-scale soil moisture is quite variable and sometimes spatially independent. Spatial patterns of soil moisture were controlled by several processes including frost table depth, microtopography, shrub presence, and topography. Dominant controls varied between different plots, further highlighting the high degree of spatial variability of soil moisture in this environment. These results will provide SAR soil moisture retrieval models with information to enhance prediction of surface soil moisture given SAR backscatter values in organic soils underlain by permafrost in the arctic tundra.

Furthermore, the feasibility of utilizing SAR to retrieve soil moisture information in this environment was investigated by assessing the sensitivity of SAR to soil moisture measured in-situ. Linear regression analysis demonstrated strong correlations between RADARSAT-2 backscatter ($\sigma^0_{HV/HH}$) and 5 cm soil moisture ($R^2 = 0.688$), as well as showing sensitivity to 20 cm soil moisture. It is possible that the SAR signal can penetrate deeper into the porous organic soil to respond to deeper moisture contents. Additionally, given that the two depths of measurements are strongly correlated, surface soil moisture measurement from satellites, which are normally sensitive to the top ~5 cm, could be used to infer deeper soil moisture contents which are commonly of interest. The observed sensitivity was then extrapolated to create an empirical model to model soil moisture across the landscape and an investigation of the dominant landscape controls on soil moisture patterns observed from RADARSAT-2 was completed.
Topographic variables (wetness index, slope) as well as canopy height and snow persistence all somewhat correlated to modeled soil moisture patterns, with topography demonstrating the strongest control. Methodologies of Chapter 2 were conducted at too-fine a scale to directly detect correlation between topography and soil moisture in many instances; however Chapter 3 showed that topography (mainly wetness index) did impart some control on modeled soil moisture patterns, which supports the theory in Chapter 2 that soil moisture variability was controlled by topography at a larger scale.

It is anticipated that these results will facilitate retrieval of active layer soil moisture measurements in organic permafrost soils of the arctic tundra over large areas from remote satellites. This is important for providing northern research with large scale soil moisture measurements for implementation into hydrologic, climatic, and biogeochemical models to improve prediction of several environmental processes in the arctic. These measurements will be valuable for understanding and modeling environmental processes, including permafrost thaw patterns and vegetation shifts, and will support monitoring and conservation efforts of Canada’s North, which is of utmost importance given the strong influence of climate change in the Arctic.

4.1. Future research opportunities

From these results, it is suggested that future research conducting ground validation measurements for SAR soil moisture retrieval should sample at sampling intervals greater than 7 m but less than 70 m to cover a larger area and to capture the spatial variability imparted from topography, which better parallels the resolution of the satellite. Temporal variability of soil moisture in the environment should also be explored in more detail. SAR soil moisture retrieval models can now be adjusted, or new ones created, with the statistical characteristics presented
here, to further improve accuracy of soil moisture retrieval in the arctic tundra. The effects of surface roughness, vegetation, and soil density on the SAR signal also need to be investigated more thoroughly to improve accuracy.

Future research could benefit from exploring the utility of remote sensing platforms that use longer wavelengths, such as L-band (e.g. SMAP), to model soil moisture over this environment. Multiple remote sensing platforms could also be used to classify the landscape into different land covers in predict where soil moisture can be modeled with RADARSAT-2, and where other platforms can be more useful (e.g. L-band in vegetated areas, since the L-band wavelength provides better canopy penetration). Examination of the sensitivity of RADARSAT-2 to canopy height can also be further explored by testing multiple polarimetric variables and satellite configurations. This could provide detailed maps of vegetation across the northern boreal treeline that could help monitor vegetation changes in Canada’s north.
References


