Evaluating the affect of seasonal soil moisture and vegetation change on C-band SAR backscatter over corn fields in SW Ontario

by

Joshua MacDougall

A Thesis presented to The University of Guelph

In partial fulfilment of requirements for the degree of Master of Science in Geography

Guelph, Ontario, Canada

© Joshua MacDougall, July, 2017
ABSTRACT

EVALUATING THE AFFECT OF SEASONAL SOIL MOISTURE AND VEGETATION CHANGE ON C-BAND SAR BACKSCATTER OVER CORN FIELDS IN SW ONTARIO

Joshua MacDougall
Advisor:
University of Guelph, 2017
Professor A. A. Berg

Soil moisture estimates using C-band SAR over agricultural fields have a backscatter signal that saturates early in the growing season, especially at high incidence angles. This research derives these saturation points using a statistical approach on corn fields just south of Elora, Ontario using RADARSAT-2 overpassess with incidence angles ≥45°. Vegetation water content (VWC) and backscatter are segmented before and after saturation, as well as overall to assess their relationship. These saturation points are used to segment in-situ soil moisture and backscatter. The saturation points of VWC are 0.14, 0.17, and 1.69 kg m\(^{-2}\) for HH, HV, and VV polarizations respectively. The results indicate that VWC dominates the backscatter until saturation but that soil moisture is always a contributing factor to the backscatter signal. VV exhibited the latest saturation point and the correlations it exhibited with VWC and soil moisture were unexpected and require further investigation.
ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Aaron Berg for his continued assistance and support throughout this process over the last two years. You provided me with an opportunity to pursue a topic of interest and developed my critical thinking skills. This opportunity also provided me a chance to relocate close to my family again, and I am grateful for that.

Thank you to everyone who assisted me with my field data collection as without you this research would not have been possible. This list includes Tracy Rowlandson, Travis Burns, Melanie Chabot, Elené Üeckermann, and Jenelle White.

Lastly, I would like to thank my family and friends for encouraging me to pursue this opportunity and providing me with continued support throughout the process.
# TABLE OF CONTENTS

List of Tables ........................................................................................................ vi

List of Figures ........................................................................................................ vii

Chapter 1.0 ............................................................................................................. 1

  1.1 Introduction .................................................................................................... 1

  1.2 Thesis Objectives ........................................................................................ 4

  1.3 Thesis Outline .............................................................................................. 4

Chapter 2.0 Literature Review ............................................................................... 5

  2.1 Introduction .................................................................................................... 5

      2.1.1 The Importance of Soil Moisture ......................................................... 5

      2.1.2 Climate Interactions ............................................................................ 5

      2.1.3 Flood and Drought .............................................................................. 7

      2.1.4 Agriculture and Ecology .................................................................. 8

  2.2 Microwave Remote Sensing of Soil Moisture ........................................... 9

      2.2.1 The SAR Backscatter Equation ......................................................... 11

  2.3 SAR Vegetation Models ............................................................................... 14

      2.3.1 WCM .............................................................................................. 15

      2.3.2 MIMICS Model ............................................................................... 16

      2.3.3 Decomposition Models .................................................................... 17

  2.4 Conclusions ................................................................................................. 19
Chapter 3.0 Vegetation Water Content derived saturation points of C-band SAR at large incidence angles over corn fields

3.1 Introduction................................................................. 21

3.2 Research Methods........................................................ 23

3.2.1 Study Area ................................................................ 23

3.2.2 Field Data................................................................. 24

3.2.3 RADARSAT-2 Backscatter Data................................. 27

3.2.4 Data Processing ......................................................... 27

3.3 Results........................................................................... 29

3.4 Discussion................................................................. 33

3.4.1 Field Measurements................................................ 33

3.4.2 Vegetation Backscatter Response............................... 36

3.4.3 Soil Moisture Relationships................................. 38

3.5 Conclusions.......................................................... 39

Chapter 4.0 Summary and Conclusions.................................. 41

References.......................................................................... 44
LIST OF TABLES

Table 3.1 Coordinates (degrees minutes seconds), soil type, drainage, and topography of the four cornfields within the ERS

Table 3.2 RADARSAT-2 overpass information over the study area

Table 3.3 The saturation points for all three linear polarizations to VWC and the dates of when this would have occurred in each year. The correlation coefficients for all three linear polarizations before and after saturation and overall relationships based on two years of data

Table 3.4 The Kendall’s Tau-b results between all three linear polarizations to soil moisture using the saturation points determined by the piecewise regressions and overall relationships

Table 3.5 Average monthly precipitation (mm) at the ERS as reported by Environment Canada across both growing seasons
LIST OF FIGURES

Figure 3.1 Map of the study area in relation to the town of Elora and the city of Guelph within Southern Ontario

Figure 3.2 Daily averaged VWC values for 2015 (black) and 2016 (grey) with the standard deviations indicated by the error bars

Figure 3.3 Daily averaged POGO soil moisture values for 2015 (black) and 2016 (grey) with the standard deviations indicated by the error bars

Figure 3.4 The piecewise regression between VWC and HV, VV and HH with the standard errors of each saturation point (0.03, 0.58 and 0.02) respectively.

Figure 3.5 The relationship between the network measured soil moisture (y-axis) and the spatially averaged soil moisture across each field (x-axis) for 2015 (a to d) and 2016 (e and f)
Chapter 1.0

1.1 Introduction

The variability of hydrological processes and the water content of vegetation is largely influenced by the amount of soil moisture present (Denmead & Shaw, 1962). Variables such as land use, topography, and soil pore space are some of the factors that cause soil moisture to exhibit spatio-temporal variability (Hébrard et al., 2006). There are various techniques that can be used to estimate soil moisture either in-situ or from remote sensing; however, for applications at the agricultural field scale C-band (wavelengths between 3.8 to 7.5 cm) Synthetic Aperture Radar (SAR) has been used as it provides high spatial resolution data products (Gherboudj et al., 2011; McNairn et al., 2012).

SAR systems such as RADARSAT-2 and Sentinel-1 transmit energy in the microwave C-Band towards a surface and based on surface properties a certain amount of energy is returned to the sensor, this is referred to as the radar backscatter (typically measured in dB) (Tsang, Kong & Shin, 1985). SAR systems such as RADARSAT-2 can collect fully polarimetric data because energy emitted from and received by the satellite is polarized. These linear polarizations are grouped as co-polarizations (HH and VV) and cross-polarizations (HV and VH), where H stands for horizontal polarization and V stands for vertical polarization, and the initial letter is the wave direction on transmission and the proceeding letter is that on reception (Raney, 1998).

Several properties affect the return or backscatter of energy to the satellite. These properties include: soil characteristics (surface roughness, the correlation length of roughness features and dielectric of the soil); the features of the radar (incidence angle, polarization and wavelength); and the vegetation properties (dielectric of the vegetation, shape, structure and angle) (Inoue et al., 2002; Raney, 1998; Mo, Schmugge, & Jackson, 1984). The surface dielectric, roughness, and
correlation length of roughness elements are dominant factors over bare fields (Ulaby, Dubois & Van Zyl, 1996). During the growing season vegetation dominates much of the backscatter response, overshadowing roughness elements and dielectric of the surface.

There is a long history of soil moisture retrieval over bare fields (Ulaby, Batlivala & Dobson, 1978; Wang & Choudhury, 1981; Altese et al., 1996). Separation of the dielectric properties of the surface (which relate to soil moisture) from roughness effects has been the focus of extensive research (Baghdadi et al., 2002; Baghdadi et al., 2008; Sahebi et al., 2010; Adams et al., 2013). This separation is achieved using inverse modelling of the backscatter response and is based on the dielectric of the surface and elements of the roughness such as the root-mean-square (RMS) height, using semi-empirical models, such as the Oh (Oh, Sarabandi, & Ulaby, 1992) and Dubois (Dubois et al., 1995) models or physically based models such as the Integral Equation Model (IEM) (Fung, Li, & Chen, 1992). The addition of vegetation during the growing season adds another factor to account for. The vegetation impacts the backscatter through volume scattering (controlled by the water content of the crop), direct backscatter from the plants, depolarization due to the crop orientation, and plant-soil double scattering (pulse interacts with the vegetation then the soil or vice versa) (Ulaby et al., 1996; Ulaby et al., 1982).

Discerning between soil and vegetation when assessing the backscatter is still a difficult task when C-band SAR is used on vegetated areas. Models have been developed to assess the contribution derived from the vegetation which include energy and wave approaches (Bracaglia, Ferrazzoli, & Guerriero, 1995; Stiles & Sarabandi, 2000); backscattering inversion models, such as the Water Cloud Model (WCM) (Attema and Ulaby, 1978; Prévot, Champion, & Guyot, 1993); and polarimetric decompositions (Cloude & Pottier, 1996; Freeman & Durden, 1998). These models depend on physical information on the crops themselves (estimated or field
measurements) and the most common metrics are Leaf Area Index (LAI) and Vegetation Water Content (VWC) (Liu et al., 2010; Inoue, Sakaiya, & Wang, 2014). Although LAI is commonly used as a vegetation metric it has proven to be unreliable on row crops at a large viewing angles, therefore, VWC is more applicable (Andrieu & Sinoquet, 1993).

Previous research assessing the association between C-band SAR and vegetation biomass data which showed significant relationships in the linear co-polarizations (Ferrazzoli et al., 1992; Pampaloni et al., 1997) as well as the cross-polarizations (Ferrazzoli et al., 1997; Inoue et al., 2014). It has also been demonstrated that for broad-leaf crops, such as corn, the backscatter signal saturates (is dominated completely by vegetation without influence from the soil surface) early in the growing season, however when saturation occurs was not determined (Ferrazzoli et al., 1997; Pampaloni et al., 1997).

The purpose of this research is to determine if saturation points could be derived by assessing the relationship between VWC and backscatter from RADARSAT-2 at high incidence angles over agricultural fields just south of Elora, Ontario. The saturation point is defined here as the specific time during the growing season when increases in VWC have minimal impacts on the backscatter signal for the remainder of the season. The implications of these saturation points were then assessed for the relationships between VWC and soil moisture to backscatter response.
1.2 Thesis Objectives

To evaluate the backscatter response to soil moisture and vegetation properties this thesis is organized around the following research objectives:

1. Measure VWC and in-situ soil moisture over two growing seasons (2015 & 2016), and coordinate these measurements with the timing of RADARSAT-2 overpasses.
2. Assess the VWC to RADARSAT-2 backscatter relationships using piecewise regression to determine saturation points.
3. Assess the relationships between VWC and soil moisture to backscatter prior to saturation, post saturation and overall to determine the impact of the saturation points.

1.3 Thesis Outline

Chapter 2.0 is a review of the pertinent literature of how SAR backscatter is impacted by different factors over vegetated surfaces, where it is comprised of contributions from the vegetation and soil moisture. The chapter also provides an overview of each of these factors and the most common tools used to evaluate the vegetation. Chapter 3.0 is a manuscript which includes a summary of the problem, methods and results. Chapter 4.0 presents a summary of the research as well as concluding remarks followed by potential considerations for future research.
Chapter 2.0 Literature Review

2.1 Introduction

This chapter covers pertinent literature that will highlight the importance of soil moisture, some of the remote sensing methods used to estimate soil moisture and then finally goes into specific details and applications of (SAR). The review begins with the general importance of soil moisture before covering its applications in climate interactions, flood and drought predictions, agriculture and in an ecological context. It then covers microwave remote sensing of soil moisture with a brief overview of passive microwave and a more detailed description of active microwave. Lastly, it goes into the specifics of one method of active microwave remote sensing (SAR), that will cover the SAR backscatter equation, SAR vegetation models and conclude by highlighting the research gap and why the research gap in the proceeding chapter was required.

2.1.1 The Importance of Soil Moisture

Soil moisture can be defined as the amount of water within the unsaturated soil surface due to snowmelt, rainfall or capillary attraction from ground water. Soil moisture only represents \(~0.05\%\) of the global hydrological cycle (Dingman, 2002). However, it is a key component of the hydrological cycle, impacting other systems such as the climate and biotic processes (Petropoulos, 2013). Soil moisture also exhibits large spatio-temporal variation as it is influenced by many factors such as topographical attributes, land use, and soil characteristics (Hébrard et al., 2006).

2.1.2 Climate Interactions

Soil moisture is linked to feedbacks with the atmosphere through evapotranspiration; the hydrological framework for this relationship comes from the original publications by Budyko
(Budyko, 1956 & 1974; Seneviratne et al., 2010). There are three climate/soil moisture regimes, which define the relationship between soil moisture and evapotranspiration: wet, dry, and a transitional state. It is in the transitional state in which soil moisture is the main controlling factor in evapotranspiration variability (Koster et al., 2004).

Another climatic factor that can be linked to soil moisture is precipitation (Boé, 2013). In previous studies, there has been a strong correlation between precipitation and soil moisture, especially during the summer months (Ruscica, Sörensson, & Menéndez, 2014). Specifically, when the lowest values of soil moisture (summer months) were compared to the wettest soil moisture values, a 25% increase in precipitation was seen (Georgescu, 2003). This link between soil moisture and precipitation is also used to improve large-scale circulation predictions, which influence precipitation forecasts. When satellite derived soil moisture estimates were incorporated into general circulation models the error of precipitation prediction values decreased (Hirabayashi et al., 2003).

Air temperature has also been shown to have strong relationships with soil moisture. It has been shown that decreased soil moisture causes decreased latent heating and increased sensible heating resulting in high daily maximum surface temperatures (Shinoda & Yamaguchi, 2003; Seneviratne et al., 2010). Similar to precipitation values, it has been shown that accurate soil moisture values can improve seasonal temperature forecasts in some regions (Zhang & Dong, 2010; Koster et al. 2010). Lastly, including soil moisture values in climatology models increased the predictability accuracy on a daily basis and during times of extreme events such as floods and droughts (Orth & Seneviratne, 2014). Increased accuracy of seasonal temperature forecasts and climatology models demonstrates the importance of accurate soil moisture
estimates due to its strong linkages with multiple climatic factors such as evapotranspiration, precipitation, and air temperature.

2.1.3 Flood and Drought

The link between soil moisture and floods is established through the rainfall to runoff relationship, where initial soil moisture conditions can influence rainfall infiltration (Bronstert et al., 2011; Merz & Plate, 1997). The rainfall to runoff relationship is commonly assessed through flood forecasting models, which aid in monitoring for flood risk mitigation (Dorigo et al., 2011). Flood modeling requires data on the wetness state of a catchment and a continuous rainfall data set (Massari et al., 2014a). Global soil moisture datasets have been able to accurately predict and have thus proven useful in areas where ground data is limited (Massari et al., 2014a; Massari et al., 2014b).

Soil moisture data is not only useful in determining the occurrence of floods but also droughts across a range of time scales (Wu & Kinter, 2009). Precipitation measurements are the foundation of all drought indices, and temperature is also an important secondary input (Heim, 2002). There are three types of drought: meteorological, hydrological, and agricultural (Hayes, Svoboda, Wall, & Widhalm, 2011). Soil moisture is often linked to agricultural droughts with indices such as the Moisture Adequacy Index (McGuire and Palmer, 1957). Recently a new drought index (Soil Moisture Drought Index) using soil moisture was developed based on the premise of how much water is needed to reach the field capacity of soil moisture (Sohrabi et al., 2015). This index showed an ability to outperform traditionally used indices (Standardized Precipitation Index and Standardized Precipitation Evapotranspiration Index) in accurately characterizing the three types of drought (meteorological, hydrological, and agricultural) (Sohrabi et al., 2015). Studies of soil moisture have demonstrated strong relationships with
natural hazards and climatic factors and increased the accuracy of estimating when used as an input for modelling (Wu & Kinter, 2009; Orth & Seneviratne, 2014).

2.1.4 Agriculture and Ecology

The association between vegetation cover and the underlying surface soil moisture can be traced back to the 1950’s. Lull & Reinhart (1955) demonstrated the inverse relationship between soil moisture and vegetation cover, while also establishing the regional variability of surface soil moisture. Denmead & Shaw (1962) further contributed to this field by establishing the direct relationship between transpiration from crops and soil moisture content. The link between soil moisture estimates and agricultural drought has provided information on agricultural productivity in previous studies (Parida et al., 2008; Tang & Piechota, 2009). More recent research has used satellite imagery to monitor soil moisture in an attempt to implement mitigation strategies to deal with the hazards associated with droughts and floods (McNairn et al., 2012).

Soil moisture plays a large role in the ecosystem structure, diversity, and functionality which is especially evident in dryland ecosystems (Rodriguez-Iturbe & Porporato, 2005). It has been demonstrated that in these ecosystems pulses of soil moisture are a main control on the ecological responses (Schwinning and Sala, 2004). The amount of soil moisture also has ecological implications within microenvironments. Previous research has demonstrated that soil moisture impacts microbial activity and growth by limiting soil respiration (Orchard & Cook, 1983; Skopp, Jawson, & Doran, 1990). Through soil moistures linkage with soil respiration, it can also be tied to global nutrient cycles such as the carbon cycle (Schlesinger & Andrews, 2000).
In summary, soil moisture is a small but very important component of Earth’s climate, hydrology, and biotic cycles. It is associated with climatic variables such as precipitation and temperature. These variables are then tied into the hydrological cycle and are associated with natural hazards such as floods and droughts, which in turn affect agricultural lands and microenvironments perpetuating influences on nutrient cycles. Therefore, providing accurate estimates of soil moisture at a range of spatial scales is of great importance.

2.2 Microwave Remote Sensing of Soil Moisture

Ground and remote-sensing techniques are both used to extract soil moisture values to create comprehensive soil moisture datasets (Bronstert et al., 2011). Point estimates determined through ground-based methods are accurate. However, they are only representative of the area of measurement and this, are affected by the high spatial variability of soil moisture (Vinnikov et al., 1996). Spatial variability of soil moisture is caused by a combination of factors, such as land use, precipitation, geology, topography, and vegetation with the impacts varying depending on the scale of the study area (Western, Bloschl, & Grayson, 1998). The varying characteristics of the soil can affect the variability in soil moisture due to differences in organic matter, porosity, and texture (Crow et al., 2012). The impacts of soil texture on the variability in soil moisture has been demonstrated on a regional scale (using satellite imagery), indicating that soils with higher sand content are consistently drier (Panciera, 2009).

Remote sensing of near surface soil moisture has advantages over ground-based estimates, including its non-destructive sampling, the lower labour and time costs, and the fact that remote-sensing based methods can capture soil moisture spatial variability over larger areas (Petropoulos, 2013). Soil moisture information has been captured using both optical and microwave sensors (Dubois, VanZyl, & Engman, 1995; Shih & Jordan, 1993). The advantages of
microwave remote sensing over optical methods include its minimal sensitivity to atmospheric scattering (i.e. scattering due to clouds, aerosols and haze) and ability to penetrate surfaces to a degree, largely dependent on wavelength (Engman, 1990; Moran et al., 2004).

Microwave remote sensing is performed using passive and active sensors. Passive microwave remote sensing uses a radiometer that measures the intensity of microwave emission from the soil surface, otherwise known as the brightness temperature (Newton et al., 1982). Changes in brightness temperature are strongly related to the dielectric properties of the soil surface, which is strongly related to the soil moisture (Wraith et al., 2005; Thomas, 1966). Two dedicated soil moisture satellite missions utilize the retrieval of microwave brightness temperatures in the L-band (wavelengths between 15 to 30 cm). These missions are the Soil Moisture and Ocean Salinity (SMOS) and the Soil Moisture Active Passive (SMAP), which are being used to develop global estimates of soil moisture at a spatial resolution of approximately 40 km with a temporal resolution of about 3 days (Kerr et al., 2012; Entekhabi et al., 2010b). Both the SMOS and SMAP missions have demonstrated soil moisture retrieval accuracies of 0.04 m$^3$/m$^3$ (Al Bitar et al., 2011; Chan et al. 2016). Although very useful in applications such as drought monitoring and weather modelling, passive microwave estimates of soil moisture are too coarse in their spatial resolution for many agricultural applications (Kerr et al., 2012).

Active microwave sensors transmit an energy pulse towards the Earth’s surface; the energy pulse interacts with the ground surface and is then returned to the satellite (Tsang, Kong & Shin, 1985). Active microwave remote sensing of soil moisture can be further broken down into two categories: non-imaging radars (altimeters and scatterometers) and imaging radars (Synthetic Aperture Radar (SAR)). Altimeters have limited applications in soil moisture estimation, further details can be found in a study by Fatras et al. (2012). Scatterometers have
had some success in soil moisture estimation however like passive methods they often provide data at a coarse spatial resolution (Bartalis et al., 2007; Brocca et al., 2011). Imaging sensors such as SAR have a significant advantage (particularly in agricultural contexts) as they can provide data at a high spatial resolution; Radarsat-2, for example, can achieve a spatial resolution of 8 m and a ground swath width between 18 to 25 km (Gherboudj et al., 2011; MacDonald Dettwiler and Associates Ltd., 1999). Further discussion will focus specifically on SAR soil moisture retrieval.

2.2.1 The SAR Backscatter Equation

SAR acquires images through measuring the radar reflectivity, otherwise known as the backscatter after interaction with a surface or object (Ulaby et al., 1986). The amount of backscatter returned to the sensor is dependent on multiple factors. These factors include the parameters from the satellite (e.g. polarization, local incidence angle and wavelength); the attributes from the soil (e.g. the correlation length of the roughness features plus the roughness features themselves and the soils dielectric); and the vegetation properties (shape, angle, structure, and dielectric of the vegetation) (Inoue et al., 2002; Raney, 1998; Mo, Schmugge, & Jackson, 1984). Since the satellite characteristics are dependent on data acquisition requirements, this section will focus on soil surface roughness parameters and vegetation cover/characteristics.

Over bare fields, the roughness of the surface is a main contributing factor controlling the amount of backscatter when a radar pulse interacts with the bare ground and returns to the satellite (Ulaby, Dubois, & Van Zyl, 1996). Therefore, the effect of surface roughness must be accurately characterized. In models, the roughness of the surface is characterized by the RMS height and the correlation length. The RMS height measures the vertical pattern of surface heights extending beyond an arbitrary plane. The correlation length is the largest distance in
which significant correlations occur when assessing the homogeneity of the heights across the surface (Gupta & Jangid, 2011; Ulaby et al., 1982).

As a radar wave encounters a surface some energy is scattered back towards the sensor, but most is scattered away from the satellites field of view. As the roughness of the surface increases so too does the surface scattering which increases reflection back to the sensor (Ulaby et al., 1982). Due to the importance of soil moisture to crops, minimal errors in the estimates on agricultural fields are required. However, furrows amplify these errors. The relationship between the angle of incidence and furrow direction, can cause up to a 19 dB decrease in backscatter when the angle of incidence is 5° off from perpendicular to the furrows angle (Dubois, Rignot, & Van Zyl, 1992).

One of the first studies to look at the impacts of surface roughness on the radar backscatter coefficient was performed by Ulaby et al. (1982). This initial research helped to form the theoretical basis for the three main models used to characterize surface roughness and ultimately surface moisture estimates. These three models are the Oh, Dubois, and Integral Equation Model (IEM). Further details of these models are covered in subsequent sections, however, the Oh and Dubois models parameterize roughness using solely the RMS height and the IEM uses the RMS height, surface correlation length, and autocorrelation function (Dubois et al., 1995; Fung, Li, & Chen, 1992; Oh, Sarabandi, & Ulaby, 1992).

When a field has vegetation cover, this must also be accounted for (in addition to the roughness) in order to accurately characterize the backscatter and estimate the soil moisture (Engman & Chauhan, 1995; Ferrazzoli et al., 1997). Accounting for the vegetation is achieved through the vegetation scattering equation outlined in Equation 1:
\[
\sigma^o_v(\theta) = \frac{\eta \cos \theta}{2\tau} \left(1 - e^{-2\tau/\cos \theta}\right)
\]

where \( \eta \) is a volume scattering factor that depends on the vegetation water content (VWC) per unit area and, \( \tau \) is the optical thickness of the vegetation layer, and \( \theta \) is the angle of incidence (Attema & Ulaby, 1978; Tsang et al., 1982). Equation 2 is the total backscattering coefficient when vegetation and soil are both accounted for:

2)

\[
\sigma^o(\theta) = \sigma^o_v(\theta) + \sigma^o_s(\theta)e^{-2\tau/\cos \theta}
\]

where \( \sigma^o_v(\theta) \) is the vegetation backscattering component, \( \sigma^o_s(\theta) \) is the soil backscattering, \( \tau \) is the optical thickness of the vegetation layer, and \( \theta \) is the angle of incidence (Attema & Ulaby, 1978; Tsang et al., 1982).

The commonly used soil moisture inversion models (Oh, Dubois, and IEM) are only valid over bare soils or sparsely vegetated soils, but most surfaces are covered to some extent by vegetation (Ulaby et al., 1982). The vegetation characteristics that contribute to the canopy (crop height, number of plants per unit area, stem density, and Leaf Area Index) and its dielectric properties (are strongly determined by the VWC) are not accounted for within these models. However, they still influence the backscatter observed (Ulaby et al., 1996; Inoue, Sakaiya, & Wang, 2014).

Overlying vegetation impacts the backscatter due to its orientation (depolarization), its geometrical relationship to the soil (double-bounce scattering), its structure (direct backscatter from the plant), and the water content of the canopy (volume scattering and influencing the radar
penetration depth) (Ulaby et al., 1996; Ulaby et al., 1982). The error from volume scattering has been shown to be larger in the cross-polarizations compared with the co-polarizations, making the co-polarizations generally more suitable for soil moisture estimation on vegetated fields. However, even the co-polarization signal shows increased backscatter resulting in an underestimated soil moisture or overestimated surface roughness when vegetation is present (Dubois et al., 1995).

The incidence angle is also a large factor when considering the impacts of vegetation. If low incidence angles are used, it has a smaller path length through the vegetation canopy and is able to better penetrate down to the soil underneath. Therefore, the backscatter signal may contain information about the soil surface, whereas vegetation cover dominates the scattering at incidence angles >30° (Mo et al., 1984; Srivastava et al., 2009).

2.3 SAR Vegetation Models

Vegetation must be accounted for (in addition to the soil characteristics) when assessing the backscatter variation over vegetated areas. The classification of the vegetation component is broken down into two categories: models used to estimate vegetation characteristics (VWC and LAI) and decomposition models, which segment the power received by the sensor into backscatter sources (surface, volume/within canopy, or double bounce backscatter) (Steele-Dunne et al., 2017). There are a breadth of models used to estimate vegetation characteristics, but two that are commonly used are the Water Cloud Model (WCM) and the Michigan Microwave Canopy Scattering Model (MIMICS) (Attema and Ulaby, 1978; Ulaby et al. 1990). In addition to the review of the WCM and MIMICS models, two commonly used decomposition models (Freeman-Durden and Cloude-Pottier) will also be reviewed (Cloude & Pottier, 1997; Freeman & Durden, 1998).
2.3.1 WCM

Attema and Ulaby (1978) developed the Water Cloud Model (WCM), which is a semi-empirical radiative transfer backscatter model. The WCM is used to model the vegetation contribution of the backscatter or it can be inversed to derive vegetation characteristics from SAR data (Van Leeuwen, Clevers, & Rijckenberg, 1994). In addition to the canopy contributions, it also accounts for the underlying soil moisture and attenuation through the canopy but ignores multiple scattering (Attema and Ulaby, 1978). To estimate the backscatter contribution from the vegetation, the model requires the inputs of incidence angle, vegetation parameters (VWC and/or LAI) as well as two model parameters that depend on canopy type and experimental data (Prévot, Champion, & Guyot, 1993).

The original model characterizes vegetation canopies as a homogenous medium with isolated scattering objects. These scattering objects are uniformly distributed with VWC being used as the canopy descriptor (Attema and Ulaby, 1978). However, due to the model’s semi-empirical nature the model has been altered numerous times based on studies with varying parameters. The first major improvement was the modification of the model to include LAI as a model parameter (Ulaby et al. 1984). The next was adapting the model to account for crop specific information such as leaf size (Paris, 1986). Lastly, the model was altered to be a multi-layer model with the canopy structure as non-homogenous and accounting for different structures within the canopy (leaves, stems, branches etc.) (Bernard et al., 1987).

The greatest strength of the WCM model is that it is semi-empirical and can be parametrized based on different crops and locations with experimental data. However, this semi-empirical foundation also leads to some of the disadvantages of the model because if the experimental data set is not robust it could provide inaccurate results. This model variation based
on data also demonstrates that there is no general theoretical background to determine the required model parameters (Attema and Ulaby, 1978; Prévot, Champion, and Guyot 1993). Another issue is there are no set units for the different versions of the WCM, which leads to ambiguity of model fit due to some studies reporting in natural units and others in logarithmic units (Paris, 1986; Van Leeuwen et al., 1994). The WCM has also shown variances with different polarizations, with VV performing best for monitoring early crop growth, whereas, HH is more accurate in later stages (Le Toan et al., 1989).

### 2.3.2 MIMICS Model

The Michigan Microwave Canopy Scattering (MIMICS) model was developed by Ulaby et al. (1990). It is a radar scattering model, based on radiative transfer theory and was originally developed for forest canopies; where the forest canopy is divided into three regions: the underlying soil, the trunks, and the crown (Ulaby et al. 1990). Within each region, there are both geometric and dielectric parameters that must be accounted for. The geometric parameters for each region consist mainly of the height and diameters of all sections within each region (leaves, branches, trunk, etc.). These same sections also have a dielectric parameter that must be factored in (Ulaby et al., 1990). Unlike the WCM, MIMICS does not ignore multiple scattering and accounts for scattering directly from each region and between all three regions (Monsivais-Huertero et al., 2010). MIMICS more accurately assesses scattering and reflectivity for each region through incorporating energy extinction, emission, and an average height field for each region (Ulaby et al., 1990).

Even though the MIMICS model was originally intended for forestry, it has been modified and applied to agriculture and various crops. The first application was performed on wheat and canola using both L and C bands. Agricultural applications were achieved by
modifying the trunk region (residual from the models original applications in forestry) portions of the equations to fit the geometry of the crops more accurately and inputting LAI into the crown parameters (Toure et al., 1994). He et al. (2015) recently published research using a similar variation of the model on wheat but expanded the analysis to two additional microwave bands (S and X) (He et al., 2015). The modified trunk region technique also has been applied to model a corn canopy (Monsivais-Huerter and Judge, 2011). The model has also expanded to assess the canopy of other crops such as soybeans (De Roo et al., 2001), rice (Kumar, Kumari, & Saha, 2013), and grasses (Monsivais-Huerter et al. 2010), by entirely removing the trunk region portions of the equations.

Like the WCM, the MIMICS model is applicable to a broad range of crops by adapting the underlying equations. The effectiveness of the model is variable due to different crop types. Applications of the MIMICS model of corn at L-band, determined HH was the most sensitive to the corn canopy and during the reproductive stage the ears were the dominant contributor (Monsivais-Huerter and Judge, 2011). However, due to the amount of data required the MIMICS model has limited applications in the non-expert community. Moreover, although the MIMICS model accounts for the various regions of the crop, it is still a simplification of the real crop (Steele-Dunne et al., 2017).

2.3.3 Decomposition Models

Decomposition models take the backscatter from polarimetric radar data and segments them into scattering contributions. The backscatter is broken down into one of three sources: volume scattering (multiple scattering occurring within the canopy), surface scattering (directly from the vegetation or ground), and double-bounce scattering (scattering that interacts with two or more components, e.g. stem and ground) (Cloude & Pottier, 1997).
The Freeman-Durden model assesses the backscatter contributions in three parts, and each represents a percentage of the backscatter. The breakdown of the contributions into percentages allows for easy interpretation in determining which is the dominant and secondary scattering mechanisms over a given study site (Freeman & Durden, 1998). This model has been assessed for field detection between unharvested and post-harvest agricultural fields at C-band. The model was more accurate at higher incidence angles and that surface scattering was the most sensitive to variations in the soil surface (Adams et al., 2013a). The model has also been assessed with relation to LAI over vegetated fields of corn at C-band. The volume scattering parameter was the dominant contributor and had significant correlations to LAI at low incidence angles (Jiao et al., 2011). Additionally, the model has been assessed at L-band in which the contributions shifted from being dominated by surface scattering in May to volume scattering in August. It was also able to determine crop classifications more accurately than using any of the linear polarizations (McNairn et al., 2009).

The Cloude-Pottier decomposition is a Bernoulli statistical model, which breaks down the backscatter into eigenvalues (estimating the intensity of each mechanism), and eigenvectors (characterizes the three scattering mechanisms). Three parameters can then be derived from these outputs, which are entropy, anisotropy, and alpha-angle; they are used to form graphics of scatterers into nine zones (Cloude & Pottier, 1997). Entropy refers to the amount of randomness from backscatter with values closer to one indicative of multiple scattering and values closer to zero indicative of surface scatterers. Anisotropy represents the importance of secondary and tertiary scattering mechanisms. Alpha-angle indicates the dominant scattering source (Alberga, Satalino, & Staykova, 2008). Over bare agricultural fields the Cloude-Pottier model agrees with the Freeman-Durden model that surface scattering was the dominant contributor (Adams et al.,
2013b). Over vegetated fields, the Cloude-Pottier model did not demonstrate a significant relationship with LAI regardless of incidence angle (Jiao et al., 2011). However, it was able to demonstrate the most accurate crop classification when compared to the linear polarizations and the Freeman-Durden model (Jiao et al., 2014).

The SAR vegetation models previously discussed, aim to characterize the vegetation component of the SAR backscatter. However, they fail to address one of the limitations of SAR; backscatter saturation (Moran et al., 1998; Wigneron et al., 1999). Backscatter saturation occurs when vegetation reaches a certain size and beyond that point any further increase in vegetation has a minimal impact on the backscatter (Ferrazzoli et al., 1997; Imhoff, 1995). McNairn and Brisco (2005) conducted a review paper on agricultural applications of C-band SAR; they identify the need for future research to assess the effects of backscatter saturation to more accurately determine soil conditions later in the growing season. Imhoff, Carson, and Johnson (1998) highlight the need for the saturation phenomenon to be accurately assessed to determine accurate biomass inventories. Previous research of agriculture has estimated the saturation point (between C-band SAR and vegetation properties) but it has not been statistically determined (Ferrazzoli et al., 1992; Pampaloni et al., 1997; Jiao et al., 2011). Imhoff (1995) used regression analysis to determine the point when backscatter saturates due to increasing forest biomass; a similar methodology was applied in the research conducted in Chapter 3. Once the saturation point was determined, the significance of this saturation point was assessed on the backscatter and its relationships to VWC and soil moisture.

2.4 Conclusions

Soil moisture is largely important for many processes that occur within the hydrological cycle, climate interactions, biotic cycles, and plays an important role in agriculture. It can be
assessed through multiple techniques but for field level estimation SAR is the optimal technique. To accurately assess soil moisture, the radar backscatter equation must be accurately solved. Accurately solving the radar backscatter equation is an ongoing process that requires accurately assessing two main components: the soil characteristics and the vegetation characteristics. There are multiple models for characterizing the impact of the vegetation such as the WCM, MIMICS, and decomposition models. Previous research has assessed these models on various crop types and SAR configurations. However, there is limited research into when in the growing season C-band backscatter is most relatable to vegetation characteristics or soil moisture estimates. This variation in the backscatter signal over vegetated surfaces is due to the well-known saturation effect between crop characteristics (VWC) and backscatter, which is especially apparent in broad leaf crops. Previous research on agriculture has estimated the saturation point but it has not been statistically determined and the implications of the saturation point on the backscatter response has not been assessed. This would be a novel finding as it can guide when accurate soil moisture and vegetation estimates can be achieved based on current methods and where improvements need to be made.
Chapter 3.0 Vegetation Water Content derived saturation points of C-band SAR at large incidence angles over corn fields

3.1 Introduction

Soil moisture plays a vital role in influencing the spatial variability of hydrological processes and is essential in monitoring water uptake by crops. Accurate soil moisture data is crucial for continuous flood modeling and drought observations (Massari et al., 2014b; Mozny et al., 2012). Synthetic aperture radar (SAR) microwave remote sensing is an effective tool to assess these issues at the field level and capture the spatial variability of the soil moisture (McNairn et al., 2012). C-band SAR imaging of soil moisture depends on the energy returned from the soil surface, which is referred to as the radar backscatter. Backscatter is directly related to soil moisture (Engman & Chauhan, 1995).

The quantity of energy that is backscattered from a surface is dependent on the radar specifications, such as the incidence angle, wavelength, and polarization (Inoue et al., 2002). Physical properties of the surface also impact the amount of backscatter returned to the instrument. In particular, soil characteristics (Root Mean Square height, surface correlation length, and dielectric of the soil) and vegetation properties (dielectric of the vegetation, shape, structure, and angle) (Mo, Schmugge, & Jackson, 1984) have the greatest impact on the backscatter intensity. Over bare fields and at high incidence angles, surface scattering is sensitive to surface roughness (Adams et al., 2013a). Microwave polarization is also sensitive to the soil properties and surface roughness over bare fields. In particular, HH has been shown to be very sensitive to soil and surface roughness (Baghdadi et al., 2002a; Baghdadi et al., 2002b; Beaudoin, Toan, & Gwyn, 1990), but a few studies have also shown strong correlations with HV (McNairn et al., 2001; McNairn et al., 2002). Several semi-empirical (Oh and Dubois) and physical (IEM) retrieval models have been developed to take into account these sensitivities and
relate the retrieved backscatter to soil moisture over bare field conditions (Dubois, VanZyl, & Engman, 1995; Fung, Li, & Chen, 1992; Oh, Sarabandi, & Ulaby, 1992).

Agricultural fields only remain bare for a short period between snowmelt and crop emergence. The overlying vegetation introduces another series of factors which influences the backscatter; direct backscatter from the plants, volume scattering by the vegetation canopy with vegetation water content (VWC) dictating the radar penetration depth (aside from frequency), depolarization from the orientation of the plant, and plant-soil double scattering (pulse interacts with the vegetation then the soil or vice versa) (Ulaby et al., 1996; Ulaby et al., 1982). The error of volume scattering has been shown to be larger in HV than HH; however HH can result in an increased backscatter yielding an underestimated soil moisture when vegetation is present (Dubois et al., 1995).

Distinguishing between backscatter contributions from the vegetation or the soil remains a significant challenge in SAR surveillance of agricultural fields. The main types of models used to account for the backscatter contribution from vegetation are polarimetric decompositions (Cloude & Pottier, 1996; Freeman & Durden, 1998), energy and wave approaches (Bracaglia, Ferrazzoli, & Guerriero, 1995; Stiles & Sarabandi, 2000), and backscattering model-based retrieval algorithms such as the Water Cloud Model (WCM) (Attema and Ulaby, 1978; Prévot, Champion, & Guyot, 1993).

The main ground vegetation parameters that are useful for understanding variability of the backscatter from crops are Leaf Area Index (LAI) and Vegetation Water Content (VWC) (Liu et al., 2010). The relationship between LAI and VWC has been assessed over numerous types of crops such as corn, soybean, rice, and sugarcane (Inoue, Sakaiya, & Wang, 2014; Jiao et al., 2011; Lin et al., 2009; Notarnicola & Posa, 2007). However, LAI measurements on row
crops are unreliable when the viewing/incident angle is large as is the case in this thesis (Andrieu & Sinoquet, 1993).

The correlations between biomass data and cross polarizations (HV) have shown significant relationships in prior research (Ferrazzoli et al., 1997; Inoue et al., 2014). Additionally, linear co-polarizations have also shown significant relationships with biomass (Ferrazzoli et al., 1992; Pampaloni et al., 1997). It is known that for broad leaf crops such as corn, the backscatter has a rapid increase but then saturates early in the growing season (Ferrazzoli et al., 1997; Pampaloni et al., 1997). The saturation point is reached when increases in VWC have minimal impacts on the backscatter signal for the remainder of the season. However, the point at which this saturation occurs due to increased VWC has not been assessed. The objective of this research was to determine when linear polarizations from C-band SAR reach a saturation point due to the VWC (corn). Relationships among the linear polarizations, soil moisture, and VWC were assessed before and after these saturation points to identify dominant factors contributing to backscatter.

3.2 Research Methods

3.2.1 Study Area

The study area was located just south of the town of Elora, Ontario within the University of Guelph Elora Research Station (ERS), indicated in Figure 3.1. The soil at the ERS is a Guelph series loam. Within the ERS, four cornfields were assessed within a 9-km² area. Their respective coordinates and field characteristics are in Table 3.1. All four fields can be identified within the grey-brown podzol great soil group, with slight variations of loam soil types (Ontario Department of Agriculture, 1963). The row direction of all four fields was ~45° in respect to North.
Figure 3.1 Map of the study area in relation to the town of Elora and the city of Guelph within Southern Ontario (ESRI, 2016).

Table 3.1 Coordinates (degrees minutes seconds), soil type, drainage, and topography of the four cornfields within the ERS (Ontario Department of Agriculture, 1963).

<table>
<thead>
<tr>
<th>Field Number</th>
<th>Coordinates</th>
<th>Soil Type</th>
<th>Drainage</th>
<th>Topography</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>43°39'12.5&quot;N 80°24'57.9&quot;W</td>
<td>Burford Loam</td>
<td>Good</td>
<td>Smooth, very gentle sloping</td>
</tr>
<tr>
<td>3</td>
<td>43°38'23.1&quot;N 80°24'44.8&quot;W</td>
<td>London Loam</td>
<td>Imperfect</td>
<td>Smooth, very gentle sloping</td>
</tr>
<tr>
<td>4</td>
<td>43°38'02.3&quot;N 80°23'45.7&quot;W</td>
<td>London Loam</td>
<td>Imperfect</td>
<td>Smooth, very gentle sloping</td>
</tr>
<tr>
<td>5</td>
<td>43°37'38.3&quot;N 80°23'55.7&quot;W</td>
<td>Guelph Loam</td>
<td>Good</td>
<td>Smooth, moderately sloping</td>
</tr>
</tbody>
</table>
3.2.2 Field Data

During the 2015 and 2016 growing seasons, field data were collected on each of the research fields. During each visit, near surface soil moisture was measured across each field using a handheld Stevens® Hydra Probe (POGO). The Hydra Probes have four tines extending from the head of the instrument to a depth of 5 cm and uses the principles of frequency domain reflectometry to measure the dielectric permittivity of soils (Stevens Water Monitoring Systems Inc., 2007). Sixteen locations per field were marked with a GPS and repeatedly sampled in triplicate at each location following the SMAPVEX 12 protocol (McNarin et al., 2015). The 16 sites at each field were used for both growing seasons so a time series could be produced.

During the first eight visits to each field, two of 16 locations had soil cores extracted and bulk density was determined to calibrate the soil moisture data. Once extracted, the soil cores were transported to the sediment analysis lab to be weighed, oven dried at 105°C for 10 to 24 hours and weighed again to determine soil moisture. The difference of pre vs. post dry mass provided the gravimetric soil moisture in g/g and was then converted to volumetric values using the density of the soil and is expressed as m³/m³ (ASTM, 1979; Robinson et al., 2008). The calibration of the POGO instrument closely follows Rowlandson et al. (2013) where site-specific calibrations were shown to increase the accuracy of the measurements.

In addition to the POGO soil moisture measurements, an in-situ soil moisture network was installed at each field. A Stevens® Hydra Probe was inserted into the soil at a depth of 5 cm within the cropping area where it measured the Real Dielectric Constant (RDC) at 30-minute intervals. During installation of the 5 cm probes, a soil core was extracted for field specific calibrations of each probe. This extraction was done to achieve an accuracy of the Stevens® Hydra Probes to an RMSE of ≤0.04 m³/m³ that cannot be achieved by simply using the
manufacturer based calibrations (Entekhabi et al., 2010a; Vaz et al., 2013). A similar wet-up to dry down procedure demonstrated by Burns et al., 2014 was conducted with two main modifications. First, the soil structure was maintained by keeping the soil core undisturbed within its sampling ring. Secondly, water was introduced from the bottom to allow for uniform lateral wetting of the soil (Burns, et al., 2014).

During the measurement of POGO data, Vegetation Water Content (VWC) was extracted via destructive sampling on each field using location 1 of 16. One point was sampled continuously across the two growing season to limit the impacts of the within-field spatial variability in crop characteristics (Taylor et al., 2003). The above ground biomass of ten plants (five from two adjacent rows) was removed at each site, put into large paper bags and into clear plastic bags to help prevent moisture loss (Bell & Fischer, 1994). The bags were transported to the lab where the plastic bags were removed, the paper bags and their contents were weighed, then dried at 60°C from 24 to 72 hours (drying times increased with increasing biomass) and weighed again. The difference between the two masses determined the vegetation water content of the corn. The water mass (kg) was then converted into kg m⁻² by using the crop and row spacing of each field so that the mass of liquid water per ground area could be determined.

Table 3.2 RADARSAT-2 overpass information over the study area

<table>
<thead>
<tr>
<th>Date</th>
<th>Beam</th>
<th>Incidence Angle</th>
<th>Orbital Pass</th>
<th>Azimuth Angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-Jun-15</td>
<td>31</td>
<td>49°</td>
<td>Ascending</td>
<td>82°</td>
</tr>
<tr>
<td>9-Jun-15</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
<tr>
<td>14-Jun-15</td>
<td>29</td>
<td>48°</td>
<td>Descending</td>
<td>279°</td>
</tr>
<tr>
<td>3-Jul-15</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
<tr>
<td>27-Jul-15</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
<tr>
<td>13-Aug-15</td>
<td>31</td>
<td>49°</td>
<td>Ascending</td>
<td>82°</td>
</tr>
<tr>
<td>20-Aug-15</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
<tr>
<td>25-Aug-15</td>
<td>30</td>
<td>48°</td>
<td>Descending</td>
<td>279°</td>
</tr>
<tr>
<td>20-Jun-16</td>
<td>31</td>
<td>49°</td>
<td>Ascending</td>
<td>82°</td>
</tr>
<tr>
<td>27-Jun-16</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
<tr>
<td>2-Jul-16</td>
<td>29</td>
<td>48°</td>
<td>Descending</td>
<td>279°</td>
</tr>
<tr>
<td>14-Jul-16</td>
<td>31</td>
<td>49°</td>
<td>Ascending</td>
<td>82°</td>
</tr>
<tr>
<td>7-Aug-16</td>
<td>31</td>
<td>49°</td>
<td>Ascending</td>
<td>82°</td>
</tr>
<tr>
<td>14-Aug-16</td>
<td>26</td>
<td>45°</td>
<td>Ascending</td>
<td>81°</td>
</tr>
</tbody>
</table>
(McNairn et al., 2015). These processes were repeated across both growing seasons.

### 3.2.3 RADARSAT-2 Backscatter Data

This study used satellite imagery from RADARSAT-2. RADARSAT-2 is equipped with a C-band SAR that operates at a 5.6 cm wavelength allowing for high spatial resolution (8 m pixel size and a ground swath width between 18 to 25 km) (MacDonald, Dettwiler & Associates Ltd., 1999). A series of RADARSAT-2 overpasses occurred over the study area across 2015 and 2016. All overpass dates, incidence angles, orbital pass, and azimuth angles that were used are found in Table 3.2. All acquisitions were at high incidence angles (≥ 45°) and the antenna was always pointing from the same direction (i.e. ascending vs. descending passes). The images from these dates were used to extract backscatter values. Extraction was completed in the RADARSAT-2 Toolbox by first applying a 5x5-boxcar speckle filter to reduce noise (McNairn et al., 2010; Merzouki et al., 2011). A radiometric calibration was applied to the linear polarization images (HH, HV, and VV) to convert values into dB. Lastly, georeferenced shapefiles of each field were used to retrieve mean backscatter per field while using a one-pixel wide buffer to reduce edge effects (Adams et al., 2013).

### 3.2.4 Data Processing

The POGO soil moisture data had limited collection dates that occurred on the same day as the overpass data, due to external factors such as crew availability and weather. The continuous soil moisture dataset from the network did not have this problem, allowing the network soil moisture dataset to be used to assess relationships with the backscatter. The network soil moisture lacked the spatial variability across the field as it was acquired from one location. The four network sites were also placed at the edges of the fields, within cropping area which has been shown to experience a bias in relation to the field averaged soil moisture (Rowlandson
et al., 2015). Therefore, the in-situ POGO field data was used to correct for bias within the network data and upscale it to the field level. Bias correction was achieved by assessing a 1:1 relationship on each field between the two soil moisture datasets. The correlation between the two datasets was determined and the bias was identified by calculating the difference between each soil moisture measurement from the two sources on a per field per year basis. Any further mention of soil moisture in this paper will be referring to the spatially up-scaled network soil moisture.

Like the POGO data, VWC data was limited to collection that coincided on the dates of overpasses. Fortunately, VWC follows a positive linear trend due to crop growth, over the growing season until senescence begins and then it transitions into a negative linear trend. This linear trend allows for the application of a linear interpolation between dates to obtain data for each overpass date (Jackson et al., 2004).

The first step was determining when the backscatter response saturates to VWC. Previous research determined the SAR backscatter saturation to increased biomass in forest stands by using regression functions to calculate the point on the X-axis (biomass) where the regression line is near or at zero (Imhoff, 1995). A piecewise regression, performed using SAS (9.4 64-bit version), was selected as it can estimate saturation points in the data by using multiple regressions that are linked at a joint point (Bowley, 2015). The common point is often unknown and must be estimated by applying a nonparametric smoothing to the data using a local polynomial regression (LOESS). A linear regression is then performed on the data before the breakpoint to determine the y-intercept and the slope (Ryan & Porth, 2007). These three parameters (saturation point, y-intercept and slope) were determined for each linear polarization (HH, VV, and HV) to VWC relationship and then used as starting parameters to compute the
respective piecewise regressions. A simple linear regression could not be used to characterize the relationship over the entire growing season as it does not accurately account for the rapid initial increase in the relationship between VWC and backscatter. A piecewise regression was used to estimate the saturation points as it has been shown to accurately characterize data with two distinct phases, a high response rate and a relatively low response rate separated by a saturation point (Ryan and Porth, 2007).

The saturation points determined by the piecewise regressions were used to segment all data sets into ‘before saturation’ and ‘after saturation’ categories. The correlation coefficients between VWC and backscatter were then determined for before saturation, after saturation, and without segmentation (overall). Kendall’s Tau-b rank correlations were used to assess the relationships before saturation, after saturation and overall for soil moisture to backscatter. Kendall’s Tau-b was chosen due to the non-normal distribution of soil moisture and it has strong statistical properties for small sample sizes (Bowley, 2015). Since both soil moisture and VWC were evaluated against backscatter to determine the dominant factor, the relationship between the two also needed to be assessed. The same correlation analysis (Kendall’s Tau-b) was also conducted between soil moisture to VWC to assess their relationship.

3.3 Results

Across the two growing seasons, there was broad range of values that were observed in the field measurements. The daily mean values of soil moisture ranged from 0.07 to 0.41 m\(^3\) m\(^{-3}\) with an average of 0.29 m\(^3\) m\(^{-3}\). Figures 3.2 and 3.3 provide some insight to the field data collected during the 2015 and 2016 growing seasons. Figure 3.2 illustrates the VWC from the corn and the daily averaged POGO soil moisture is shown in Figure 3.3. Peak values of VWC for
2015 occurred at 6.05 kg m\(^{-2}\) and in 2016 at 5.95 kg m\(^{-2}\). The bias correction for the network soil moisture is displayed in Figure 3.5.

The saturation points that were computed for the three linear polarizations to VWC were 0.14 kg m\(^{-2}\) for HH, 0.17 kg m\(^{-2}\) for HV, and 1.6 kg m\(^{-2}\) for VV. The dates that correspond to these values and the correlation coefficients for the before and after saturation categories can be found in Table 3.3. The monthly totals for precipitation across both growing seasons from Environment Canada (2015 & 2016) are displayed in Table 3.5. Additionally, the results displaying the saturations for all three linear polarizations can be found in Figure 3.4. These same saturation points were then used to segment the soil moisture to backscatter data sets. The Kendall’s Tau-b results can be found in Table 3.4. A Kendall’s Tau-b = -0.42 was determined between the two ground measurements (VWC and soil moisture).
Figure 3.3 Daily averaged POGO soil moistrues values for 2015 (black) and 2016 (grey) with the standard deviations indicated by the error bars.

Figure 3.4 The piecewise regression between VWC and HV, VV and HH with the standard errors of each inflection point (0.03, 0.58 and 0.02) respectively.
Figure 3.5 The relationship between the network measured soil moisture (y-axis) and the spatially averaged soil moisture across each field (x-axis) for 2015 (a to d) and 2016 (e and f)
Table 3.3 The saturation points for all three linear polarizations to VWC and the dates of when this would have occurred in each year. The correlation coefficients for all three linear polarizations before and after saturation and overall relationships based on two years of data.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Saturation Point (kg m$^{-2}$)</th>
<th>2015</th>
<th>2016</th>
<th>r Before</th>
<th>r After</th>
<th>r Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>VWC:HH</td>
<td>0.14*</td>
<td>June 10$^{th}$</td>
<td>June 8$^{th}$</td>
<td>0.81</td>
<td>-0.04</td>
<td>0.36*</td>
</tr>
<tr>
<td>VWC:HV</td>
<td>0.17*</td>
<td>June 13$^{th}$</td>
<td>June 10$^{th}$</td>
<td>0.66</td>
<td>0.02</td>
<td>0.41*</td>
</tr>
<tr>
<td>VWC:VV</td>
<td>1.60*</td>
<td>July 3rd</td>
<td>June 26$^{th}$</td>
<td>0.41</td>
<td>0.16</td>
<td>0.31*</td>
</tr>
</tbody>
</table>

*Statistical significance based on a p-value < 0.05

Table 3.4 The Kendall’s Tau-b results between all three linear polarizations to soil moisture using the saturation points determined by the piecewise regressions and overall relationships.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$\tau$-b Before</th>
<th>$\tau$-b After</th>
<th>$\tau$-b Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil moisture:HH</td>
<td>0.14</td>
<td>0.34*</td>
<td>0.08</td>
</tr>
<tr>
<td>Soil moisture:HV</td>
<td>0.00</td>
<td>0.46*</td>
<td>0.08</td>
</tr>
<tr>
<td>Soil moisture:VV</td>
<td>0.06</td>
<td>0.46*</td>
<td>0.19</td>
</tr>
</tbody>
</table>

*Statistical significance based on a p-value < 0.05

Table 3.5 Average monthly precipitation (mm) at the ERS as reported by Environment Canada across both growing seasons

<table>
<thead>
<tr>
<th>Month</th>
<th>2015 Precip. (mm)</th>
<th>2016 Precip. (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>April</td>
<td>77.3</td>
<td>57.8</td>
</tr>
<tr>
<td>May</td>
<td>48</td>
<td>57.3</td>
</tr>
<tr>
<td>June</td>
<td>175.9</td>
<td>53</td>
</tr>
<tr>
<td>July</td>
<td>66.8</td>
<td>102.4</td>
</tr>
<tr>
<td>August</td>
<td>80.6</td>
<td>152.6</td>
</tr>
<tr>
<td>September</td>
<td>53.1</td>
<td>77.1</td>
</tr>
<tr>
<td>Total</td>
<td>501.7</td>
<td>500.2</td>
</tr>
</tbody>
</table>

3.4 Discussion

3.4.1 Field Measurements

In-situ soil moisture stations have been shown to be representative of the conditions within the immediate surrounding area (Brocca et al., 2010). However, soil moisture exhibits strong spatial variability and a more accurate representation of larger areas requires measurements from different points across that area (Robock et al., 2000). Heathman et al.
(2012) demonstrated the bias issue with in-situ stations and noted the benefit that would have been achieved from field-averaged soil moisture data. The POGO soil moisture measurements in this research spanned the entirety of each field using two large transects of eight points each. The purpose was to try to account for the field level spatial variability in soil moisture, which is known to be an issue (Western, Bloschl, & Grayson, 1998). The adjusted network soil moisture estimates were bias corrected based on the spatially averaged soil moisture estimates. The bias values indicated in Figure 3.5 demonstrate whether the network has a wet bias (positive value) or dry bias (negative value) in comparison to the spatially averaged values. Across both years, only 1 field (field 1 - 2015) showed a strong bias (wet) and the remaining five fields showed minimal bias (two dry and 3 wet). Adams et al. (2015) demonstrated that horizontally oriented probes (the orientation of the network probes in this study) estimate wetter soil moisture estimates. Probe orientation did not seem to be a source of error within this research as the network data was not consistently wetter than the POGO data. The soil characteristics within Table 3.1 does not show indications of why field 1 would demonstrate a bias in 2015, as it has good drainage, a similar soil type, and topography to the other fields (Ontario Department of Agriculture, 1963). The weaker correlation in Figure 3.5 shown for field 1 in 2016 is likely attributed to in-situ probe error due to POGO estimates exhibiting similar error bars between 2015 and 2016 in Figure 3.3. Probe error also occurred on two stations (fields 3 and 4), where the in-situ probe completely failed in 2016, which is why they were not included in the analysis.

Crop variables such as VWC have been shown to have within-field spatial variability (Taylor et al., 2003). The quality of the datasets have been shown to greatly improve by using spatially averaged data instead of measurements at a single point location (Wood, Taylor, & Godwin, 2003). Unfortunately, due to limited resources (both equipment and field assistants) and
the necessity to create a time series across each field, the retrieval of VWC was limited to one location per field. This single location extraction of VWC is what causes the large standard deviation error bars with crop development in Figure 3.2. Large standard deviations have been shown in other studies when using single location soil moisture data as well (Drake, 1976).

Determining the crop response to decreased soil moisture is a difficult task as it depends on intensity and duration of reduced soil moisture conditions (Hsiao, 1973). It also varies based on species and variety of crop as well as the development stage of that crop (Doorenbos & Kassam, 1979). The correlation analysis between soil moisture and VWC (Kendall’s Tau-b = -0.42) demonstrates the water uptake by the vegetation reducing the soil moisture. Corn has demonstrated a high tolerance to decreased soil moisture during the vegetative and ripening stages with detrimental impacts occurring most often during the flowering stages (Claassen & Shaw, 1970). On average corn reaches the peak of its flowering stage at the end of July/beginning of August (Hanway, 1963). The peak of flowering coincides with the peak in VWC observed in Figure 3.2.

The incorporation of soil moisture in global circulation models reduces the errors in precipitation estimates (Hirabayashi et al., 2003) and makes drought indices more accurate than using just precipitation (Sohrabi et al., 2015). The strong relationship between precipitation and soil moisture is shown when comparing the monthly precipitations (Table 3.5) to POGO soil moisture (Figure 3.3). In 2015, the most amount of precipitation occurred in June which caused a series of increased soil moisture values until almost mid July. In 2016, there was less than 58 millimeters for three consecutive months resulting in lower soil moisture values throughout the summer. The largest increase in soil moisture shown in Figure 3.3 was observed mid-to-late
August and into September. The most precipitation within the six-month period of 2016 also occurred in August.

Many types of corn are resistant to large fluctuations in soil moisture and similar results should be observed when precipitation values are compared to corn water content. Previous research by Campos et al. (2006) had varying water treatments applied to multiple types of corn at different growth stages. It was determined that the majority of corn types were resistant to minimal irrigation applications and the most detrimental impacts were during flowering. The persistence of corn growth despite large fluctuations in soil moisture is a possible reason for the patterns seen between monthly precipitation (Table 3.5) and corn VWC (Figure 3.2). VWC followed a similar pattern across both growing seasons with 2016 having greater values majority of the season but especially in July to mid-August. July to mid-August is the period when corn is flowering (Hanway, 1963) and most susceptible to drought conditions (Claassen & Shaw, 1970). In 2016, the bulk of precipitation was received between July to mid-August and is therefore a possible reason for the variation in VWC between 2015 and 2016.

3.4.2 Vegetation Backscatter Response

In broad leaf crops (e.g. corn) the impact of scattering is more pronounced than absorption of the signal, with the response being unique for each polarization (Macelloni et al., 2001). Cross-polarizations (HV) are representative of volume scattering within the crop canopy and have been shown to have the best relationship with C-band SAR for determining crop productivity and increased biomass (McNairn, Hochheim, & Rabe, 2004; Wiseman et al., 2014). Co-polarizations (HH and VV) have been shown to be more sensitive to surface scattering from the canopy (Jiao et al., 2011). All three linear polarizations in this study have significant overall relationships with respect to VWC as seen in Table 3.3. Ferrazzoli et al. (1997) demonstrated
strong relationships for HH and HV to VWC (incidence angle = 35°), where HV had the strongest relationship (r = 0.31). Pampaloni et al. (1997) had a similar study that demonstrated the relationship of VV to VWC which also showed a strong relationship (r =0.48).

Ferrazzoli et al. (1997) notes an early saturation effect for both HH and HV when examining Figure 7 and Figure 8 respectively in the original paper. Pampaloni et al. (1997) observed a saturation point of 2 kg m$^{-2}$ (incidence angle = 23°) between VV and VWC but the mechanisms of why saturation occurred then were not elaborated on. The saturation points in this study of 0.14, 0.17 and 1.6 kg m$^{-2}$ for HH, HV, and VV respectively, were all significant. All three linear polarizations exhibited positive relationships prior to saturation and had almost no relationship post-saturation (excluding VV). The saturation point in this study of 1.6 kg m$^{-2}$ with an incidence angle $\geq$ 45° seems reasonable when compared to the results stated for Pampaloni et al. (1997). It is a reasonable result at high incidence angles due to the longer path length through the vegetation occurring at larger incidence angles which causes the backscatter signal to saturate earlier in the growing season (Soria-Ruiz, Fernandez-Ordonez, & McNairn, 2009). None of the pre-saturation correlations were significant; which is likely due to the impact of a small sample size in these portions of the datasets (Bowley, 2015).

The late saturation of VV to VWC was unexpected as in general the loss factor of vertical polarizations is greater than in horizontal polarizations, especially when they interact with vegetation with vertical stalks such as corn (Ulaby et al., 1986; Engman, 1991). However, Romshoo et al. (2002) demonstrated that at C-band HH was more sensitive to VWC than VV. Even though the VV to VWC relationship in this study is surprising (compared to the bulk of the literature) it has been shown previously and requires further investigation. Additional crop types and various incidence angles should be examined in future studies determining these saturation
points. Assessment of saturation points at smaller incidence angles would result in a shorter path length through the vegetation and saturation later in the season should be expected (Soria-Ruiz, Fernandez-Ordóñez, & McNairn, 2009).

### 3.4.3 Soil Moisture Relationships

Previous research using C-band SAR has demonstrated that smaller incidence angles are better suited for soil moisture and larger incidence angles are better suited for vegetation monitoring (Ulaby, 1974; Ulaby, 1975). The weak overall relationships shown in Table 3.4 further supports that when using high incidence angle imagery over vegetated surfaces, soil moisture has a weak relationship with backscatter. Therefore high incidence angle imagery was ideal for extracting vegetation based backscatter saturation points. Although not the original intention of this study, it does provide some interesting information of the soil moisture to backscatter relationships at high incidence angles. Some more recent studies emphasize this point and only use acquisitions with small incidence angles = 10° when evaluating soil moisture (Ferrazzoli et al., 1992) and larger incidence angles = 35° when evaluating vegetation information (McNairn et al., 2002). Other studies use a combination of incidence angles (Gherboudj et al., 2011; Joseph et al., 2008; Trudel, Charbonneau, & Leconte, 2012) but the assessment of soil moisture exclusively at high incidence angles is very limited.

Previous research has shown that HH exhibits a strong relationship with soil moisture over fields with minimal vegetation cover (Sahebi & Angles, 2010; Salgado et al., 2001). The strong relationship between HH and soil moisture with minimal vegetation cover is shown in Table 3.4 as HH has the strongest relationship to soil moisture values prior to saturation. Unfortunately, as was the case with the pre-saturation datasets for VWC, none of the relationships are significant, likely due to the small sample size. Post-saturation, all three linear
polarizations have significant relationships to soil moisture. The relationships post-saturation is due to the VWC saturating the signal and beyond that point any increase in VWC has minimal impact on the backscatter signal (Soria-Ruiz et al., 2009). After saturation, fluctuations in the backscatter signal are likely attributed to another factor, which appears to be soil moisture. Over the course of the growing season with no segmentation, the relationship to soil moisture appears to be weak (excluding VV). Romshoo et al. (2002) concluded that the backscatter can be attributed to both soil moisture and vegetation cover and this study indicates similar results as soil moisture may never be the dominant factor but it contributes to variation in the backscatter signal.

As was the case in the VWC relationships, VV provides an interesting result with respect to soil moisture. Based on the points made in section 4.2, VV should have the weakest relationship with soil moisture but its relationship (post-saturation) is equally as strong as HV. Interestingly, VV had the latest saturation point with VWC and the strongest relationships with soil moisture, which typically indicates the greatest penetration ability (McNairn et al., 2002). In future studies VV needs to be an area of focus to determine if these results were caused by; the exclusively large incidence angles, crop row direction to azimuth relationship, or crop type.

3.5 Conclusions

Vegetation water content, in-situ soil moisture measurements and RADARSAT-2 backscatter values were recorded for four agricultural fields across the 2015 and 2016 growing seasons. Saturation points of 0.14, 0.17, and 1.6 kg m$^{-2}$ of HH, VV, and HV respectively were derived from their relationships to VWC over two growing seasons. They all demonstrated stronger relationships to backscatter pre-saturation vs. post saturation. All three polarizations demonstrated significant relationships throughout the growing season to VWC. Strong overall
relationships between vegetation parameters and backscatters has been demonstrated before. This research establishes that these strong overall relationships are largely driven by the pre-saturation values. The results for the VV relationship to VWC have been demonstrated before (Pampaloni et al., 1997) but the general consensus does not agree on such a late saturation point occurring and requires further investigation.

The same saturation points derived from VWC were used to assess the relationships between soil moisture and the three linear polarizations. The relationships were significant post-saturation, suggesting that soil moisture always has an impact on the backscatter, even at high incidence angles. The overall results for HH and HV align with previous research, demonstrating soil moisture has a minimal impact on backscatter throughout a growing season. However, just assessing the overall relationships would be ignoring the saturation points that are evident in the data. The VWC to VV results proved contradictory to what would be expected based on previous literature, as it was the only significant relationship overall.

This study seems to contradict previous research of SAR backscatter with respect to VWC and soil moisture. However, assessment of the data based on saturation points has not been performed before and therefore provides interesting insight into these relationships. The strength of this study and its results comes from the data collection that spanned two full growing seasons, on the same fields, with one crop type with the same row direction and exclusively at high incidence angles. The specificity of this research also highlights the need for this approach to be assessed on other crop types and varying incidence angles as it is so specific. The utility of this study is that it provides a distinct breakpoint in the relationship between a vegetation parameter and backscatter based on statistics. The knowledge of these saturation points will aid in strengthening the development of soil moisture retrieval models using C-band SAR.
Chapter 4.0 Summary and Conclusions

This research assessed whether saturation points could be determined over agricultural fields in SW Ontario and what the implications of using them to assess the relationships between VWC and soil moisture to backscatter. Using four corn fields just south of Elora, Ontario VWC and soil moisture were measured for two growing seasons (2015 and 2016) for a total of 27 field visits. Fourteen RADARSAT-2 overpasses occurred over the study area and dictated which field data could be used to assess the relationship between the satellite and the ground measurements. The VWC to backscatter saturation points derived from piecewise regressions were 0.14, 0.17, and 1.60 kg m$^{-2}$ for HH, HV, and VV respectively. Based on these saturation points the relationships of the two ground variables to the backscatter were assessed, demonstrating that VWC is the dominant factor in the backscatter prior to saturation but soil moisture is dominant post saturation. Soil moisture being the dominant factor post saturation indicates that soil moisture always has an impact on the backscatter, even at high incidence angles over large biomass crops such as corn. VV also demonstrated surprising results as it had the latest saturation point and the strongest overall relationship with soil moisture.

The first objective of this thesis was to measure VWC and in-situ soil moisture over two growing seasons (2015 & 2016), and coordinate these measurements to the timing of RADARSAT-2 overpasses. The raw measurements of VWC and soil moisture were obtained over the two growing seasons. The timing of the VWC measurements did not always align with the timing of the overpasses but through linear interpolation this was achieved. The in-situ soil moisture estimates formed a continuous dataset that was available on all the overpass dates. However, a bias issue is apparent when using a single soil moisture station to represent an entire
field (Heathman et al., 2012). Spatially distributed measurements were also sampled to compensate for bias and make the in-situ measurements more accurate.

The second objective was to determine when an increase in VWC no longer had a significant impact on RADARSAT-2 backscatter. The saturation point was determined using a piecewise regression, this has been used in previous research where two variables demonstrate a relationship similar to that observed in this thesis (a phase of a high response rate and another of a relatively low response rate, separated by a saturation/ break point) (Ryan and Porth, 2007).

The third objective was to assess the relationships between VWC to backscatter and soil moisture to backscatter before saturation, after saturation and overall to determine the impacts of a saturation point. The early saturation points between VWC with HH and HV and a later saturation point between VWC with VV seen in this thesis have been noted before in previous research (Ferrazzoli et al., 1997; Pampaloni et al., 1997). Previous research has demonstrated that overall biomass estimates (VWC) are the dominant factor and soil moisture has weak relationships over the growing season in relation to backscatter (Ferrazzoli et al., 1997; Pampaloni et al., 1997). The overall results provided in this research align with these conclusions (excluding VV), however based on the results presented these relationships should not be assessed as one continuous data set. The need to assess the backscatter differently based on time of the year is demonstrated by the drastic changes in relationship strength on either side of saturation for both backscatter to ground characteristic datasets. The VV relationships contradict previous literature, that indicates when imaging crops with a dominant vertical structure (such as corn) the loss factor of vertical polarizations is greater than in horizontal polarizations (Ulaby et al., 1986; Engman, 1991). However, the use of saturation point to assess backscatter to ground characteristics has not been used before and requires further investigation.
Future research should initially assess these saturation points at similar satellite parameters but on a variation of crops (either a grass species or a crop with less vertical structure). This crop variation would help determine if these results were crop dependent or not. Additionally, variations in the incidence angle would also provide insight if the incidence angle is the driver of the timing of these saturation points. Lastly, if vegetation measurements were taken on a larger number of fields and multiple points per field the spatial variability could be characterized.
References


https://doi.org/10.1029/2007GL031088


https://doi.org/10.1016/0034-4257(82)90052-9


