UTILIZING REMOTELY PILOTED AIR SYSTEMS IN THE DELINEATION OF FUNCTIONAL LAND MANAGEMENT ZONES

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Saskatoon, SK, Canada

By
Lukas Alexander Raphael Smith

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College of Graduate and Postdoctoral Studies
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Saskatoon, Saskatchewan
Canada, S7N 5C9

Head, Department of Soil Science
College of Agriculture and Bioresources
University of Saskatchewan
51 Campus Dr.
Saskatoon, SK
Canada, S7N 5A8

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ABSTRACT

Global food production must increase significantly before 2050 to ensure food security. This necessitates the intensification of agriculture to keep with land resource constraints. Meanwhile, climate change is occurring, and these two factors are exerting pressure on the medium through which food production occurs: the soil. Soil provides many of the ecosystem services provided by farmland and is essential for functions such as food production, water storage, carbon cycling and storage, functional and intrinsic biodiversity, as well as nutrient cycling. In order for agriculture to intensify sustainably, these soil functions must be maintained. However, we do not currently have a baseline measure of the overall functions soils are providing which is needed in order to track how climate change and agricultural intensification are impacting the soil. Precision agriculture provides an avenue to achieve this and management zones are essential to precision agriculture. Traditional methods of sampling to gather soil information are labor intensive and time consuming; it is necessary to find faster alternatives. Remote sensing and digital soil mapping (DSM) are two technologies with great potential for quickly gathering soil information at large spatial scales. The objectives of this study were to: 1) test remote sensing methods for the interpolation of surficial soil organic carbon using a remotely piloted air system (RPAS); and 2) develop a method of management zone delineation that accounts for multiple soil functions. Remote sensing was found to be the most effective at estimating soil organic carbon (SOC) through the use of DSM. SOC and topography were found to be key factors for multiple soil functions. These factors were used to develop a management zone delineation method that was indicative of multiple soil functions. An RPAS is not necessary for this method but remote sensing data is essential. This method assists land users to, within a familiar framework, quickly estimate and manage for multiple soil functions. It produces a measure of soil health that enables land productivity and value to be maximized while providing the opportunity to respond timely to the effects of climate change and agricultural intensification.

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LIST OF ABBREVIATIONS

BD	Bulk density
CIG	Chlorophyll Index-Green
CLC	Conservation Learning Centre
DEM	Digital elevation model
DSM	Digital soil mapping
DTM	Digital terrain model
EC	Electrical conductivity
FLM	Functional land management
FLMZ	Functional land management zones
GCP	Ground control point
GIS	Geographic information system
Grav.	Gravimetric
MSLD	Modified soil line distance
NIR	Near infrared
OC	Organic carbon
ON	Organic nitrogen
PCA	Principal component analysis
RPAS	Remotely piloted air system
SDNWA	St. Denis National Wildlife Area
SLED	Soil line Euclidean distance
SMMRS	Soil moisture monitoring by remote sensing
SOC	Soil organic carbon
SOM	Soil organic matter
SR	Simple ratio
TC	Total carbon
TN	Total nitrogen

Chapter 1.0

General Introduction

1.1 Context

Global populations are rapidly increasing and the Food and Agriculture Organization suggests that primary food production will need to increase by up to 60% by 2050 (Coyle et al., 2016). A further challenge is climate change, which has – and will continue to – pressure the environment's resiliency. A major question for global food security is whether food production can be achieved at higher than current rates without undermining ecological functions and ecosystems services (Squire et al., 2015). To ensure food security there is pressure for the intensification of agricultural inputs. Intensification needs to be sustainable, which means increasing food production from current agricultural areas while reducing or decoupling negative environmental impacts (Schulte et al., 2014). Agricultural intensification has been linked to problems such as reduced water quality and biodiversity, and it can significantly decrease resiliency to change (Power, 2010). There is a need to characterize the resiliency of key soil ecosystem services in Canadian agricultural landscapes as resilience controls the points at which ecosystem services shift (Ludwig et al., 2018). Assessing and linking soil ecosystem services to land resource policy and management is necessary. It has been suggested that the inclusion of soils in policy and decision making is essential and an important determinant in a country's economic status (Adhikari and Hartemink, 2016).

Soil is responsible for many ecological functions and ecosystem services, including: food production; water storage, purification, and regulation; carbon cycling and storage; functional and intrinsic biodiversity; as well as nutrient cycling and provision (O'Sullivan et al., 2015; Poggio and Gimona, 2016). The amount of function provided varies depending on soil properties, topography, land use, and management (Noorbakhsh et al., 2008; Parent et al., 2008; Schulte et al., 2014). Poor agricultural management of soils in the past has led to catastrophes such as wind erosion events in the 1930s (Pennock et al., 2011), and a significant decrease in soil organic matter (Anderson and Cerkowniak, 2010). Therefore, it is important not only to manage farmland soils to increase food production, but to preserve and enhance the other soil functions for the entire ecosystem.

Modern agricultural practices such as 'Precision Agriculture' (PA) try to manage for soil variability by dividing fields into management zones that can receive customized inputs to maximize crop productivity within each zone. Historically, PA has largely been focused on the management of cropland (Schellberg et al., 2008) and management zones focused on a single soil function: crop productivity. Present methods of management-zone delineation may have the potential to indicate variation in multiple soil functions under different land uses as key soil properties related to plant productivity are also related to other soil functions (Adhikari and Hartemink, 2016). PA needs to expand to include more land uses within an agricultural landscape as well as more soil functions to allow for holistic decision-making that maximizes the total ecosystem services provided by soil in agricultural landscapes.

Climate change pressures are occurring now and can affect the soil. In order to measure this effect a baseline measure of soil and its functions is needed now, and remote sensing and digital soil mapping can be part of the solution. Digital soil mapping development has been driven by food security, ecosystem health, and climate change, and its goal is to provide high quality spatial soil information (Zhang et al., 2017). Replacing and or supplementing on-ground methods with remote-sensing and digital soil mapping methods will significantly decrease the time needed to collect the necessary soil data to delineate functional land management zones. Remotely Piloted Air Systems (RPAS) have higher spatial resolution (Matese et al., 2015) and can have higher temporal resolutions than satellites, with relatively low operational costs (Zhang and Kovacs, 2012). Utilizing RPAS allows for management decisions based on data collected from the flying platform to be made quickly after a flight.

1.2 Research Objectives

There were two primary objectives for this research. The first was to test remote sensing methods of sampling and interpolating surficial soil organic carbon using an RPAS against physical soil sampling methods. The second was to develop and test a method for delineating management zones that are indicative of multiple soil functions.

The management zones delineated in this project will provide the framework for identifying soil functions in a landscape and then quantifying and valuing the provided ecosystem services. As such, the management zones developed will be referred to as ‘Functional Land Management Zones’. The framework will be explicitly linked to the sustainability metrics soil landforms used by Agriculture and Agri-Food Canada. This project is a sub-project within a larger study on “Understanding Resilience in Agroecosystems” with a focus on landscapes in transition. In the face of climate change, this study seeks to determine the ecosystem services provided by soils under different land use and quantify agroecosystem resilience so that resiliency can be enhanced through the optimization of soil quality and key ecosystem services (Bedard-Haughn, unpublished, 2016). As such the sub-project described in this thesis utilizes data collected by peers for other sub-projects.

1.3 Organization of Thesis

This thesis is written in the manuscript-style format. Chapter One and Two provide a general introduction and a literature review, respectively. Chapter Three focusses on testing RPAS methods of measuring surficial soil organic carbon while Chapter Four explores the implementation of these methods in delineating management zones that are indicative of multiple soil functions. Chapter Five summarizes the two research Chapters (Three and Four), commenting on how the research can be applied and improved upon. Appendix A provides additional soil and plant indices data collected for the study. Appendix B provides the zone delineation method implemented in Chapter Four. Finally, Appendix C contains zone delineation maps for the St. Denis National Wildlife Area and the Conservation Learning Centre.

Chapter 2.0

LITERATURE REVIEW

Over 110 billion dollars of Canada's GDP is from the agriculture and agri-food industry (Agriculture and Agri-Food Canada, 2017). Most of Canada's farmland is found in the Prairie Provinces with Saskatchewan itself having 38% of the total (Veeman and Veeman, 2015). In 2011, the total farm area in Saskatchewan was 25 million hectares (61.6 million acres) of which 59.1% was cropland (field crops and hay) (Statistics Canada, 2016), and approximately 27% was pasture land (Government of Saskatchewan, 2015). Besides crop production and providing space and feed for livestock, farmland can provide many other benefits. These non-market benefits can include plant and wildlife habitat, soil erosion control, flood protection, improved water quality, carbon sequestration, scenic views and recreation opportunities (Ministry of Agriculture and Lands, 2007). Agriculture is an essential industry that provides economic, societal, and environmental benefit.

Of the many ecosystem services and benefits the soil provides, Schulte et al. (2014) identified five key soil functions: food, fibre, and fuel production, water purification, carbon sequestration, habitat for biodiversity, and recycling of nutrients/agro-chemicals. Soil is the medium in which plants are grown for food, forage, and bioenergy (Greiner et al., 2017). It holds water for plant use and it maintains surface and groundwater quality by buffering and filtering organic compounds (Jónsson and Davídsdóttir, 2016; Greiner et al., 2017). Soil has high value in terms of mitigating global climate change as it has greater carbon storage potential than vegetation and the atmosphere (Srivastava et al., 2012). Previous cultivation has resulted in soil carbon stores being halved in agricultural areas, by implementing better management practices these stores can be restocked (McCarl et al., 2007). Soils are a habitat for millions of species including bacteria, fungi, and microfaunal grazers which provide benefits such as nutrient mineralization and excretion for plant uptake, toxin remediation, and improving soil structure and resiliency (Birgé et al., 2016; Jónsson and Davídsdóttir, 2016). Lastly, soils provide an environment for nutrient storage and cycling and they have the ability to absorb and retain solutes and contaminants (Jónsson and Davídsdóttir, 2016; Greiner et al., 2017).

In order to meet the challenges of producing enough food for a growing global population and making more efficient and considered use of natural resources, sustainable food production is at the top of the global policy agenda (Schulte et al., 2014). A critical aspect of sustainable food production is good soil management and Schulte et al. (2014) responded by introducing the concept of "Functional Land Management" (FLM). This concept aims to optimize the multi-functionality of soils and land use to meet agricultural and environmental targets at local and national levels. Their group has since sought to expand the FLM framework and has developed the concepts of demand and supply of soil function, providing a 'proof of concept' at a national level, relating a soils' function to land use (Schulte et al., 2014). They have examined the trade-off between primary productivity and carbon storage in response to the intervention of drainage systems (O'Sullivan et al., 2015). Then they reviewed soil function under different soil drainage and land use scenarios (Coyle et al., 2016) and assessed how soil management and land use management interact in meeting multiple targets simultaneously (Valujeva et al., 2016). Also, they designed an optimized catchment based on soil function targets and identified gaps in implementation of the proposed design (O'Sullivan et al., 2017). The idea of managing soil for multiple ecosystem functions was also explored by Williams et al. (2016). They used the term "Soil Functional Zone Management" which entailed the creation and management of distinct yet complementary zones with the potential to reduce trade-offs between soil quality and short-term productivity through non-uniform management of tillage and crop residues. The aforementioned work of Schulte's research group was mostly focused on, and conducted in, Ireland. Williams' study was conducted in the USA. While managing for soil function has been explored in Canada (Saad et al., 2011) it requires further exploration and there is a lack of methods available for land users to implement soil FLM.

Precision Agriculture (PA) has been said to be "one of the top ten revolutions" in agriculture (Mulla, 2013) and a key direction in modern agricultural development (Zhang et al., 2014). PA dates back to the 1980s and has been commercially practiced since the 1990s (Mulla, 2013). PA can improve farm management of inputs: increasing crop productivity while simultaneously decreasing negative environmental effects. By customizing the inputs applied to different parts of a field, less chemicals can be used which not only lowers the cost associated with fertilizer, pesticides, herbicides, and fungicides but reduces the risk of these inputs contaminating the surrounding air, soil and water (Mulla, 2013; Zhang et al., 2014). Further benefits can include lower fuel costs, more precise hybrid selection and rental agreements better aligned with actual crop productivity (Mulla, 2013). When PA began, there were two primary schools of thought: 1) management based on soil mapping units and; 2) management based on homogenous sub-field units called management zones (also referred to as Site-Specific Crop Management). For each soil mapping unit or management zone a customized management practice is applied.

Management zones became more widely adopted when it was shown that soil mapping units were too large-scale to capture in-field variability (Mulla, 2013). In a recent survey of western Canadian farmers, 93% agreed or strongly agreed that PA is useful and 75% said they intended to use more PA tools in the future. For the 2016 season, 48% of respondents claimed to use PA tools and/or services on their whole farm while 37% claimed to use them on only a portion of their farm. However, 49% of respondents did not use prescription maps or variable-rate technology to apply variable or unique rates to their fields. The largest perceived barriers to adopting PA technology were price, internet speeds and/or cellular data coverage, lack of knowledgeable people, continuously evolving technology, and incompatible (old) farm equipment (Steele, 2017). PA adoption rates are significant in Canada (Mulla, 2013) and there is room for current PA users to adopt further PA tools and services, but barriers still exist.

It has been suggested that a better definition of PA would include the use of information technologies and encompass every agricultural activity: plant production, animal production and welfare, management of natural resources, agricultural landscape management, and post-harvest processing of raw material. PA practices can be applied to other land uses such as grasslands and pasture but constraints such as low economic value, the natural heterogeneity of grasslands, and the spatial patterns of biomass created by grazing animals have limited its application (Schellberg et al., 2008; Cicore et al., 2016). In its current capacity, PA allows for an increase in crop productivity while simultaneously preserving the environment, but the practice of PA still needs to be expanded to be further implemented with land uses other than crop fields and to account for the management of multiple soil functions.

Regardless of how PA is defined, management zones are an important consideration (Elstein, 2003) and a popular basis for implementing variable rate technology (Song et al., 2009). There are many methods for delineating management zones; many require soil mapping. Variables like soil electrical conductivity, yield data, soil texture, topography, soil organic matter and various soil nutrients have all been used to delineate management zones (Gozdowski et al., 2014), but the soil properties have typically only been considered in the context of crop yield. The same soil properties could also be looked at in the context of other soil functions. For example, a delineation method may use soil organic matter content as a variable as it is related to soil organic carbon (SOC) content. Not only does SOC content indicate potential crop yield (Gozdowski et al., 2014) but it also provides a measure of carbon sequestration. Also, the amount of nutrients in soil impacts plant growth, and nutrient cycling is also a soil function as it can absorb and detoxify organic wastes (Coyle et al., 2016). Other links between soil properties and functions exist as well (Birgé et al., 2016); measuring key soil properties not only allows for crop performance to be predicted but the ability of the soil to provide other functions can also be assessed. Management zones have been implemented in grassland management (Pena-Yewtukhiw et al., 2017) but a lack of literature on the topic suggests this is not a common practice. Invasive and non-invasive soil sampling, landscape factors from DEMs, remote sensing imagery and photography have all been used as approaches for delineating management zones (Buttafuoco et al., 2010; Gozdowski et al., 2014). Grid sampling is a common method of characterizing spatial variation and zone delineation but it is labor intensive and time consuming and therefore not viable from a site-specific crop management perspective (Song et al., 2009; Moral et al., 2010). Management zones are essential for the implementation of precision agriculture and the utilization of remote sensing technology allows for more efficient management zone delineation.

Current soil maps are often lacking in detail and resolution. In order to deal with global food security, climate change pressures, land degradation, and ecosystem health (issues closely related to soil function), detailed and accurate spatial data is required; and this is the driving force behind digital soil mapping (DSM) (Zhang et al., 2017). DSM (also known as predictive soil mapping) has been defined as “the creation and population of spatial information systems by the use of field and laboratory observational methods coupled with spatial and non-spatial inference systems” (Zhang et al., 2017). Its major components are: an input (legacy soil observations, statistical sampling techniques, and environmental co-variates [Minasny et al., 2013]), a process (building models relating soil observations with environmental co-variates), and an output (spatial soil information systems including rasters of predictions) (Minasny and McBratney, 2016). Environmental co-variates can also effectively be used as inputs as well (Taghizadeh-Mehrjardi et al., 2016). The applications of DSM range from agricultural management to ecosystem services. DSM can be used in the management zone delineation process but more sophisticated technologies for predicting soil properties across a landscape with high resolution and accuracy are needed (Zhang et al., 2017).

Remote sensing has a long history of being used to consistently and repeatedly gather spatial data at large scales (Redhead et al., 2012). In the 1930s, aerial photos were being used for precise measurements of cropland area (Zhang and Kovacs, 2012) and satellite-based remote sensing has been used for agriculture since the 1970s (Mulla, 2013). Remote sensing can also be important in the mapping and modelling of soil properties (Poggio and Gimona, 2016). Other applications include measuring crop yield, biomass, crop nutrient and water stress, and the spread of weeds, insects and plant diseases (Mulla, 2013). Remote sensing has also proven useful for the management of forage (Cicore et al., 2016), grassland (Dusseux et al., 2015) and pasture (Edirisinghe et al., 2011). Despite all this, the use of satellite and aerial remotely sensed data is not yet widespread. Although, spatial and temporal resolution have improved greatly in recent years, they have traditionally served as barriers to satellite use (Mulla, 2013). Using aircraft for remote sensing can come with its own limitations such as the inability to provide images at low altitudes and low speeds (Huang et al., 2016). Cloud cover can also severely limit the use of satellite and aerial imagery (Mulla, 2013). In the recent survey of western Canadian farmers, 17% did not look at imagery or maps of their fields and 59% did not look at in-season crop imagery or remote sensing of their crops and fields. Of those who did utilize in-season imagery and remote sensing, 28% used satellite and 19% used RPAS imagery (Steele, 2017). The use of remote sensing for agriculture will only continue to grow into the future as the utilization of remote sensing technology allows for more efficient management zone delineation.

In recent years, the use of RPAS has increased significantly (Toth and Jóźków, 2016). Remotely sensed data from an RPAS platform provides high resolution data with great control over the timing of surveys (Matese et al., 2015). The high temporal resolution that can be achieved with an RPAS system means within 1-2 days an RPAS flight can be made, the data processed and interpreted, and an appropriate management response determined. Not only could this make a significant difference in regards to managing for pests and disease but it has been concluded that the temporal variability of crop production indicators is often larger in magnitude than is spatial variability (Schellberg et al., 2008), and this variability could be better managed for. Initially, barriers such as the high cost and low reliability of RPASs, lack of commercial sensors, high cost of sensors, limited payload, low-battery life and regulatory issues prevented their widespread use, but many of these issues have been addressed and as a result, RPAS use has grown. There still exist challenges in the use of RPASs such as evolving regulations, the need for certification, training for data interpretation, the need for a powerful computer and expensive software (or paying for data to be processed via cloud services), management of large data volumes, and a lack of standard methodology for their use (Hardin and Jensen, 2011; Wright, 2014; Zhang et al., 2014; Matese et al., 2015; Shi et al., 2016). However, the potential benefits of RPAS remote sensing are great, the technology is swiftly advancing, and costs continue to decrease. It has been demonstrated that RPASs can be successfully and efficiently used for agricultural decision support (Herwitz et al., 2004). RPASs have great potential for helping make land management decisions in mixed-use areas at the field scale (quarter-section or section level) but with evolving regulations and technological advances there is a need to further explore their potential and work towards standardizing methodologies.

Moving forward, agricultural practices will need to take into consideration all land uses and soil functions and FLM should be the framework that Canadian agriculture adapts as a solution. Precision agriculture improves field productivity in a more economic and environmental manner (Mulla, 2013) and could be made to fit within this framework through the use and optimization of management zones. In order to create management zones that are effective for FLM, spatial soil data at large scales are required. Typically, this has involved laborious, time consuming practices. Tools such as remote sensing and DSM can quicken this process (Song et al., 2009; Minasny et al., 2013) but there is a need to further explore these alternate modelling and soil mapping technologies (Gray et al., 2015; Zhang et al., 2017), especially before they can be implemented into a method for delineating functional land management zones.

Chapter 3.0

REMOTELY PILOTED AIR SYSTEM BASED REMOTE SENSING AND DIGITAL SOIL MAPPING OF SURFICIAL SOIL ORGANIC CARBON IN ANNUAL AND PERENNIAL LANDSCAPES

3.1 Preface

In order for Remotely Piloted Air System (RPAS) and Digital Soil Mapping (DSM) to be integrated into a methodology for creating functional land management zones, they must first be assessed in their ability to replace or supplement soil sampling. This research chapter explores the effectiveness of RPAS at estimating surficial soil organic carbon through remote sensing indices and predictive modelling.

3.2 Abstract

Physical soil sampling for soil properties and for the interpolation of soil properties at the field scale can be labor intensive and time consuming. Climate change pressures and the need for agricultural intensification have created the need for quicker and more efficient ways to measure soil properties and the soil functions they indicate. In order to monitor soil change caused by climate change we need to establish a baseline now. Two technologies have emerged to meet this challenge: remote sensing and digital soil mapping. Remote sensing allows for large areas to be mapped and imaged, from which information about surface soil organic carbon (SOC) may be extracted. Digital soil mapping (DSM) allows for soil data to be combined with co-variates such as topographical data to interpolate SOC over large areas. Each method only requires soil sampling for training, significantly reducing the number of samples needed when compared to methods like grid sampling. The objectives of this chapter were to: 1) evaluate a remote sensing index method for estimating surficial soil organic carbon using an RPAS, and 2) evaluate a method for estimating surficial soil organic carbon using DSM and an RPAS. It was shown that in cropland both technologies were useful for measuring surficial soil carbon, with digital soil mapping having more accurate results. When compared to physical sampling and dry combustion analysis, in cropland, the best remote sensing index method had an r^2 of 0.348 while the digital soil mapping method had an r^2 of 0.690. It was also shown that digital soil mapping can be utilized for multiple land uses. In grassland the digital soil mapping method had an r^2 of 0.606 when compared to physical sampling and dry combustion analysis.

3.3 Introduction

Precision Agriculture (PA) plays an important role in achieving sustainable agriculture (Lindblom et al., 2017) and the use of management zones is an important aspect of PA (Elstein, 2003). While there are many soil measures that can be used for delineating management zones; soil organic carbon has been shown to be one of the most relevant (Gozdowski et al., 2014). Currently, grid sampling is a common method for capturing soil property variation but it is laborious (Song et al., 2009); replacing grid soil sampling with a quicker method would allow for soil property variation to be more readily considered when delineating management zones.

Within the past decade the use of Remotely Piloted Air System (RPAS) for remote sensing has risen exponentially (Bareth et al., 2016). This is due to their high spatial and temporal resolution, low operational costs (Zhang and Kovacs, 2012), and accessibility (Bareth et al., 2016). RPAS allows for management decisions to be quickly made based on data collected from the platform providing successful and efficient agricultural decision support (Herwitz et al., 2004). However, RPAS users still face many challenges such as evolving regulations and a lack of standard methodology for their use (Hardin and Jensen, 2011; Wright, 2014). RPAS adoption for land management has the potential to provide efficient and effective land assessment but, considering its challenges and technological advances (Matese et al., 2015), the platform requires further exploration in its ability to aid in measuring soil properties.

Remote sensing is well established in precision agriculture as a support for crop management (Bareth et al., 2016). It can be used to quickly obtain spatial information over large areas (Song et al., 2009) and has proven useful for the management of cropland, grassland, and forest (Edirisinghe et al., 2011; Dusseux et al., 2015; Cicore et al., 2016). It has also shown promise for estimating multiple soil properties (Poggio and Gimona, 2016). Soil organic matter (SOM) when greater than 2 percent, largely controls the reflectance of the soil (Fox and Sabbagh, 2002). SOM is complex and difficult to measure (Cameron and Breazeale, 1904; Rowell, 2000) and is usually estimated from soil organic carbon (SOC) (Pribyl, 2010). The Soil Line Euclidean Distance (SLED) method looks at the relationship between the red and near-infrared reflectance of bare soil in order to predict SOM and SOC (Fox and Sabbagh, 2002; Ladoni et al., 2010; Croft et al., 2012; Hassan-Esfahani et al., 2015). When remotely sensing bare soil, the red and near-infrared reflectance have a linear relationship and the line formed by this relationship is referred to as the soil line.

Another methodology that is able to quickly and inexpensively estimate SOC over large areas is digital soil mapping (DSM) (Wang et al., 2017). DSM combines field sampling and laboratory analysis with modelling software to predict and map soil properties. It has seen a steady rise in the literature over the past years due to the increasing availability of spatial data and computing power, as well as the development of data mining and GIS tools (Minasny and McBratney, 2016). Topography based attributes are the most commonly used covariates for the DSM of soil carbon (Minasny et al., 2013). SOC has been shown to correlate strongly with topography, especially in the upper soil layer (Florinsky et al., 2002; Wang et al., 2017). Tree-based models have been found to have superior predictive performance than many other methods, due to their ability to deal with linear and non-linear soil property relationships with covariates (Heung et al., 2016; Wang et al., 2017). It has also been shown that Tree-based DSM can be successfully applied in hummocky terrain (Kiss, 2018).

The objectives of this study were to: 1) evaluate a remote sensing index method for estimating surficial SOC using an RPAS; and 2) evaluate a method for estimating surficial SOC using DSM and an RPAS.

3.4 Materials and Methods

3.4.1 Study site

This study was conducted at the St. Denis National Wildlife Area (SDNWA) in South-Central Saskatchewan, 40 km east of Saskatoon (see Fig 3.1). The SDNWA has hummocky topography and is in the Moist Mixed Grassland ecoregion (HABISask, 2018). The soils are mapped as part of the Weyburn association (University of Saskatchewan, 2018) and were found to be mostly Dark Brown Chernozems at higher slope positions and Black Chernozems at lower slope positions. The SDNWA features both annual cropland and perennial grassland. The cropland was planted to barley for the 2018 season and the grassland is hayed tame forage (grass mix- primarily brome).

3.4.2 Sampling design

Two different sampling designs (Fig. 3.1) were used for this study: transect and random stratified sampling. The random stratified points were stratified by slope position (upper-, back-, foot-slope, and depression) and transects were nested within these points. Soil organic carbon (SOC) data was sampled from the random stratified points and was supplemented with transect SOC data provided by another research project (Aguiar, 2019). The location for each sampling point was recorded using a Trimble GeoExplorer 2005 Series GeoXT GPS (Trimble California, U.S.A) which had an accuracy up to 0.43 m.

3.4.3 Soil sampling and analysis

For both cropland and grassland physical surface samples (0-15cm) were taken from the random stratified points using a Dutch auger in May 2017, a year prior to RPAS flights. A sub-sample of these were then ball ground and analyzed for SOC via dry combustion without pre-treatment (Wang and Anderson, 1998) using a LECO C632 elemental analyzer (LECO, Michigan, U.S.A.) at a furnace temperature of 840°C. No pretreatment is necessary because there is a temperature gap between when SOC is completely combusted (420°C) and when carbonates start to decompose (850°C) (Wang and Anderson, 1998).

3.4.4 Remotely piloted air system operation

RPAS flights were conducted in September 2018, when the crop had been removed and the grasslands had been hayed. A DJI Phantom 4 (DJI, Shenzhen, China) RPAS equipped with a Parrot Sequoia (Parrot Drones SAS, Paris, France) multi-spectral camera and sun sensor was flown once over the sampling area one hour after solar noon. The sun sensor corrects for any changes in sunlight occurring during flights. RGB (Red, Green, Blue; standard colour imagery) as well as Red, Green, and Near-infrared (NIR) imagery were captured. The RPAS was flown at a height of 90 m and speed of 10 $m \cdot s^{-1}$, with a frontlap (top and bottom image overlap) and sidelap (left and right image overlap) of 75%. Before and after each flight imagery of a calibration panel was collected to correct flight imagery during processing. Imagery captured by the DJI Phantom 4 Pro camera had a pixel size of 3.78 cm and imagery captured by the Parrot Sequoia had a pixel size of 9.11 cm. Flights were programmed using the DroneDeploy app (DroneDeploy, California, U.S.A). Three ground control points were previously installed on the site within the sampling area and their positions recorded using a Trimble GeoExplorer 2005 Series GeoXT GPS (Trimble California, U.S.A).

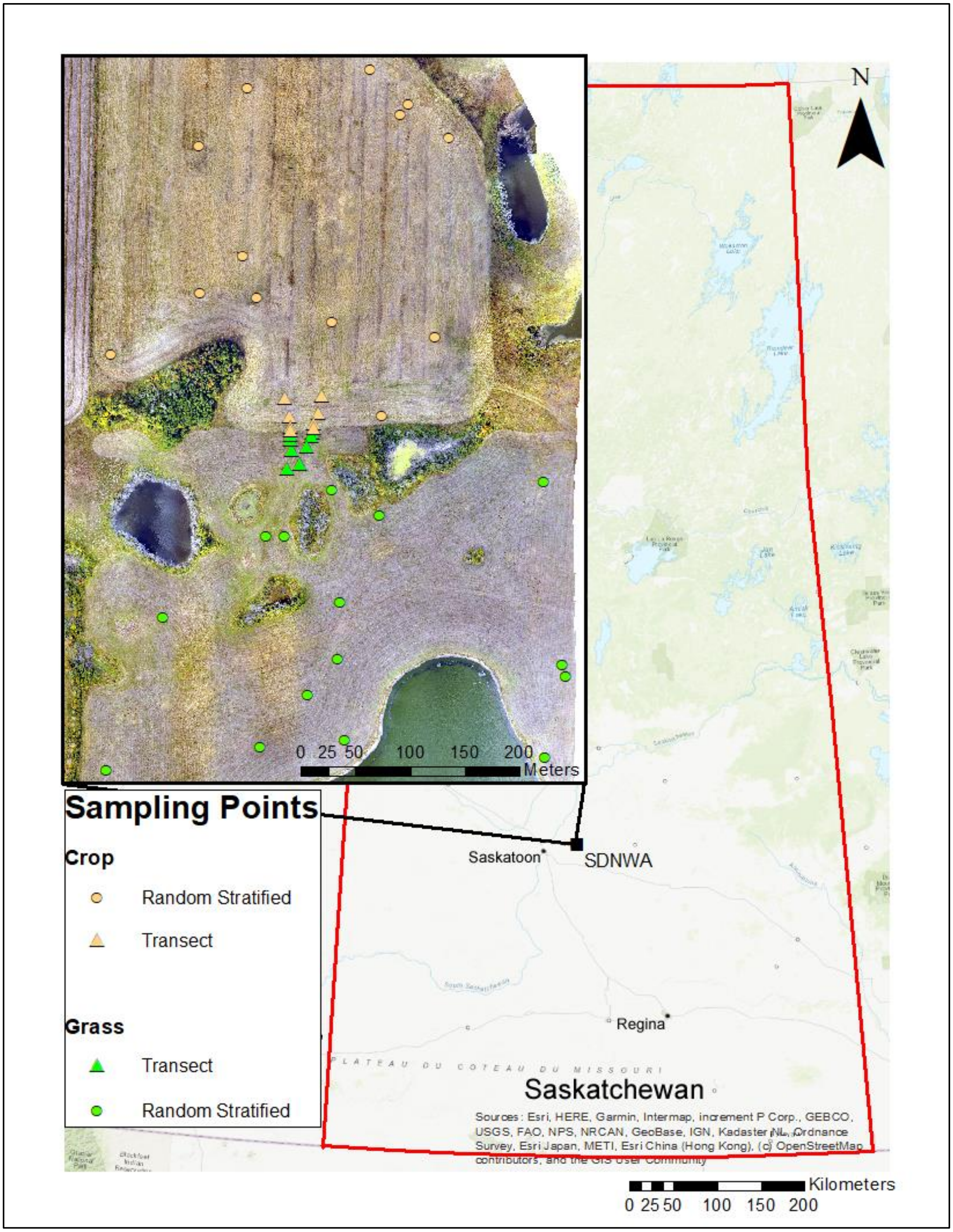


Figure 3.1. Map showing the location of the study site within the province of Saskatchewan as well as the sampling points and sampling designs used in the study.

3.4.5 Extracting remote sensing values

Tiles of remotely sensed images for red and NIR bands were mosaicked and geo-rectified with the ground control points using Pix4D Desktop (2018), then imported into ArcGIS Desktop (ESRI, 2017). In ArcGIS, a 0.5-m radius graphic buffer was drawn around each sampling point and the red- and NIR-reflectance values within the resulting polygons were extracted using zonal statistics. Remote sensing values were also extracted for a 20-m grid that extended across the cropland in the sampling area.

3.4.6 Statistical analysis

Statistical analysis was completed using R (R Core Team, 2018). Comparisons between red and NIR reflectance, and soil properties were done based on Fox and Sabbagh's (2002) soil line Euclidean distance (SLED) formula (Formula 3.1). NIR reflectance values were plotted against the red reflectance values from the 20-m grid (Fig. 3.2) to construct what is referred to as the NIR-red spectral space (Zhang et al., 2019). The distribution of points within the NIR-red reflectance space have a triangle distribution pattern with the bottom of the triangle representing the bare soil line (Zhang et al., 2019). SLED calculates the Euclidean distance of the sampled pixel's reflectance values away from the minimum point (left-most extreme point) of the bare soil line point to estimate soil organic carbon (SOC) (Fox and Sabbagh, 2002).

Formula 3.1: Soil Line Euclidean Distance

SLED= $\sqrt{(\mathrm{NIR}_{\mathrm{SL}} - \mathrm{NIR}_{\mathrm{min}})^2 + (\mathrm{R}_{\mathrm{SL}} - \mathrm{R}_{\mathrm{min}})^2}$

NIR= Near infrared reflectance

R= Red reflectance

SL= Sample location

Min= Minimum point on soil line

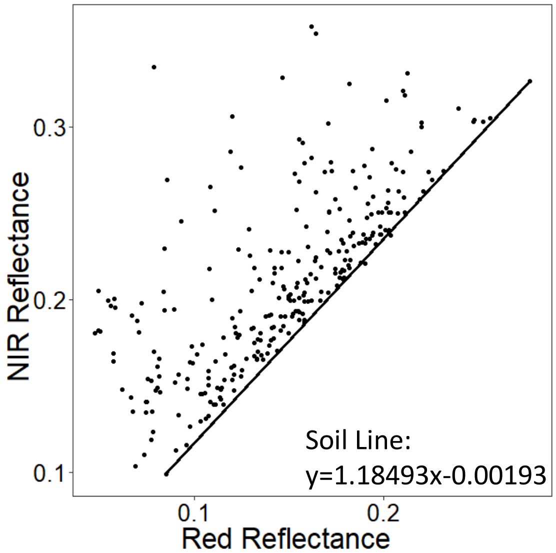


Figure 3.2. Plot showing the relationship between near infrared reflectance (NIR) and red reflectance of soil, in a cropland after harvest. The line indicates bare soil (i.e., soil line).

This study also modified the SLED formula (Formula 3.2) in attempts to provide smoother results than SLED. This modification is referred to as Modified Soil Line Distance (MSLD). Instead of relating a sample point directly to the minimum point on the soil line MSLD calculates what the near infrared reflectance value of the sample point would be if it fell directly on the soil line based on its corresponding red reflectance value. The Euclidean distance of that sampling point from the minimum point of the soil line is then used to estimate SOC.

Formula 3.2: Modified Soil Line Distance

MSLD= $\sqrt{R^2 + [M(R + I)]^2}$

R= Red reflectance

M= Slope of soil line

I= Intercept of soil line

Many of the points in Fig. 3.2 are away from the soil line. Points closest to the soil line are either bare soil or have very low vegetative cover. Points far from this line indicate the presence of vegetative material covering the soil. SLED (and subsequently MSLD) is meant to be used when the soil is bare and does not account for soil cover. In attempts to account for the vegetative cover a threshold parallel to the soil line was set where sample points above threshold line were excluded from analysis (Fig. 3.3). Since the grassland had little to no bare soil SLED and MSLD were only performed on the cropland.

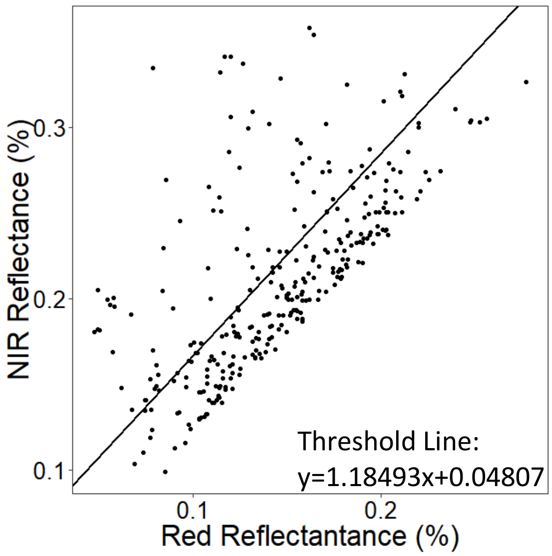


Fig. 3.3 Plot showing the relationship between near infrared reflectance (NIR) and red reflectance of soil in a cropland after harvest. Points above the threshold were excluded from analysis due to excess vegetative cover.

3.4.7 Digital soil mapping

Digital soil modelling was completed utilizing the point cloud data collected with the RPAS. Using the point cloud data Pix4D Mapper Pro outputs a digital surface model. A digital surface model includes features like vegetation and buildings. This model was taken into SAGA GIS (Conrad et al., 2015) and converted into a digital terrain model (DTM) (represents a bare earth surface) using a slope filter (Vosselman, 2000). A selection of elevation derived co-variates based on or related to previous DSM research were chosen for the digital soil modelling of soil organic carbon (Table 3.1). Nineteen of the crop sampling points that measured soil organic carbon were also used as co-variates in the crop model and 20 of the grassland points were used in the grassland model. Of these points, 75% were randomly selected to train the corresponding model. DSM uses both the co-variate data and the training points were used to interpolate SOC across the extent of the DTM coverage via random forest regression. The remaining 25% of the points were used for internal model testing. The best models (Fig. 3.4) were selected based on this internal validation. In order to provide a measure of significance, a linear regression was applied to the model results using both the training and validation points.

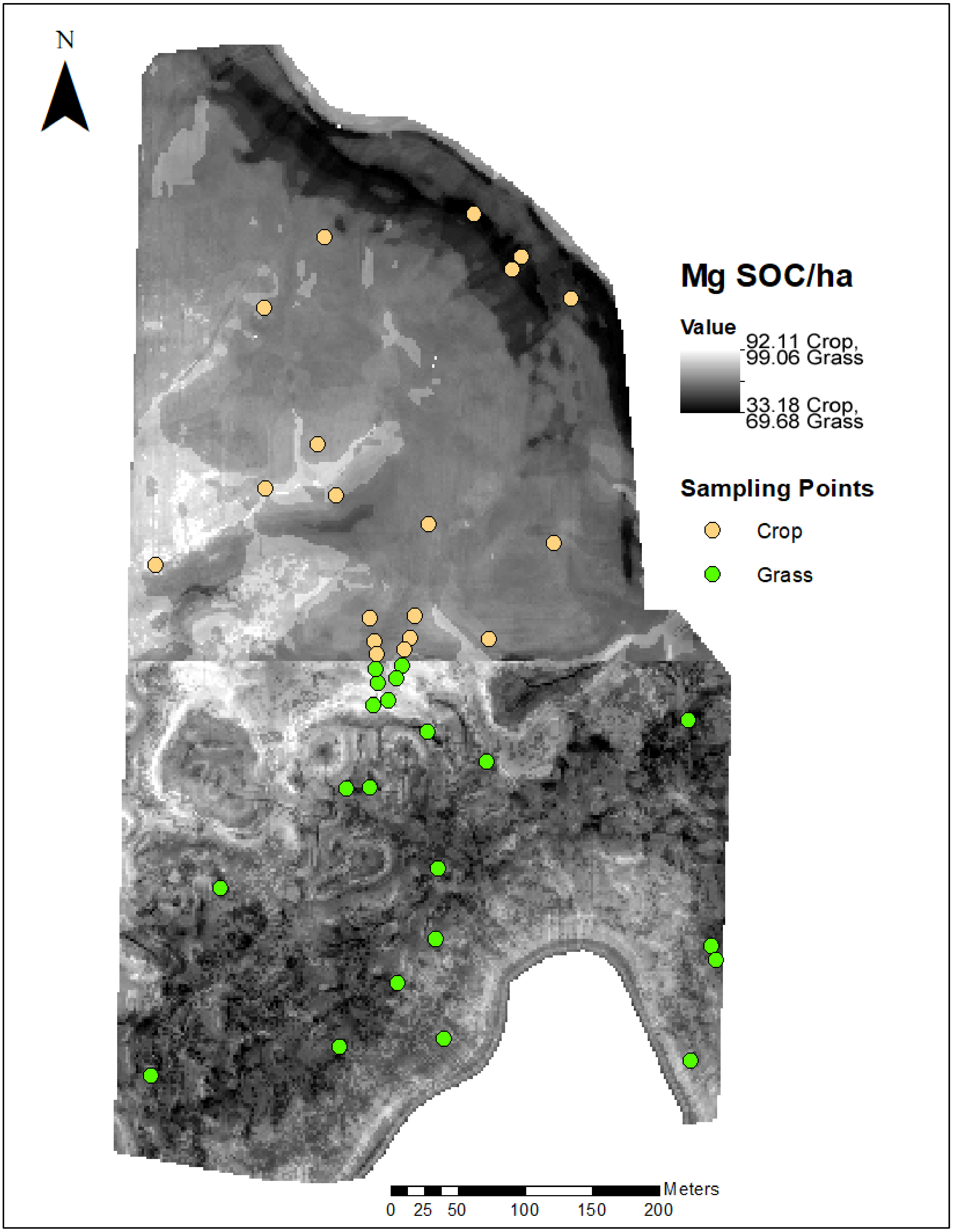


Figure 3.4. Map showing the results of digital soil mapping for organic carbon to a depth of 15 cm. Two models are shown, one run exclusively with crop points and one run exclusively with grass points. Results are based on factors derived from a digital surface model produced by the remotely piloted air system and soil sampling.

Table 3.1 Co-variates used for digital soil mapping models and their references.

Co-variate	Reference
Aspect	Kiss (2018)
Catchment Area	Kiss (2018)
Channel Network Base	This study
Channel Network Distribution	This study
Chlorophyll Index-Green	This study
Convergence Index	Kiss (2018)
Digital Terrain Model	McBratney et al. (2003)
Downslope Curvature	This study
Local Curvature	This study
Local Downslope Curvature	This study
Local Upslope Curvature	This study
LS (Slope length and steepness) Factor	Kiss (2018)
Modified Catchment Area	This study
Normalized Difference Vegetation Index (NDVI)	Malone et al. (2009)
Plan Curvature	Kiss (2018)
Profile Curvature	Kiss (2018)
Relative Slope Position	Behrens et al. (2010)
Slope	Kiss (2018)
Stream Power Index	This study
Topographic Position Index	Nussbaum et al. (2018)
Topographic Wetness Index	Kiss (2018)
Total Catchment Area	This study
Upslope Curvature	This study
Valley Depth	Kiss (2018)

3.5 Results and Discussion

3.5.1 Soil line-based indices

Even without accounting for excessively vegetated data points soil organic carbon (SOC) was found to have a logarithmic relationship with both SLED (Fig. 3.5A) and MSLD (Fig. 3.5C). The predictive capability of the MSLD relationship was found to be three times higher than that the SLED relationship. However, the strength of the MSLD correlation with SOC was relatively low with an r^2 of 0.307. When excessively vegetated data points were removed from analysis the strength of both the SLED and MLSD correlations improved. The SLED improvement was threefold (Fig. 3.5B) while the MSLD r^2 only improved by 0.041 (Fig. 3.5D).

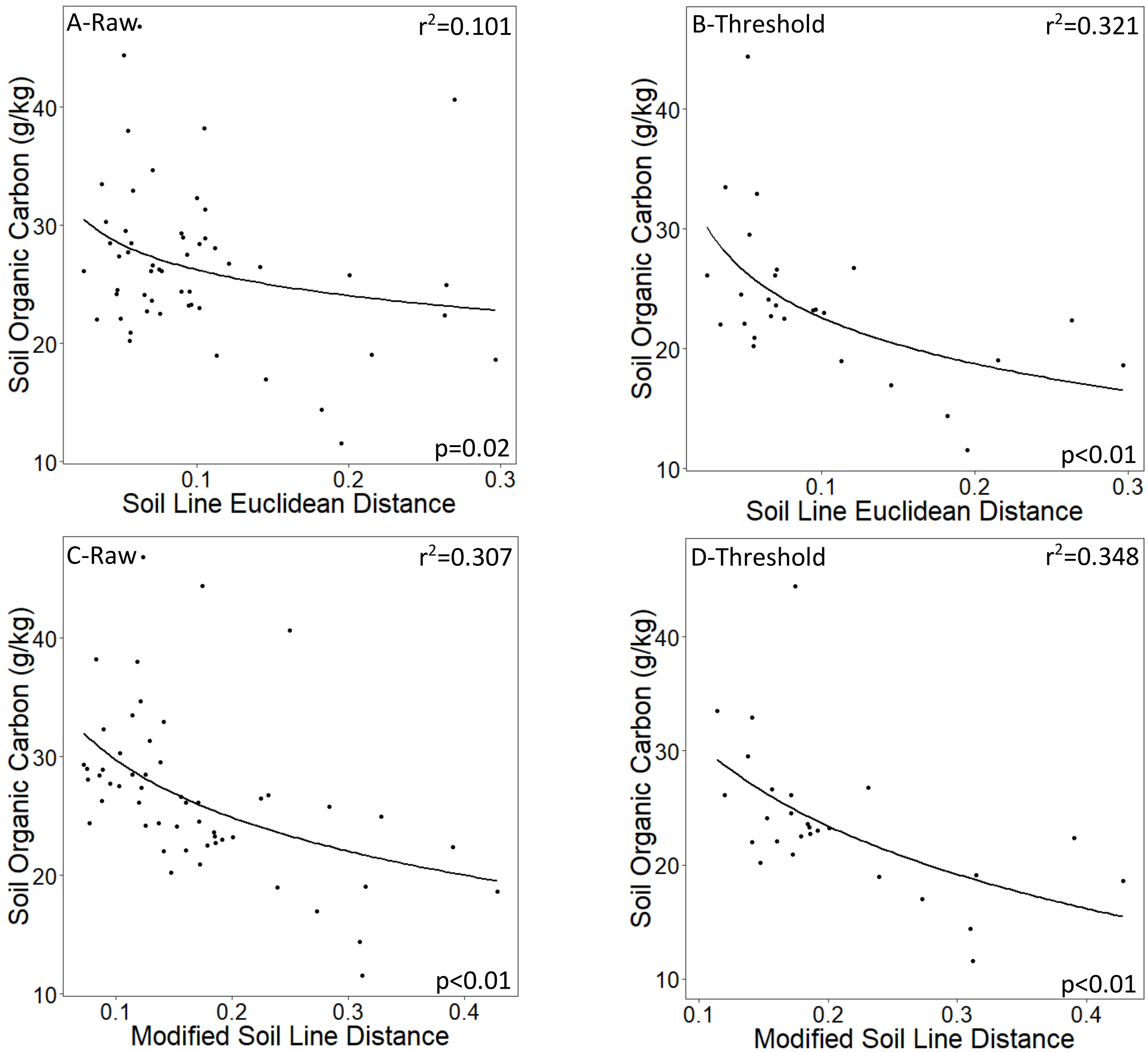


Figure 3.5. Plots from post-harvest cropland showing: A) the logarithmic relationship between soil organic carbon (SOC) and the Euclidean distance between NIR and red reflectance B) the logarithmic relationship between soil organic carbon (SOC) and the Euclidean distance between NIR and red reflectance, data points with reflectance values above a threshold have been removed to account for excess vegetative cover; C) the logarithmic relationship between measured soil organic carbon (SOC) and the modified Euclidean distance between NIR and red reflectance and; D) the logarithmic relationship between measured soil organic carbon (SOC) and the modified Euclidean distance between NIR and red reflectance, data points with reflectance values above a threshold have been removed to account for excess vegetative cover.

Fox and Sabbagh (2002) found highly correlated two-parameter exponential decay relationships between SLED and soil organic matter (SOM) at their two study sites with r^2 values of 0.68 and 0.79. While the Fox and Sabbagh study was measuring SOM, the relationship between SOM and SOC is generally consistent within an area (Heaton et al., 2016), and at this site the SOM would be approximately 50% SOC (Pribyl, 2010). This likely did not contribute to the difference in results. In Fox and Sabbagh's study most reflectance collection locations fell within 5 degrees of the soil line while in this study there was much greater variance (see Fig 3.2). Conservation tillage is practiced at this study site and as result crop stubble, residue, and some weed growth was prevalent throughout the site. This soil cover significantly increased the variance of NIR and red reflectance. Using MSLD was comparatively as effective for improving the estimation capability of SLED as removing excessively vegetated data points but both approaches were still inhibited by a lack of bare soil and had relatively low predictive capabilities.

3.5.2 Digital soil mapping

Digital soil mapping (DSM) of the cropland out-performed the soil line based approachess implemented in this study. The correlation of the model's internal validation (Fig. 3.6) was twice as strong as that of MSLD with a threshold applied (Fig 3.5) and was comparable to the results of Fox and Sabbagh's (2002) study. DSM of the grassland was still effective and outperformed the soil line approaches but its correlation was weaker than that of the cropland model (Fig. 3.6).

The factors most likely contributing to the lower performance in grassland are heterogeneity in both the soil conditions and plant communities. One feature of the grassland portion of the study site is a long slope leading to a large pond. This area is stonier than the rest of the site with less plant growth. The hummocky terrain of the site has resulted in many small wetlands occupying the site, so certain areas are consistently wetter and more plant productivity occurs around these wetlands. This also contributes to heterogeneity in the make-up of plant communities throughout the site. Plant community heterogeneity is a known issue when it comes to the agricultural management of grasslands (Schellberg et al., 2008). Heterogeneity in soil conditions and plant communities means the input of SOM and SOC will vary greatly as well which makes it more difficult to effectively model.

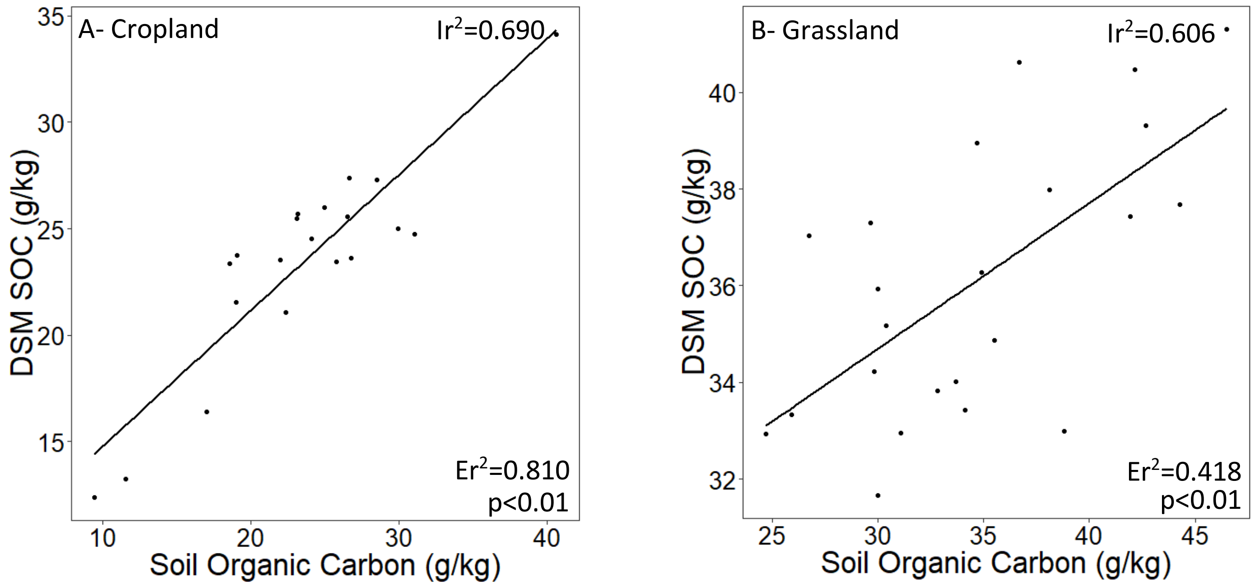


Figure 3.6. Plots showing the linear relationship between sampled soil organic carbon values and soil organic carbon values estimated using Digital Soil Mapping in: A) a cropland after harvest and; B) a grassland after haying. Ir^2= internal model validation r^2, Er^2= external validation r^2 (model results against all sampled results).

The largest advantage DSM has over the soil line methods of SOC is that vegetative cover is not a significant factor. DSM can be based entirely on topographical co-variates which removes the influence of soil cover. DSM requires more physical sampling than the soil line approaches (which still need some samples to tie results to actual values) in order to train the models but it is still an improvement over intensive sampling practices like grid sampling for estimating SOC across large areas. Another advantage of DSM is cost. While the soil line methods implemented in this study required the purchase and use of an expensive multi-spectral sensor. DSM only required the use of the camera that the RPAS came equipped with. A further advantage to not requiring an additional sensor is that the complexity of imagery collection and processing is decreased. The multi-spectral sensor requires the use of a calibration panel and the mosaicking of two sets of images instead of just one. The time needed for both imagery collection and processing was increased when using the multi-spectral sensor.

3.6 Conclusions

RPAS based remote sensing methods for estimating surficial SOC can be successfully implemented and MSLD is an improvement over SLED. However, the heterogeneity of soil cover negatively affects the ability of these approaches to provide results with a strong predictive capacity. Where a best management practice like conservation tillage is applied to cropland the effectiveness of soil line methods will be limited, even when attempts are made to account for vegetative cover. The high-resolution imagery produced by RPAS makes it easier to distinguish between vegetated and bare soil pixels, but if most of the pixels are vegetated then little benefit is provided by this advantage.

The predictive strength of the remote sensing reliant methods of SOC measurement implemented in this study show that although remote sensing cannot replace physical sampling entirely (especially when soil cover is prevalent), it can supplement and reduce physical soil sampling through DSM. The digital terrain models that can be produced by RPAS are essential to topography-based DSM and do not require an expensive multi-spectral sensor (which also adds complexity to image collection and processing). While DSM still has error, and is not absolutely accurate, it does capture the relative differences in SOC which is enough to inform the delineation of management zones for precision agriculture.

Chapter 4.0

DELINEATING FUNCTIONAL LAND MANAGEMENT ZONES IN ANNUAL AND PERENNIAL LANDSCAPES

4.1 Preface

This chapter utilizes the existing framework of precision agriculture and management zones to provide a quick and efficient way of capturing the variability of the soil properties that are key to soil functions across agricultural landscapes. This in turn provides the method by which soil function can be quickly and efficiently estimated, tracked, and valued.

4.2 Abstract

Soil provides many of farmland's ecosystem services and is essential for functions such as: food production, water storage, carbon cycling and storage, functional and intrinsic biodiversity, and nutrient cycling. It is important to manage farmland soils to increase both crop productivity and these other environmental benefits. Precision agriculture is seen to be an effective management tool for sustainably managing agricultural production; management zones are an integral part of its implementation. Management zones have the potential to be utilized not only to capture variation in plant productivity but in other soil functions as well. The objective of this chapter was to develop and assess a zone delineation method that considers multiple soil functions. The capacity of the soil to perform soil functions depends on certain key properties: slope, soil carbon, nitrogen, phosphorus, and texture. Soil organic carbon (SOC) correlates well with most of the key soil properties and it can be quickly measured and interpolated across a field by combining remotely piloted air systems and digital soil mapping. It was used in conjunction with slope position to create functional land management zones (FLMZs). The FLMZ method had mixed results. In terms of plant productivity in cropland and grassland, the delineated zones could capture within-field variation, but were far less effective when factors unrelated to SOC were impacting plant growth. The FLMZ method successfully indicated within-field variation of the soil potential to provide other soil functions related to SOC. The management zones seen as best for plant productivity did not always line up with the zones estimated to be best at providing other soil functions.

4.3 Introduction

Food production needs to increase by 60% by 2050 (Coyle et al., 2016) but a major question is whether this can be achieved without decreasing ecosystem function. Poor soil management practices can lead to significant decreases in function (Anderson and Cerkowniak, 2010; Pennock et al., 2011). In agricultural areas, soil is essential for many ecosystem functions including: food production; water storage, purification, and regulation; functional and intrinsic biodiversity; carbon cycling and storage; as well as nutrient cycling and provision (O'Sullivan et al., 2015; Poggio and Gimona, 2016). It is necessary to understand how to manage for soil function in order to achieve sustainability (Poggio and Gimona, 2016). Managing soil for multiple functions requires further research in Canada and better methods of implementation need to be developed.

Agricultural areas are a mosaic of croplands, shelterbelts, woodlands, wetlands, roads, buildings, pastures, and grasslands. These different land uses provide many soil-derived functions and differ in their capacity to provide each function depending on their management and soil properties (Schulte et al., 2014; Coyle et al., 2016). A specific example is that annual cropping systems have significantly less belowground plant matter than natural grassland systems (Fuller, 2010). Certain soil properties are important or key to the different soil functions. For crop yield management the most considered soil properties are: electrical conductivity (measure of salinity [Scudiero et al., 2016]), texture, topography, organic matter, carbon, phosphorus, potassium, and nitrogen. Out of these, texture and organic carbon content have been highlighted as the most important (Gozdowski et al., 2014). Water storage, purification, and regulation have been linked to soil organic matter, organic carbon, bulk density, texture, and topography (Biswas and Si, 2011; Birgé et al., 2016; Greiner et al., 2017). Soil pH, nitrogen, carbon, phosphorus, salinity, and topography are all key to microbial activity and biodiversity (Birgé et al., 2016; Wickings et al., 2016; Xue et al., 2018). Carbon sequestration and nutrient provision are soil functions inherent to soil properties and can be directly measured, but these functions are both influenced by topography (Guo et al., 2011; Miller, 2016). The importance of soil organic carbon and topography is well-established in the literature (Table 4.1), as is the pattern that increasing soil carbon tends to increase soil N and P stocks as well as other nutrients (Milne et al., 2015). The interrelation among soil function and properties means that the key soil properties for multiple soil functions overlap making simultaneous management of these functions possible.

Table 4.1. Summary of soil properties most relevant to soil functions and references.

Soil Function	**Key Soil Properties**	**Reference(s)**
Carbon Sequestration	*Organic Carbon*, *Total Carbon*, *Topography*	Guo et al., (2011)
Water Storage, Cycling, and Purification	Bulk Density, *Organic Carbon*, Organic Matter, Salinity, Texture, *Topography*	Biswas and Si, (2011); Birgé et al., (2016); Greiner et al., (2017)
Habitat for Microbial Biodiversity	*Carbon*, Nitrogen, pH, Phosphorus, Salinity, *Topography*	Birgé et al., (2016; Wickings et al., (2016); Xue et al., (2018)
Nutrient Cycling	*Carbon*, Nitrogen, pH, Phosphorus, *Topography*	Guo et al., (2011); Miller, (2016)
Plant Productivity	*Carbon*, Electrical Conductivity, Nitrogen, Organic Matter, Phosphorus, Potassium, Texture, *Topography*	Gozdowski et al., (2014)

Precision Agriculture (PA) is heralded as a key direction for sustainable agricultural development (Moral et al., 2010; Zhang et al., 2014). Management zones are the basic unit with which PA is applied. These homogenous sub-field units allow for the rate of application of inputs like fertilizer, herbicides, and pesticides to be adjusted for what each zone specifically requires. Not only does this reduce chemical costs but it also reduces the risk of environmental contamination; reducing the amount of chemicals applied reduces the potential for contamination via runoff or drift (Mulla, 2013). Management zone delineation methods are often centered around soil properties and their measurement (Gozdowski et al., 2014). When used to delineate management zones, soil properties are typically only considered in their relation to crop yield.

Since management zones have been focused on crop productivity, management zones are primarily implemented in cropland. Previous research has also been conducted on the implementation of management zones in grassland and while it can be successful (Pena-Yewtukhiw et al., 2017) there are multiple constraints limiting its application (Schellberg et al., 2008; Cicore et al., 2016). The soil function primarily considered in these studies was plant productivity but grazing was a limiting factor. In the absence of grazing, grassland management zones could better capture variability. The overall value of cropland and grassland could be calculated by applying a management zone method that focusses on the key soil properties for multiple soil functions allowing for the ability of the soil to provide these functions to be estimated.

The objectives of this study were to: 1) develop a method for delineating management zones that is indicative of multiple soil functions; and 2) assess the ability of a management zone delineation method based on organic carbon and slope position to capture spatial variation of key soil properties and plant growth in both annual cropland and perennial grassland.

4.4 Materials and Methods

4.4.1 Study Sites

This study was conducted at two sites in central Saskatchewan (see Fig. 4.1): the St. Denis National Wildlife Area (SDNWA) and the Conservation Learning Centre (CLC). The SDNWA is located 40 km east of Saskatoon, in the Moist Mixed Grassland ecoregion (HABISask, 2018). The soils are mapped as part of the Weyburn association (University of Saskatchewan, 2018) and were primarily found to be Dark Brown Chernozems at upper slope positions and Black Chernozems at lower slope positions. The CLC is located 23 km south of Prince Albert, in the Boreal Transition ecoregion (HABISask, 2018). The soils are a part of the Blaine Lake and Hamlin soil associations (University of Saskatchewan, 2018) and were primarily found to be Black Chernozems [Soil classifications for a subset of the sample points can be found in Appendix A]. Both sites feature hummocky topography and contain perennial grassland (hayed tame forage; grass mix- primarily brome) as well as annual cropland. Both sites were seeded in May; barley at the SDNWA and wheat at the CLC. Both sites had fertilizer applied in May after soil sampling. At the SDNWA granular fertilizer was applied at a rate of 95 kg/ha actual N, 37 kg/ha actual P, and 17 kg/ha actual S. At the CLC liquid fertilizer was applied at a rate of 90 kg/ha actual N and 28 kg/ha actual P.

4.4.2 Sampling design

Sampling points were selected via random stratification based on slope position. Both sites were segmented into four slope classes using the Miller method (Miller and Schaetzl, 2015) and 40 points were selected for both grassland and annual cropland at both sites (see Fig. 4.2 and 4.3).

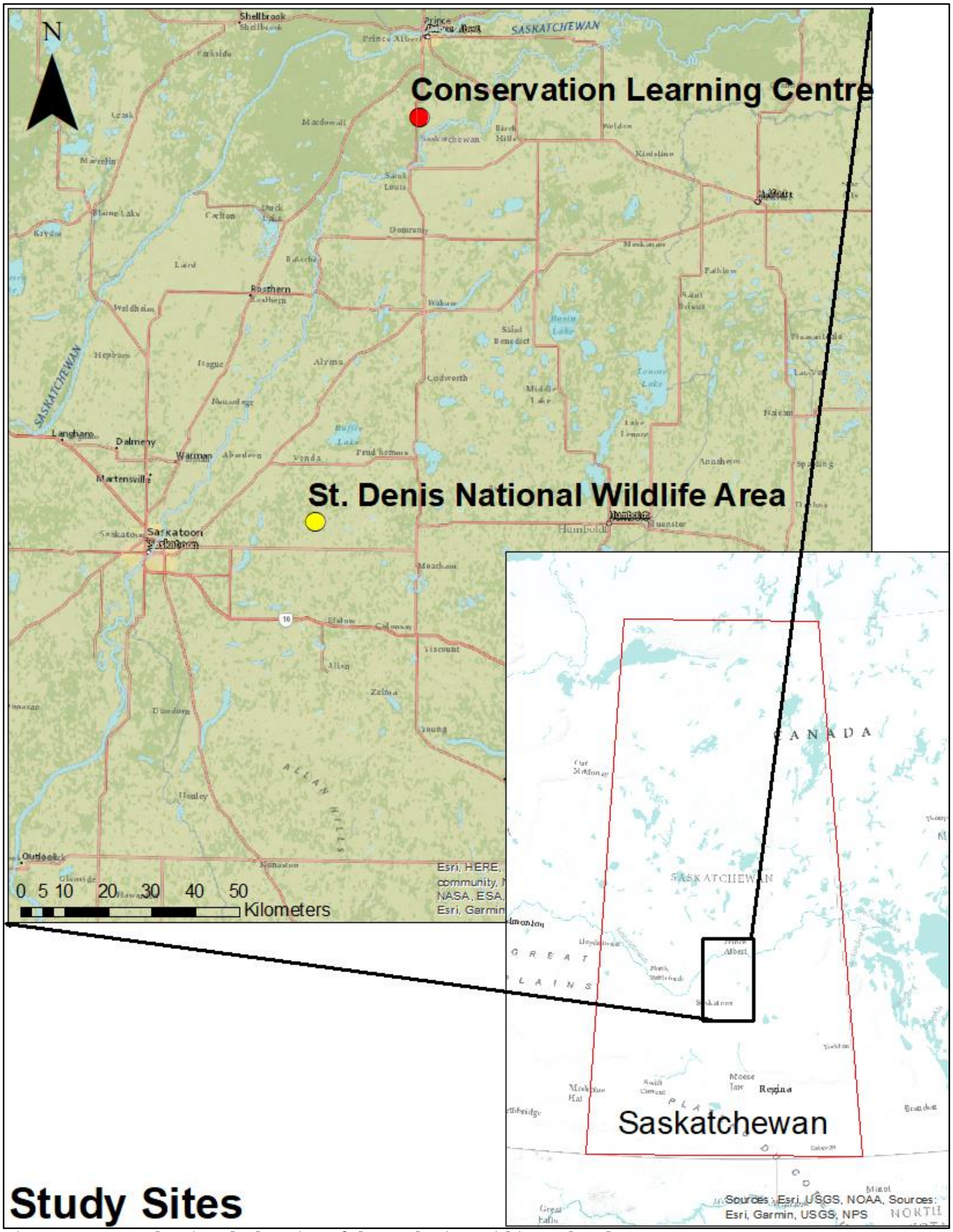


Figure 4.1. Map showing the location of the study sites within Saskatchewan.

Figure 4.2. Map of the Conservation Learning Centre study site showing the slope position delineation of the site and the sample point locations.

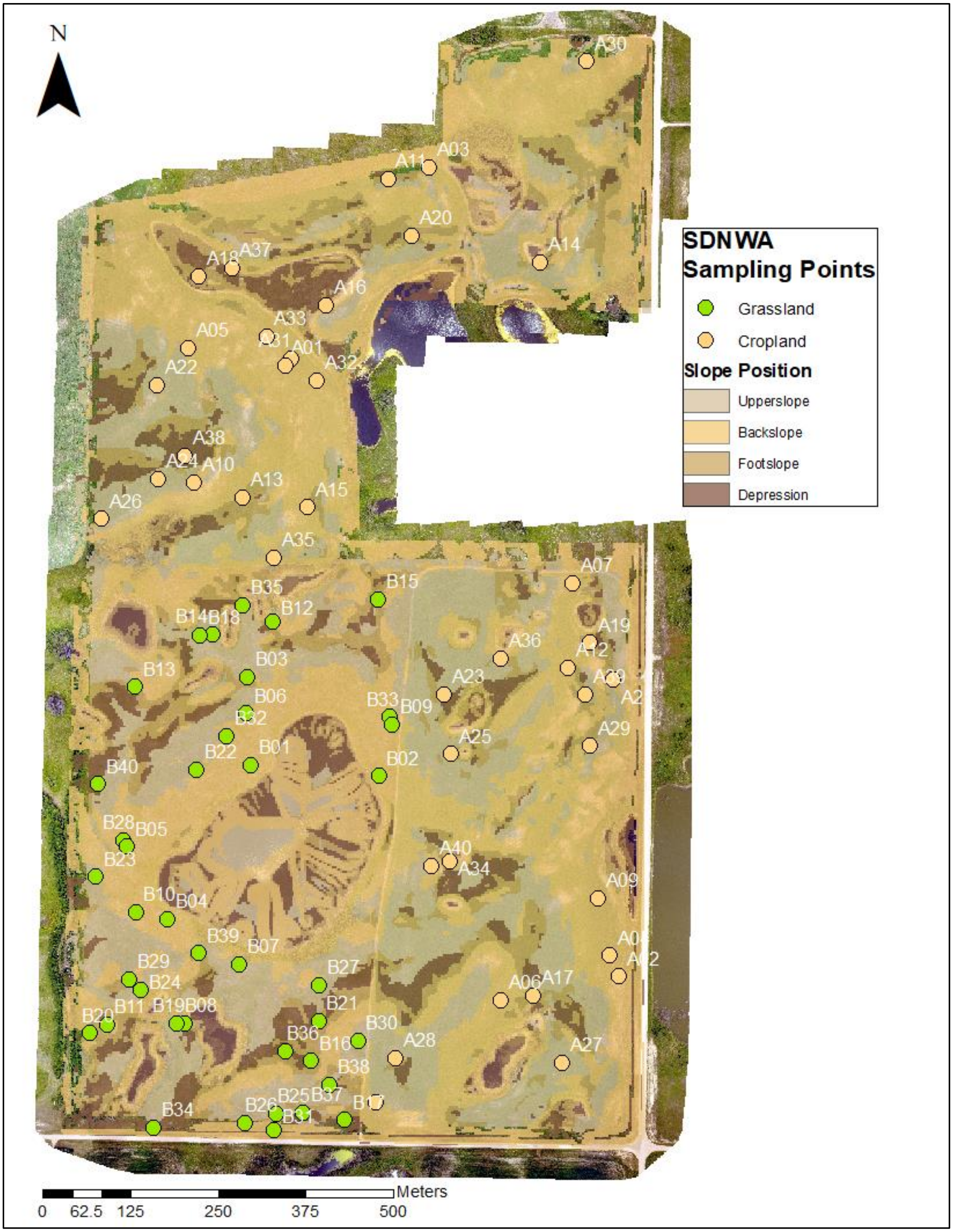


Figure 4.3. Map of the St. Denis National Wildlife Area study site showing the slope position delineation of the site and the sample point locations. The space between B01, B02, B04, and B07 is occupied by a large wetland which prevents accurate sensing of the elevation.

4.4.3 Soil analysis

This study focused on soil properties to a depth of 15 cm. This shallow depth allows for quicker measurement and the potential to be tied to reflected radiation measured from a remote piloted air system (RPAS). The RPAS sensors do not sense radiation from beneath the soil surface. Soil samples were collected from all sampling points using E-365 edelmen augers (Eijkelkamp Soil & Water, Gelderland, the Netherlands) in both the spring of 2017 and 2018. Samples were sealed in bags and stored in a 4°C fridge between collection and subsampling for soil moisture analysis (began day after collection). The remaining soil was subsequently air-dried and ground. Further subsampling occurred for the purposes of ball-grinding. All samples were analyzed for gravimetric soil moisture, total and organic carbon, total and organic nitrogen, pH, electrical conductivity (EC), phosphorus (P), and texture. Soil organic carbon (SOC), total soil carbon (TC) and total soil nitrogen (TN) were analyzed via dry combustion. SOC and TC were measured using a LECO C632 elemental analyzer (LECO, Michigan, U.S.A.): SOC at a furnace temperature of 840°C (Wang and Anderson, 2000) and TC at a furnace temp of 1100°C (Skjemstad and Baldock, 2007). A LECO TruMac CNS analyzer (LECO, Michigan, U.S.A.) was used to measure TN at a furnace temp of 1350°C (Rutherford et al., 2007). Mineral nitrogen (MN) -nitrate and ammonium- were measured via KCl extraction (Houba et al., 2000) and colorimetry using an AutoAnalyzer (SEAL, Wisconsin, U.S.A.). Organic nitrogen (ON) was then calculated by subtracting the combined values of nitrate and ammonium from TN. The EC and pH were measured via water extraction and pH/conductivity meter (Miller and Curtin, 2007). A modified Kelowna extraction (Qian et al., 1994) and colorimetry using an AutoAnalyzer (SEAL, Wisconsin, U.S.A.) was used to measure P. Hand texturing was completed for all sampled points and particle size analysis using a pipette method (Indorante et al., 1990) was completed for a subset of the samples. Additionally, in the fall of 2018 soil cores were collected from a subset of the sampling points to a depth of 1 m. Bulk density (BD) was calculated for the subset using the 0-15 cm segment of their cores. The remainder of the sample points had their BD interpolated using kriging.

4.4.4 Reducing key soil properties

To develop a delineation method based on all ten of the sampled properties would be counter-productive as the goal of this research is for this method to be quick and efficient method. It was necessary for a reduction in the number of soil properties considered in the method. Only carbon and topography were relevant to all the considered soil functions. Therefore it was decided that organic carbon and topography (slope position) would be the key properties considered in the delineation of functional land management zones (FLMZ). To corroborate the merits of this decision, once soil analyses were completed principal component analysis using R (R Core Team, 2018) was performed on the dataset to look at the relationships between the full set of measured soil properties.

4.4.5 Remotely piloted air system operation

In 2018, RPAS flights were conducted at the SDNWA on June 28 and July 27 and at the CLC on July 5 and 31. Flight days were chosen based on crop growth stages. The first flight was meant to coincide with stem elongation and the second flight was meant to coincide with heading (just before ripening). All flights were conducted using a DJI Phantom 4 (DJI, Shenzhen, China) with an attached Parrot Sequoia (Parrot Drones SAS, Paris, France) multi-spectral camera and sun sensor. The sun sensor corrects for any changes in sunlight occurring during flights. The DJI Phantom 4 internal camera captured RGB (Red, Green, Blue; standard colour) imagery while the Parrot Sequoia captured Red, Green, and Near-infrared (NIR) imagery. Flights were programmed using the DroneDeploy app (DroneDeploy, California, U.S.A). Flight parameters were consistent with a flight height of 90 m and speed of 10 $m \cdot s^{-1}$. All flights had 75% frontlap (top and bottom image overlap) and 75% sidelap (left and right image overlap). Before and after each flight imagery of a calibration panel (white card) was collected and those reflectance values were used to correct flight imagery during processing. Imagery captured by the DJI Phantom 4 Pro camera had a pixel size of 3.78 cm and imagery captured by the Parrot Sequoia had a pixel size of 9.11 cm. Flights were all flown within two hours of solar noon.

4.4.6 Ground control points

Both sites had ground control points (GCPs) installed for geo-correction and geo-rectification. These GCPs consisted of orange five gallon pail lids with a black ‘x’ painted on them, mounted on wooden stakes to prevent them from becoming covered by vegetation. GCPs were installed in a rough ‘x’ pattern across each study area (10 GCPs at SDNWA, 20 GCPs at CLC). The location of GCPs was recorded using a Trimble GeoExplorer 2005 series GeoXT GPS (Trimble, California, U.S.A.) with an accuracy of up to 0.43 meters.

4.4.7 Processing imagery

The imagery from both the DJI Phantom 4 camera and Parrot Sequoia were processed using the Pix4D Desktop (2018). This software mosaicked together the captured images and geo-rectified them using the GCPs during processing. The outputs of Pix4D were an orthomosaic (colour image), digital surface model, and reflectance maps of the bands captured by the Parrot Sequoia Camera. Pix4D can also output a digital terrain model but its quality was poor when compared to knowledge of the site. In order to create a more accurate digital terrain model the Pix4D DSM was taken into SAGA GIS (Conrad et al., 2015) where the DTM filter (slope-based) tool was used to create a DTM. Both a visual inspection and a GIS comparison to previous LIDAR-based DEM for SDNWA proved the final product of this method to be a more accurate representation of the site compared to the Pix4D produced DTM.

4.4.8 Quantifying productivity

The reflectance maps were used to calculate the plant productivity index Chlorophyll Index-Green (CIG) (Peng and Gitelson, 2012) within Pix4D and maps of this index were created for each site. This index was used to quantify crop and plant productivity when assessing the performance of the FLMZs. 20 points for each cover type at each site (except for SDNWA as the crop was reaped prior to sampling) were subsampled for yield. At each point a quadrat (1-m^2 for cropland and 0.5-m^2 for grassland) was laid out and the contained plant/crop was harvested. Samples were air dried then the grass samples were weighed for dry matter yield and the crop samples were weighed and threshed to determine grain yield. These results were used to confirm and calculate the relationship between CIG and productivity (Fig. 4.4). For cropland a change in CIG of 1 was equivalent to approximately 1.4 t/ha dry matter yield and in grassland a change in CIG of 1 was equivalent to approximately 1.3 t/ha dry matter yield.

Formula 4.1: Chlorophyll Index-Green

$$CIG = \frac{NIR}{Green} - 1$$

NIR= Near-infrared reflectance

Green= Green reflectance

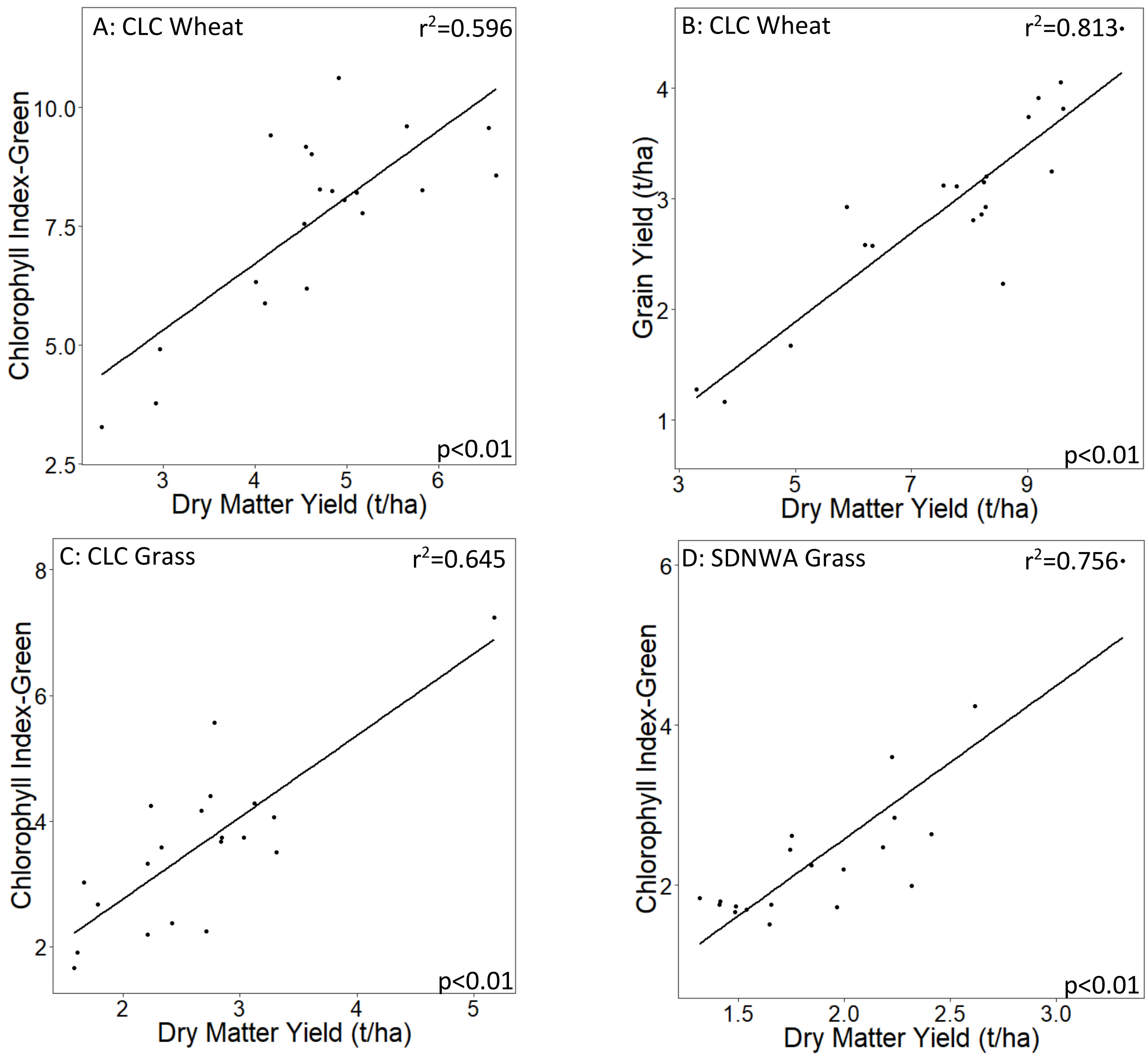


Figure 4.4. Plots showing: A) the linear relationship between Chlorophyll Index-Green (CIG) and the dry matter yield of wheat at the Conservation Learning Centre (CLC); B) the linear relationship between grain yield and the dry matter yield of wheat at the CLC; C) the linear relationship between Chlorophyll Index-Green (CIG) and dry matter yield of the grassland at the CLC and; D) the linear relationship between Chlorophyll Index-Green (CIG) and dry matter yield of the grassland at the St. Denis National Wildlife Area.

4.4.9 Digital soil mapping

A selection of elevation related co-variates based on previous DSM research were chosen for the digital soil modelling of soil organic carbon (Chapter 3: Table 3.1). These elevation co-variates were all created using SAGA GIS tools based on the DTM produced in SAGA. An additional co-variate was the surficial (0-15 cm) organic carbon data collected from the random stratified sampling. The same co-variates were used for both cover types at both sites. However, for each site, only the organic carbon data for the matching cover type was used for modelling; separate models were created for each cover type at each site. Of the 40 sampling points for each cover type and site, 75% were randomly selected to train the model and the remaining 25% were used to test the model. After the best models were selected, the models were tested again using all corresponding sampling points, including samples collected by other groups in the project. For the purposes of management zone delineation, all models were broken into three classes of relative SOC using Jenks natural breaks optimization (in ArcGIS): high, medium, and low SOC. These classifications were then compared to the sample data to check for significant differences between the groups at $p<0.1$. The CLC crop, SDNWA crop and SDNWA grass models were all left as three classes while the CLC grass model was reduced to two classes (high and low SOC).

4.4.10 Slope position classification

A slope position classification was performed based on a 3-m resolution DTM created for the sites using the Miller method (Miller and Schaetzl, 2015). The Miller method requires the software ArcGIS (ESRI, 2017) and GRASS (GRASS Development Team, 2017). In this method there are three steps performed to classify a site into five slope positions (see Fig. 4.5). Once the classification was performed for each site, slope position classes were used to choose sampling points (summit and shoulder were combined into 'upper slope'). Once the points were selected the Miller method classes were ground-truthed to test the model. When broken into four slope classes the models were close to 63% accurate. When footslope and toeslope classes were combined the models were close to 74% accurate. Therefore, three slope classes were used moving forward.

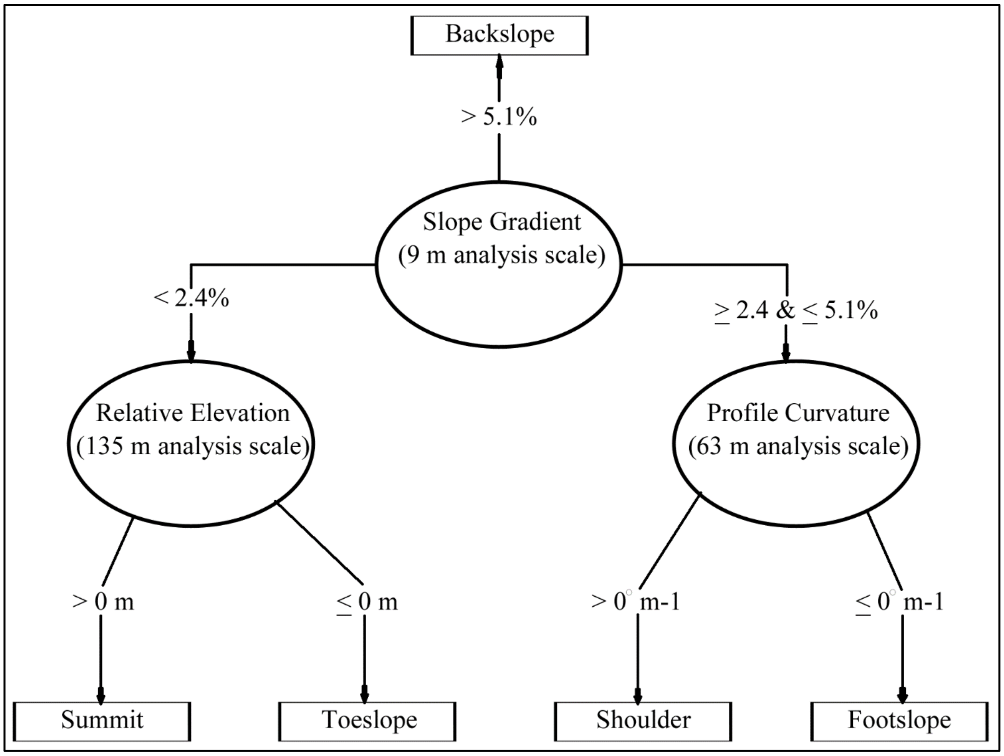


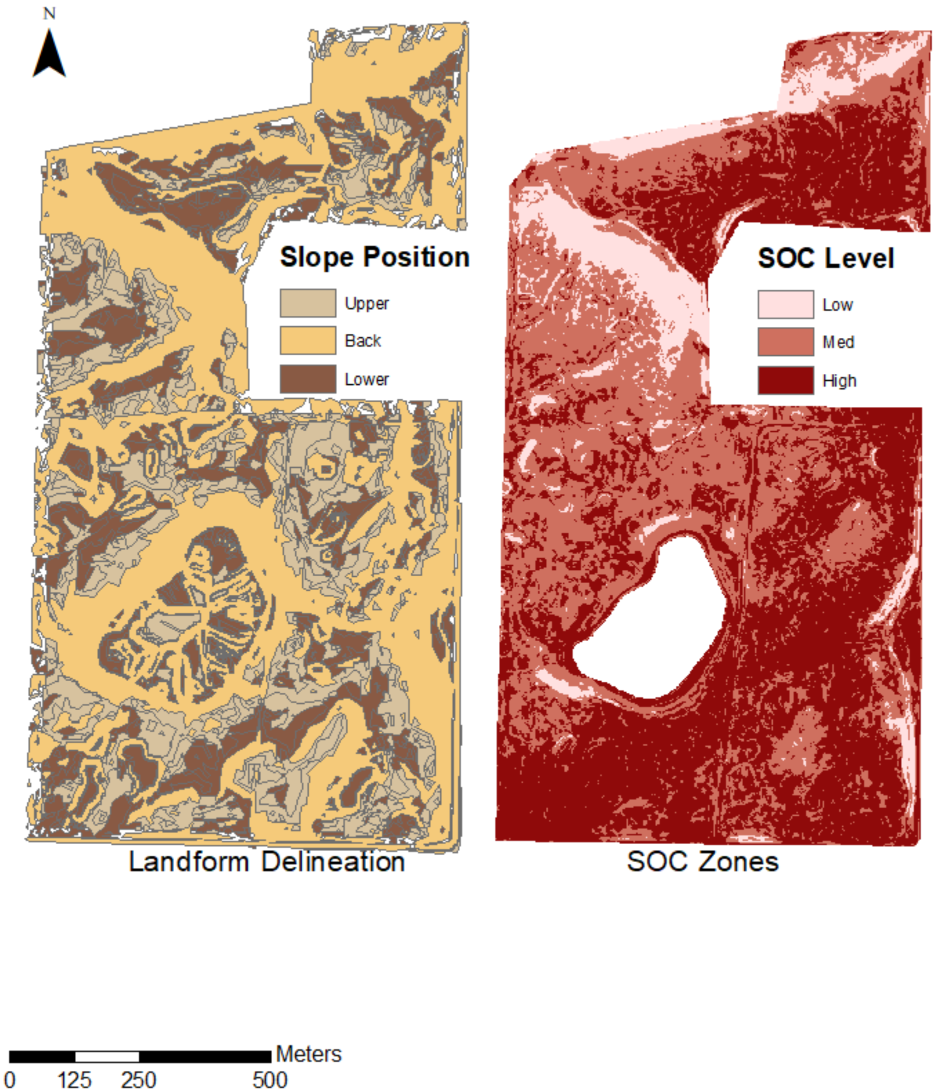
Figure 4.5. Flow chart showing breakpoints for slope position classification using the Miller method (Miller and Schaetzl, 2015).

4.4.11 Delineating functional land management zones

Once the digital soil modelling and slope classification were completed, the functional land management zones were delineated based on the three slope classes and the 2-3 organic carbon classes (see Fig. 4.6). In ArcGIS a 3-m grid was overlain on each cover type at both sites to form a basis for the FLMZ. Each 3x3 block within the grids were then attributed the slope and carbon class values covering its position. The SOC classes were numbered 3-1 (HighC, MediumC, LowC) or 2-1 (HighC, LowC). The slope classes were numbered 1-3 (Upper, Backslope, Lower). The resulting Table was then brought into Management Zone Analyst software (Fridgen et al., 2004) which performs fuzzy classification to create zones of similar clusters. The analysis was performed using the carbon classes and slope classifications. The number of zones tested were from 3-9 zones (9 zones being maximum number of zones possible with two factors with three levels each and the analytical capacity of the program) and whichever number of zones had the smallest entropy and best fuzzy performance index were selected. This resulted in the SDNWA cropland being delineated into seven zones, the CLC cropland and SDNWA grassland into five zones, and the CLC grassland into four zones [A summary of the FLMZ methodology can be found in Appendix B].

4.4.12 Functional land management zone comparison

Statistical analysis of the FLMZs was completed using R (R Core Team, 2018). Tukey tests were applied to compare soil properties and productivity between zones. The threshold for significance was $p<0.1$.



Slope Classification	Relative SOC Content	Initial Zone
Upper	High	Upper_HighC
Upper	Medium	Upper_MedC
Upper	Low	Upper_LowC
Back	High	Back_HighC
Back	Medium	Back_MedC
Back	Low	Back_LowC
Lower	High	Lower_HighC
Lower	Medium	Lower_MedC
Lower	Low	Lower_LowC

FLMZ Input Factors

Figure 4.6. Map showing the factors intersected to create the functional land management zones and the initial zones created. Soil organic carbon was predicted using digital soil mapping. Slope positions were defined using the Miller method (Miller and Schaetzl, 2015).

4.5 Results

4.5.1 Soil property relationships

In the cropland, carbon, moisture, and many of the nutrients were positively correlated, and these properties had a negative correlation with bulk density (Fig. 4.7). The grasslands shared these correlations but the correlations were weaker and P and moisture were less correlated with OC and the other nutrients (especially at the Conservation Learning Centre).

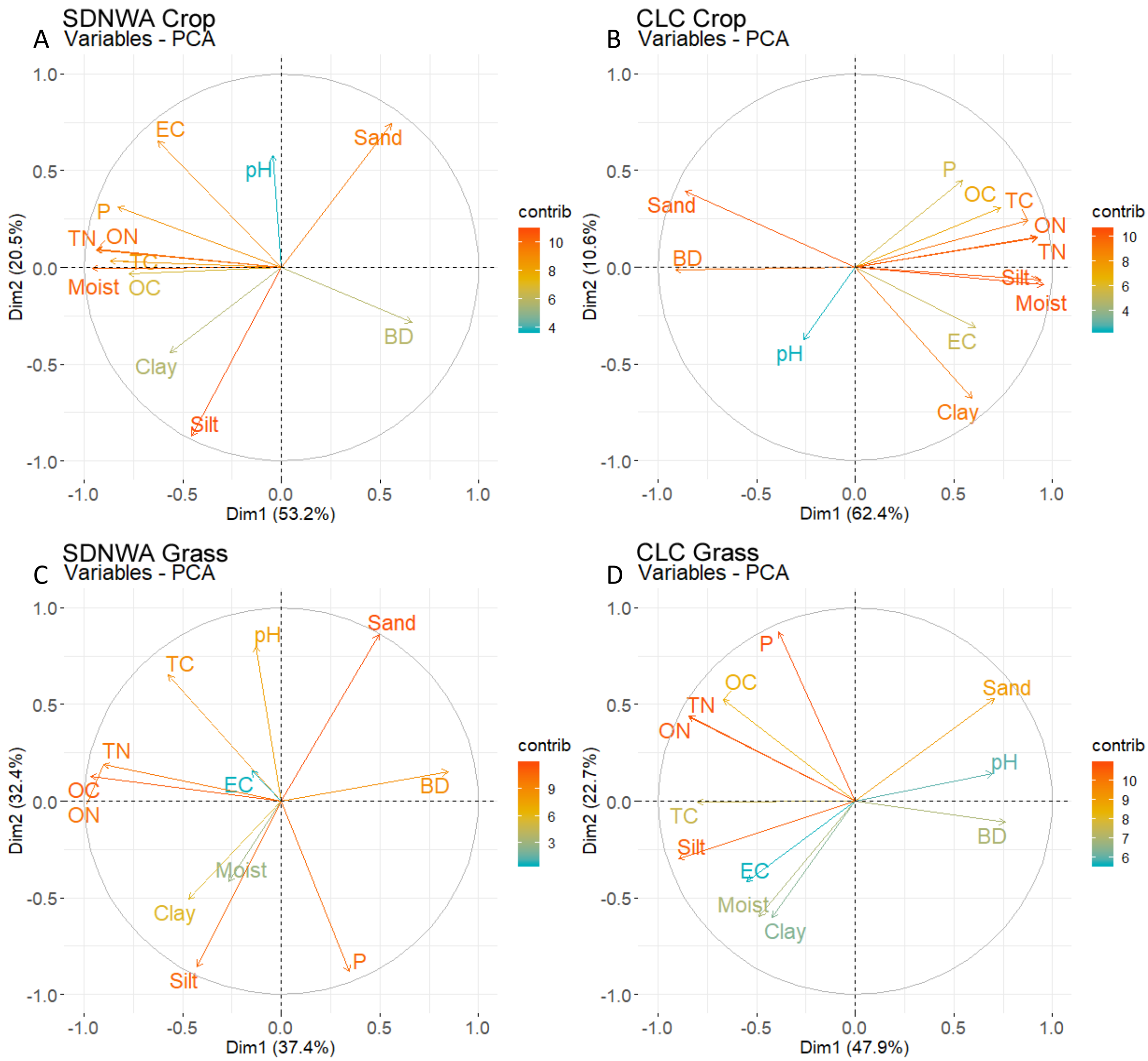


Figure 4.7. Plots showing the results of principal component analysis of soil properties in cropland at the: A) St. Denis National Wildlife Area and B) Conservation Learning Centre; and in grassland at C) St. Denis National Wildlife Area and D) Conservation Learning Centre. contrib= ranking form high to low of how much each variable contributes to the variance of the data. BD= bulk density, EC= electrical conductivity, Moist= gravimetric soil moisture, OC= organic carbon, ON= organic nitrogen, TC= total carbon, TN= total nitrogen.

4.5.2 SDNWA cropland

In the cropland at the SDNWA the FLMZ method was successful at highlighting spatial differences in crop productivity. However, there was high variation in the results (Fig. 4.8). The end output for the FLMZ method in the cropland at the SDNWA is shown in Fig. 4.9 for crop productivity [Delineation maps for the grassland at the SDNWA and both cover types at the CLC can be found in Appendix C]. Crop productivity was highest in the Lower_MedHighC zones and lowest in the LowerBack_LowC zones. Organic carbon was higher in the Back_HighC, Lower_MedHighC, and Upper_HighC zones and lower in the Back_MedC, LowerBack_LowC, and Upper_LowC zones (Fig. 4.10). This is expected as organic carbon is one of the factors used in the FLMZ method. Total carbon, organic nitrogen, and moisture tended to be higher in the Back_HighC, Lower_MedHighC, and Upper_HighC zones and lower in the Back_MedC and LowerBack_LowC zones (Table 4.2). Mineral nitrogen tended to be higher in "HighC" zones (except for Lower_MedHighC zones). Phosphorus tended to be higher in the Upper_HighC zones and lower in the Back_MedC zones but the difference was not significant. Generally when organic carbon was higher so were the other soil nutrients and moisture but this trend was weaker when it came to crop productivity. The notable exceptions were that Back_HighC zones had more productivity than Back_MedC zones and the Upper_MedC zones had more productivity than Upper_HighC zones.

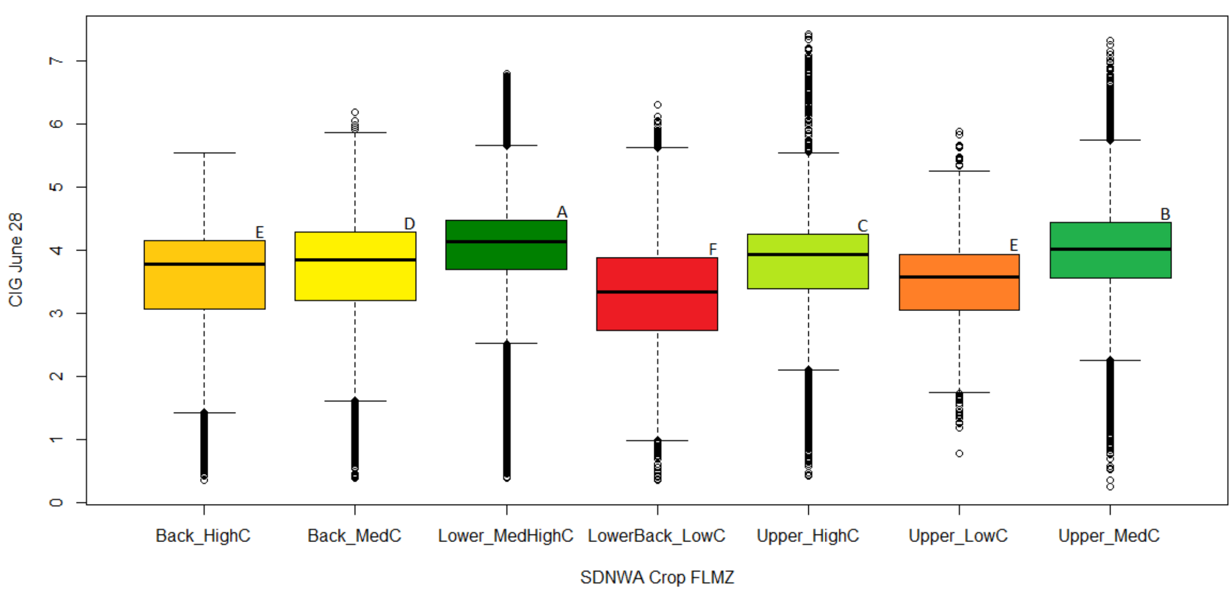


Figure 4.8. Boxplot showing crop productivity indicated by Chlorophyll Index-Green compared to the functional land management zones in the cropland at the St. Denis National Wildlife Area.

Figure 4.9. Final delineation of functional land management zones in the cropland at the St. Denis National Wildlife Area based on fuzzy clustering of soil organic carbon and slope position. Zones are ranked based on the crop productivity (as shown by Chlorophyll Index-Green).

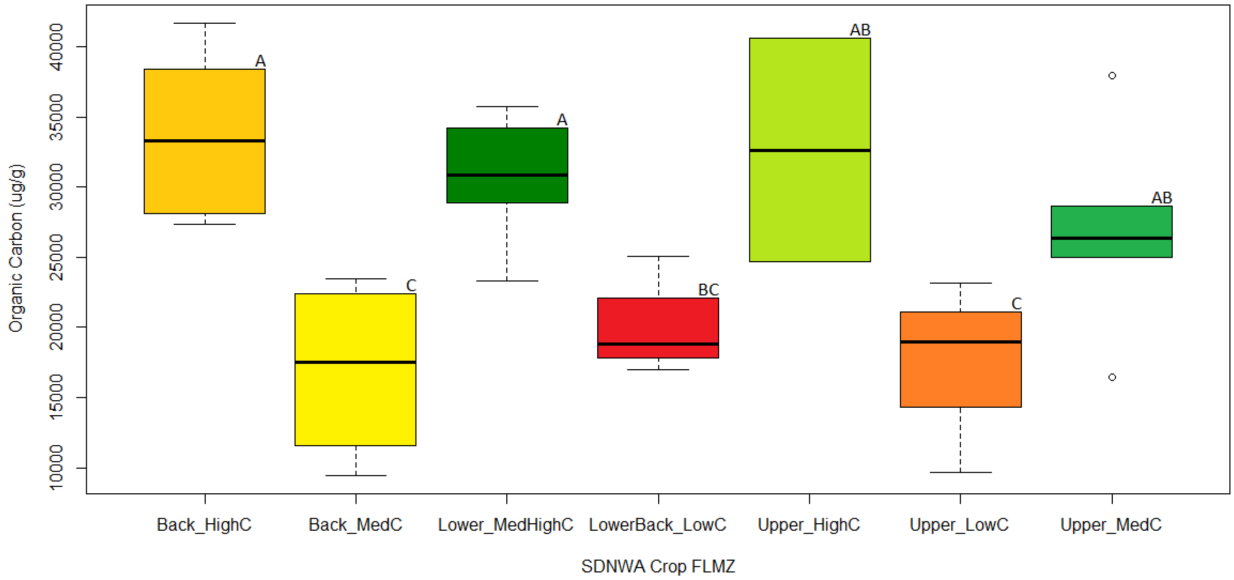


Figure 4.10. Boxplot showing soil organic carbon compared to the functional land management zones in the cropland at the St. Denis National Wildlife Area.

4.5.3 CLC cropland

In the cropland at the CLC spatial variation was highlighted and statistical differences between the different FLMZs were found but practically there was little difference between the zones (Fig. 4.11). Crop productivity was highest in the Upper_MedHighC zones and lowest in the LowerBack_HighC zones. As expected, organic carbon was highest in the LowerBack_HighC zones and lowest in the Lower_MedLowC and UpperBack_LowC zones (Fig. 4.12). The LowerBack_High zone also had the highest total carbon, organic nitrogen, moisture, and tended to have higher phosphorus (Table 4.2). The "Lower" zones had the highest salinity and tended to have lower mineral nitrogen. The UpperBack_LowC zones had the lowest total carbon, organic nitrogen, moisture, and among the lowest salinity with the Upper_MedHighC, UpperBack_LowC, and Back_MedC zones. The Back_MedC zones tended to have the lowest phosphorus. The CLC cropland zones had strong trends when it came to soil properties. The Lower_MedHighC zones had higher soil nutrients and moisture. This did not match up as well with crop productivity since the Lower_MedHighC zones had the lowest productivity but the Upper_MedHighC zones did have the highest productivity (Table 4.2).

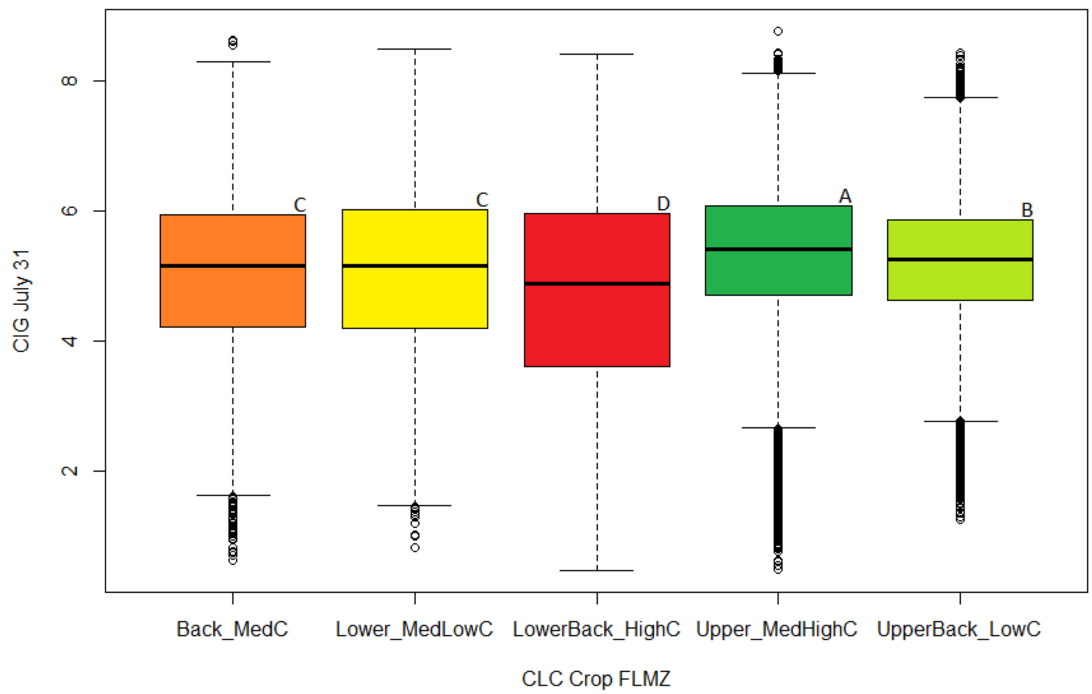


Figure 4.11. Boxplot showing crop productivity indicated by Chlorophyll Index-Green compared to the functional land management zones in the cropland at the Conservation Learning Centre.

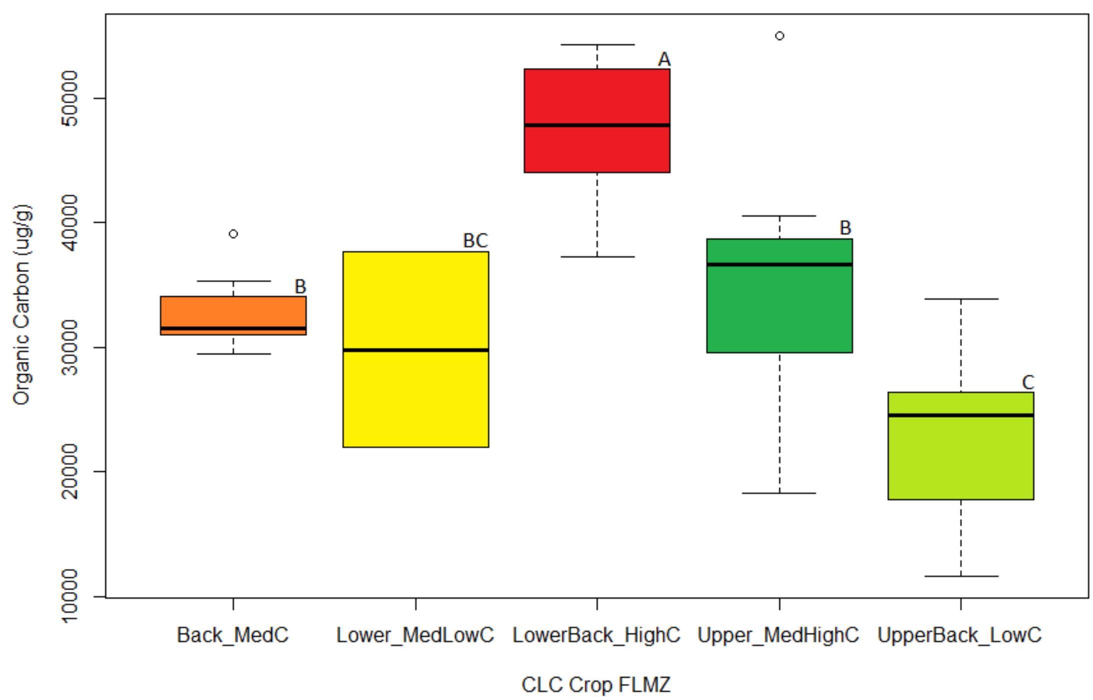


Figure 4.12. Boxplot showing soil organic carbon compared to the functional land management zones in the cropland at the Conservation Learning Centre.

Table 4.2. Summary of key soil properties within each management zone showing medians and standard error. Listed in order from highest to lowest productivity as indicated by the Chlorophyll Index-Green. Highest values are bolded and lowest values are italicized.

	Total Carbon		Mineral Nitrogen		Organic Nitrogen		P		Moisture		pH		EC	
	µg/g	SE	µg/g	SE	µg/g	SE	µg/g	SE	g/g	SE		SE	µS/cm	SE
SDNWA Crop FLMZ														
Lower_MedHighC	34000^{a}	2277	13.1^{a}	4.31	3139^{a}	200	8.32^{a}	2.73	**0.30**^{a}	0.02	-	-	-	-
Upper_MedC	28500^{ab}	2801	**24.9**^{a}	3.99	2474^{ab}	256	9.86^{a}	2.61	0.23^{bcd}	0.01	-	-	-	-
Upper_HighC	**34300**^{ab}	13786	24.2^{a}	0.98	**3148**^{a}	904	**18.1**^{a}	14.0	**0.30**^{abc}	0.07	-	-	-	-
Back_MedC	*14050*^{c}	2895	14.1^{a}	4.22	*1463*^{b}	243	*5.17*^{a}	4.01	*0.15*^{d}	0.01	-	-	-	-
Back_HighC	34250^{ab}	3835	17.2^{a}	5.55	2653^{a}	436	7.74^{a}	14.2	0.24^{ab}	0.04	-	-	-	-
Upper_LowC	33200^{ab}	9823	12.7^{a}	2.73	2069^{ab}	182	4.79^{a}	0.86	0.22^{abcd}	0.06	-	-	-	-
LowerBack_LowC	21550^{bc}	2151	*11.4*^{a}	3.97	2535^{ab}	682	6.64^{a}	2.01	0.16^{cd}	0.02	-	-	-	-
CLC Crop FLMZ														
Upper_MedHighC	29000^{b}	3343	17.5^{a}	4.06	2603^{b}	371	6.51^{a}	0.97	0.23^{b}	0.02	6.48^{a}	0.18	*120*^{c}	370
UpperBack_LowC	*21700*^{c}	3781	**22.3**^{a}	4.06	*1805*^{c}	372	7.61^{a}	0.95	*0.20*^{b}	0.01	**6.95**^{a}	0.19	156^{bc}	369
Lower_MedLowC	31450^{bc}	2258	*11.6*^{a}	4.08	2662^{abc}	280	6.29^{a}	0.45	0.27^{b}	0.01	6.87^{a}	0.19	**940**^{ab}	275
Back_MedC	30200^{b}	1709	17.7^{a}	3.91	2700^{b}	214	*5.32*^{a}	0.43	0.25^{b}	0.01	*6.38*^{a}	0.20	141^{bc}	75
LowerBack_HighC	**45050**^{a}	2504	12.6^{a}	3.64	**3933**^{a}	346	**9.15**^{a}	0.80	**0.34**^{a}	0.01	6.52^{a}	0.18	641^{a}	275
CLC Grass FLMZ														
LowerBack_HighC	46200^{ab}	3548	7.07^{a}	0.50	3648^{a}	413	**4.88**^{a}	0.71	0.34^{a}	0.05	7.33^{a}	0.36	463^{a}	214
Upper_HighC	**49500**^{a}	3408	6.12^{a}	0.49	**4108**^{a}	413	3.87^{a}	0.40	**0.38**^{a}	0.04	*6.66*^{a}	0.33	474^{a}	169
LowerBack_LowC	*33950*^{b}	3455	**8.70**^{a}	0.50	*2424*^{b}	404	4.12^{a}	0.72	*0.28*^{a}	0.05	7.04^{a}	0.33	*334*^{a}	221
Upper_LowC	41500^{b}	4184	*6.05*^{a}	0.54	3093^{ab}	438	*3.29*^{a}	0.40	0.31^{a}	0.05	**7.36**^{a}	0.32	**682**^{a}	115
SDNWA Grass FLMZ														
Lower_MedHighC	40250^{a}	2595	7.82^{a}	1.41	**3417**^{a}	137	**3.61**^{a}	0.19	**0.30**^{a}	0.02	*7.29*^{a}	0.11	277^{a}	14
Back_MedC	*34500*^{a}	2591	9.22^{a}	1.35	2382^{b}	137	3.43^{a}	0.23	*0.21*^{a}	0.02	7.57^{a}	0.09	**289**^{a}	21
Upper_LowMedC	37600^{a}	3042	**10.7**^{a}	1.53	2466^{b}	237	2.86^{a}	0.17	*0.21*^{a}	0.03	**7.80**^{a}	0.15	*237*^{a}	274
UpperBack_HighC	**41100**^{a}	3071	7.79^{a}	1.53	3279^{a}	247	3.34^{a}	0.19	0.26^{a}	0.03	7.38^{a}	0.15	275^{a}	278
LowerBack_LowC	37250^{a}	2870	*7.40*^{a}	1.55	*2376*^{b}	183	*2.59*^{a}	0.18	*0.21*^{a}	0.03	7.35^{a}	0.16	280^{a}	258

4.5.4 CLC grassland

The FLMZ method performed best at the CLC Grassland. It successfully highlighted spatial variation in plant productivity and each zone was different (Fig. 4.13). As expected, organic carbon was highest in the Upper_HighC zones and lowest in the LowerBack_LowC and Upper_LowC zones (Fig. 4.14). The "HighC" zones had the highest total carbon and organic nitrogen (Table 4.2). The LowerBack_HighC zones tended to have the highest phosphorus while the Upper_HighC zones tended to have the highest moisture. The LowerBack_LowC and Upper_LowC zones had the lowest total carbon and organic nitrogen. These zones also tended to have the lowest moisture. The Upper_LowC zones tended to have lower phosphorus and higher salinity. All zones had similar levels of mineral nitrogen but the "LowerBack" zones tended to have more. The CLC grassland had the strongest trends with soil nutrients (except for mineral nitrogen) and moisture and crop productivity all being higher in the same zones.

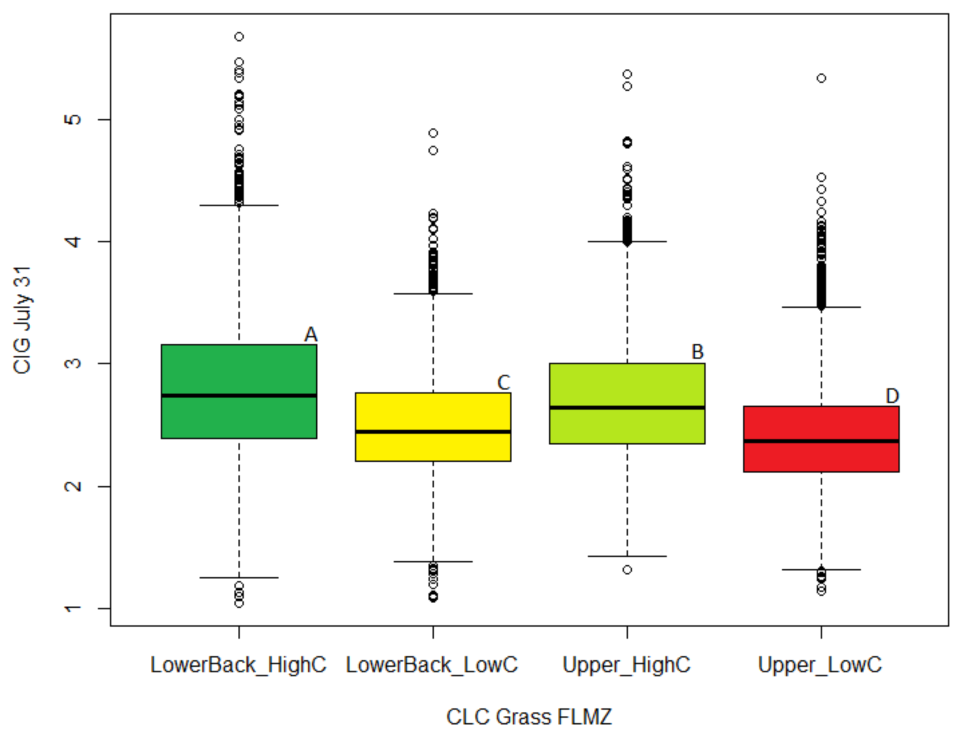


Figure 4.13. Boxplot showing crop productivity indicated by Chlorophyll Index-Green compared to the functional land management zones in the grassland at the Conservation Learning Centre.

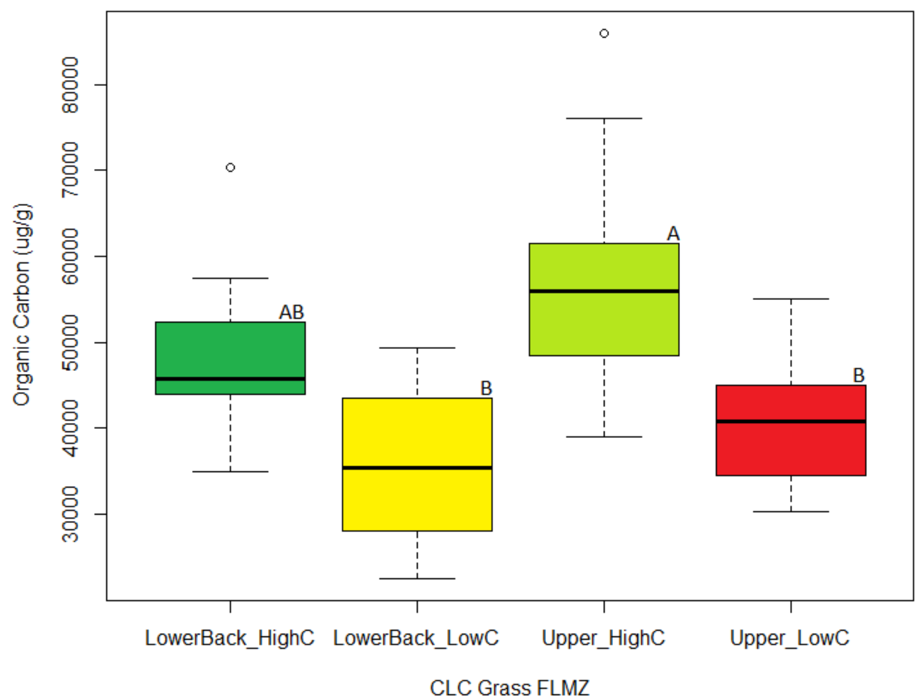


Figure 4.14. Boxplot showing soil organic carbon compared to the functional land management zones in the grassland at the Conservation Learning Centre.

4.5.5 SDNWA grassland

In the SDNWA Grassland, the FLMZ method highlighted spatial trends in crop productivity but there were fewer differences and again there was a lot of variation (Fig. 4.15). Crop productivity was highest in the Lower_MedHighC zones and lowest in the UpperBack_HighC and LowerBack_LowC zones. As expected, organic carbon was highest in the LowerMed_HighC and UpperBack_HighC zones and lowest in the remaining zones (Fig 4.16). Organic nitrogen had the same pattern whilst mineral nitrogen had no pattern. There was no differences in the other soil properties but moisture and Phosphorus tended to be higher in the Lower_MedHighC zones (Table 4.2). Except for mineral nitrogen, the trend for crop productivity, organic carbon, nutrients, and moisture was that in the zones where one of these measures was higher, the rest were high, and where one of these measures were lower, the rest were low.

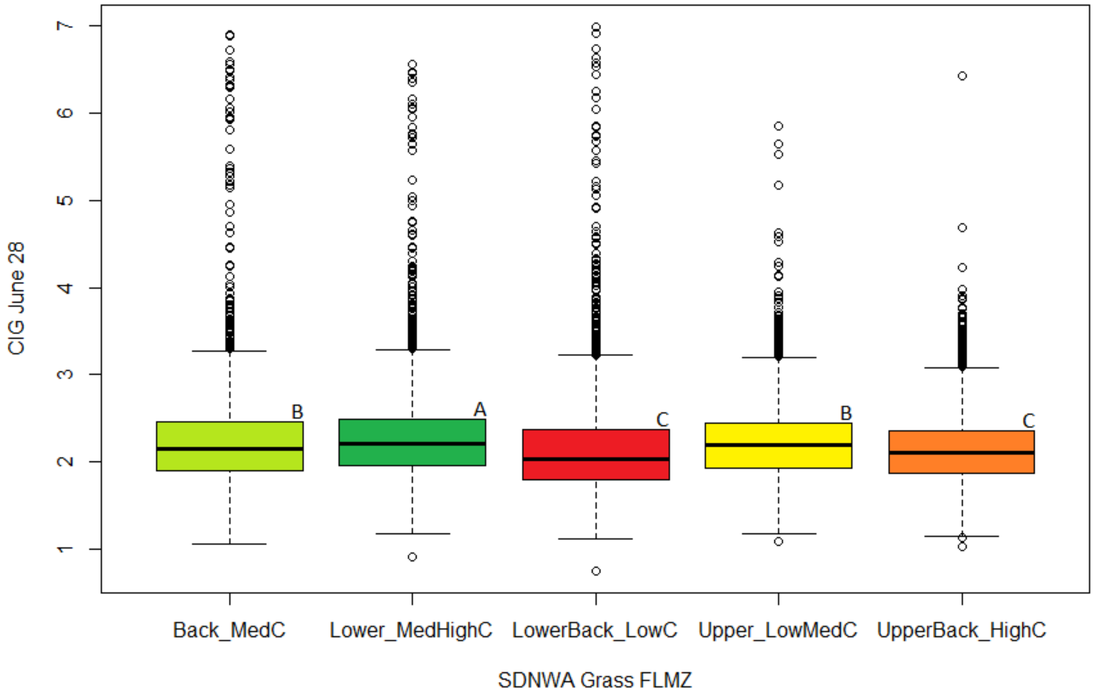


Figure 4.15. Boxplot showing crop productivity indicated by Chlorophyll Index-Green compared to the functional land management zones in the grassland at the St. Denis National Wildlife Area.

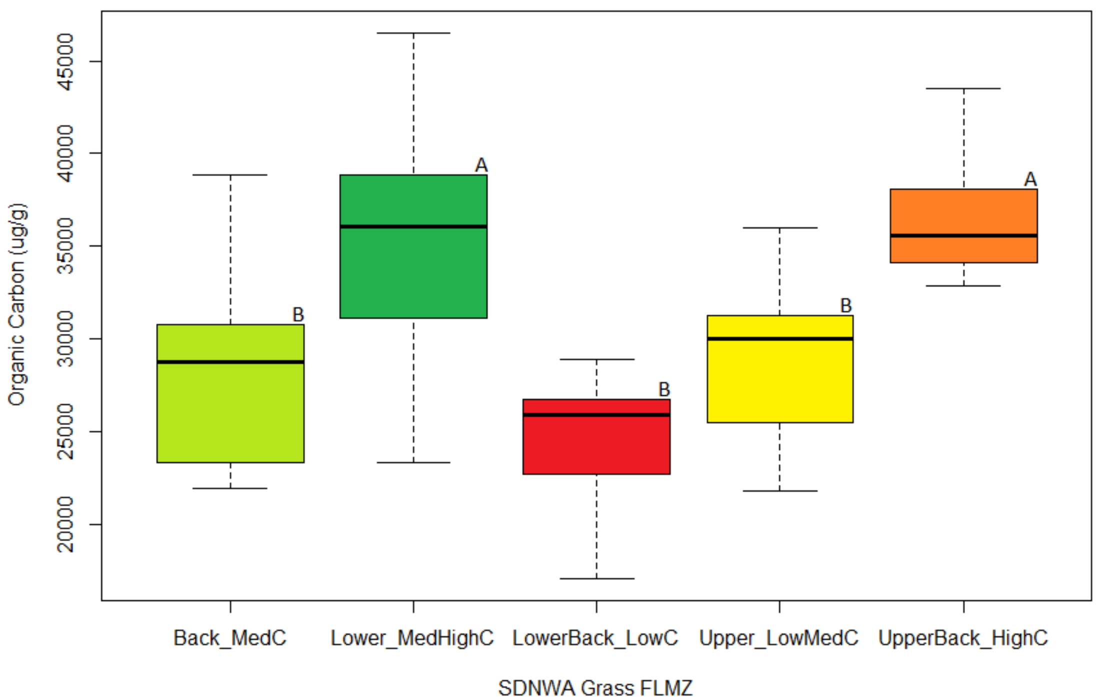


Figure 4.16. Boxplot showing soil organic carbon compared to the functional land management zones in the grassland at the St. Denis National Wildlife Area.

4.6 Discussion

Overall, the management zone methodology did successfully highlight spatial differences in plant productivity in both cropland and grassland. However, zones that were best in terms of key soil properties were not always best when it came to plant productivity (although, they were usually amongst the best). While the zones could be found to be different statistically in terms of productivity, it did not always translate into measurable practicable differences. For instance in the cropland at CLC the two top performing zones were found to be statistically different but in terms of yield the difference amounts to <0.15 t/ha. Also, the consistent presence of many outliers likely means factors affecting crop growth at both sites were not always captured by the method or reflect an error in the modelling of SOC and/or classification of slope position. This method also essentially uses two topography-based factors which likely reduced its ability to highlight soil variation in the landscape if the factors had strong inter-correlation. Including a supplemental soil factor in the method such as soil texture may have improved the final zonation especially since topography is such an important aspect of SOC distribution in hummocky landscapes and texture is important to predicting plant productivity. An added benefit to including soil texture would be increased insight into the soil's capability to store and cycle water. Increasing the resolution of the DEM or scale of analysis for slope delineation (<3m) could increase the accuracy of classification by decreasing but this would require further testing.

Lower slope ("Lower") zones combined with higher carbon ("MedC" to "HighC") zones tended to have higher soil nutrients and moisture. However mineral nitrogen tended to be lower at lower slope positions regardless of organic carbon levels (except for the CLC grassland). These zones also had the greatest productivity except for the cropland at the CLC. The "LowerBack_HighC" and the "Lower_MedLowC" zones in the cropland at the CLC had higher EC than the other zones and were moderately saline so this could have affected productivity. The agricultural capability rating for the CLC indicated that salinity could have a slight effect (University of Saskatchewan, 2018). The "Lower_MedLowC" zones were additionally affected by lower soil nutrient levels. Both sites have most of the lower slope areas being dominated by wetlands and wetland vegetation. These areas were avoided as much as possible for analysis, but between the wetland vegetation and the planted cropland there was often an area with little crop growth. Seeding could have occurred close enough to the wetland to be negatively impacted by the amount of moisture; the “LowerBack_HighC” zones had the highest moisture. This effect may have been more pronounced at the CLC due to the site being relatively flatter than the SDNWA. Steeper basins could better contain the wetland influence.

Other than the CLC cropland, “LowerBack_LowC” zones had amongst the least productivity. These zones were also amongst the lowest in terms of soil nutrients (except for mineral nitrogen at the CLC grassland). Competition with wetland species and too much moisture are also possible driving factors for this result. The agricultural capability rating of both sites indicated that excess water could be an issue (University of Saskatchewan, 2018).

Backslope zones (“Back”) were the most varied in terms of their plant productivity and mineral nitrogen. When paired with higher levels of OC (“HighC”) plant productivity was usually higher. These zones had higher organic carbon, organic nitrogen, phosphorus, and moisture as well. When independent of other slope positions the same was true for mineral nitrogen. The exceptions were the aforementioned “LowerBack_HighC” zones in the CLC cropland, and the “UpperBack_HighC” zones in the grassland at the SDNWA. These “UpperBack_HighC” zones primarily occur on a large backslope surrounding a pond at the site. This backslope is particularly rocky and not an ideal medium for plant growth. While the nutrients for these zones were higher, due to the sampling density being insufficient to represent site variability, most of the sampling points for these zones were not on this backslope so they do not reflect this feature. This area being defined as “HighC” is likely a result of the biases inherent in the digital soil mapping model. The model uses mostly slope based co-variates and it tends to assume that areas with higher carbon occur lower in the landscape with converging micro-topography and this backslope has those features.

Tillage erosion is a major controlling factor in the distribution of SOC in hummocky agricultural landscapes. Past tillage results in soil and nutrient removal from upper slopes (especially those near backslopes) and accumulation at the bottom of slopes (Pennock et al., 2011). This study was reflective of this, except for mineral nitrogen. At the study sites the effect of tillage was most apparent in the “Upper” slope zones; they either had amongst the highest or lowest productivity. The exception was the aforementioned “UpperBack_HighC” zones at the SDNWA. Their productivity was dependent on whether they were "MedC" to "HighC", or "LowC"; the higher the SOC class the greater the productivity. Upperslope areas near the edge of slopes (shoulders), especially steeper slopes, would be the most eroded and have more water runoff and thus have amongst the lowest SOC and nutrients. The potential for moisture limitations is mentioned in the agricultural capability rating of both sites (University of Saskatchewan, 2018). Larger and more stable upperslope areas would just have local infilling of micro-topography with tillage and would be able to build up larger SOC stores resulting in more available nutrients (Pennock, 2003). The effect of tillage and soil redistribution is less apparent at the CLC than the SDNWA as the CLC is relatively flatter. The agricultural capability rating for the SDNWA indicates that erosion and topography could be limiting factors while the rating for the CLC does not (University of Saskatchewan, 2018). Practices such as no-till and conservation till are likely already benefitting overall soil function through improved carbon sequestration and decreased soil disturbance.

Patterns in key soil properties were more consistent between sites and land use. Zones with higher OC ("HighC") usually had the highest amount of soil nutrients and moisture and "LowC" zones the lowest amount. In terms of nutrients the exception was mineral nitrogen, which were generally lower at lower slope positions. As for zones, the exception was "Back_MedC" in both land uses at the SDNWA. These had amongst the lowest amounts of nutrients and moisture. In the grassland at the SDNWA many of the sampling points in these zones fell in the aforementioned backslope category, so these points captured the poor soil quality. The likely possibilities why the "Back_MedC" zones in the cropland had such low soil nutrients are: sampling bias, poor slope classification, or both. With a low sample number the sampling points ended up in spots with poor soil quality, and or with, rocky backslopes. When inspecting the zone delineation it appears that some of the areas classified as backslope are in locations that should be classified as upper (shoulder specifically) slope positions. Although ground-truthing was performed, sample points were left as classified by the model in order for the results to reflect how the FLMZ delineation method performed without modification.

Mineral N is the plant available form of nitrogen and is important for crop yield (Barker, 1999). However, its spatial and temporal variability makes it difficult to measure and manage for

(Vagstad et al., 1997). Mineral N availability is influenced by all factors which impact microbial activity as soil microbes are responsible for the mineralization of N (Barker, 1999). These factors include: soil moisture, temperature, texture, pore space, and compaction as well as residue inputs and management practices (Walley, 2011). A further complication to this study was that mineral N was applied as fertilizer in the cropland at both sites after sampling occurred. Therefore, mineral N was likely not a limiting factor to crop growth at the study sites. Measured mineral N levels for the grasslands were potentially more reflective of actual availability, but no statistical differences were found between the different FLMZs in either site or land use. It is unknown what the mineral N availability was at the time when required by the grasses and crops at the study sites.

Since the FLMZ method deals primarily with SOC, it is best suited for informing the application of management practices that affect and increase SOC. Conservation tillage is one management practice that can be adopted to improve SOC and as of 2014, 75% of cropland in the Canadian Prairies is under some form of conservation tillage (Awada et al., 2014). Not only does Conservation tillage increase SOC stocks but it can contribute to reductions in all forms of land degradation and increase soil microbial activity (Sharma et al., 2013; Awada et al., 2014). Another management practice that can be implemented is the use of green manure. The incorporation of green manure has shown to increase both carbon sequestration and soil structure (Garcia-Franco et al., 2015). Changing the type of fertilizer applied to cropland can also be beneficial in regards to SOC. The use of animal manure as fertilizer can both help to conserve and improve SOC (Fließbach et al., 2007; Chirinda et al., 2010; Ren et al., 2014).

4.7 Conclusion

The FLMZ method successfully identified much of the differences in plant productivity in both grassland and cropland, however, when fields have unique limiting factors to growth they are not well-served by a blanket method such as this and the differences in plant productivity between zones is not always practicably different. The FLMZ method performed best when estimating the other soil functions. For example patterns of water storage, organic nitrogen and phosphorus cycling, carbon storage, and habitat for biodiversity more consistently corresponded with the FLMZs. The FLMZ method was less effective at indicating patterns of mineral N. Zones with higher SOC and zones at lower slopes or stable upper slopes were more likely to have higher plant productivity, organic carbon, organic nitrogen, phosphorus, and moisture. Lower slopes have benefitted from the accumulation of soil and soil nutrients and stable upper slopes have retained soil and nutrients due to reduced erosion.

The potential of the FLMZ method was best demonstrated in the grassland at the CLC. The patterns of plant productivity and estimates of the other soil functions were consistent. This illustrates that through the FLMZ the ability of soil to perform multiple functions can be estimated simultaneously. The FLMZ methods works best to inform the adoption of management practices that improve SOC and the soil function of carbon storage. Any functions improved by increasing the quantity and quality of SOC will also benefit. Furthermore, this method demonstrates that land uses other than cropping can be managed for multiple soil functions as well. Topography and SOC are already commonly used as factors for delineating management zones in crop areas. Land users already have the tools and techniques needed to adopt the methodology. Management practices that improve SOC storage (and in turn other soil functions) also already exist. This highlights the importance of education; land users need to learn this so that the management of multiple soil functions in both cropland and grassland can incorporated into mainstream agriculture.

Chapter 5.0

SYNTHESIS AND CONCLUSIONS

Remote sensing can provide a wealth of information about landscapes that is useful for estimating the soil function of sites. This is especially beneficial when it comes to the remote sensing of soil organic carbon (SOC). Traditional methods of collecting spatial SOC data (such as grid sampling) can be replaced and/or supplemented with the use of remote sensing. Significantly less soil sampling needs to occur when using remote sensing data indices; they can be used to choose ideal sampling locations and/or provide an estimate of SOC. Although, an overall reduction in management practices like intensive tillage and summer fallow has decreased the feasibility of using bare-soil dependent remote sensing indices. However, with the emergence of digital soil mapping (DSM) remote sensing remains an asset for SOC estimation. DSM is not reliant on a bare soil surface so conservation tillage does not prevent remote sensing from being effective at reducing soil sampling or estimating SOC. While soil sampling is a requirement of DSM only enough soil samples to train the models are necessary. DSM estimates SOC through the use of soil sampling, environmental co-variates, and modelling. Many or all of the co-variates can be either topography based and/or vegetative index based. Digital terrain models and vegetation indices are outputs of remote sensing. DSM does have error but its accuracy is sufficient for agricultural practices such as delineating management zones.

Management zone delineation methods often use spatial soil and landscape information as a basis. Two such properties, SOC and topography, are key for multiple soil functions including: plant productivity, water storage and cycling, nutrient cycling, carbon sequestration, and habitat for biodiversity. By using these key properties to create a management zone delineation method it is possible to estimate multiple soil functions in both cropland and grassland. The functional land management zone (FLMZ) method tested in this study combined slope classification, the DSM of SOC, and fuzzy clustering, to delineate management zones in annual cropland and hayed grassland fields with hummocky topography. These FLMZs successfully captured spatial variation and patterns in plant productivity and multiple soil properties including soil organic carbon, organic nitrogen, phosphorus, and moisture. This indicates that the FLMZ method can be successfully implemented for estimating multiple soil functions simultaneously.

The FLMZ method was developed utilizing data collected by a remotely piloted air system (RPAS). RPAS has a few major advantages over the other main remote sensing platforms (aircraft and satellite). These advantages are: greater control over flight timing, being able to fly under clouds (which can block or reduce the quality of imaging), and increased spatial resolution. However, the latter was not a factor as the resolutions required for analysis (two meters- DSM, three meters- slope classification) and the resolution of the FLMZs (three meters) is achievable using all the main remote sensing platforms. Also, with technological advances the gap in spatial resolution is decreasing. The main disadvantage of using an RPAS is scalability. The area you can efficiently cover using a rotary wing RPAS is only a single field. Rotary wing RPAS are relatively slow, requiring more time to cover large areas and increasing flight time means more batteries are required. Being that a focus of the FLMZ method is time efficiency, when applying it at large scales it would be better to use a remote sensing platform that can cover greater spatial extents more efficiently. A fixed wing RPAS would be able to cover larger areas in less time and with fewer batteries. However, satellite and aircraft are better suited for this purpose. The FLMZ method does not require the use of an RPAS, as long as the right data (point-cloud or light detection and ranging) is available at a sufficient resolution then the DSM and slope classification can be completed.

The FLMZ method is beneficial not only from an agricultural perspective but also from an environmental perspective. The FLMZ method facilitates sustainable agricultural intensification; precision agriculture can be practiced while maintaining soil health. Management zones are an essential part of the framework for the precision agriculture. Working within the framework of an established practice makes adopting and implementing the method easier for agricultural land managers. The FLMZ method can be used to simultaneously estimate multiple soil functions quickly, efficiently, and with limited soil sampling giving land managers the information necessary to manage for these soil functions. Land managers can increase the overall value of their cropland and grassland by introducing practices that increase crop productivity and increase or preserve other soil functions as well. Managing soils for SOC increases the ability of soil to provide multiple functions. Modern agricultural practices such as conservation tillage already consider SOC and where practiced overall soil function is increasing. The ability of the FLMZ method to be rapidly applied also makes it ideal for gaining a soil function baseline and tracking changes in SOC. This is important in light of issues like climate change and agricultural intensification. Both are occurring now and the rates at which they are or will change is increasing. Being able to gauge and monitor a soil's response to these pressures allows land managers to react accordingly.

The FLMZ method works best where there are not site-unique limiting factors to plant growth in a field as the zones which are best for different soil functions are more consistent in this scenario. In this regard the FLMZ method could be improved by including soil texture as an additional soil factor. This addition would also increase the effectiveness of the method at estimating water cycling and storage. The tradeoff is that this inclusion could increase the amount of soil sampling required and would increase the amount of soil analysis required. This would both complicate the method and increase the time needed to perform it.

The FLMZ method could be a valuable tool for ensuring global food security while facing the pressures of climate change, but further evaluation is required. While this study consistently found patterns in key soil properties, due to a low sample size, differences in property values between FLMZ were often indiscernible statistically. Future research could better assess the method by increasing the sampling density. This would also improve the chances of more sample points falling within each management zone class, allowing for better statistical comparisons. Future research could further compare measurements of the soil functions focused on in this study to the FLMZs and further define the relationships between the functions and the method's factors (topography, SOC, possibly soil texture) to improve the estimation capability of the method. Future research could test if the FLMZ method enables better prediction of management effects (e.g. fertilizer and seeding rates, grazing regimes). The FLMZ method could be made more effective by finding more management practices (ideally that benefit multiple soil functions) that can be implemented based on the information provided by the method. Future research could also explore the inclusion of other soil factors like soil texture in the method. The impact of these inclusions on the performance and efficiency of the method could be measured. Lastly, future research could also derive remote sensing data from satellite and/or aircraft in order to compare the costs/benefits of the different platforms for this application.

Chapter 6.0

REFERENCES

Adhikari, K., and A.E. Hartemink. 2016. Linking soils to ecosystem services - a global review. Geoderma 262: 101-111.

Agriculture and Agri-Food Canada. 2017. We grow a lot more than you may think. Government of Canada. http://www.agr.gc.ca/eng/about-us/publications/we-grow-a-lot-more-than-you-may-think/?id=1251899760841 (accessed 20 Nov. 2017).

Aguiar, M. 2019. Vegetation and soil biodiversity across perennial grassland-annual cropland edges. University of Saskatchewan. (September). https://harvest.usask.ca/handle/10388/12426

Anderson, D., and D. Cerkowniak. 2010. Soil formation in the Canadian Prairie region: factors of soil formation. Prairie Soils Crop. J. 3: 57-64.

Awada, L., C.W. Lindwall, and B. Sonntag. 2014. The development and adoption of conservation tillage systems on the Canadian Prairies. Int. Soil Water Conserv. Res. 2(1): 47-65.

Bareth, G., A. Bolten, M.L. Gnyp, S. Reusch, and J. Jasper. 2016. Comparison of uncalibrated RGBVI with spectrometer-based NDVI derived from UAV sensing systems on field scale. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. - ISPRS Arch. 41(July): 837-843.

Barker, B. 1999. Understanding N mineralization. Top Crop Manager. Annex Business Media. https://www.topcropmanager.com/understanding-n-mineralization-10515/ (accessed 12 Dec. 2019).

Behrens, T., A.X. Zhu, K. Schmidt, and T. Scholten. 2010. Multi-scale digital terrain analysis and feature selection for digital soil mapping. Geoderma 155(3-4): 175-185.

Birgé, H.E., R.A. Bevans, C.R. Allen, D.G. Angeler, S.G. Baer, D.H. Wall. 2016. Adaptive management for soil ecosystem services. J. Environ. Manage. 183: 371-378.

Biswas, A., and B.C. Si. 2011. Revealing the controls of soil water storage at different scales in a hummocky landscape. Soil Sci. Soc. Am. J. 75(4): 1295-1306.

Buttafuoco, G., A. Castrignano, A.S. Colecchia, and N. Ricca. 2010. Delineation of management zones using soil properties and a multivariate geostatistical approach. Ital. J. Agron. 5(4): 323-332.

Cameron, F.K., and J.F. Breazeale. 1904. The organic matter in soils and subsoils. J. Am. Chem. Soc. 26(1): 29-45.

Cicore, P., J. Serrano, S. Shahidian, A. Sousa, J.L. Costa, J.F.M da Silva. 2016. Assessment of the spatial variability in tall wheatgrass forage using LANDSAT 8 satellite imagery to delineate potential management zones. Environ. Monit. Assess. 188(9).

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., and Böhner, J. 2015. System for automated geoscientific analyses (SAGA) v. 2.1.4, Geosci. Model Dev., 8, 1991-2007, doi:10.5194/gmd-8-1991-2015.

Coyle, C., R.E. Creamer, R.P.O. Schulte, L. O'Sullivan, and P. Jordan. 2016. A functional land management conceptual framework under soil drainage and land use scenarios. Environ. Sci. Policy 56: 39-48.

Croft, H., N.J. Kuhn, and K. Anderson. 2012. On the use of remote sensing techniques for monitoring spatio-temporal soil organic carbon dynamics in agricultural systems. Catena 94: 64-74.

Dusseux, P., L. Hubert-Moy, T. Corpetti, and F. Vertès. 2015. Evaluation of SPOT imagery for the estimation of grassland biomass. Int. J. Appl. Earth Obs. Geoinf. 38: 72-77.

Edirisinghe, A., M.J. Hill, G.E. Donald, and M. Hyder. 2011. Quantitative mapping of pasture biomass using satellite imagery. Int. J. Remote Sens. 32(10): 2699-2724.

Elstein, D. 2003. Management zones help in precision agriculture. Agric. Res. 51(8): 17.

ESRI. 2017. ArcGIS Desktop: Release 10.5. Redlands, CA.

Fließbach, A., H.R. Oberholzer, L. Gunst, and P. Mäder. 2007. Soil organic matter and biological soil quality indicators after 21 years of organic and conventional farming. Agric. Ecosyst. Environ. 118(1-4): 273-284.

Florinsky, I. V., R.G. Eilers, G.R. Manning, and L.G. Fuller. 2002. Prediction of soil properties by digital terrain modelling. Environ. Model. Softw. 17(3): 295-311.

Fox, G.A., and G.J. Sabbagh. 2002. Estimation of soil organic matter from red and near-infrared remotely sensed data using a Soil Line Euclidean Distance technique. Soil Sci. Soc. Am. J.: 1922-1929.

Fridgen, J.J., N.R. Kitchen, K.A. Sudduth, S.T. Drummond, W.J. Wiebold, C.W. Fraisse. 2004. Management zone znalyst (MZA): software for subfield management zone delineation. Agron. J. 96(1): 100-108.

Fuller, L. 2010. Chernozemic soils of the prairie region of Western Canada. Prairie Soils Crop. J. 3: 37-45.

Garcia-Franco, N., J. Albaladejo, M. Almagro, and M. Martínez-Mena. 2015. Beneficial effects of reduced tillage and green manure on soil aggregation and stabilization of organic carbon in a Mediterranean agroecosystem. Soil Tillage Res. 153: 66-75.

Government of Saskatchewan. 2015. Saskatchewan provincial pasture lands. Saskatchewan. Government of Saskatchewan. https://www.saskatchewan.ca/government/public-consultations/past-consultations/pasture-land-consultation/get-informed#the-land (accessed 20 May 2019).

Gozdowski, D., M. Stepien, S.S. Samborski, E.S. Dobers, J. Szatylowicz, J. Chormanski. 2014. Determination of the most relevant soil properties for the delineation of management zones in production fields. Comm. Soil Sci. Plant Anal. 45(17): 2289-2304.

GRASS Development Team. 2019. Geographic resources analysis support system (GRASS) Software, Version 7.6. Open Source Geospatial Foundation. http://grass.osgeo.org (accessed 15 Feb. 2019).

Gray, J.M., T.F.A. Bishop, and X. Yang. 2015. Pragmatic models for the prediction and digital mapping of soil properties in eastern Australia. Soil Res. 53(1): 24-42.

Greiner, L., A. Keller, A. Grêt-Regamey, and A. Papritz. 2017. Soil function assessment: review of methods for quantifying the contributions of soils to ecosystem services. Land Use Policy. 69(June): 224-237.

Guo, P.T., W. Wu, H. Bin Liu, and M.F. Li. 2011. Effects of land use and topographical attributes on soil properties in an agricultural landscape. Soil Res. 49(7): 606-613.

HABISask. 2018. Map. HABISask. Government of Saskatchewan. https://gisappl.saskatchewan.ca/Html5Ext/?viewer=habisask (accessed 16 May 2019).

Hardin, P.J., and R.R. Jensen. 2011. Small-scale unmanned aerial vehicles in environmental remote sensing: challenges and opportunities. GIScience Remote Sens. 48(1): 99-111.

Hassan-Esfahani, L., A. Torres-Rua, A. Jensen, and M. McKee. 2015. Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. Remote Sens. 7(3): 2627-2646.

Heaton, L., M.A. Fullen, and R. Bhattacharyya. 2016. Critical analysis of the van Bemmelen conversion factor used to convert soil organic matter data to soil organic carbon data: comparative analyses in a UK loamy sand soil. Espaco Alberto. 6(1): 35-44.

Herwitz, S.R., L.F. Johnson, S.E. Dunagan, R.G. Higgins, D. V. Sullivan, J. Zheng, B.M. Lobitz, J.G. Leung, B.A. Gallmeyer, M. Aoyagi, R.E. Slye, J.A. Brass. 2004. Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support. Comput. Electron. Agric. 44(1): 49-61.

Heung, B., H.C. Ho, J. Zhang, A. Knudby, C.E. Bulmer, M.G. Schmidt. 2016. An overview and comparison of machine-learning techniques for classification purposes in digital soil mapping. Geoderma 265: 62-77.

Houba, V.J.G., E.J.M. Temminghoff, G.A. Gaikhorst, and W. van Vark. 2000. Soil analysis procedures using 0.01 M calcium chloride as extraction reagent. Comm. Soil Sci. Plant Anal. 31(9&10): 1299-1396.

Huang, Y., S.J. Thomson, H.J. Brand, and K.N. Reddy. 2016. Development and evaluation of low-altitude remote sensing systems for crop production management. Int. J. Agric. & Biol. Eng. 9(4): 1-11.

Indorante, S.J., L.R. Follmer, R.D. Hammer, P.G. Koenig, 1990. Particle-size analysis by a modified pipette procedure. Soil Sci. Soc. of Am. J. 54(2): 560-563.

Jónsson, J.Ö.G., and B. Davídsdóttir. 2016. Classification and valuation of soil ecosystem services. Agric. Syst. 145: 24-38.

Kiss, J. 2018. Predictive mapping of wetland types and associated soils through digital elevation model analyses in the Canadian Prairie Pothole region. University of Saskatchewan. (July). https://harvest.usask.ca/handle/10388/11058.

Ladoni, M., S.K. Alavipanah, H.A. Bahrami, and A. A. Noroozi. 2010. Remote sensing of soil organic carbon in semi- arid region of Iran. Arid Land Res. and Manage. 24(4): 271-281.

Lindblom, J., C. Lundström, M. Ljung, and A. Jonsson. 2017. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. Precis. Agric. 18(3): 309-331.

Ludwig, M., P. Wilmes, and S. Schrader. 2018. Measuring soil sustainability via soil resilience. Sci. Total Environ. 626: 1484-1493.

Malone, B.P., A.B. McBratney, B. Minasny, and G.M. Laslett. 2009. Mapping continuous depth functions of soil carbon storage and available water capacity. Geoderma 154(1-2): 138-152.

Matese, A., P. Toscano, S.F. Di Gennaro, L. Genesio, F.P. Vaccari, J. Primocerio, C. Belli, A. Zaldei, R. Bianconi. B. Gioli. 2015. Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. Remote Sens. 7(3): 2971-2990.

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. Geoderma 117 (1-2): 3-52.

McCarl, B.A., F.B. Metting, and C. Rice. 2007. Soil carbon sequestration. Clim. Change 80(1-2): 1-3.

Miller, Jim. J, and D. Curtin. 2007. Electrical conductivity and soluble ions. In: Carter, M.R., and E.G. Gregorich, editors, Soil sampling and methods of analysis 2nd Edition. CRC Press, Boca Raton, Florida. p. 161-171.

Miller, J. 2016. Soil pH affects nutrient availability. Univ. Maryl. Ext. (July): 1-5. doi: 10.13140/RG.2.1.2423.5768.

Miller, B.A., and R.J. Schaetzl. 2015. Digital classification of hillslope position. Soil Sci. Soc. Am. J. 79(1): 132.

Milne, E., S.A. Banwart, E. Noellemeyer, D.J. Abson, C. Ballabio, F. Bampa, A. Bationo, N.H. Batjes, M. Bernoux, T. Bhattacharyya, et al. 2015. Soil carbon, multiple benefits. Environ. Dev. 13: 33-38.

Minasny, B., and A.B. McBratney. 2016. Digital soil mapping: a brief history and some lessons. Geoderma 264: 301-311.

Minasny, B., A.B. McBratney, B.P. Malone, and I. Wheeler. 2013. Digital mapping of soil carbon. Advances in Agronomy 118: 1-47.

Ministry of Agriculture and Lands. 2007. Public amenity benefits and ecological services provided by farmland to local communities in the Fraser Valley. Government of British Columbia. https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/agriculture-and-seafood/agricultural-land-and-environment/strengthening-farming/800100-1_public_amenity_benefits_report.pdf (accessed 16 April 2017).

Moral, F.J., J.M. Terrón, and J.R.M. da Silva. 2010. Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. Soil Tillage Res. 106(2): 335-343.

Mulla, D.J. 2013. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. Biosyst. Eng. 114(4): 358-371.

Noorbakhsh, S., J. Schoenau, B. Si, T. Zeleke, and P. Qian. 2008. Soil properties, yield, and landscape relationships in south-central Saskatchewan Canada. J. Plant Nutr. 31(March): 539-556.

Nussbaum, M., K. Spiess, A. Baltensweiler, U. Grob, A. Keller, L. Greiner, M.E. Schaepman, A. Papritz. 2018. Evaluation of digital soil mapping approaches with large sets of environmental covariates. Soil 4(1): 1-22.

O'Sullivan, L., R.E. Creamer, R. Fealy, G. Lanigan, I. Simo, O. Fenton, J. Carfrae, R.P.O. Schulte. 2015. Functional land management for managing soil functions: A case-study of the trade-off between primary productivity and carbon storage in response to the intervention of drainage systems in Ireland. Land Use Policy 47: 42-54.

O'Sullivan, L., D. Wall, R. Creamer, F. Bampa, and R.P.O. Schulte. 2017. Functional land management: bridging the think-do-gap using a multi-stakeholder science policy interface. Ambio (2016): 1-15.

Parent, A.C., M.C. Belanger, L.E. Parent, R. Santerre, A.A. Viau, F. Antcil, M.A. Bolinder, C. Tremblay. 2008. Soil properties and landscape factors affecting maize yield under wet spring conditions in eastern Canada. Biosyst. Eng. 99(1): 134-144.

Pena-Yewtukhiw, E.M., D. Mata-Padrino, and J.H. Grove. 2017. Interactions between landscape defined management zones and grazing management systems. Adv. Anim. Biosci. 8(02): 787-791.

Peng, Y., and A.A. Gitelson. 2012. Remote estimation of gross primary productivity in soybean and maize based on total crop chlorophyll content. Remote Sens. Environ. 117: 440-448.

Pennock, D.J. 2003. Terrain attributes, landform segmentation, and soil redistribution. Soil Tillage Res. 69(1–2): 15-26.

Pennock, D., A. Bedard-Haughn, and V. Viaud. 2011. Chernozemic soils of Canada: genesis, distribution, and classification. Can. J. Soil Sci. 91(5): 719-747.

Pix4D. 2018. Pix4D desktop: Release 4.3. Lausanna, Vaud, Switzerland.

Poggio, L., and A. Gimona. 2016. Assimilation of optical and radar remote sensing data in 3D mapping of soil properties over large areas. Sci. Total Environ. 579: 1094-1110.

Power, A.G. 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. B 365(2010): 2959-2971.

Pribyl, D.W. 2010. A critical review of the conventional SOC to SOM conversion factor. Geoderma 156(3-4): 75-83.

Qian, P., J.J. Schoenau, and R.E. Karamanos. 1994. Simultaneous extraction of available phosphorus and potassium with a new soil test: a modification of Kelowna extraction. Comm. Soil Sci. Plant Anal. 25:627-635.

R Core Team .2017. R: A language and environment for statistical computing: Release 3.5. R Foundation for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org/.

Redhead, J., M. Cuevas-Gonzales, G. Smith, F. Gerard, and R. Pywell. 2012. Assessing the effectiveness of scrub management at the landscape scale using rapid field assessment and remote sensing. J. Environ. Manage. 97(1): 102-108.

Ren, T., J. Wang, Q. Chen, F. Zhang, and S. Lu. 2014. The effects of manure and nitrogen fertilizer applications on soil organic carbon and nitrogen in a high-input cropping system. PLoS One 9(5).

Rowell, M.J. 2000. Measurement of soil organic matter: a compromise between and efficacy and environmental friendliness. Agricola 2000: 66-69.

Rutherford, P.M., W.B. McGill, and J.M. Arocena. 2007. Total Nitrogen. In: Carter, M.R., and E.G. Gregorich, editors, Soil sampling and methods of analysis 2nd Edition. CRC Press, Boca Raton, Florida. p. 239-250.

Saad, R., M. Margni, T. Koellner, B. Wittstock, and L. Deschênes. 2011. Assessment of land use impacts on soil ecological functions: development of spatially differentiated characterization factors within a Canadian context. Int. J. Life Cycle Assess. 16(3): 198-211.

Schellberg, J., M.J. Hill, R. Gerhards, M. Rothmund, and M. Braun. 2008. Precision agriculture on grassland: applications, perspectives and constraints. Eur. J. Agron. 29(2-3): 59-71.

Schulte, R.P.O., R.E. Creamer, T. Donnellan, N. Farrelly, R. Fealy, C. O'Donoghue, D. O'hUallachain. 2014. Functional land management: a framework for managing soil-based ecosystem services for the sustainable intensification of agriculture. Environ. Sci. Policy 38: 45-58.

Scudiero, E., T.H. Skaggs, and D.L. Corwin. 2016. Comparative regional-scale soil salinity assessment with near-ground apparent electrical conductivity and remote sensing canopy reflectance. Ecol. Indic. 70: 276-284.

Sharma, P., G. Singh, and R.P. Singh. 2013. Conservation tillage and optimal water supply enhance microbial enzyme (glucosidase, urease and phosphatase) activities in fields under wheat cultivation during various nitrogen management practices. Arch. Agron. Soil Sci. 59(7): 911-928.

Shi, Y., J.A. Thomasson, S.C. Murray, N.A. Pugh, W.L. Rooney, S. Shafian, N. Rajan, G. Rouze, C.L.S. Morgan, H.L. Neely. 2016. Unmanned aerial vehicles for high-throughput phenotyping and agronomic research. PLoS One 11(7): e0159781.

Skjemstad, J.O., and J.A. Baldock, 2007. Total and Organic Carbon. In: Carter, M.R., and E.G. Gregorich, editors, Soil sampling and methods of analysis 2nd Edition. CRC Press, Boca Raton, Florida. p. 225-237

Song, X., J. Wang, W. Huang, L. Liu, G. Yan, R. Pu. 2009. The delineation of agricultural management zones with high resolution remotely sensed data. Precis. Agric. 10(6): 471-487.

Squire, G.R., C. Hawes, T.A. Valentine, and M.W. Young. 2015. Degradation rate of soil function varies with trajectory of agricultural intensification. Agric. Ecosyst. Environ. 202: 160-167.

Srivastava, P., A. Kumar, S.K. Behera, Y.K. Sharma, and N. Singh. 2012. Soil carbon sequestration: An innovative strategy for reducing atmospheric carbon dioxide concentration. Biodivers. Conserv. 21(5): 1343-1358.

Statistics Canada. 2016. 2011 Farm and farm operator data. Statistics Canada. http://www.statcan.gc.ca/pub/95-640-x/2011001/p1/prov/prov-47-eng.htm (accessed 20 Nov. 2017).

Steele, D. 2017. Analysis of precision agriculture adoption & barriers in western Canada: producer survey of western Canada. Agriculture and Agri-food Canada. https://www.realagriculture.com/wp-content/uploads/2017/04/Final-Report-Analysis-of-Precision-Agriculture-Adoption-and-Barriers-in-western-Canada-April-2017.pdf (accessed 6 June 2017).

Taghizadeh-Mehrjardi, R., K. Nabiollahi, and R. Kerry. 2016. Digital mapping of soil organic carbon at multiple depths using different data mining techniques in Baneh region, Iran. Geoderma 266: 98-110.

Toth, C., and G. Jóźków. 2016. Remote sensing platforms and sensors: A survey. ISPRS J. Photogramm. Remote Sens. 115: 22-36.

University of Saskatchewan. 2018. Map. Saskatchewan soil information system. University of Saskatchewan https://sksis.usask.ca/#/map (accessed 16 May 2019).

Vagstad, N., H.O. Eggestad, and T.R. Høyås. 1997. Mineral nitrogen in agricultural soils and nitrogen losses: relation to soil properties, weather conditions, and farm practices. Ambio 26(5): 266-272.

Valujeva, K., L. O'Sullivan, C. Gutzler, R. Fealy, and R.P.O. Schulte. 2016. The challenge of managing soil functions at multiple scales: an optimisation study of the synergistic and antagonistic trade-offs between soil functions in Ireland. Land Use Policy 58: 335-347.

Vosselman, G. 2000. Slope based filtering of laser altimetry data. IAPRS, Vol. XXXIII, Part B3, Amsterdam, the Netherlands. pp. 935-942

Walley, F. 2011. Nitrogen mineralization: what's happening in your soil? Canola Watch. Canola Council of Canada. https://www.canolawatch.org/wp-content/uploads/2011/11/Fran-Walley-Nitrogen-Mineralization-2005-Canola-College.pdf (accessed 12 Dec. 2019).

Wang, D.L., and D.W. Anderson. 2000. Pedogenic carbonate in Chernozemic soils and landscapes of southeastern Saskatchewan. Can. J. Soil Sci. 80(2): 251-261.

Wang, S., Q. Zhuang, Q. Wang, X. Jin, and C. Han. 2017. Mapping stocks of soil organic carbon and soil total nitrogen in Liaoning province of China. Geoderma 305(120): 250-263.

Wickings, K., A.S. Grandy, and A.N. Kravchenko. 2016. Going with the flow: landscape position drives differences in microbial biomass and activity in conventional, low input, and organic agricultural systems in the Midwestern U.S. Agric. Ecosyst. Environ. 218: 1-10.

Williams, A., D.A. Kane, P.M. Ewing, L.W. Atwood, A. Jilling, M. Li, Y. Lou, A.S. Davis, A.S. Grandy, S.C. Huerd, et al. 2016. Soil functional zone management: a vehicle for enhancing production and soil ecosystem services in row-crop agroecosystems. Front. Plant Sci. 7(February): 1-15.

Wright, D. 2014. Drones: Regulatory challenges to an incipient industry. Comput. Law Secur. Rev. 30(3): 226-229.

Xue, P.P., Y. Carrillo, V. Pino, B. Minasny, and A.B. McBratney. 2018. Soil properties drive microbial community structure in a large scale transect in south eastern Australia. Sci. Rep. 8(1): 1-11.

Zhang, C., and J.M. Kovacs. 2012. The application of small unmanned aerial systems for precision agriculture: A review. Precis. Agric. 13(6): 693-712.

Zhang, G. lin, F. Liu, and X. dong Song. 2017. Recent progress and future prospect of digital soil mapping: a review. J. Integr. Agric. 16(12): 2871-2885.

Zhang, C., D. Walters, and J.M. Kovacs. 2014. Applications of low altitude remote sensing in agriculture upon farmers' requests- a case study in northeastern Ontario, Canada. PLoS One 9(11): 17–19.

Zhang, J., Q. Zhang, A. Bao, and Y. Wang. 2019. A new remote sensing dryness index based on the near-infrared and red spectral space. Remote Sens. 11(4).

Appendix A

SAMPLE POINT CLASSIFICATION SHEETS AND ANALYSIS DATA

The following information was obtained from soil cores and mimics the format of the soil classification sheets used to classify the samples. These sample points are a subset of the data. Ten points were chosen per site per land use.

SDNWA Cropland

Sample Name	Sub Group	Great Group	Order	Slope Position		
A01	Gleyed	Dark Brown	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-11	Sandy Clay Loam	10YR 3/3		0	
Bm	11-30	Sandy Clay Loam	10YR 4/6		0	
Ccagj	30-81+	Clay Loam	10YR 5/3	10YR 5/6 Few, distinct, fine	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
A03	Orthic	Black	Chernozem	Back/Foot		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-20	Clay	10YR 2/1		0	
AB	20-42	Clay	10YR 3/3		0	
Bm	42-100	Clay Loam	10YR 4/6		0	rocks
Cca	100-106+	Sandy Clay Loam	10YR 5/3		2	rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
A06	Gleyed	Dark Brown	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-14	Sandy Clay Loam	10YR 2/2		0	rocks
Bm	14-35	Sandy Clay Loam	10YR 4/6		0	rocks, clay skins
Ck	35-98+	Clay Loam	10YR 5/4		1	rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
A10	Rego	Dark Brown	Chernozem	Upper/Back		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-19	Sandy Clay Loam	10YR 3/3		0	rocks
ACk	19-38	Sandy Clay Loam	10YR 4/4		1.5	rocks
Ck	38-73+	Sandy Clay Loam	10YR 5/4		1.5	rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
A13	Orthic	Black	Chernozem	Foot/Back		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-28	Sandy Clay Loam	10YR 2/1		0	
Bm	28-59	Sandy Clay Loam	10YR 3/3		0	
Cgj	59-102+	Sandy Clay Loam	10YR 5/6	very faint	0	sandy, rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
A15	Orthic	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-24	Clay	10YR 2/1		0	
Bm	24-50	Clay	10YR 4/4		0	
Apbk	50-77	Clay Loam	10YR 3/3		0.5	potential buried Ah horizon
Cca	77-105+	Clay Loam	10YR 4/4		2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
A17	Orthic	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-21	Clay Loam	10YR 2/1		0	
Bm	21-30	Sandy Clay	10YR 4/2		0	clay skins
C	30-85	Silty Clay	10YR 4/1		0	
Cgj	85-99+	Silty Clay	10YR 5/2	10YR 6/8 common, faint, fine	0	

Sample Name	Sub Group	Great Group	Order	Slope Position		
A27	Orthic		Regosol	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-6	Sandy Clay	10YR 2/1		0	
AC	6-19	Sandy Clay	10YR 4/4		0	
Ck1	19-43	Silty Clay	10YR 3/3		1	
Ck2	43-103+	Silty Clay	10YR 4/4		1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
A36	Gleyed	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-33	Clay	10YR 2/1		0	
Bmgj	33-66	Silty Clay	10YR 4/3	7.5YR 5/6 few, faint, fine	0	
Cgj	66-86	Silty Clay	10YR 6/2	7.5YR 5/6 few, faint, med	0	sandy
Ckgj	86-110+	Clay Loam	10YR 5/2	7.5 YR 6/4 few, distinct, med	0.5	

Sample Name	Sub Group	Great Group	Order	Slope Position		
A37	Gleyed Calcareous	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-9	Sandy Clay	10YR 2/1		0	
Bm	9-33+	Sandy Clay	10YR 4/3	few, faint, fine	2	very rocky, sandy

CLC Cropland

Sample Name	Sub Group	Great Group	Order	Slope Position		
C02	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-9	Sandy Clay Loam	10 YR 2/1		0	
AB	9-21	Sandy Clay Loam	10 YR 3/2.5		0	
Bm	21-65	Sandy Clay Loam	10 YR 4/6		0	faint mottles
C	65-94	Sandy Loam	10 YR 5/3		0	faint mottles
IICkgj	94-100+	Silty Clay	10 YR 5/3	10 YR 4.5/2 distinct	1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C04	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-13	Sandy Clay	10 YR 2/1.5		0	
Bm	13-40	Sandy Clay	10 YR 4/4		0	
Ck	40-75	Sandy Loam	10 YR 5.5/4		1	
Cca	75-100+	Sandy Clay	10 YR 6/4		2	clay skins, some grey chunks

Sample Name	Sub Group	Great Group	Order	Slope Position		
C12	Gleyed	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap1	0-21	Sandy Clay Loam	10 YR 2/1		0	
Ap2	21-36	Sandy Clay	10 YR 3/3		0	
Bgj	36-68	Sandy Clay Loam	10 YR 4/3	10 YR 6/6 many, distinct, fine-med	0	
Ccagj	68-92+	Sandy Clay Loam	10 YR 7/1	10 YR 6/6 many, distinct, med	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C13	Orthic	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-44	Clay	10 YR 2/1		0	
Bm	44-60	Sandy Clay Loam	10 YR 4.5/4		0	
Cca	60-70+	Clay	10 YR 5.5/3.5		1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C19	Orthic	Black	Chernozem	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap1	0-12	Sandy Clay	10 YR 2/1		0	
Ap2	12-22	Sandy Clay	10 YR 2.5/2		0	
Bm	22-58	Sandy Clay	10 YR 4/4		0	
Ccagj	58-100+	Silty Clay	10 YR 5/3	10 YR 4/4.5 few, faint	2.5	grey, white, orange mottling

Sample Name	Sub Group	Great Group	Order	Slope Position		
C21	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap1	0-7	Clay Loam	10 YR 2/1		0	salts present
Ap2	7-24	Clay Loam	10 YR 3/2		0	
Bm	24-50	Sandy Clay Loam	10 YR 4/6		0	
Ccag	50-90	Clay	10 YR 4/2	Gley 2 5/10B many, prominent, med	2	grey, white, orange
Ckg	90-95+	Clay	10 YR 4/4	7.5 YR 5/8 common, prominent fine-med	1.5	grey, white, orange

Sample Name	Sub Group	Great Group	Order	Slope Position		
C24	Orthic		Regosol	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Apk	0-7	Loamy Sand	10 YR 2/2		2	
ACk	7-18	Sand	10 YR 4/4		3	
Ck1	18-51	Sand	10 YR 4/6		1	faint mottles
Cca	51-63	Sandy Loam	10 YR 5/3		2	clay lense mix of light and dark
Ck2	63-80+	Loamy Sand	10 YR 5/3		1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C33	Gleyed	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-36	Clay	10 YR 2/1		0	
Bgj	36-59+	Sandy Clay	10 YR 4.5/2	10 YR 5/6 common, distinct, fine	0	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C36	Eluviated	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-23	Sandy Clay	10 YR 2/1		0	
Aej	23-36	Clay	10 YR 4/2		0	
Bm	36-56	Clay	10 YR 3.5/3		0	
Cgj	56-88+	Sandy Clay Loam	10 YR 4/3	7.5 YR 4/6 many, distinct, med	0	

Sample Name	Sub Group	Great Group	Order	Slope Position		
C40	Orthic	Black	Chernozem	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-5	Sandy Clay	10 YR 3/1		0	
Bm1	5-30	Silty Clay	10 YR 4/2		0	
Apb	30-50	Sandy Clay	10 YR 3/1		0	
Bm2	50-60	Sandy Clay	10 YR 5/3		0	
Ck	60-98+	Silty Clay	10 YR 3.5/3		1	

CLC Grassland

Sample Name	Sub Group	Great Group	Order	Slope Position		
D01	Calcareous	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah1	0-30	Clay	10 YR 2/1.5		0	
Ah2	30-38	Clay	10 YR 3/2.5		0	
Cca	38-68+	Clay	10 YR 5/4 (moist)		2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D06	Orthic	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah1	0-15	Sandy Clay Loam	10 YR 2/2		0	
Ah2	15-31	Sandy Clay Loam	10 YR 3.5/3.5		0	
Bm	31-77	Sandy Clay Loam	10 YR 4/6		0	faint mottles
Ccagj	77-86	Sandy Clay Loam	10 YR 6/1	10 YR 6/8 common, distinct, fine	2.5	
Ckgj	86-97+	Sandy Clay Loam	10 YR 5/5	10 YR common, distinct, fine	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D11	Orthic	Humic	Gleysol	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
LFH	2-0					
Ah	0-14	Sandy Loam	10 YR 2/1		0	
Aegk	14-21	Sandy Clay Loam	10 YR 4/2	5 YR 5/8 few, prominent, fine	1	
Ahk	21-46	Sandy Clay Loam	10 YR 3/1		1	
Bgk	46-60	Sandy Clay Loam	10 YR 5/2	7.5 YR 5/8 few, prominent, fine	1	
Cgk	60-80+	Sandy Loam	10 YR 5/3	Gley 1 4/N med, prominent, common	1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D12	Calcareous	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-27	Sandy Clay	10 YR 2/1		0	
Bmk	27-47+	Silty Clay	10 YR 4.5/2.5		1	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D15	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah1	0-16	Clay Loam	10 YR 2/1		0	
Ah2	16-33	Sandy Clay Loam	10 YR 3/2.5		0	
Bm	33-64	Sandy Clay Loam	10 YR 4/6		0	
Ccagj1	64-76	Sandy Clay Loam	10 YR 4/3.5	7.5 YR 4/6 common, distinct, med	2	
Ccagj2	76-94+	Sandy Clay Loam	10 YR 5/3	7.5 YR 4/6 common, distinct, med	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D16	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-39	Clay Loam	10 YR 2/2		0	
Bm	39-67	Clay	10 YR 3/2		0	
Cca	67-100+	Silty Clay	10 YR 4.5/3		2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
D25	Rego	Black	Chernozem	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (dry)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah1	0-12	Clay	10 YR 2/1.5		0	
Ah2	12-39	Sandy Clay	10 YR 3/2		0	
Cca	39-84+	Clay	10 YR 4.5/3.5 (moist)		2	

Sample Name	**Sub Group**	**Great Group**	**Order**	**Slope Position**		
D27	Orthic	Black	Chernozem	Upperslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-17	Clay Loam	10 YR 2/1		0	
Bm	17-36	Clay	10 YR 3.5/2		0	
Cca	36-69+	Clay Loam	10 YR 6/4		2	

Sample Name	**Sub Group**	**Great Group**	**Order**	**Slope Position**		
D42	Orthic	Black	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-27	Clay Loam	10 YR 2/1		0	
Bm	27-54	Sandy Clay Loam	10 YR 4.5/6		0	
Cca	54-93+	Silty Clay	10 YR 6/4		2	

<u>SDNWA Grassland</u>

Sample Name	**Sub Group**	**Great Group**	**Order**	**Slope Position**		
B04	Gleyed	Humic	Regosol	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-23	Clay Loam	10YR 2/2		0	
ACk	23-32	Sandy Clay Loam	10YR 3/3		0.5	sandy, some rocks
Ckgj	32-81+	Sandy Clay Loam	10YR 5/4	10YR 5/6 faint, common, fine	2	sandy, pockets of darker material

Sample Name	Sub Group	Great Group	Order	Slope Position		
B06	Gleyed	Humic	Regosol	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ahk	0-15	Clay Loam	10YR 2/2		0.5	
ACk	15-30	Clay Loam	10YR 4/3		2	
Ckgj	30-90+	Clay Loam	10YR 6/4	10YR 5/8 faint, few, fine	2	Rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
B07	Gleyed	Black	Chernozem	Back/Upper		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-19	Clay	10YR 2/1		0	
AB	19-30	Clay	10YR 4/3		0	
Bm	30-43	Clay	10YR 4/4		0	
Ccagj	43-80+	Clay Loam	10YR 5/4	10YR 5/6 few, faint, fine	2	very faint mottles

Sample Name	Sub Group	Great Group	Order	Slope Position		
B10	Gleyed Calcareous	Dark Brown	Chernozem	Backslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ahk	0-16	Sandy Clay Loam	10YR 3/3		1.5	rocks
Bmk	16-46	Sandy Clay Loam	10YR 4/4		2	rocks
Ckgj	46-89+	Sandy Clay Loam	10YR 5/2	10YR 5/8 few, faint, fine	2	rocks

Sample Name	Sub Group	Great Group	Order	Slope Position		
B14	Gleyed Calcareous	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-14	Sandy Clay	10YR 2/1		0	
Bkgj1	14-28	Clay	10YR 3/2	7.5 YR 4/4 common, distinct, med	2	
Bkgj2	28-50	Clay Loam	10YR 4/2	7.5 YR 5/6 common, distinct, med	2	
Ckgj	50-70+	Clay Loam	10YR 5/2	7.5 YR 6/6 many, distinct, coarse	2	matrix mostly orange

Sample Name	Sub Group	Great Group	Order	Slope Position		
B16 (B13?)	Orthic	Black	Chernozem	Footslope		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-16	Clay Loam	10YR 2/2		0	
Bm	16-29	Clay Loam	10YR 3/3		0	
C	29-45	Silty Clay Loam	10YR 4/2		0	
Cca1	45-70	Silty Clay Loam	10YR 5/1		1.5	very faint mottles
Cca2	70-78	Silty Clay Loam	10 YR 5/2		2	
Ccag	78-102+	Silty Clay Loam	10 YR 5/2	10 YR 6/8 many, coarse, prominent	2.5	mostly orange mottles

Sample Name	Sub Group	Great Group	Order	Slope Position		
B18	Gleyed Calcareous	Black	Chernozem	Depression/Foot		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ahk	0-16	Sandy Clay Loam	10YR 2/2		0.5	
Bkgj	16-39	Clay Loam	10YR 4/3	7.5 YR 5/4 common, distinct, med	2	
Ckgj	39-79+	Clay Loam	10YR 5/2	10 YR 7/6 common, faint, med	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
B36	Gleyed Calcareous	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-14	Sandy Clay Loam	10 YR 2/2		0	
Bkgj	14-63	Clay	10 YR 4/2	10 YR 5/6 few, fine, faint	0.5	
Ccagj	63-100+	Silty Clay Loam	10 YR 5/1	10 YR 6/8 common, med, distinct	2	

Sample Name	Sub Group	Great Group	Order	Slope Position		
B37	Orthic	Black	Chernozem	Depression		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ah	0-18	Clay Loam	10 YR 2/1		0	
AB	18-30	Clay Loam	10 YR 3/3		0	
Bm	30-70	Clay	10 YR 4/4		0	clay skins
Cca	70-100+	Clay Loam	10 YR 5/4		2	

Sample Name	**Sub Group**	**Great Group**	**Order**	**Slope Position**		
B40	Calcareous	Black	Chernozem	Upper/Back		
Horizon	**Horizon Thickness (cm)**	**Texture Class**	**Matrix Colour (moist)**	**Mottles**	**Efferve scence (0-3)**	**Comment**
Ap	0-25	Clay Loam	10 YR 2/1		0	
Bmk	25-33	Silty Clay	10 YR 3/3		1.5	
Ahb	33-45	Clay Loam	10 YR 3/2		0.5	
Ck1	45-69	Clay Loam	10 YR 5/4		2	
Ck2	69-107+	Sandy Clay Loam	10 YR 5/3	10 YR 6/6 few, fine, faint	2	salts/carbon ates visible

Table A.1. Results of soil sample data to a depth of 15 cm in the cropland at the St. Denis National Wildlife Area.

Point	A Horiz. Depth	Depth to Gley	Depth to $CaCO_3$	BD	OC	TC	Moist	pH	EC	TN	MN	P	Hand Texture	Sand	Silt	Clay
	cm	cm	cm	g/cm^3	µg/g	µg/g	g/g		µS/cm	µg/g	µg/g	µg/g		%	%	%
SDNWA Crop																
A01	24	-	0	2.01	11580	12600	0.14	7.81	222	1495	15.8	6.08	SaCL	54	28	18
A02	17	-	0	1.81	20650	22900	0.16	N/A	N/A	1465	17.8	3.83	SaCL	N/A	N/A	N/A
A03	38	-	-	1.86	28120	28900	0.25	7.29	217	2472	14.8	8.64	C	40	39	21
A04	17	-	68	1.81	27340	21100	0.19	N/A	N/A	1978	18.3	6.84	SaCL	N/A	N/A	N/A
A05	21	-	-	1.81	22360	11100	0.16	N/A	N/A	1707	12.5	4.58	SaCL	40	32	28
A06	10	-	0	1.80	25080	26000	0.20	7.68	350	2455	21.7	9.52	SaCL	43	35	22
A07	13	-	0	1.81	31810	35100	0.23	N/A	N/A	2890	41.4	3.76	CL	N/A	N/A	N/A
A08	21	-	19	1.81	37930	36000	0.24	N/A	N/A	2459	32.8	11.8	SaCL	N/A	N/A	N/A
A09	18	-	19	1.81	34850	33400	0.23	N/A	N/A	2441	28.3	4.98	SaCL	N/A	N/A	N/A
A10	8	-	0	1.57	19080	21600	0.13	7.55	306	1515	9.1	3.42	SaCL	59	26	15
A11	25	-	0	1.62	30820	42100	0.32	N/A	N/A	3188	48.5	5.71	SaCL	N/A	N/A	N/A
A12	26	-	55	1.62	34240	32600	0.28	N/A	N/A	3167	21.2	5.72	SiC	29	46	25
A13	10	-	76	1.44	26750	24800	0.23	6.64	164.6	2378	11.2	8.32	C	36	43	21
A14	33	22	46	1.62	41670	42600	0.39	N/A	N/A	4278	13.5	61.4	CL	N/A	N/A	N/A
A15	33	83	-	1.83	25790	28400	0.29	7.27	278	3317	24.0	4.71	C	44	34	22
A16	33	-	0	1.62	33210	49600	0.35	N/A	N/A	3728	3.8	5.65	C	N/A	N/A	N/A
A17	16	80	-	1.60	34720	33600	0.28	7.71	544	3254	19.2	27.6	CL	32	40	28
A18	>65	0	60	1.60	35740	40600	0.52	N/A	N/A	2998	3.5	10.8	SaC	N/A	N/A	N/A
A19	17	18	0	1.60	28860	35300	0.30	N/A	N/A	2117	7.1	8.04	C	N/A	N/A	N/A
A20	26	0	0	1.60	32640	36400	0.39	N/A	N/A	3772	10.6	16.9	CL	N/A	N/A	N/A
A21	15	-	59	1.80	26220	27700	0.22	N/A	N/A	2546	24.6	8.63	SiC	N/A	N/A	N/A
A22	29	-	30	1.80	18990	21100	0.18	N/A	N/A	2082	12.7	6.14	SaCL	N/A	N/A	N/A
A23	11	-	50	1.80	24670	23300	0.25	N/A	N/A	2450	23.4	6.97	SaC	N/A	N/A	N/A
A24	14	-	42	1.80	24950	24700	0.20	N/A	N/A	2385	11.5	9.63	SaCL	N/A	N/A	N/A
A25	15	50	77	1.80	28920	27300	0.27	N/A	N/A	3794	24.2	12.3	CL	N/A	N/A	N/A
A26	27	75	-	1.80	40610	45300	0.36	N/A	N/A	3894	25.0	29.3	CL	19	52	29

Table A.1. (con't).

A27	7	-	0	1.80	9650	33200	0.22	8.06	376	1840	17.6	4.79	SaC	28	40	32
A28	7	-	0	1.80	23180	48200	0.33	N/A	N/A	2335	10.2	3.77	SaCL	N/A	N/A	N/A
A29	12	-	-	1.80	35520	35200	0.29	N/A	N/A	2693	13.1	10.8	SaCL	N/A	N/A	N/A
A30	19	-	58	1.80	23460	21600	0.19	N/A	N/A	2235	31.5	23.7	SaC	N/A	N/A	N/A
A31	15	-	0	1.81	14400	15500	0.15	N/A	N/A	1285	11.4	3.16	SaCL	N/A	N/A	N/A
A32	15	-	-	1.81	17000	21500	0.14	N/A	N/A	4142	7.7	4.18	SaCL	N/A	N/A	N/A
A33	-	-	0	1.81	9460	9150	0.13	N/A	N/A	769	8.0	5.76	SaC	52	31	17
A34	17	-	-	1.62	38400	38100	0.35	N/A	N/A	3589	16.1	57.9	C	30	43	27
A35	19	-	63	1.62	26500	25600	0.23	N/A	N/A	2663	31.0	10.1	CL	N/A	N/A	N/A
A36	28	-	0	1.68	29900	33400	0.30	7.93	506	2955	26.2	27.6	C	36	35	29
A37	29	57	0	1.45	23300	34000	0.31	8.08	641	2104	7.3	6.74	SaC	56	25	18
A38	9	-	9	1.80	18600	17600	0.19	N/A	N/A	2651	13.8	9.11	SaC	N/A	N/A	N/A
A39	13	-	38	1.80	28650	29300	0.24	N/A	N/A	2652	25.3	19.2	SaCL	N/A	N/A	N/A
A40	10	-	0	1.80	16420	37800	0.24	N/A	N/A	1339	19.8	3.52	SaC	N/A	N/A	N/A

Table A.2. Results of soil sample data to a depth of 15 cm in the cropland at the Conservation Learning Centre.

Point	A Horiz. Depth	Depth to Gley	Depth to $CaCO_3$	BD	OC	TC	Moist	pH	EC	TN	MN	P	Hand Texture	Sand	Silt	Clay
	cm	cm	cm	g/cm^3	µg/g	µg/g	g/g		µS/cm	µg/g	µg/g	µg/g		%	%	%
CLC Crop																
C01	10	45	30	1.68	30540	30200	0.23	5.81	103	2684	19.3	4.08	SaCL	53	30	17
C02	9	94	94	1.65	33900	29900	0.25	6.84	165	1564	10.5	5.18	SaCL	49	26	25
C03	5	20	28	1.72	17860	14800	0.18	5.92	72	1776	11.7	7.97	SaC	N/A	N/A	N/A
C04	13	-	40	1.79	19710	18600	0.18	6.42	115	1698	38.4	11.3	SaC	51	26	23
C05	20	50	31	1.68	39070	38400	0.31	6.98	175	2830	6.5	5.32	CL	N/A	N/A	N/A
C06	9	-	9	1.68	16380	15100	0.14	7.55	187	1092	34.2	5.79	SaL	N/A	N/A	N/A
C07	12	55	55	1.68	26790	25500	0.27	6.91	184	2834	19.9	11.8	CL	N/A	N/A	N/A
C08	15	40	51	1.68	32910	30200	0.24	6.43	101	2715	14.8	6.11	C	39	39	22
C09	8	-	34	1.72	21930	22800	0.23	6.96	1700	1671	10.5	3.90	C	N/A	N/A	N/A
C10	18	80	65	1.68	29470	27300	0.23	6.12	124	2589	18.3	4.06	CL	N/A	N/A	N/A

Table A.2. (con't).

C11	15	54	73	1.68	35310	32200	0.25	5.88	141	3014	33.5	5.99	C	N/A	N/A	N/A
C12	36	36	68	1.71	31420	29700	0.26	6.61	220	3213	13.0	5.74	SaCL	N/A	N/A	N/A
C13	44	-	60	1.64	31220	28300	0.26	6.52	125	2621	17.5	5.23	C	47	33	19
C14	20	34	34	1.64	37630	40100	0.30	6.77	179	3676	12.8	8.69	SaC	51	30	19
C15	15	55	29	1.72	36630	28100	0.28	6.82	319	2783	12.9	6.51	C	N/A	N/A	N/A
C16	29	29	74	1.60	52040	42500	0.31	6.39	1921	3397	7.3	8.59	C	N/A	N/A	N/A
C17	18	32	32	1.60	45440	43900	0.29	5.97	146	2546	12.8	4.30	C	N/A	N/A	N/A
C18	N/A	N/A	N/A	1.72	37750	35000	0.23	6.48	120	2123	23.6	7.72	CL	N/A	N/A	N/A
C19	12	58	58	1.63	54960	29000	0.23	6.85	121	2770	16.0	11.7	SaC	48	26	26
C20	8	28	28	1.72	27740	26900	0.21	6.22	140	2642	24.7	7.25	SC	34	36	31
C21	24	50	60	1.70	28000	27200	0.21	6.06	63	2596	10.8	5.48	CL	60	21	19
C22	6	30	30	1.72	24760	23100	0.22	7.34	198	1749	14.1	4.38	CL	N/A	N/A	N/A
C23	9	45	16	1.72	17720	14400	0.18	6.98	145	1930	13.2	3.24	SaC	75	12	13
C24	7	-	0	1.77	11660	21200	0.15	7.71	324	908	8.5	4.69	LSa	N/A	N/A	N/A
C25	8	-	8	1.72	38940	36400	0.26	6.52	145	2619	25.0	5.67	SaCL	N/A	N/A	N/A
C26	11	40	40	1.72	24220	22200	0.21	8.45	147	2734	70.2	8.31	CL	N/A	N/A	N/A
C27	8	-	40	1.68	18290	17300	0.23	6.32	92	1965	16.8	5.83	SaC	N/A	N/A	N/A
C28	15	-	37	1.72	25170	23700	0.23	7.36	90	2277	23.1	23.6	SaC	N/A	N/A	N/A
C29	10	45	55	1.72	38450	32600	0.28	5.81	150	3435	22.1	9.13	C	N/A	N/A	N/A
C30	11	59	59	1.72	32820	30500	0.23	6.04	113	2794	13.8	4.89	SaC	N/A	N/A	N/A
C31	7	-	32	1.68	24960	19300	0.20	6.28	103	2322	57.4	11.6	SaL	N/A	N/A	N/A
C32	20	-	34	1.68	31530	28700	0.27	6.38	547	1789	17.7	4.31	C	N/A	N/A	N/A
C33	36	36	N/A	1.52	42490	43700	0.34	5.82	931	4010	21.6	8.77	C	29	38	34
C34	9	30	32	1.64	40550	44700	0.33	5.67	95	3215	70.9	20.6	C	N/A	N/A	N/A
C35	15	15	53	1.64	37220	36900	0.33	6.94	307	2959	12.6	8.40	C	N/A	N/A	N/A
C36	36	56	N/A	1.67	49980	46200	0.34	7.6	240	4352	12.7	11.3	SaC	38	39	23
C37	31	45	66	1.60	45550	49300	0.42	6.12	350	4060	17.2	13.0	CL	N/A	N/A	N/A
C38	28	28	49	1.60	54210	59800	0.39	6.64	2040	4686	9.6	9.54	C	N/A	N/A	N/A
C39	42	42	N/A	1.60	52570	52600	0.42	7.46	1126	3890	11.8	14.3	CL	N/A	N/A	N/A
C40	5	-	60	1.68	26040	25700	0.30	7.79	288	1879	33.5	9.46	SaC	29	34	38

Table A.3. Results of soil sample data to a depth of 15 cm in the grassland at the Conservation Learning Centre.

Point	A Horiz. Depth	Depth to Gley	Depth to $CaCO_3$	BD	OC	TC	Moist	pH	EC	TN	MN	P	Hand Texture	Sand	Silt	Clay
	cm	cm	cm	g/cm^3	µg/g	µg/g	g/g		µS/cm	µg/g	µg/g	µg/g		%	%	%
CLC Grass																
D01	38	-	63	1.35	57250	60700	0.53	6.34	1656	4723	4.9	5.55	C	37	37	26
D02	30	30	45	1.54	53260	58300	0.41	8.34	1107	3898	6.1	3.79	CL	N/A	N/A	N/A
D03	62	74	61	1.54	51880	56800	0.34	8.43	836	4360	7.2	5.73	SaC	N/A	N/A	N/A
D04	45	45	80	1.54	55990	57800	0.46	6.66	474	5121	13.5	6.73	C	N/A	N/A	N/A
D05	60	-	40	1.54	44480	43200	0.37	7.65	3480	3932	14.9	8.97	SaCL	N/A	N/A	N/A
D06	31	77	77	1.58	43960	43300	0.35	6.94	303	3003	5.9	4.53	SaCL	63	19	18
D07	38	80	55	1.54	38950	38400	0.34	7.11	259	2834	14.2	3.87	CL	N/A	N/A	N/A
D08	71	0	-	1.54	57440	52000	0.47	6.72	1752	4644	6.2	9.61	SaC	N/A	N/A	N/A
D09	39	47	77	1.28	39530	38200	0.38	7.02	1137	3465	6.6	6.14	C	35	35	30
D11	46	14	14	1.27	52420	53600	0.53	6.68	1490	4627	7.1	4.99	SaL	44	29	27
D12	27	-	27	1.62	44110	39300	0.42	6.75	331	2238	6.6	4.38	SaC	46	25	29
D13	38	10	-	1.28	40030	40400	0.50	6.49	294	3624	5.8	6.26	C	N/A	N/A	N/A
D14	19	N/A	26	1.51	30340	34200	0.31	7.06	887	2514	5.0	4.01	SC	N/A	N/A	N/A
D15	33	64	70	1.50	45350	43600	0.27	8.29	384	3312	7.1	4.42	CL	54	23	23
D16	39	-	67	1.42	44160	41200	0.30	7.93	260	3613	8.9	5.43	CL	47	25	28
D17	N/A	N/A	N/A	1.51	22570	21300	0.15	7.06	158	1473	8.4	4.12	SaCL	N/A	N/A	N/A
D18	18	-	-	1.51	42980	39900	0.29	6.43	221	2627	9.0	4.13	L	23	36	41
D19	30	-	66	1.51	46190	48800	0.27	6.32	154	3686	7.5	3.46	C	N/A	N/A	N/A
D20	26	26	26	1.51	32350	31500	0.31	8.41	477	3303	10.0	3.14	SaC	N/A	N/A	N/A
D21	19	5	40	1.51	49410	56300	0.51	8.18	4340	2139	9.2	5.48	SaC	21	47	32
D22	33	-	25	1.28	47760	48100	0.38	8.43	1634	2897	4.6	2.56	SC	16	38	46
D23	20	-	48	1.36	36110	33100	0.25	7.85	164	2244	3.6	2.73	SaC	N/A	N/A	N/A
D24	56	-	90	1.36	43360	44400	0.36	6.3	1234	3398	3.8	3.22	CL	N/A	N/A	N/A
D25	39	-	39	1.43	76020	48700	0.37	6.47	417	4114	6.4	3.41	C	25	32	42
D26	59	-	-	1.36	25570	26200	0.28	7.48	355	2765	11.1	3.38	C	N/A	N/A	N/A
D27	17	-	36	1.32	39920	42000	0.30	6.43	344	3063	4.9	3.00	CL	34	31	35
D28	63	75	-	1.36	30520	29700	0.27	7.54	337	2710	11.0	3.19	CL	N/A	N/A	N/A

Table A.3. (con't).

D29	27	-	0	1.36	31410	21700	0.16	6.99	184	1618	3.7	2.32	SaCL	N/A	N/A	N/A
D30	12	-	31	1.36	32790	34700	0.26	6.64	126	2761	7.6	3.07	C	N/A	N/A	N/A
D31	20	21	67	1.54	61470	58300	0.42	5.33	2470	4988	4.2	3.52	C	N/A	N/A	N/A
D32	25	60	72	1.54	70390	62700	0.49	8.06	524	5165	7.4	4.64	C	N/A	N/A	N/A
D34	34	20	26	1.28	48450	45100	0.38	7.05	602	3396	6.1	3.23	SaCL	61	22	17
D35	32	-	-	1.30	85940	49500	0.25	6.61	222	4147	7.0	5.90	CL	51	28	21
D36	12	-	27	1.51	34920	33000	0.22	8.34	401	2657	6.5	4.76	CL	N/A	N/A	N/A
D38	46	-	-	1.51	45600	48300	0.39	8.21	1507	4070	5.5	3.70	CL	N/A	N/A	N/A
D39	44	-	68	1.36	38160	41000	0.30	7.72	3730	2761	6.6	4.84	CL	N/A	N/A	N/A
D40	24	-	-	1.36	55020	58200	0.39	6.01	229	4777	11.2	5.81	C	N/A	N/A	N/A
D41	42	78	-	1.36	41580	38500	0.27	6.76	167	3135	7.2	3.36	SaC	N/A	N/A	N/A
D42	27	-	54	1.50	44040	42100	0.34	6.38	617	1653	4.1	3.19	CL	54	23	23

Table A.4. Results of soil sample data to a depth of 15 cm in the grassland at the St. Denis National Wildlife Area.

Point	A Horiz. Depth	Depth to Gley	Depth to $CaCO_3$	BD	OC	TC	Moist	pH	EC	TN	MN	P	Hand Texture	Sand	Silt	Clay
	cm	cm	cm	g/cm^3	µg/g	µg/g	g/g		µS/cm	µg/g	µg/g	µg/g		%	%	%
SDNWA Grass																
B01	18	28	25	1.61	33710	31500	0.22	7.34	218	3287	7.8	3.34	SaCL	N/A	N/A	N/A
B02	15	-	13	1.61	35540	46500	0.26	8.1	275	2777	7.1	3.05	SaCL	N/A	N/A	N/A
B03	18	-	28	1.61	24670	31900	0.21	7.6	378	2672	10.6	4.01	SaCL	N/A	N/A	N/A
B04	10	-	21	1.69	27500	34700	0.20	7.7	241	2185	5.9	2.75	CL	45	33	22
B05	18	-	24	1.61	21930	31800	0.16	7.75	233	2110	9.1	3.51	SaC	N/A	N/A	N/A
B06	23	-	23	1.50	32840	34600	0.23	7.57	271	2458	10.2	3.32	CL	38	40	22
B07	20	-	40	1.39	36470	35000	0.25	7.72	278	3371	11.5	3.86	C	24	45	31
B08	16	30	0	1.61	36010	48300	0.32	8.1	214	2757	5.7	4.77	SaCL	N/A	N/A	N/A
B09	25	-	30	1.61	38840	40200	0.21	7.2	319	2254	9.4	3.35	SaCL	N/A	N/A	N/A
B10	14	-	0	1.64	21980	38500	0.16	7.52	303	2290	14.6	3.54	SaCL	47	33	20
B11	11	-	0	1.41	26710	40300	0.22	7.89	228	2421	7.4	3.23	SaCL	N/A	N/A	N/A
B12	15	35	29	1.41	29750	31800	0.27	7.11	280	2171	5.2	3.00	SaC	41	34	25

Table A.4. (con't).

B13	22	-	37	1.41	46490	44000	0.39	6.75	1927	3229	3.6	2.94	C	N/A	N/A	N/A
B14	8	8	8	1.55	38070	43000	0.48	7.32	527	3185	5.4	3.85	SaC	27	51	22
B15	14	-	43	1.41	31140	29000	0.29	7.02	1181	3660	7.3	3.06	SaC	N/A	N/A	N/A
B16	12	80	87	1.21	38820	41000	0.31	7.21	194	3488	9.5	3.64	CL	23	53	25
B17	15	95	105	1.48	42500	45800	0.36	6.91	239	3362	8.0	4.98	C	N/A	N/A	N/A
B18	17	16	19	1.61	29980	37600	0.47	7.2	847	2914	6.6	3.83	SaCL	34	44	22
B19	18	0	0	1.48	40260	45800	0.82	7.2	841	3528	5.3	9.13	SaC	N/A	N/A	N/A
B20	20	-	-	1.48	37930	38000	0.29	7.45	256	3301	6.0	20.8	CL	N/A	N/A	N/A
B21	17	50	76	1.38	23330	44100	0.29	7.64	292	3542	11.5	3.57	SCL	21	55	24
B22	23	-	36	1.38	30390	28700	0.21	7.53	268	3020	5.7	3.56	C	N/A	N/A	N/A
B23	16	-	18	1.38	30760	32500	0.21	7.8	222	2554	13.8	2.85	SaCL	N/A	N/A	N/A
B24	28	-	-	1.38	43520	45600	0.27	7.05	198	3523	19.1	5.02	SaCL	31	43	27
B25	11	-	15	1.38	23380	23900	0.20	7.86	244	2250	8.3	2.91	C	N/A	N/A	N/A
B26	16	-	0	1.38	31150	47100	0.27	7.83	275	2638	5.7	2.69	SaC	N/A	N/A	N/A
B27	18	-	0	1.38	27610	40300	0.16	7.37	326	2477	10.7	2.45	SaCL	N/A	N/A	N/A
B28	14	-	25	1.38	28870	29200	0.19	7.24	294	2619	9.1	2.39	SaCL	N/A	N/A	N/A
B29	10	-	0	1.38	25910	36200	0.18	7.46	279	2332	7.4	2.54	SaCL	N/A	N/A	N/A
B30	12	-	0	1.38	21750	42900	0.15	7.89	230	1907	11.0	2.21	SaCL	N/A	N/A	N/A
B31	10	-	18	1.61	34290	41100	0.27	7.39	325	3393	5.8	2.86	C	N/A	N/A	N/A
B32	24	-	62	1.61	34140	27900	0.25	7.38	275	2457	14.5	2.75	SaCL	N/A	N/A	N/A
B33	20	-	21	1.61	29980	34300	0.18	7.39	308	2497	9.3	2.51	SaCL	N/A	N/A	N/A
B34	18	-	45	1.41	35220	41800	0.31	7.53	273	3647	9.4	9.14	C	N/A	N/A	N/A
B35	15	20	20	1.41	25860	38500	0.32	7.05	2200	2316	1.9	2.64	SaC	N/A	N/A	N/A
B36	16	20	96	1.61	22720	24800	0.39	6.98	182	2504	9.9	24.0	SaCL	14	61	26
B37	22	-	75	1.29	35350	38200	0.30	7.37	228	3108	7.6	3.76	CL	24	49	27
B38	12	-	0	1.38	17070	38300	0.19	7.55	281	2346	7.0	2.40	SaCL	N/A	N/A	N/A
B39	27	-	68	1.41	31790	29300	0.23	7.17	237	2282	11.5	2.86	CL	N/A	N/A	N/A
B40	18	-	12	1.12	36720	39500	0.26	7.65	319	3738	8.8	3.38	CL	27	48	25

Table A.5. Final zone delineation and remote sensing vegetation indices for sample points in the cropland at the St. Denis National Wildlife Area. NDVI= Normalized Difference Vegetation Index, CIG=Chlorophyll Index-Green.

Point	MidCIG	MidNDVI	LateCIG	LateNDVI	FLMZ
	June 28	June 28	July 27	July 27	
A01	3.57	0.81	2.17	0.59	Back_MedC
A02	1.37	0.58	1.30	0.80	Back_MedC
A03	3.63	0.86	3.44	0.76	Back_HighC
A04	4.01	0.87	1.52	0.67	Back_HighC
A05	2.81	0.78	2.08	0.40	Back_MedC
A06	4.22	0.88	2.58	0.70	LowerBack_LowC
A07	4.13	0.88	2.96	0.71	Back_HighC
A08	3.41	0.83	1.82	0.77	Upper_MedC
A09	3.88	0.86	1.49	0.58	Back_HighC
A10	2.92	0.78	1.58	0.78	LowerBack_LowC
A11	3.62	0.85	2.82	0.66	Lower_MedHighC
A12	4.23	0.88	2.46	0.67	Lower_MedHighC
A13	4.13	0.87	1.97	0.63	Lower_MedHighC
A14	4.89	0.89	4.04	0.56	Back_HighC
A15	5.24	0.90	2.67	0.57	Lower_MedHighC
A16	1.06	0.39	2.71	0.75	Lower_MedHighC
A17	3.22	0.84	5.71	0.62	Lower_MedHighC
A18	2.21	0.69	4.08	0.84	Lower_MedHighC
A19	1.77	0.67	3.18	0.84	Lower_MedHighC
A20	4.33	0.88	1.72	0.79	Lower_MedHighC
A21	3.43	0.84	2.27	0.53	Upper_MedC
A22	3.52	0.83	2.58	0.82	Upper_LowC
A23	3.93	0.87	2.98	0.72	Upper_HighC
A24	5.96	0.91	2.27	0.38	Upper_MedC
A25	4.07	0.88	3.62	0.78	Lower_MedHighC
A26	6.79	0.92	4.16	0.83	Upper_HighC
A27	3.82	0.86	2.38	0.56	Upper_LowC
A28	3.65	0.85	2.89	0.65	Upper_LowC
A29	4.15	0.88	1.44	0.42	Lower_MedHighC
A30	4.65	0.88	1.75	0.44	Back_MedC
A31	4.31	0.86	2.50	0.58	Back_MedC
A32	2.90	0.77	2.54	0.44	LowerBack_LowC
A33	3.33	0.80	2.36	0.81	Back_MedC
A34	3.90	0.89	3.57	0.50	Back_HighC
A35	4.48	0.87	3.17	0.73	Upper_MedC
A36	4.72	0.91	3.59	0.73	Lower_MedHighC
A37	1.89	0.62	1.84	0.74	Lower_MedHighC
A38	3.42	0.83	3.05	0.90	LowerBack_LowC
A39	4.78	0.89	1.92	0.77	Upper_MedC
A40	2.43	0.71	2.14	0.57	Upper_MedC

Table A.6. Final zone delineation, yield data, and remote sensing vegetation indices for sample points in the cropland at the Conservation Learning Centre. NDVI= Normalized Difference Vegetation Index, CIG=Chlorophyll Index-Green.

Point	Dry Weight	Grain Weight	Yield	MidCIG	MidNDVI	LateCIG	LateNDVI	FLMZ
	g	g	bu/ac	July 5	July 5	July 31	July 31	
C01	961	382.0	56.8	3.35	0.86	6.30	0.89	Back_MedC
C02	633	257.4	38.3	N/A	N/A	N/A	N/A	UpperBack_LowC
C03	755	312.2	46.4	1.82	0.66	4.34	0.80	UpperBack_LowC
C04	918	391.4	58.2	1.54	0.63	4.55	0.84	UpperBack_LowC
C05	902	374.5	55.7	N/A	N/A	N/A	N/A	Back_MedC
C06	N/A	N/A	N/A	1.04	0.48	2.44	0.61	UpperBack_LowC
C07	821	285.8	42.5	N/A	N/A	N/A	N/A	UpperBack_LowC
C08	N/A	N/A	N/A	1.57	0.59	5.51	0.86	Back_MedC
C09	N/A	N/A	N/A	3.03	0.84	5.57	0.87	Lower_MedLowC
C10	N/A	N/A	N/A	2.96	0.82	3.70	0.80	Back_MedC
C11	N/A	N/A	N/A	2.80	0.81	6.94	0.89	Back_MedC
C12	825	315.2	46.9	N/A	N/A	N/A	N/A	Back_MedC
C13	806	280.8	41.7	2.39	0.75	4.79	0.85	Upper_MedHighC
C14	N/A	N/A	N/A	4.88	0.88	7.05	0.90	Lower_MedLowC
C15	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Upper_MedHighC
C16	492	167.7	24.9	1.96	0.67	3.19	0.79	LowerBack_HighC
C17	N/A	N/A	N/A	1.81	0.69	6.63	0.89	LowerBack_HighC
C18	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Upper_MedHighC
C19	620	258.2	38.4	1.61	0.61	4.23	0.82	Upper_MedHighC
C20	1063	453.9	67.5	3.39	0.86	4.36	0.84	UpperBack_LowC
C21	N/A	N/A	N/A	0.42	0.20	1.48	0.47	Upper_MedHighC
C22	N/A	N/A	N/A	1.57	0.61	3.95	0.79	UpperBack_LowC
C23	N/A	N/A	N/A	1.90	0.64	5.95	0.87	UpperBack_LowC
C24	329	128.0	19.0	N/A	N/A	N/A	N/A	UpperBack_LowC
C25	N/A	N/A	N/A	2.59	0.75	4.56	0.84	Upper_MedHighC
C26	N/A	N/A	N/A	0.78	0.22	4.15	0.84	UpperBack_LowC
C27	N/A	N/A	N/A	2.24	0.73	5.45	0.86	Upper_MedHighC
C28	N/A	N/A	N/A	2.15	0.65	6.02	0.88	Upper_MedHighC
C29	N/A	N/A	N/A	2.80	0.80	5.42	0.88	Upper_MedHighC
C30	N/A	N/A	N/A	0.63	0.30	2.06	0.62	Upper_MedHighC
C31	827	293.2	43.6	2.01	0.69	6.16	0.89	UpperBack_LowC
C32	N/A	N/A	N/A	1.63	0.62	1.70	0.48	Back_MedC
C33	589	292.7	43.5	N/A	N/A	N/A	N/A	LowerBack_HighC
C34	778	311.6	46.3	2.41	0.65	5.70	0.87	Upper_MedHighC
C35	N/A	N/A	N/A	0.74	0.24	3.20	0.77	LowerBack_HighC
C36	829	320.3	47.6	2.84	0.84	4.66	0.87	LowerBack_HighC
C37	857	223.2	33.2	1.70	0.58	6.20	0.88	LowerBack_HighC
C38	378	116.4	17.3	1.00	0.39	2.70	0.71	LowerBack_HighC
C39	942	325.2	48.3	N/A	N/A	N/A	N/A	LowerBack_HighC
C40	957	405.3	60.3	N/A	N/A	N/A	N/A	UpperBack_LowC

Table A.7. Final zone delineation, yield data, and remote sensing vegetation indices for sample points in the grassland at the Conservation Learning Centre. NDVI= Normalized Difference Vegetation Index, CIG=Chlorophyll Index-Green.

Point	FreshWeight	DryWeight	MidCIG	MidNDVI	LateCIG	LateNDVI	FLMZ
	g	g	July 5	July 5	July 31	July 31	
D01	236.5	89.5	1.79	0.65	2.35	0.66	Upper_High
D02	350.9	105.9	1.55	0.75	1.98	0.74	Upper_High
D03	N/A	N/A	N/A	N/A	N/A	N/A	LowerBack_High
D04	597.7	181.2	0.72	0.35	2.62	0.74	Upper_High
D05	N/A	N/A	2.15	0.74	2.45	0.72	Upper_Low
D06	279.2	101.4	2.45	0.77	2.93	0.76	Upper_High
D07	N/A	N/A	1.31	0.50	1.69	0.51	Upper_High
D08	N/A	N/A	2.17	0.73	3.06	0.78	LowerBack_High
D09	322.8	110.0	N/A	N/A	N/A	N/A	LowerBack_Low
D11	274.7	87.6	1.95	0.68	3.28	0.84	LowerBack_High
D12	266.7	91.8	2.93	0.76	2.81	0.73	LowerBack_Low
D13	247.2	104.1	2.20	0.77	2.45	0.73	LowerBack_High
D14	N/A	N/A	1.08	0.51	1.73	0.60	Upper_Low
D15	126.3	66.8	N/A	N/A	N/A	N/A	LowerBack_High
D16	156.7	75.5	1.68	0.64	2.00	0.72	LowerBack_High
D17	N/A	N/A	1.23	0.54	2.03	0.70	LowerBack_Low
D18	117.2	54.6	1.82	0.66	2.16	0.72	LowerBack_Low
D19	N/A	N/A	2.39	0.73	3.00	0.79	LowerBack_High
D20	N/A	N/A	1.89	0.71	2.52	0.71	Upper_Low
D21	421.5	139.2	2.46	0.81	2.70	0.79	LowerBack_Low
D22	N/A	N/A	N/A	N/A	N/A	N/A	Upper_Low
D23	N/A	N/A	N/A	N/A	N/A	N/A	Upper_Low
D24	N/A	N/A	1.97	0.73	2.35	0.69	Upper_Low
D25	180.3	59.2	1.14	0.52	1.96	0.67	Upper_High
D26	N/A	N/A	0.77	0.40	1.74	0.64	LowerBack_Low
D27	101.7	47.8	1.50	0.62	2.38	0.74	Upper_Low
D28	N/A	N/A	N/A	N/A	N/A	N/A	LowerBack_Low
D29	N/A	N/A	1.76	0.65	2.51	0.70	LowerBack_Low
D30	269.5	106.9	2.12	0.76	2.74	0.75	Upper_Low
D31	N/A	N/A	1.64	0.66	2.19	0.62	Upper_High
D32	N/A	N/A	2.12	0.70	2.88	0.77	LowerBack_High
D34	257.9	93.5	2.37	0.78	2.56	0.79	Upper_High
D35	155.5	56.1	1.72	0.65	3.39	0.81	Upper_High
D36	N/A	N/A	2.17	0.69	3.33	0.81	LowerBack_High
D38	N/A	N/A	0.84	0.42	1.56	0.54	Upper_Low
D39	297.5	93.4	N/A	N/A	N/A	N/A	Upper_Low
D40	N/A	N/A	N/A	N/A	N/A	N/A	Upper_Low
D41	97.1	41.6	N/A	N/A	N/A	N/A	Upper_Low
D42	219.5	82.9	1.50	0.57	2.31	0.69	LowerBack_High

Table A.8. Final zone delineation, yield data, and remote sensing vegetation indices for sample points in the grassland at the St. Denis National Wildlife Area. NDVI= Normalized Difference Vegetation Index, CIG=Chlorophyll Index-Green.

Point	FreshWeight	DryWeight	MidCIG	MidNDVI	LateCIG	LateNDVI	FLMZ
	g	g					
B01	92.9	37.7	1.86	0.63	1.51	0.52	UpperBack_High
B02	115.5	61.8	2.61	0.77	1.98	0.63	UpperBack_High
B03	N/A	N/A	1.75	0.61	1.52	0.55	Back_Med
B04	N/A	N/A	1.50	0.56	1.21	0.48	Back_Med
B05	N/A	N/A	1.69	0.60	1.27	0.52	Back_Med
B06	N/A	N/A	2.18	0.69	1.50	0.53	UpperBack_High
B07	N/A	N/A	2.11	0.69	1.88	0.63	UpperBack_High
B08	N/A	N/A	2.22	0.78	1.94	0.70	Upper_LowMed
B09	79.5	43.2	3.34	0.81	1.54	0.52	Back_Med
B10	N/A	N/A	1.29	0.52	1.15	0.47	Back_Med
B11	N/A	N/A	1.58	0.61	1.29	0.55	LowerBack_Low
B12	197.2	65.9	2.48	0.75	2.19	0.69	Lower_MedHigh
B13	127.0	45.9	1.93	0.69	1.40	0.62	Lower_MedHigh
B14	167.4	71.0	2.70	0.81	2.83	0.82	UpperBack_High
B15	N/A	N/A	2.07	0.68	2.23	0.68	Lower_MedHigh
B16	N/A	N/A	2.00	0.71	2.00	0.64	Lower_MedHigh
B17	N/A	N/A	1.85	0.69	1.87	0.67	Lower_MedHigh
B18	223.9	90.2	2.46	0.78	2.46	0.79	Upper_LowMed
B19	338.9	151.2	3.10	0.80	3.56	0.87	UpperBack_High
B20	120.4	61.1	1.43	0.59	1.33	0.52	Lower_MedHigh
B21	115.7	49.8	2.61	0.77	1.90	0.64	Lower_MedHigh
B22	N/A	N/A	1.99	0.67	1.78	0.60	Back_Med
B23	108.7	55.0	1.85	0.61	1.69	0.54	Upper_LowMed
B24	125.6	65.6	2.05	0.72	1.94	0.69	UpperBack_High
B25	78.1	42.3	1.96	0.68	1.67	0.59	Upper_LowMed
B26	N/A	N/A	1.74	0.62	1.00	0.41	Back_Med
B27	N/A	N/A	2.29	0.71	1.48	0.52	Upper_LowMed
B28	N/A	N/A	1.64	0.60	1.40	0.53	LowerBack_Low
B29	82.3	43.3	1.84	0.65	1.50	0.56	LowerBack_Low
B30	N/A	N/A	2.68	0.74	1.70	0.57	Upper_LowMed
B31	N/A	N/A	1.40	0.57	1.34	0.48	UpperBack_High
B32	N/A	N/A	2.24	0.67	1.72	0.58	UpperBack_High
B33	80.4	43.8	2.31	0.71	2.16	0.63	Back_Med
B34	N/A	N/A	1.57	0.58	1.57	0.55	Lower_MedHigh
B35	N/A	N/A	1.77	0.66	1.61	0.62	LowerBack_Low
B36	216.4	105.8	3.00	0.85	2.17	0.75	LowerBack_Low
B37	115.1	56.2	1.85	0.70	1.81	0.67	Lower_MedHigh
B38	77.6	43.9	1.74	0.62	1.57	0.55	LowerBack_Low
B39	81.7	44.9	2.65	0.76	1.86	0.61	Upper_LowMed
B40	91.5	41.7	2.29	0.74	2.02	0.67	Lower_MedHigh

Appendix B

THE FUNCTIONAL LAND MANAGEMENT ZONE DELINEATION METHOD

Software Needed:
ArcGIS (This method outline assumes prior experience with ArcMap)
ArcGIS- Relief Analysis Toolbox: https://www.geographer-miller.com/relief-analysis-toolbox/
GRASS: https://grass.osgeo.org/
Management Zone Analyst:
https://www.ars.usda.gov/research/software/download/?softwareid=24&modecode=50-70-10-00
R: https://www.r-project.org/
SAGA: http://www.saga-gis.org/en/index.html

Data Needed:
DTM/DEM raster (3 m ≥ resolution)
SOC measurements and UTM co-ordinates for ≥20 points
*CIG raster
*NDVI raster

**not required but can improve DSM results*

Step One: Slope Classification

1. Load a 3 m DTM/DEM into ArcMap or load a higher resolution DEM/DTM and use the 'resample' tool (select 'bilinear' as the resampling technique parameter) to convert it to a 3 m resolution.

2. Follow the "Relief Analysis Instructions" included in the download for the Relief Analysis Toolbox. Those unfamiliar with GRASS will also need to follow the "Profile Curvature in Grass" instructions found at https://www.geographer-miller.com/relief-analysis-toolbox/ .

3. Once Hillslope position classification has been completed reduce the classes to three by combining "Summit" slope positions with "Shoulder" slope positions (1 and 2) and "Footslope" positions with "Toeslope" positions (4 and 5) using the 'Reclassify' tool, set new values to 1,2,3. (1 being upper slopes, 2 being backslopes and 3 being lower slopes).

4. Convert the resulting raster into a polygon shapefile using the 'Raster to Polygon' tool.

Step Two: Preparing Co-variates for Digital Soil Mapping

1. Load a 2 m DTM/DEM (3 m should work as well) into SAGA (File>Open).

2. Create selected topography based co-variates (refer to Table 3.1) by running the appropriate 'Terrain Analysis' tools. Some co-variates will need to be created first to enable the creation of others. (Geoprocessing>Terrain Analysis>Channels/Terrain Classification/Basic Terrain Analysis etc.>Select the loaded DTM/DEM as the grid system and the elevation via the drop down menus> Okay).

3. Export the co-variates as TIFFs to a sub-folder (Geoprocessing>File>Grid>Export>Export GeoTIFF> Select the loaded DTM/DEM as the grid system via the drop down menu, the desired co-variate via the interface provided after pressing '…' beside 'Grid(s)' [must be done one at a time] and specify the correct folder by pressing '…' beside 'File'>Okay)

4. Save any additional co-variates (such as vegetation indices) as TIFFs to the same sub-folder.

ALL CO-VARIATE RASTERS AND SOC DATA MUST HAVE THE SAME SPATIAL EXTENT AND BE IN THE SAME CO-ORDINATE SYSTEM

5. Add the SOC data as a .csv (to a folder that includes the co-variate sub-folder) in this format:

Sample Point	elevation	x	y	SOC

Step Three: Digital Soil Mapping

1. Use the following R-code (credit: Jeremy Kiss, Megan Horachek) as a template for your own data.

```
setwd("C:/Users/las821/Documents/Stats/SD_DSM/Crop")
#Load libraries
#from geostats lecture: all good in version 3.5.1
library(sp)
library(rgdal)
library(maptools)
library(gstat)
library(rgeos)
library(MASS)
#from regression modeling lecture: all good in version 3.5.1
require(GSIF)
require(rgdal)
require(aqp)
require(randomForest)
require(plyr)
require(ggplot2)
require(e1071)
#from covariates lecture: good in version 3.5.1
library(raster)
#for CART: all good in version 3.5.1
require(rpart)
require(rpart.plot)


library(MASS)
#for random selection: all good in version 3.5.1
library(dplyr)
```

```
library(caret)
library(RSAGA)
library(gdalUtils)

#for goof?
library(ithir) #package 'ithir' is not available (for R version 3.5.1)

### give access to help files, but need to run the code for the goof function seperately to use it
install.packages("devtools")

library(devtools)

install_bitbucket("brendo1001/ithir/pkg")

#does not work
#install.packages('ithir', dependencies=TRUE, repos='http://cran.rstudio.com/')
install.packages("Goof")

#Load sample Points
pts.load <-
read.csv("C:/Users/las821/Documents/Stats/SD_DSM/Crop/SDW_crop_spr17_pts.csv")

str(pts.load)

#ID X & Y coordinates
pts.xy <- data.frame(pts.load$x, pts.load$y)
colnames(pts.xy) <- c("x", "y")

#Convert to spatial points data frame
pts <- SpatialPointsDataFrame(pts.xy, pts.load, proj4string = CRS("+proj=utm +zone=13
+datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0"))

#Clean env
rm(pts.load, pts.xy)

####LOADING COVARIATE STACKS
```

```
# tell R where our rasters are
cov.path <- "C:/Users/las821/Documents/Stats/SD_DSM/Crop/cov2" ###Specify here what
rasters you want to use

list.files(path = cov.path, pattern = "\\.tif$",
          full.names = TRUE)
```

```
#Perform raster stack without loading any into memory
files <- list.files(path = cov.path,
                    pattern = "\\.tif$", full.names = TRUE)
# stack rasters
Cov.Stack <- raster(files[1])

for (i in 2:length(files)) {
  Cov.Stack <- stack(Cov.Stack, files[i])
}

Cov.Stack

#add coordinate ref.
crs(Cov.Stack) <- "+proj=utm +zone=13 +datum=WGS84 +units=m +no_defs +ellps=WGS84
+towgs84=0,0,0"

#Extract raster stack values to points
pts.cov <- extract(Cov.Stack, pts  , #########<<<<--- need to specify which points and change
the name of the pts.cov to the appropriate site
                   sp = 1,    method = "simple")

pts.cov

###Split into a training and test set

set.seed(108888) #set random seed

training <- sample(nrow(pts.cov), 0.75 * nrow(pts.cov))
train.pts <- pts.cov[training, ]
test.pts <- pts.cov[-training, ]

training
#save points
setwd<-("C:/Users/las821/Documents/Stats/SD_DSM/Crop")
save(train.pts, file = "train.pts.rda")
save(test.pts, file = "test.pts.rda")

#convert to data.frame
train.pts <- train.pts@data
test.pts <- test.pts@data

#### A Depth Models

#set wd
setwd("C:/Users/las821/Documents/Stats/SD_DSM/Crop")
```

```
#convert SOC from int to num
train.pts[,5] <- as.numeric(train.pts[,5])
test.pts[,5] <- as.numeric(test.pts[,5])

str(train.pts)
test.pts

##Random Forest

rf.SOC.model <- train(x = train.pts[, 6:29], y = train.pts$Mg_SOC_ha,
                      method = "rf", ntree =1000, importance = T,
                      tuneLength = 5,trControl = trainControl(method = "repeatedcv", number = 5,
repeats = 10))

rf.SOC.model

#Variable importance
varImp(rf.SOC.model)

save(rf.SOC.model , file = "rf.SOC.model.rda")
load(file = "rf.SOC.model.rda")
rf.SOC.model

#### Accuracy metrics for test set

#predict classes
test_pred <- predict(rf.SOC.model, newdata = test.pts[,6:29] )

#compare predictions with observations
test.goof <- goof(observed = test.pts[,5], predicted= test_pred)

test.goof

#Create list of outputs
GOOF.rf.list <- c( "rf", test.goof$R2, test.goof$concordance, test.goof$RMSE, test.goof$bias)

### CART

rpart.SOC.model <- train(x = train.pts[, 6:29], y = train.pts$Mg_SOC_ha,
                         method = "rpart",
                         tuneLength = 50,
                         trControl = trainControl(method = "repeatedcv",
                                                  number = 5, repeats = 10))

rpart.SOC.model
```

```
save(rpart.SOC.model , file = "rpart.SOC.model.rda")
load(file = "rpart.SOC.model.rda")
rpart.SOC.model

#### Accuracy metrics for test set

#predict classes
test_pred <- predict(rpart.SOC.model, newdata = test.pts[,6:29] )

#compare predictions with observations
test.goof <- goof(observed = test.pts$Mg_SOC_ha, predicted= test_pred)

test.goof

#Create list of outputs
GOOF.rpart.list <- c( "rpart", test.goof$R2, test.goof$concordance, test.goof$RMSE,
test.goof$bias)

### CART with bagging

treebag.SOC.model <- train(x = train.pts[, 6:29], y = train.pts$Mg_SOC_ha,
                  method = "treebag", tuneLength = 2,
                  importance = T,
                  trControl = trainControl(method = "repeatedcv",
                                 number = 5, repeats = 20),
                  nbagg= 1000)

treebag.SOC.model

save(treebag.SOC.model , file = "treebag.SOC.model.rda")
load(file = "treebag.SOC.model.rda")
treebag.SOC.model
#### Accuracy metrics for test set

#predict classes
test_pred <- predict(treebag.SOC.model, newdata = test.pts[,6:29] )

#compare predictions with observations
test.goof <- goof(observed = test.pts$g_SOC_kg, predicted= test_pred)

test.goof

#Create list of outputs
GOOF.treebag.list <- c( "treebag", test.goof$R2, test.goof$concordance, test.goof$RMSE,
test.goof$bias)
```

```
### Creat GOOF table from each list

GOOF.table <- rbind(GOOF.rf.list, GOOF.rpart.list, GOOF.treebag.list)
GOOF.table <- as.data.frame(GOOF.table)
colnames(GOOF.table) <- c("Model", "R2", "concordance", "RMSE", "bias")

write.csv(GOOF.table, file = "")
```

2. Using the goof tables or summary(insert model here) select the most accurate model.

3. Save the selected model as a raster using the following code as a template (credit: Jeremy Kiss Megan Horachek)

```
############## MAPPING

#parallel processing
install.packages("doParallel")
library(doParallel)
cl <- makeCluster(detectCores() -2, type='PSOCK')
registerDoParallel(cl)

####LOADING COVARIATE STACKS
```

```
###########Loading in Covariate Stack -
# tell R where our rasters are
cov.path <- "C:/Users/las821/Documents/Stats/SD_DSM/Crop/cov2" ###Specify here what rasters you want to use

list.files(path = cov.path, pattern = "\\.tif$",
           full.names = TRUE)

#Perform raster stack without loading any into memory
files <- list.files(path = cov.path,
                    pattern = "\\.tif$", full.names = TRUE)
# stack rasters
Cov.Stack <- raster(files[1])

for (i in 2:length(files)) {
  Cov.Stack <- stack(Cov.Stack, files[i])
}

Cov.Stack

#add coordinate ref.
```

```
crs(Cov.Stack) <- "+proj=utm +zone=13 +datum=WGS84 +units=m +no_defs +ellps=WGS84
+towgs84=0,0,0"

####%%% set work directory to where you want to save outputs
setwd("C:/Users/las821/Documents/Stats/SD_DSM/Crop")

#List of models
rf.SOC.model
rpart.SOC.model
treebag.SOC.model

###  apply the model directly to the raster stack
#Need to apply model and set the name you want to save

SOC.pr.map <- predict(Cov.Stack, treebag.SOC.model, filename = "treebag_SOC.tif",
                format = "GTiff", datatype = "FLT4S", overwrite = TRUE  )

SOC.pr.map2 <- predict(Cov.Stack, rf.SOC.model, filename = "randomf_SOC.tif",
                format = "GTiff", datatype = "FLT4S", overwrite = TRUE  )


SOC.pr.map3 <- predict(Cov.Stack, rpart.SOC.model, filename = "rpart_SOC.tif",
                format = "GTiff", datatype = "FLT4S", overwrite = TRUE  )
```

Step Four: Preparing Data for Fuzzy Classification

1. Load selected DSM model raster into ArcMap.

2. Change the symbology of the DSM raster to three classes by using ‘Natural Breaks (Jenks)’ under ‘Classified’.

3. Use the tool ‘Reclassify’ to change from the old values (SOC estimate) to new values (from 1-3, 1 being lower SOC, 2 being medium SOC, 3 being higher SOC).

4. Convert the reclassified raster to a polygon shapefile using the ‘Raster to Polygon’ tool.

5. Use the ‘Intersect’ tool to combine the SOC class polygon and the previously completed slope classification polygon into a new shapefile (it may be helpful to edit the resulting table to make the column for both of the factors easy to identify).

6. Export the table for the resulting shapefile as a .txt file.

Step Five: Fuzzy Classification

1. Launch the Management Zone Analyst software and open the previously created .txt file. (View>Start>Choose File…)

2. Move the SOC classes and slope position classes into the 'Selected Variables' box using the arrows. Click 'Next'.

3. Click next (computing statistics is optional). In the 'Delineate Zones' window leave all options as default, and select the maximum and minimum number of zones you wish to perform fuzzy classification on*. Click 'Classify'. Choose the output file location and name, click 'Save'. Once the analysis has been completed click 'Next'

**This study used 3 and 9 as the maximum and minimum, respectively. It may be best to move in overlapping sets of 3 and 4, repeating this step as necessary to complete the analysis for the desired number of zones. The software often crashes if more than 9 zones are set as the maximum. It also often crashes if there is too large of gap between the minimum and maximum number of zones.*

4. Save the performance indices to a file. Click 'Next'. Using the 'Post Classification Analysis' window as well as the saved performance indices find the number of zones that has the lowest 'Normalized Classification Entropy' and 'Fuzziness Performance Index'. This zone delineation will provide you with zones that are the most different.

5. Bring the data from file you created and saved that includes the number of zones with the best performance indices in step 3 into excel. Save the file into a format you can use in ArcMap (.csv, .txt, etc.)

6. Bring the file you created in step 5 into ArcMap.

Step Six: Creating a FLMZ Map

1. Use the 'Join' function to add the results from the Management Zone Analyst software (the file that was created in excel) to your intersected polygon shapefile.

2. Export the polygon as a new feature class to save the join.

3. Use the 'Dissolve' tool to create a new shapefile with a reduced number of polygons by using the column containing the desired number of zones as the 'Dissolve_Field'.

4. Decipher what each zone number represents based on the SOC class and slope class from the feature created in step 2. Add a column to the table of the shapefile created in step 3 and use the edit function to name each feature accordingly.

5. Change the symbology of the shapefile to 'Categories' based on the added column (choose the added column as the 'Value Field').

Appendix C

FUNCTIONAL LAND MANAGEMENT ZONE MAPS

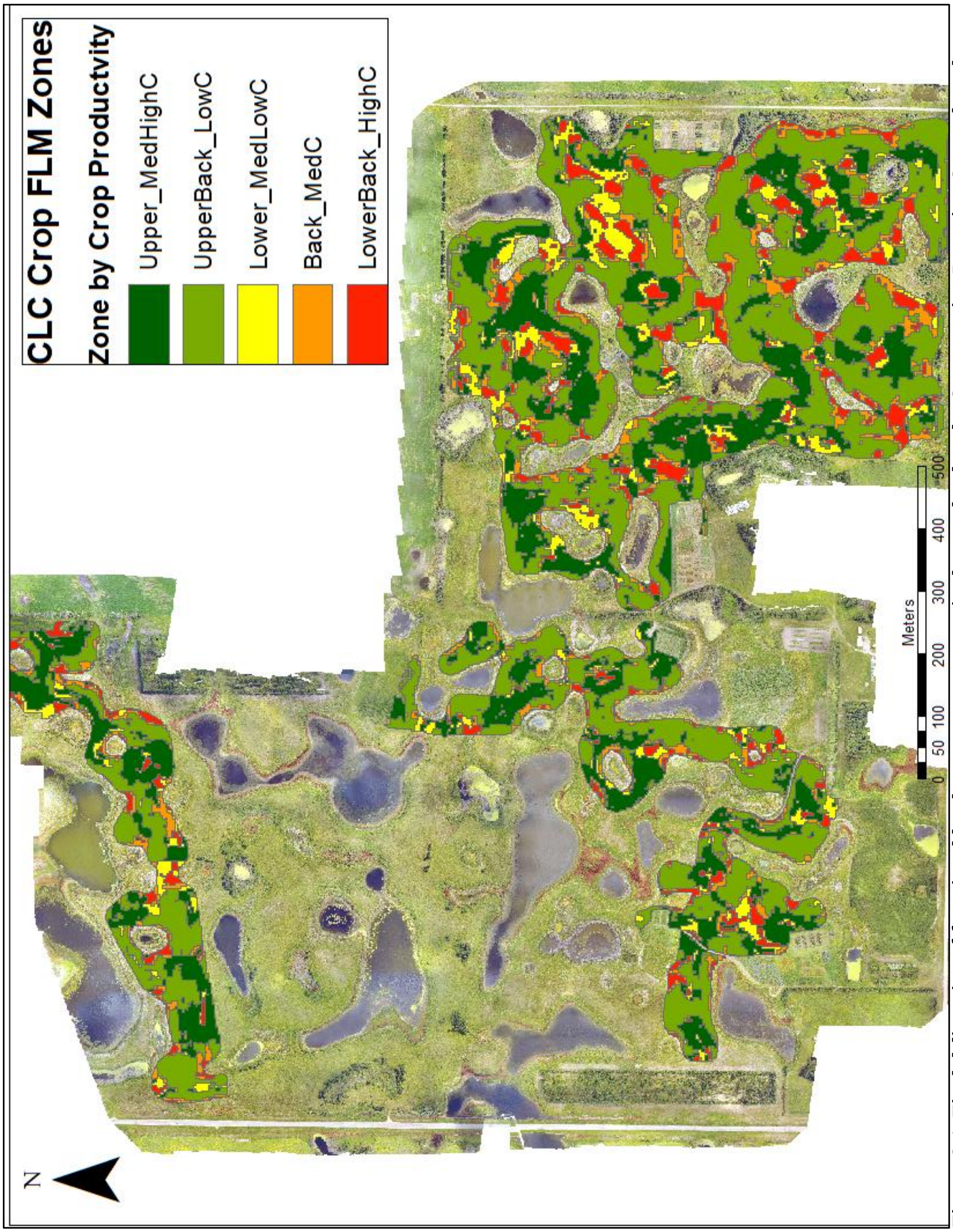


Figure C.1. Final delineation of functional land management zones in the cropland at the Conservation Learning Centre based on fuzzy clustering of soil organic carbon and slope position. Zones are ranked based on the crop productivity (as shown by Chlorophyll-Green Index).

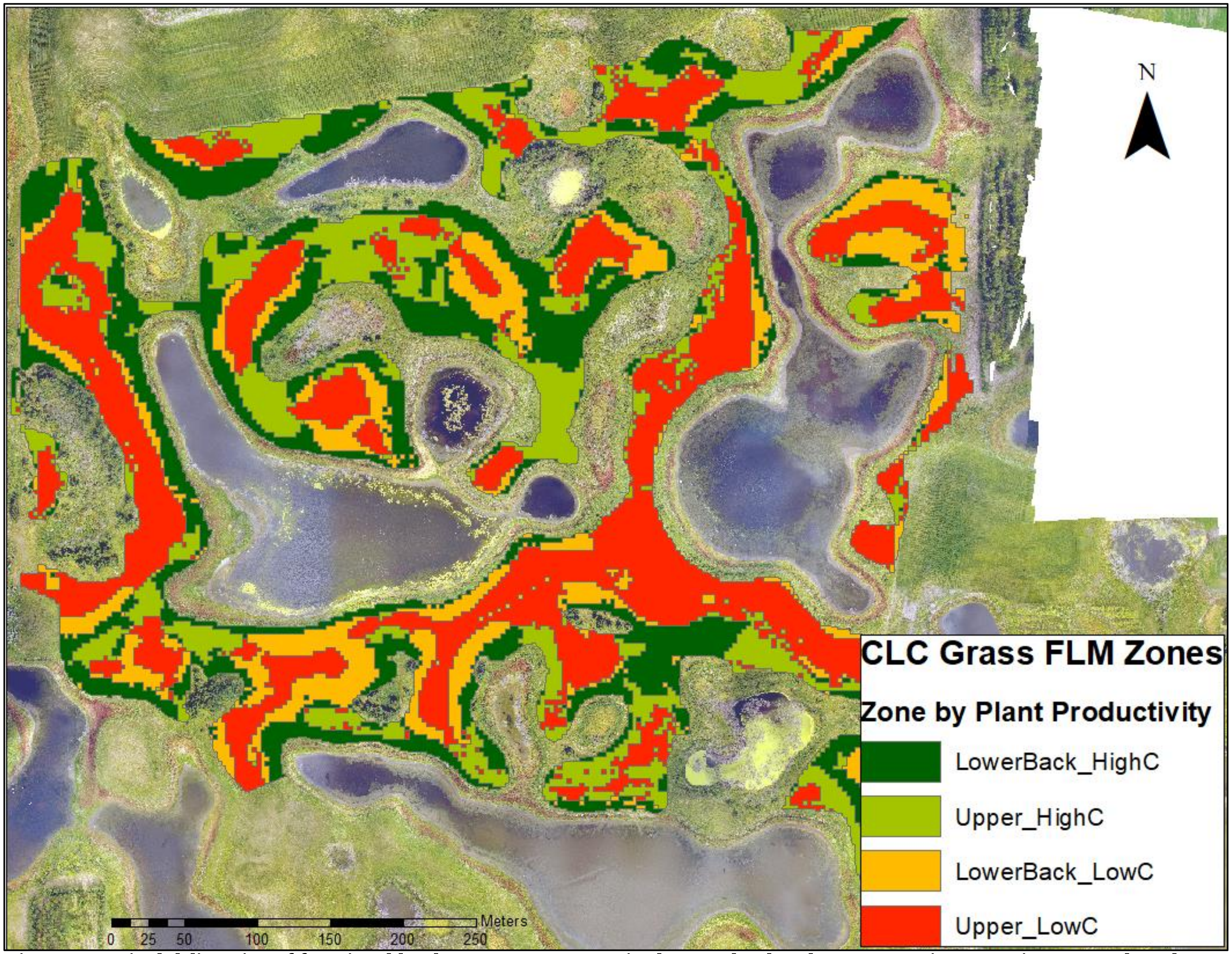


Figure C.2. Final delineation of functional land management zones in the grassland at the Conservation Learning Centre based on fuzzy clustering of soil organic carbon and slope position. Zones are ranked based on the crop productivity (as shown by Chlorophyll-Green Index).

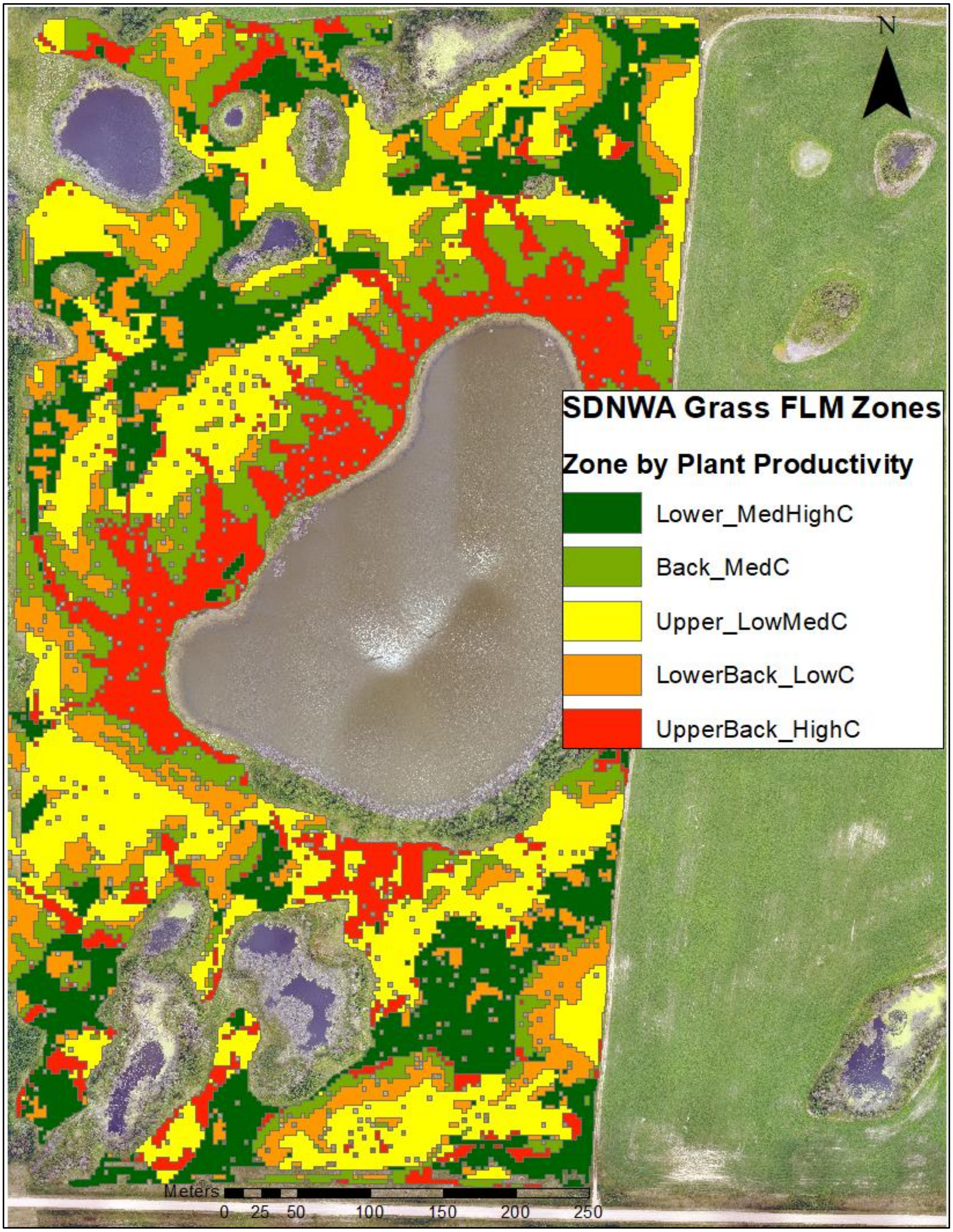


Figure C.3. Final delineation of functional land management zones in the grassland at the St. Denis National Wildlife Area based on fuzzy clustering of soil organic carbon and slope position. Zones are ranked based on the crop productivity (as shown by Chlorophyll Index -Green).