Suitable locations for reference plots based on the Nitrogen Sufficiency Index (NSI)

Eugenio Landeiro Reyes

A thesis submitted to the Faculty of Graduate and Postdoctoral Studies
in partial fulfillment of the requirements
for the degree Master in Science
in Geography

DEPARTMENT OF GEOGRAPHY
FACULTY OF ARTS
UNIVERSITY OF OTTAWA
OTTAWA, ONTARIO
CANADA

ABSTRACT

Nitrogen (N) is critical to the quantity and quality of agricultural yields. Excess N fertilization is costly, both economically and environmentally (nitrate leaching, eutrophication, greenhouse gas release, soil degradation). This research identifies zones that could substitute the field-long N-rich strips by using spatial analysis of the nitrogen sufficiency index (NSI) and the relation with Apparent Electrical Conductivity (ECa), Elevation, Slope and Soil. NSI calculated from ECa grouped into three classes was capable of minimizing the effects on NDVI. Correlation coefficients (R) between three-class NSI and NSI calculated from the nearest ECA values were very high for all the fields with values between $0.82 < R < 0.94$, with the highest coefficients associated with fields in 2005 and 2007. Meanwhile, three-class NSI coefficients were consistently significant in relation to the NSI reference, with an average of $R=0.79$ for all the fields. The highest coefficient was detected for 2007, with $R=0.89$, whereas the lowest values were associated with 2006 ($R=0.67$). In the case of elevation grouped into four classes, the correlation results were not statistically significant, with overall average values of $R<0.70$. The maps elaborated from the NSI for ECa grouped into three classes show a high level of accuracy compared to the NSI reference map. The new N-rich zones not only can contribute to mitigating the environmental impact of agricultural practices (reducing 77% of N inputs) but also be an accurate source of data for the analysis of NSI and within-field N variability.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to everyone who contributed directly or indirectly to the accomplishment of this thesis. First, I would to thank to the University of Ottawa Faculty of Graduate and Postdoctoral Studies for offering me an Admission Scholarship that covered my tuition and other monetary matters. Also I want to express my sincere gratitude to Dr. Addu Bannari, my former supervisor who also made possible that I could get involved in the Master program at the Department of Geography of the Faculty of Arts and for all the knowledge and support he offered to me. A particular thanks to Dr. Nicolas Tremblay and his team from the Horticultural R&D Centre, Agriculture and Agri-Food, St-Jean-sur-Richelieu, Quebec for giving me the opportunity to work on this project, and special to Yacine Bouroubi for his support and time for the data processing and analysis. I also would to express my appreciation for my current supervisor Dr. Mike Sawada and his assistance and support needed to successfully complete this thesis. My sincere gratitude to my dear friend Sasha Kebo for the time and help reviewing my work. Finally, I would like to thank all of my family members (here in Canada and abroad) for their support during all these years and especially my wife Gail Whittaker, to whom I extend my greatest gratitude.

Table of Contents

LIST OF TABLES

List of Figures

Abbreviations and Acronyms

C	Carbon
CI	Chlorophyll Index
DEM	Digital Elevation Model
DGPS	Differential GPS
ECa	Apparent Electrical Conductivity
ELE	Elevation
GIS	Geographic Information Systems
GPS	Global Positioning System
N	Nitrogen
N_2O	Nitrous oxide
NDVI	Normalized Difference Vegetation Index
$NDVI_{NRich}$	NDVI from the saturated plots (N-rich)
$NDVI_{Sat}$	NDVI from the saturated plots (N-rich)
NH_3	Ammonia
Nil-N	Strips that don't receive N fertilizer
NIR	Near Infra-Red
NRI	Nitrogen Reflectance Index
N-rich	Saturated plots (reference) with non-limiting N
NSI	Nitrogen Suffiency Index
NSI_{2ecaCl}	NSI calculated from ECa class Two
$NSI_{3ecaAreas}$	NSI calculated from ECa class Three (new areas)
NSI_{3ecaCl}	NSI calculated from ECa class Three
NSI_{4ecaCl}	NSI calculated from ECa class Four
NSI_{ECa}	Alternative NSI for the Apparent Electrical Conductivity (ECa)
NSI_{Ele}	Alternative NSI for the Elevation
$NSI_{Elevation}$	Alternative NSI for the Elevation
NSI_{neca}	NSI calculated from nearest neighbour of ECa
NSI_{Ref}	Alternative NSI calculated from the nearest neighbour
NSI_{Slope}	Alternative NSI for the Slope

NSI_{Slp}	Alternative NSI for the Slope
NSI_{Soil}	Alternative NSI for the Soil
NUE	Nitrogen Use Efficiency
R	Correlation coefficient
R^2	Coefficient of determination
RP	Reference plot
SLP	Slope
TP	Tested plot
Vis	Vegetation indices
VRN	Variable-rate Nitrogen
Zn	Zinc

1. Introduction

The application of fertilizer nitrogen (N) is one of the main methods farmers use to improve the quantity and quality of agricultural production (Weiss and Baret, 2000; Schmidt *et al*., 2002; Pena-Yewtukhiw *et al*., 2008). However, apart from an economic (cost-benefit) perspective of increasing yields, excess nitrogen fertilization could have negative impacts on the crops through increasing sensitivity to lodging, pests, and on the environment through nitrate leaching and greenhouse gases (N2O and NH3) emission (Weiss and Baret, 2000; Haboudane *et al*., 2002).

Soil fertility, type and terrain features (slope and elevation) are some of the parameters affecting crop productivity in specific field locations (Kravchenko and Bullok, 2000; Bakhsh *et al*., 2000; Kaspar *et al*., 2004). Many current agricultural production methods do not take into account the variability of the soils and topography within fields and assume they are uniform (Weiss and Baret, 2000). Farming with the assumption of a uniform field contributes to a waste of resources and money, but also introduces an excessive amount of fertilizer (N surplus) that leads to a potential source of environmental pollution (Haboudane *et al*., 2004; Pena-Yewtukhiw *et al*., 2008), for instance, eutrophication of lakes and other bodies of water.

Precision farming, often referred to as Precision Agriculture (Brisco *et al*., 1998; Haboundane *et al*., 2002; Zillmann *et al*., 2006), is an leading approaches that equips farmers with a better understanding of within-field spatial variability of crop quality parameters and yield (Printer et al., 2003; Zillmann *et al*., 2006). Precision farming application requires detailed information on the variability patterns of the soils and topography in order to determine cause-effect relationships (Zillmann *et al*., 2006). The Normalized Difference Vegetation Index (NDVI) can indicate the current and changing state of photosynthetic capacity which can serve as one of the common sources of information used in describing crop canopy conditions. By analyzing the spectral response of the cultivars, it is possible to diagnose the fertilizer and/or water and how the needs differ within space to support spatially variable N application. NDVI is an important parameter to investigate for the assessment of productivity in agriculture (Inman *et al*., 2008). There is a strong relationship between NDVI and soils, topography, water and N availability.

According to Doerge (2005), one of the current variable N rate strategies is monitoring the N status in real time through the analysis of plant or canopy reflectance and/or the chlorophyll content to indicate the N stress (Varvel *et al*., 2007). A tractor-mounted sensor, also known as 'sensor on-the-go', is capable of collecting the reflectance measurements in the form of NDVI values, which make it possible to calculate a Nitrogen Sufficiency Index (NSI) by comparison with non N-limiting (N-rich) strips (Tremblay *et al*., 2010; Samborski et al., 2009; Doerge, 2005). The NSI was developed by Peterson *et al*. (1993) to improve N management based on chlorophyll measurements using SPAD (Soil Plant Analysis Development) units which determine the greenness of plants. More recently, some authors have substituted a chlorophyll meter for the NDVI measurement to obtain NSI values using N-rich strips. The NSI has proved to enhance Vegetation Indices (VIs) for the assessment of N stress and also to remove noise affecting raw VIs values (Tremblay *et al*., 2010).

Despite advances in crop science and precision farming, there remain uncertainties related to selection of the best crop management techniques. Continuous data collection over many years in the same field, including measurements of yield, soil variables and terrain attributes are required to obtain reliable information on the best management techniques. Integrated studies have the potential to offer more accurate results correlating spectral information with physical parameters such as soil characteristics and terrain features (Schmidt *et al*., 2002). Tremblay *et al*. (2010 and 2011) demonstrated the usefulness of the Nitrogen Suffiency Index (NSI) for the estimation of Nitrogen Use Efficiency (NUE) versus the classic VIs, namely NDVI. The major issue with application of the NSI is the requirement of field-long N-rich strips. A field N-rich strip is indeed a strip having a width of around five meters on which N fertilizer is applied in excess. The use of field-long strips require more N and are therefore more expensive and time-consuming to implement and this excess N can lead to environmental degradation. Such issues with the development of NSI using field-long N-rich reference strips can potentially be overcome with the use of smaller N-rich zones within fields that can serve as reference plots for whole-field assessments of N stress.

1.1 Research Objectives

By analyzing the influence of apparent electrical conductivity (ECa), Elevation, Slope and Soil on the N availability throughout a field, this research will identify existing N-rich zones that can be used as reference areas for nitrogen as a more efficient replacement for field-long N-rich strips. This research will focus on three main objectives.

1. To calculate alternative NSIs ($NSI_{\mathbf{ECa}}$, $NSI_{\mathbf{Ele}}$, $NSI_{\mathbf{Slp}}$, $NSI_{\mathbf{Soil}}$) from the nearest neighbouring point of NSI reference ($NSI_{\mathbf{Ref}}$).

2. Undertake an intercomparison of the indices in order to determine their relative success in characterizing N variability throughout a field.

3. Identify suitable locations for reference plots based on the NSI intercomparison.

The analysis of the data from the new reference plots (See point 3 above) will serve as a validation procedure to evaluate the accuracy of the results. All above procedures will be applied to each of four fields in this research from 2005, 2006, 2007 and 2008.

1.2 Research Hypothesis

NDVI is a useful parameter to use to understand the impact of soil texture and terrain features on the N supply. A limited number of N-Rich areas (saturated strips) can be positioned according to defined soil or terrain features so as to provide a base for NSI calculation that will adequately replace field-long N-Rich strips.

1.3 Thesis Structure

The current chapter (Chapter 1) presented the introduction and problematic of the thesis, as well as the objectives and hypothesis. Chapter 2 of the thesis will be a review and analysis of previous work on the topic of the research and the current tendency to address N assessment uncertainty in Precision farming. The methodology and procedures used in the study will be presented in Chapter 3, while the results will be discussed in Charter 4. Finally, the conclusions and recommendations will be presented in Chapter 5.

2. Nitrogen assessment for crop management: A literature review

Industrialization of agricultural practices aims to increase production and profits through a dependence on large volumes of fertilizers, pesticides, and irrigation. Establishing the correct fertilizer rate for a crop is complex, involving many different factors such as crop type, expected yield, soil nutrient availability, and changes in available nutrients during the growing period. The amount of nitrogen needed by a crop depends on the species, cultivar/variety, intended quality and is almost linearly related to the yield (Robertson and Vitousek 2009). To determine the optimum nitrogen fertilizer rate, it is important to consider the existing soil nitrogen supply. The inherent nitrogen supply includes both the inorganic nitrogen content available in the soil in early spring (mineral nitrogen) and the predicted net mineralization during the growth period.

One of the most promising systems for measuring within-field variation in crop growth is based on imaging the crop by remote sensing. Spectral indices derived from reflectance have been shown to be indirectly related to the nitrogen status of crops. The use of spectral scanning of the crop canopy during the growth period enables farmers to identify areas with different biomass development and nitrogen uptake. Based on such information, spatially variable nitrogen fertilizer application plans can be calculated to meet the optimum in each area of the field, and these can be illustrated by using a field map. In order to achieve accurate results, the reflectance data have to be agronomically calibrated to derive fertilizer recommendations.

Remote sensors can be mounted on satellites, aircraft and tractors. Aircraft and satellite mounted units are able to cover a large area in a short time; optical systems are dependent on suitable weather conditions although recent work using synthetic aperture radar appears to offer some useful data even through cloud cover. Tractor mounted sensors provide a more self-contained system which allows real time measurement and nitrogen application as a single operation while reducing time for the data collection process. In addition, the use of such systems can reduce the cost of satellite and airborne data and the dependency of the latter on the airport services and availability. Reliable equipment is now commercially available (Robertson and Vitousek 2009).

Since the chlorophyll content in the leaves and canopy is affected by N availability (Schlemmer *et al*., 2005), the chlorophyll meter (SPAD) has the ability to assess N stress. Therefore, this is one of the most common methods for N fertilizer management and recommendations. Nevertheless, a chlorophyll meter can only indicate the current plant N status, leaving a certain degree of uncertainty when determining the amount of fertilizer N that should be applied. The traditional methods for soil and plant analysis have been described in the literature as costly and time consuming (Kravchenko *et al.,* 2003; Heiniger *et al.,* 2003). In the last two decades a new source of information to assess crop status has been collected through the use of remote sensing techniques. The latter is capable of providing fast and spatially precise estimation of the crop N status; increasing not just the spatial resolution but also analyzing cultivars in a specific area in order to address the N needs by variable-rate fertilizer application (Olfs *et al.,* 2005).

Chlorophyll meters are only capable of providing data that can be used for field area-averaged N dose recommendations, or at best, for a few different zones within a given field. According to Scharf *et al.* 2006 even though the field is sampled extensively with the chlorophyll meter to accurately determine the field-average NSI, and even if the resultant N-rate recommendation is the true field-average economically optimal N rate, extensive areas of the field may still be over and/or under fertilized. Consequently, this is a justification for variable N rate applications. In contrast, tractor-mounted sensors are able to provide variable N rate 'on the go'. Tractor-mounted systems are used to control variable application of N on the go (Samborski *et al.*, 2005).

Through the use of a limited number of judiciously placed reference plots (N-rich strips) it is possible to estimate how the crops respond to the application of N fertilizer (Johnson and Raun, 2003). Consequently, the limiting factors for plant growth, except N, will equally affect the well-fertilized plots and the rest of the field. Using N-rich strips for N sensor calibration can be considered the most common practice due to its simplicity and utility. Yet, finding the right location to place the N-rich strip is hindered by the spatial variability of the soil. Therefore, the selection of the optimal spatial location for N-rich strips is often based on the farmer's experience. According to Samborski *et al*. (2005), uniform areas, as shown by soil electrical conductivity measurements indicating similar soil type, should be preferred and site-specific management of N is only beneficial on fields with evident spatial variability in plant N availability.

The aim of Precision farming is to use variable rate nitrogen fertilization within and among fields following natural mineralization patterns of N (Scharf *et al.,* (2005). Taking into account that yields targets cannot be compromise with the application of optimal N rates farmers can save up to 50 kg N ha^{-1} (up to \$50 ha^{-1}) compared to the traditional N management practices (Kitchen *et al.,* 2010). Following such approach it is not only possible to reduce N loss due to uniform fertilizer rates but also to improve the economical (farmers) and environmental impacts of the agriculture practices. (Scharf *et al.,* 2005; Shahandeh *et al.,* 2005).

2.1 Vegetation indices (VIs)

Vegetation indices are widely use in agriculture to estimate the crop condition. They can describe the vegetation density, allowing the farmers to evaluate plant germination, growth and productivity. This section will review some of the VIs used in previous studies and the methods for their calculations, as well as, the advantages and limitations for their use.

2.1.1 Normalized Vegetation Index (NDVI)

Spectral VIs are a ratio or linear combination of reflectance in the Red and NIR wavebands which are sensitive to vegetation cover**.** A commonly used VI is the NDVI (Rouse *et al.,* 1973), which is the difference between the Red and NIR reflectance measurements divided by their sum (Equation 2.1). NDVI values range from 0 to 1, where higher values are related to dense, healthy, green vegetation and values close to zero indicate bare ground or very sparse vegetative cover; also low values can be related to the presence of water, snow or clouds (Griffith *et al.,* 2002).

$$\text{NDVI} = (\text{NIR-Red}) / (\text{NIR+Red}) \qquad (2.1)$$

Many studies involve the NDVI as a good indicator of the relative healthiness of the plant. By the evaluation of the biomass, we are usually able to tell how well the plant is doing and if the plant is under stress (Moran *et al.*, 1997; Haboudane *et al.*, 2002). However, the plants must be of the same type and maturity (as different plants will have different NDVI), and most NDVI images are only good in showing where the stress might be occurring but not the cause (Chen *et al.*, 2003; Pinter *et al.*, 2003). Many factors affect the health of crops; these include soil texture differences, rainfall amounts, thin plant populations, topography (affecting water availability, organic matter, etc.), nitrate availability, micronutrients, insect damage, and diseases (Bannari *et al.*, 1995 and 1996; Schmidt *et al.*, 2002). Some problems occur naturally in the field (such as soil textural differences), and some are seasonal (such as heavy or light rains).

a) **b)**

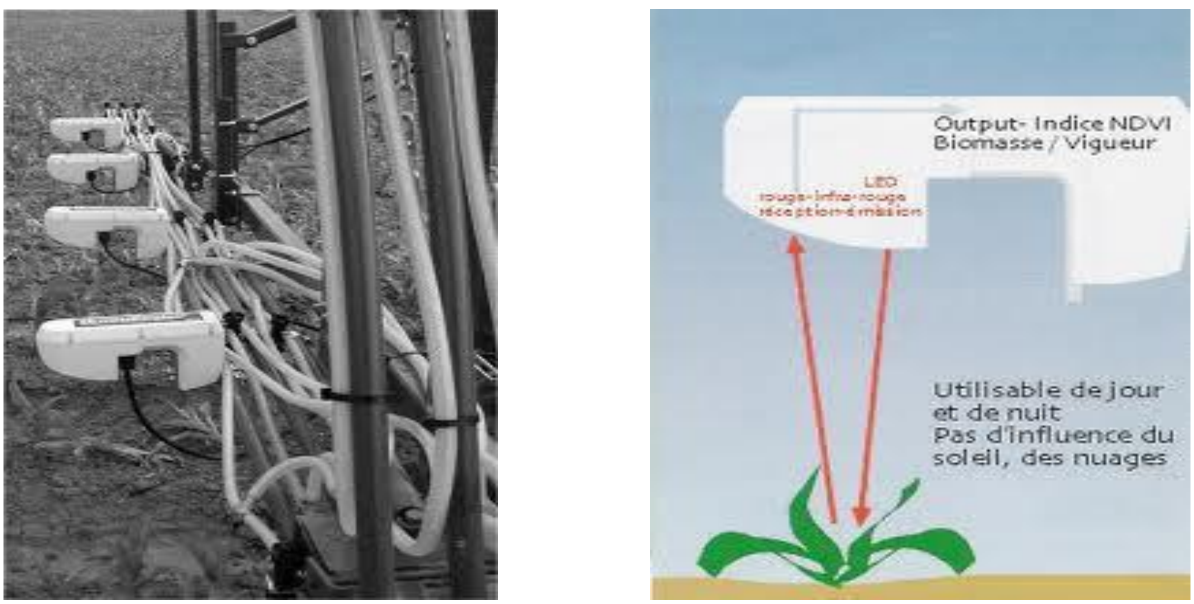


Figure 2.1. Greenseeker sensor: a) Capture of information. b) Tractor-mounted sensors on-the-go (Source: NTech Industries, Inc)

Vegetation Indices have been developed, in the past 40 years, to relate reflectance from leaves or canopies with canopy characteristics (Bannari *et al.* 1995). Using the NDVI for quantitative assessments raises a number of issues that limit the actual usefulness of this index if they are not properly addressed. The = value of the NDVI is sensitive to a number of confounding factors (Bannari *et al.*, 1995). Despite the wide use of this VIs for crop monitoring (Haboudane *et al.*, 2002), several studies note the limitation of NDVI in the presence of soil and topographic variability (Bannari *et al.*, 1995 and 1996; Schmidt *et al.*, 2002).

Li *et al.* (2001) studied the correlation between spectral reflectance and VI, soil water and texture, topography and N management. NDVI values increase proportionally with a higher level of irrigation. The authors pointed out that heterogeneous distribution of NDVI for areas with the same fertilization and irrigation regime reflect the influence of the elevation and soil texture on the water and N distribution throughout the fields, as well as plant growth. They suggest that NDVI mapping could be useful to identify real-time spatial distribution patterns of crop parameters.

Nonetheless, previous research (Bannari *et al.*, 1995 and 1996) has exposed limiting factors that can help understand NDVI readings, including the field characteristics soil variability, topography and water content and those related to atmospheric and sensor calibrations. All these factors have a cumulative impact on the accuracy of the analysis and results of NDVI measurements.

One of the new sources for acquiring NDVI are tractor-mounted systems. Tractor-mounted systems are equipped with a sensor (Figure 2.1a) that measures crop characteristics. These results are processed and used for on-the-go N application. GreenSeeker (Ntech Industry, Ukiah, CA, EUA) is one of the three available solutions which can assess the plant N status in real time (Samborski *et al.*, 2009). This sensor calculates NDVI using red (650 +/- 10nm) and NIR (770 +/- 15nm) light (Pena-Yewtukhiw *et al.*, 2008). GreenSeeker sensors have a 24 inches field of view. Optimal sensing height is 32-48 inches above the plant (Figure 2.1b). The percent of area coverage obtained from each mapping system depends upon the spacing and number of sensors used.

Unlike aerial and satellite imagery services, GreenSeeker's ground based sensors provide real time data, regardless of weather conditions. The data can be used to make variable rate applications, map crop health/biomass and vigour, e.g. NDVI maps (Figure 2.2), create management zones, identify pest and disease problems, evaluate the efficiency of drainage systems, modify soil sampling strategies, monitor and modify irrigation schedules and determine optimum harvesting dates.

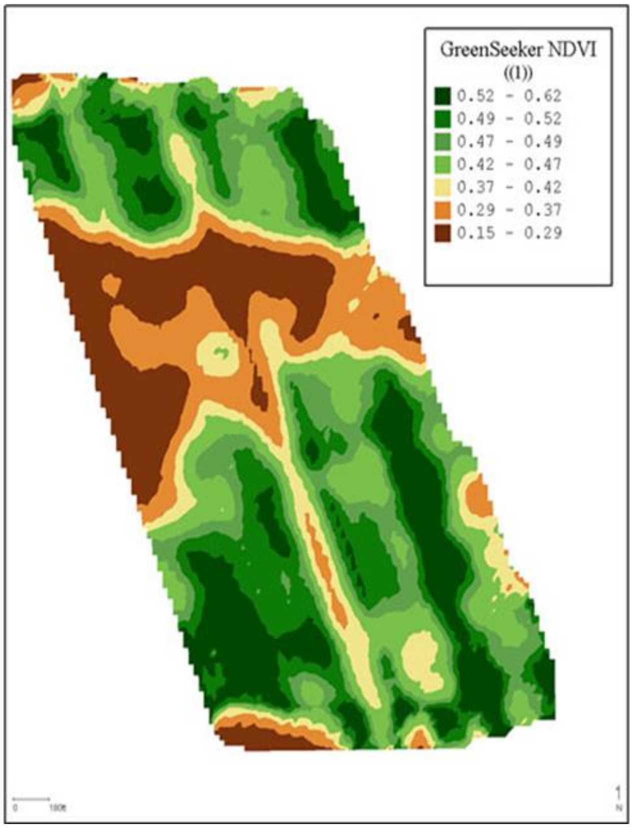


Figure 2.2. NDVI values provided by the GreenSeeker (Source: NTech Industries, Inc.)

2.1.2 Nitrogen Sufficiency Index (NSI)

Since the use of NDVI to evaluate biomass (N assessment) presents some limitations, other indices have been proven estimators for N fertilizer management. Nitrogen Sufficiency Index (NSI) was presented by Peterson *et al.* (1993) in order to achieve N assessment in the field based on the Chlorophyll Index (CI). The CI value of the field to be fertilized can be compared with the one of the well-fertilized reference plots in the form of a normalized NSI (Peterson *et al.*, 1993). It is calculated as follows:

$NSI(\%) = CI \text{ from a } TP / CI \text{ from a } RP \qquad (2.2)$

Where CI = chlorophyll meter reading, TP = tested plot, and RP = reference plot (well-fertilized). In the context of this research, the NDVI will substitute the Chlorophyll Index (Equation 2.3) in the equation for the calculation of NSI, since both indices have been used to analyze the N status of crops. This new approach also has the advantage that the data collection for NDVI is a less time consuming (GreenSeeker) task than the use of Chlorophyll meter (SPAD):

$$NSI = 100*(NDVI / NDVI_{\mathbf{NRich}}) \qquad (2.3)$$

Where NDVI represent the measurements for the whole field, while the $NDVI_{\mathbf{NRich}}$ refers to the values from the reference plot

In the literature the NSI has been reported as an index that allows the characterization of corn N status even under other nutrients deficiency and it was found to be related to the relative grain yield (Pagani *et al.,* 2009). Moreover, NSI value can be useful to indicate the moment of N application and to help calibrate N rates in order to increase the N-efficiency use (Godoy *et al.,* 2003). According to Diker and Baush (2003), the relationship between NSI and the Nitrogen Reflectance Index (NRI) is nearly 1:1. In previous research the same authors used the NRI as an estimator of soil N and to describe the spatial variability of the plant N status. In more recent reports Tremblay *et al.* (2010) found that NSI is less influenced by the soil than classic VIs such as NDVI, and also the NSI showed more robustness than NDVI for the spatial analysis of crop response to N fertilization.

2.1.3 Summary

VIs capable of assessing the biomass and the chlorophyll status of a given crop can be obtained through a variety of sensors and platforms (Welsh *et al.,* 2003; Doerge, 2005; Hawkins *et al.,* 2007) at spatial resolutions suitable for variable-rate Nitrogen (VRN) applications. The NDVI has been identified in the literature as the most commonly used VIs for the assessment of plant biomass and therefore N status. Nitrogen availability in crops has been also estimated by the Normalizing Chlorophyll index (Peterson *et al.,* 1993). However, recent research has probed the accuracy of NSI for the analysis of plant N availability while substituting Chlorophyll Index for NDVI (Samborski *et al.*, 2009; Doerge, 2005, Tremblay *et al.,* 2010). NDVI overcomes the time consuming task of utilizing chlorophyll meters (Samborski *et al.,* 2009). As such, VIs are an important tool for the assessment of both crop N status and the availability throughout the fields.

2.2 Nitrogen rich strips' application in precision farming

Farmers have used uniform fertilization procedures based mostly on yield goals (Doerge, 2005). Towards the end of the 1990s, researchers at Oklahoma State University developed a new way to predict N fertilizer requirements by using N-rich strips (Peterson *et al*., 1993). The use of this technique allows farmers to determine the amount of fertilizer necessary to achieve the maximum yields while taking into account the spatial and temporal variability of N throughout the fields. In current agriculture practices, N-rich strips have gained popularity over the use of yield goals as a reference for N fertilizer recommendations (Doerge, 2005).

N-rich strips are typically established across the entire length of the field and their width can vary from 10 to 20 m, depending on the length of the fertilizer platform where they usually are mounted to perform the crop canopy readings. These strips are then saturated with N fertilizer, which ensures that the latter is not the limiting factor during the growing season. Therefore, these areas of the field are exposed to high levels of N which is not all absorbed by the plant, so a large percent is lost to lower soil layers due to leaching process (Roberson *et al.,* 2010; Tremblay *et al.,* 2010; Hong *et al*., 2008). N-rich strips are often used in conjunction with canopy sensors (used for the calculation of the plants' biomass) in order to determine in-season N rates and also serve to estimate the potential yield for a given field (Raun *et al*., 2002).

Although two N-rich strips are recommended per field, in practice it is common to observe the use of only one and in most of the cases established throughout the center of the field (Tremblay *et al*., 2010; Ferguson *et al.,* 2002). The N-rich strip(s) should be located in representative areas of the field such as different management or yield zones. The application rates for the N rich strip should be at least 125 percent of the total nitrogen recommended to achieve yield goal. Nevertheless, according to Sexton *et al.* (1996) when N rates exceed 100 kg/ha the fertilizer lost through leaching was increased at a very high rate (up to 45%). Therefore the author recommends using rates 5% less than the required amount to achieve maximum yields.

According to an Agronomy Technical Note prepared by the University of Missouri and USDA-Agricultural Research Service (ARS) in Missouri, in fields with high soil spatial variability, the use of multiple N-rich strips (representing such variability) is recommended. This technical material also makes some recommendations regarding the size of the reference (N- rich) plots when using active canopy sensors (sensor on-the-go). This document implies that it is essential for the reference zones to be wide enough (typically 10 m wide) in order to comply with the standards of the fertilizer application equipment where the sensor is mounted and a minimum length of 50 ft. for a single area, which can be translated into 1500 ft^2 or 140 m^2.

Establishing N-rich strips is an inconvenient and time consuming task for farmers since they have other demanding operations during the spring. In addition, the establishment of such N saturated zones often tends to be problematic and lead to confusion and errors. Recent studies (Bouroubi *et al.,* 2013) are focusing on the analysis of the natural spatial variability in the fields considering that early season N fertilizer applications may contribute to create zones with more than adequate N. Therefore, these areas could serve the same function as N-rich strips once they can be correctly identified and quantified. This scenario could potentially not just improve the time consuming task for farmers but also reduce N losses due to leaching when N-rich strips can be effectively located. The latter is the aim of the present research.

2.2.1 Summary

The technological advances in precision farming for N management has benefited producers economically while making agricultural practices less invasive on the environment. Historically, farmers have inefficiently estimated the amounts of fertilizers to apply based on yield goals. Whereas today the most common practice of sensor-based fertilization presents the possibility of evaluating crops during the growing season and making more accurate fertilization decisions. In the last decades, farmers have become more familiar with sensor-based fertilization applications which have permitted them to minimize their costs of inputs, as well as utilize N fertilizer more efficiently. Nevertheless, more research is still necessary to improve current management techniques related to N-rich strips since it creates confusion for producers and a high impact on the environment.

2.3 Role of soils in Precision Farming.

Soils are a very important element to consider in agriculture. Most fields contain spatial and temporal variability in soil properties and crop productivity (Zillmann *et al.,* 2006). Clearly, soils with higher sand than clay content will need different nutrients, provide a different environment for pests, and require different amounts of moisture for sufficient crop productivity. The percent of sand, silt or clay in a specific soil is closely related with soils` physical properties such as texture, water content, organic matter and color. Soil texture is one of the most important soil properties, particularly when dealing with water movement through the soil. Sandy soils have less water retention than soils with a higher percent of clay due to the size of the particles; at the same time soils with a high content of sand are more sensitive to erosion. Organic matter is related to the fertility of soils, which also plays a major role in water retention (Schmidt *et al*., 2002; Kay *et al.,* 2006 and Patzol *et al*., 2008). Knowing these differences is crucial to the efficient use of zone sampling, variable rate application, and other time, labour, and money-saving benefits of precision farming.

The composition of soil can vary widely, but it is a mixture of mineral particles, organic remains in various stages of decomposition, water, air and a wide variety of living organisms. The community of subsurface organisms is vital to soil condition. These organisms break down and mix the organic matter in the soil. They also help aerate the soil as they move through it, and are important nutrient recyclers, decomposing organic matter and returning nutrients to the soil.

Soils texture plays an important role in the growth and health of crops. In the last fifteen years, a number of scientists have used the Apparent Electrical Conductivity (ECa) as a variable to delineate soils maps and management zones due to the ECa capability of describing multiple soils properties (Kitchen *et al.,* 2003; Li *et al.,* 2008). According to Bausch and Brodahl, 2011 for most of non-saline soils ECa measurements are influenced by soil moisture and texture and the ECa maps could replace the second order soil surveys maps. In addition the authors stated that ECa can be use as a surrogate variable to describe soil texture when classifying corn N sufficiency throughout the reference strips. Kitchen *et al.,* 2003 stated the ECa have been reported to be linked to variation in crop production causes by soils differences due to can be affected by soil properties such clay, soil water content, temperature, salinity and oganic compounds. Another aspect that has influenced the extensive use of the parameter is that of it reducing the time-consuming task of soil sampling all throughout the fields (Kravchenko *et al.*, 2003; Heiniger *et al.*, 2003).

One of the challenges of precision farming is to understand the variability of soils within the fields. Precision farming aims to manage agricultural fields according to the specific characteristics of soil in different areas and of its influence on both crop development and yield. This new way of management has become possible since Global Positioning System (GPS) and Geographic Information Systems (GIS) became available. These two important tools enable the creation of maps to graphically represent and analyze variation of soils and crops in space and time, which are used as a base for management decisions (Pinter *et al*., 2003).

Using GIS and GPS in combination with other supplementary data such as yield monitoring and soil analysis can provide spatially linked data sets that aid in evaluating the relationship between crop yield, terrain and soil properties. The objective of spatially linked studies (e.g. Kaspar *et al*., 2003; Kravchenko and Bullock, 2000; Shahandeh *et al.,* 2005; Jiang and Thelen, 2004) is to increase the understanding of the variability of yields and the underlying limiting factors. Kaspar et al. (2003) analyzed the relationship between the soils and terrain properties using factor analysis. This study found that clay and silt were positively correlated to factor 1 (landscape position) while sand had a negative relation.

Slope was negatively correlated with silt, clay and organic matter due to erosion processes. A positive relation was also found between electrical conductivity and variables such as, clay and water content, organic matter and salinity. Nitrogen had a positive relation with factor 1 and at the same time was strongly correlated (R2= 0.88) to clay content areas. In a subsequent study Shahandeh *et al.* (2005) found that clay content was significantly related to corn yield and responsible for the variation in high and low yields. The authors also found that clay content shows almost the same spatial distribution as Nitrate N and suggest that uniform application of N would result in over fertilization in some areas and under application in others. These results suggest that analyzing the distribution of clay could be useful to estimate and infer N requirement.

Zillmann *et al.* (2006) found that for one of the fields of study where yield loss was reported, the field was dominated by a “rendzina” soil. This type of soil has reduced water holding capacity which it is assumed was the growth limiting factor. While in the rest of the field a thicker loess layer soil is linked with higher yields, due to a higher available water holding capacity. In the other field a comparative study between the yield and soil texture maps, shows that areas with low sand percent and high silt percent coincide with higher yield zones because of increasing water availability, while areas with higher sand percent are closely related to lower yield zones. The author stated that field variability of yield seems to be mainly driven by soil moisture.

Jiang and Thelen (2004) investigated the soil properties that potentially affect corn and soybean yield using principal component analysis. They found that soil texture explained more than 50% of the variability of yield, while other variables such as ECa and pH were identified as important soil variables. However, the combined effect of soil properties and topographic data explained about 30 to 85% of the variability for most of the year studied. Once more the unexplained variability is linked with factors such as water availability.

2.4 Terrain features influence in precision farming.

Terrain attributes, namely, elevation, slope and curvature in interaction with soil characteristics have a significant influence on crop development and yields (Bakhsh *et al.,* 2000; Kravchenko and Bullock, 2000; Kaspar *et al.,* 2003; Jiang and Thelen, 2004). A commonly used tool for generating topographical information is the digital elevation model (DEM). From a DEM it is possible to derive primary and secondary terrain attributes. The slope describes the rate of change in elevation, while the curvature is related to the acceleration or deceleration of the water flow (Kravchenko and Bullock, 2000).

Higher areas in the field are more affected by the erosion process than areas at the base of hills. The slopes and curvature play an important role in the water flow and soil accumulation. Lower slopes have been reported with higher yields due to the materials coming from upper levels. An increasing slope with positive curvature (convex) produces an increase of runoff and less water infiltration. Conversely, lower slopes with negative curvatures (concave) concentrate the water flow and increase the infiltration (Kravchenko and Bullock, 2000). According to these authors, elevation was a main factor in the correlation between yield-topography and curvature accounted as a second factor. Soil properties in combination with topography explained up to 80 % of the yield variability for some fields, nevertheless, for other fields, just 10 % of the yields could be explained. In this study the response of corn and soybeans yields to soil property, topography and precipitation was the same. A combination of topographical and soil data is useful to understand yield variability at the field scale. Similar results were found by Bakhsh *et al*. (2000), concluding that the interaction of soil types have an influence on yield variability (R^2 from 0.77 to 0.99)

Conversely, Kaspar *et al*. (2004) pointed out that elevation only partially explains the variability within fields, and there is a need to identify all factors controlling yields. To accomplish this goal, it would be necessary to collect continuous data over many years in the same field, related to yield, soil variables and terrain attributes. However, Kaspar *et al.* (2004) suggest that when using a large number of variables for statistical analysis (regression) it is possible to face problems such as multicollinearity. This problem can be resolved by using factor analysis, a multivariate technique, which groups variables that are highly correlated and use the groups as independent variables for regression analysis.

Kaspar et al. (2003) used factor analysis to study the relationship of corn and soybeans yields to soil and terrain properties. The authors found that factor 1 (landscape position) and factor 4 (curvature) were the most important in the regression equations for dry years. Factor 1 exhibited a positive relationship with organic slit, clay, C, N, Zn and EC while sand, soil color and slope show a negative relationship. The relationship found through factor 4 shows that yield was low in zones of the field with convex surfaces, high elevation and shallow topsoil, whereas, in areas with concave foot slope position, lower elevation and deeper topsoil yields were higher.

2.5 Summary

N excess has been recognized as an international problem linked to agriculture for at least 40 years (Smith *et al.*, 2007). On one hand N fertilizer represents a major source of nutrient for plant growth while increasing crop productivity. In the other hand N excess represents a complex environmental issue of global importance. A combination of appropriate strategies for utilizing N efficiently and guarding against unintentional loss to the environment is required. A better understanding of the relationship between the N spatial availability and the within fields natural variability can be accomplished using precision farming tools such as reference plots. Targeting the amounts of N fertilizer applied in the fields without compromising yield goals could provide measurable attenuation to N leaching. The following chapter (Chapter 3) delineates the methodological approach used in this research to determine suitable locations for reference plots (N rich) based on NSI analysis.

3. Methodology

Three steps are used to achieve the objectives outlined in the first chapter; Figure 3.1 illustrates the proposed methodology. The first step consists of pre-processing the data collected over four years (2005, 2006, 2006 and 2008) for the same number of corn fields. The next procedure was to process the data for analysis and evaluation. The statistical procedure supported the analysis of the results, followed by the last phase of the investigation, which was to determine optimal areas that can substitute the reference plots established throughout the whole extent of each field.

3.1 Study site and experimental design.

The experiments were conducted in 2005, 2006, 2007 and 2008 on corn (Zea *mays* L.) in the Montérégie region of Quebec, Canada (45° 05' 21" N, 73° 21' 03" W). The fields were adjacent to one another in St-Valentin, Quebec, Canada, (Figure 3.2). The control locations in the fields were referenced to UTM Zone 18 referenced to the North America Datum 1983. The soil profiles were similar, consisting of mainly heavy clay, loam and clay-loam textures in field areas at low elevation, loam and sandy loam in the areas at mid-elevation and sandy loam and loamy sand textures in areas at higher elevation (Tremblay *et al.*, 2010). More specific information related to each field is given in Table 3.1.

3.2.1 DEM sampling

In a GIS environment, the collected data using GPS readings can be used for inputting new information into a spatial database, as a result of the observation at a certain location. Due to the limitation of the GPS accuracy, differential GPS (DGPS) have been introduced in precision

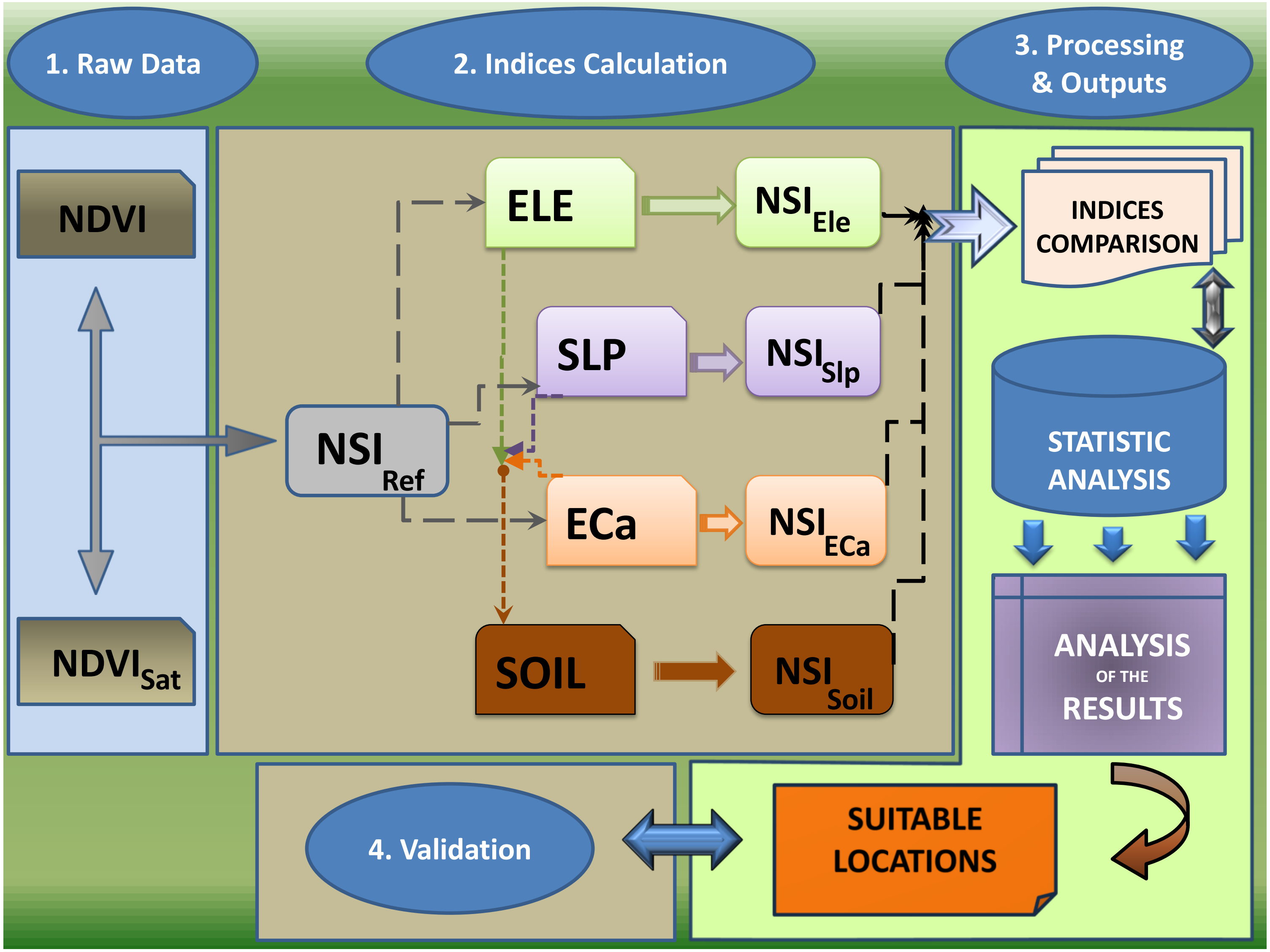


Figure 3.1. Outline of proposed research methodology where ELE, SLP and ECa refer to Elevation, slope and Apparent Electrical Conductivity, respectively.

farming practices (Kaspar *et al.,* 2003). These differential correction techniques can produce positions generally accurate to within a few centimetres.

Table 3.1. Experimental fields description. Adopted and modified from Tremblay *et al*., 2010

Year	**2005**	**2006**	**2007**	**2008**
Coordinates (UTM 18)	629589 E 4994395 N	629781 E 4994184 N	629598 E 4994275 N	629788 E 4994156 N
Field size (ha)	8.66	6.52	8.74	12.99
Sowing date	12 May	9 May	3 May	6 May
Early-season plant status observation (NDVI used to calculate NSI) and growth stage on the "V" scale	28 June V7	5 July V6-7	22 June V6	25 June V5-6
Soil description	Characterized by heavy clay, loam and clay-loam textures at low elevation, loam and sandy loam at mid-elevation and at high elevation textures were sandy loam and loamy sand			

The uses and advances of DGPS have increased the accuracy of elevation maps and terrain analysis for precision farming. Simultaneously, they have reduced the cost and the labour intensity compared to the soil sample collection (Kaspar *et al.*, 2003). In addition, DGPS receivers can be coupled with yield monitors to provide spatial coordinates for the yield monitor data, as well as other kinds of monitors to map parameters such as salinity, weed infestation, etc. The elevation (ELE) data was obtained with a DGPS (Pathfinder Pro XRB, Trimble, accuracy +/- 15 cm) mounted on an all-terrain vehicle. Across the fields, the sampling data was conducted along transects approximately 9 m apart with a density of 1 point per 6 to 12 m (Tremblay et al., 2010). For the specific purpose of this research the slope features were calculated using the 3D analyst extension of ArcGIS (ESRI, Redland, CA). Slope is an important variable since it describes the rate of elevation change and is responsible for the acceleration or deceleration of the water flow and nutrients (Kravchenko and Bullock, 2000).

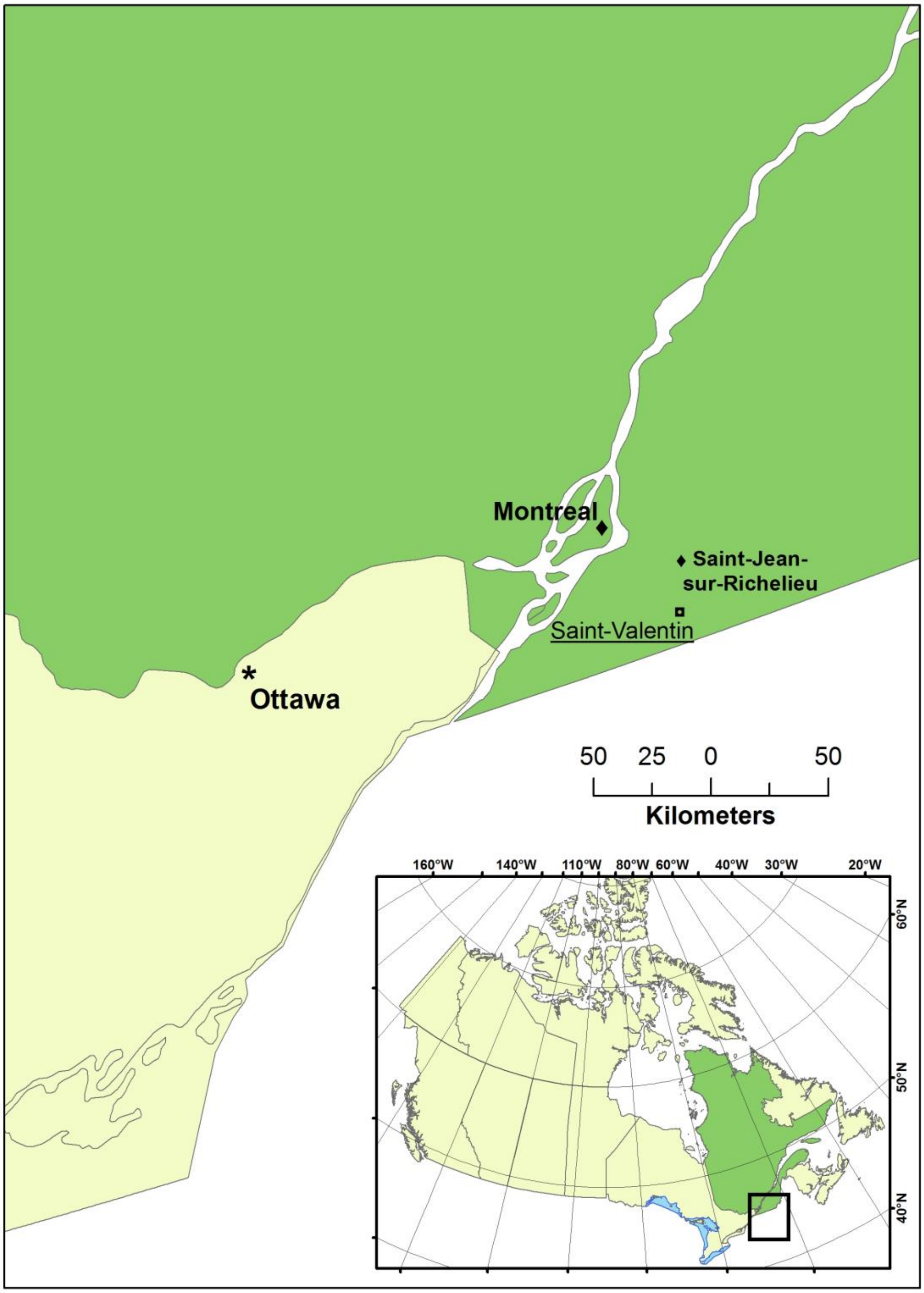


Figure 3.2. Location of the study site

3.2.2 Apparent Electrical Conductivity (ECa) measurements.

The soil electrical conductivity (ECa) is a measurement of the ability of materials to conduct electrical current for a given soil. In addition, ECa is related to some important soil properties for plant growth such as texture, chemical and nutrient content (Heiniger *et al.*, 2003; Kitchen *et al.*, 2003; Kravchenko *et al.*, 2003). This parameter was measured on bare soil in the spring before sowing for 2005 and 2006 or after harvest for 2007. Measurements were made by a VERIS model 3100 sensor (Figure 3.3) cart system (Veris technologies, Salina, KS) at shallow (about 0 to 30 cm) and deep (about 60 to 90 cm) readings. The ECa was recorded along transects that were approximately 10 m apart as a simple mono-directional scan or a bidirectional scan depending on the complexity of the terrain features.

Soil texture exerts a significant influence to the ECa, in addition to other factor such as soil moisture, depth of the arable layer and salinity of the soil (Heiniger *et al.*, 2003). A low ECa values tends to be associated with better growth conditions (Kitchen *et al.*, 2003) while soils with higher conductivity properties are linked with strong salinity conditions and limit productivity.

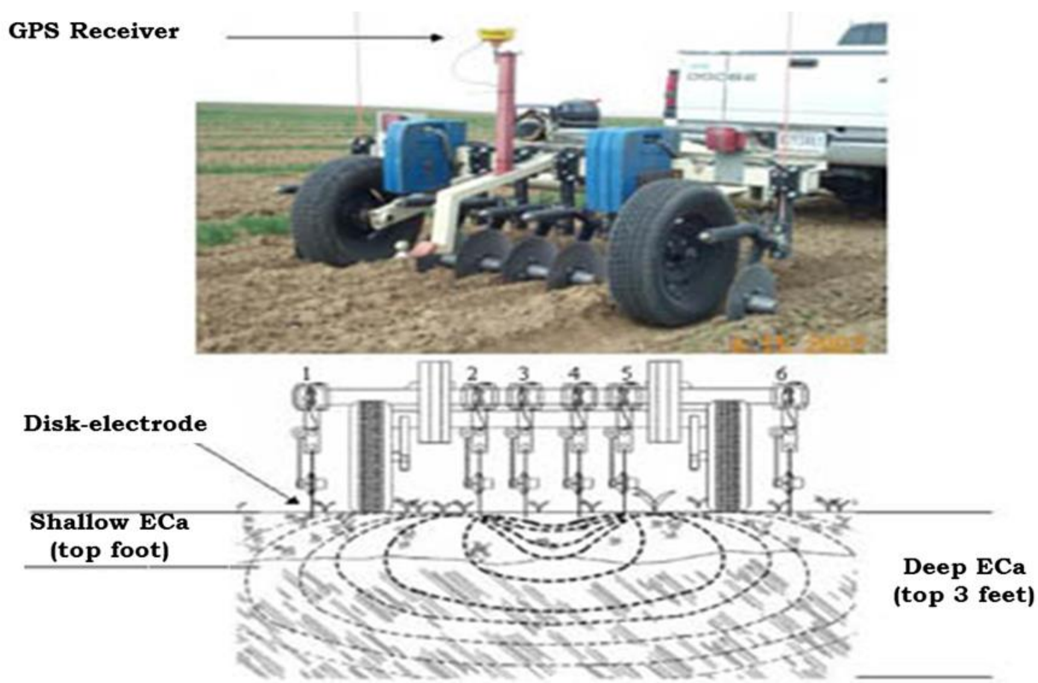


Figure 3.3. VERIS model 3100 sensor cart system. (Source: Veris Technologies, Inc.)

Since the ECa variability reflects the cumulative variability of important soil properties such as soil texture (Figure 3.4), it has been used as one of the criteria to define fertilizer management zones (Ferguson *et al.*, 2002). ECa mapping provided a useful framework for representing soil spatial heterogeneity and could potentially be applied to assess temporal impacts of management on soil conditions. For the specific purpose of this research ECa will be used as a variable to describe soil texture.

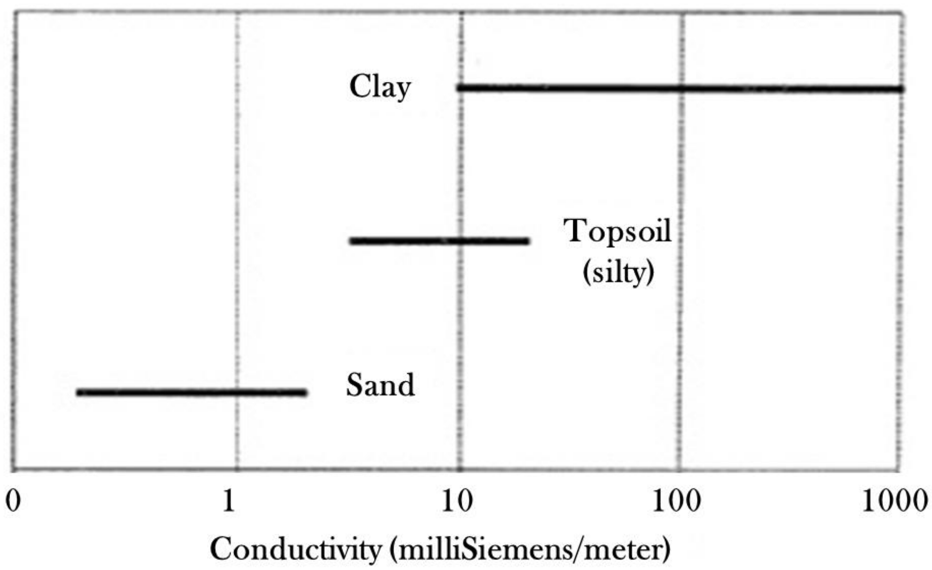


Figure 3.4. ECa values depending on texture and other soil properties. (Source: Veris Technologies, Inc.)

3.3 Nitrogen (N) rate

This research adopts two different approaches for the N treatments. Saturated strips (non N-limiting strips: 250 kg/ha N) were established in each field and extended throughout each from east to west. In these strips, N was not considered a limiting growth factor, and saturated levels were not reached in the rest of the field. For the fields in 2006 and 2007 only one rich-N strip was established while in the fields 2005 and 2008 two rich-N strips were established.

Figure 3.5 shows the structure of the strips for the field in the year 2005 while the location of strip(s) for the rest of the fields are shown in the next chapter. At sowing, all plots (except Nil-N strips) received 30 kg/ ha N broadcast, while the saturated strips received 220 kg/ha sidedressed. All trials were under conventional tillage with a row spacing of 0.75 m (Tremblay *et al.*, 2010).

3.4 Data pre-processing

The raw data acquired for each of the four fields was pre-processed. The NDVI, ECa, Elevation and Slope values were checked for normality. Figure 3.6 shows a set of sampling maps for each of the parameters to be analyzed in the study within the 2005 field. In Chapter 4, maps for all the fields are combined in one map following their original position with respect to each other. In the case of 2008 field a special arrangement was performed in order to show all the field data for every step in the analysis since this field had some overlap with the 2006 field.

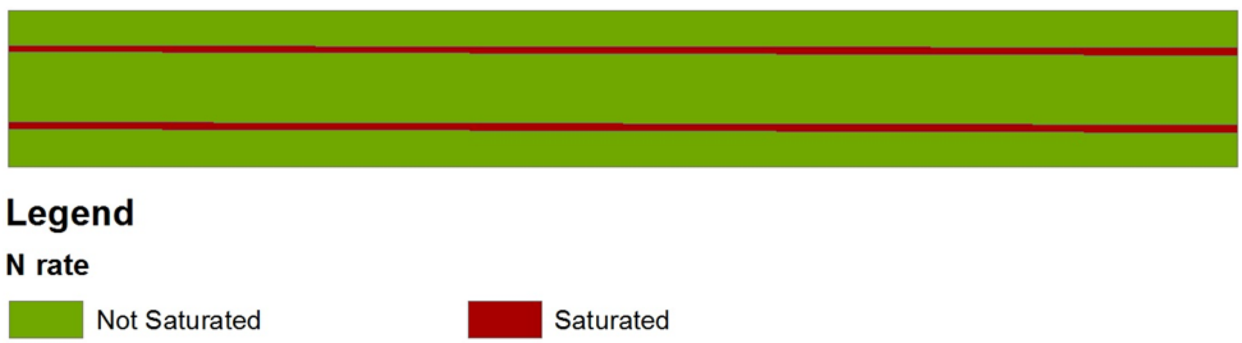


Figure 3.5. Saturated (N-rich) plots locations for field 2005.

3.5 Data processing

The data processing steps (Figure 3.1) used ArcGIS software (ESRI, 2009). The different NSIs were calculated for each variable using the NDVI from both the saturated and non-saturated areas of the fields. A comparison between all indices was used evaluate their accuracy while accounting for the N variability throughout the saturated strips and the whole field.

NDVI measurements were obtained before N application from five GreenSeeker sensors mounted on a trailer and pulled by a tractor. The NSI for every point in the field, henceforth called the NSI reference (NSI_{Ref}), was calculated based on NDVI values from both the non-saturated areas and the N rich strips (defined as $NDVI_{RichN}$). The $NDVI_{RichN}$ was arbitrarily set at the 90th percentile of NDVI values of the 20 nearest neighbours in the rich-N strip (See equation 3.1). The nearest neighbours approach is based on previous research methodology (Tremblay *et al.*, 2010) and taking into account the spatial distribution of the variables to be evaluated.

$NSI_{Ref} = (NDVI / NDVI_{RichN})*100$ (3.1)

Next, alternative NSIs (NSI_{ECa}, $NSI_{Elevation}$, NSI_{Slope} and NSI_{Soil}) were calculated by taking into account each of the variables (ECa, Eleveation, Slope and Soil). Three approaches were adopted (taking the ECa variable as example): (1) NSI_{neca} was calculated for every point as the average value of the nearest 20 points with ECa values (distributed anywhere) within the N-rich strips; (2) NSI_{2ecaCl}, NSI_{3ecaCl} and NSI_{4ecaCl} were calculated from reclassifying ECa into two, three and four classes. For each point, the average $NDVI_{RichN}$ (from points distributed anywhere) within the nearest ECa class is used; and (3) $NSI_{3ecaAreas}$ calculated after defining actual areas representing ECa grouped into three classes. Two scenarios (optimum areas) were chosen for each class in order to verify the independence of $NDVI_{RichN}$ from the choice of areas representing ECa classes.

Enhanced indices maps were obtained which will be used to analyze the capability of the NSI for each of the variables to be analyzed (NSI_{ECa}, $NSI_{Elevation}$, NSI_{Slope} and NSI_{Soil}) to describe the N availability throughout the fields. The calculation of such indices was based on the twenty closest points to the reference strip for each parameter.

The calculations for the NSI based on the closest 20 points, were done using Maplab version 7.10 (The MatWorks, Inc). The output raster file contains the measured distance from every cell to the nearest source (parameters) and the distance will be computed from cell center to cell center (Figure 3.7). The shortest distance to a source is determined, and if it is less than the specified maximum distance, the value is assigned to the cell. Cells outside the maximum distance will not be considered in the calculation (NoData value).

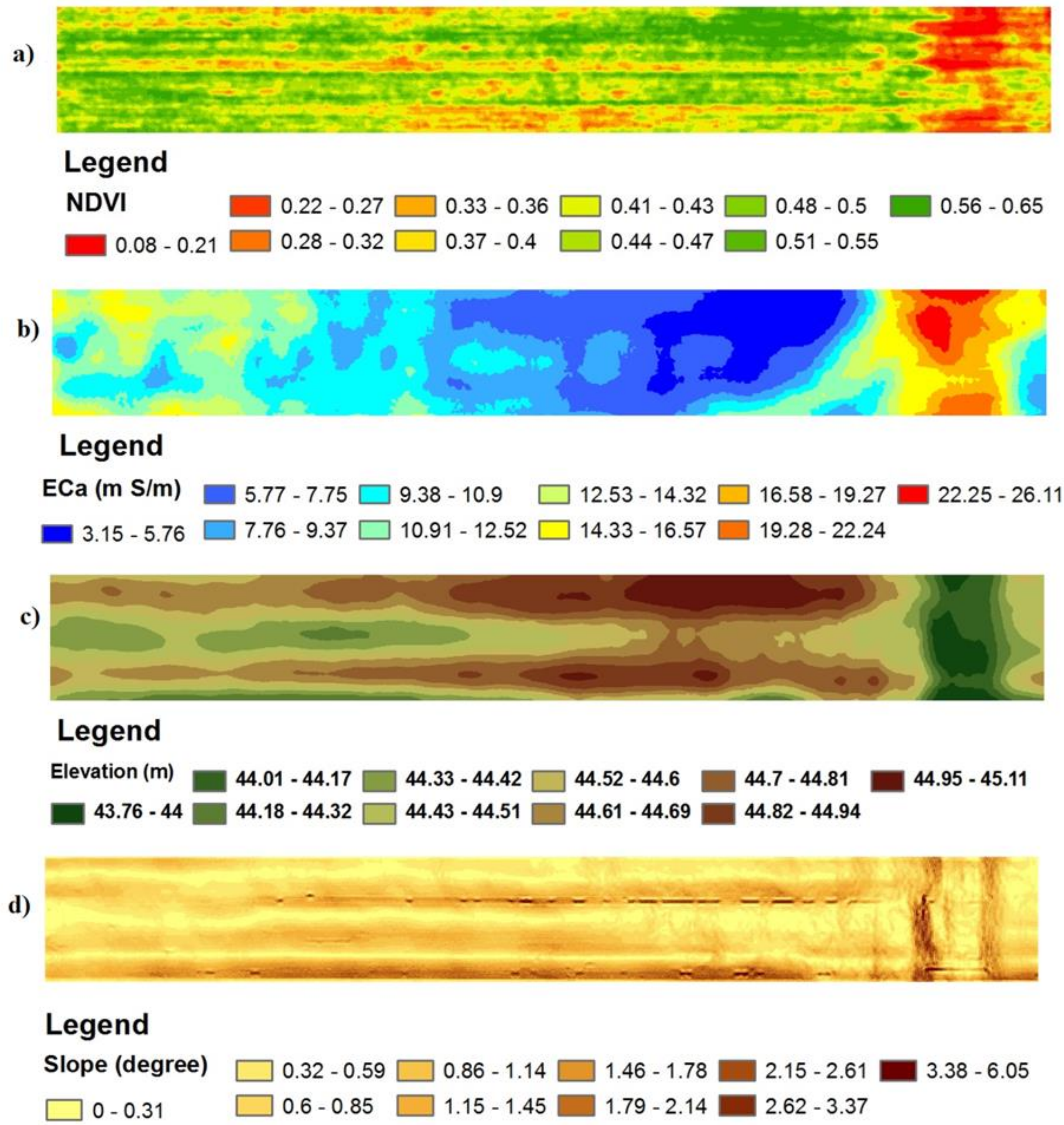


Figure 3.6. Maps of each variable for field 2005. a) NDVI, b) ECa, c) Elevation and d) Slope

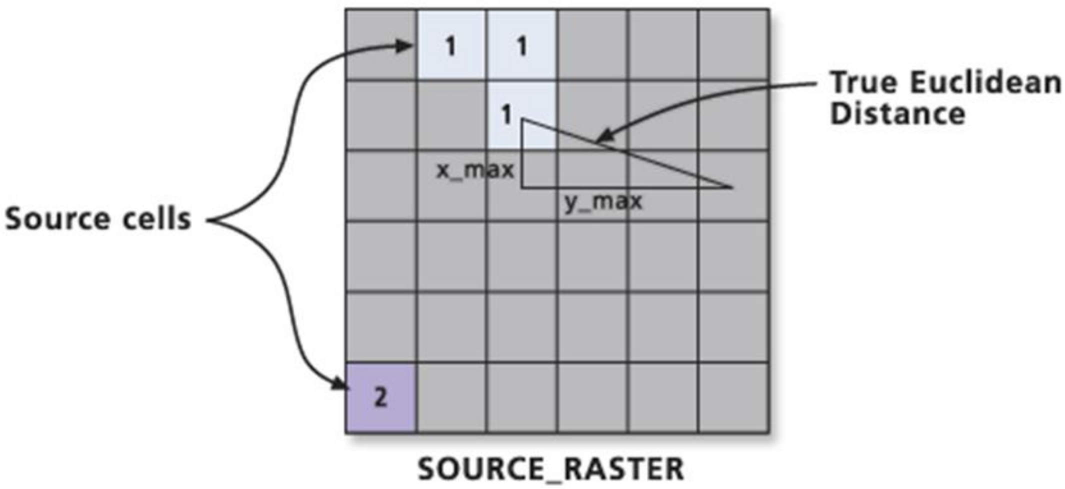


Figure 3.7. Euclidian Distance algorithm used in the calculation of alternative NSIs. (Source, ESRI 2009).

The three parameters used for the nearest neighbour approach to obtain the alternative NSIs are: ECa (Equation 3.3), Elevation (Equation 3.4), Slope (Equation 3.5) and Soil (Equation 3.7). The suffix 1 and 2 refers to the saturated and not saturated zones, respectively. The equation for each parameter can be written as:

$$NSI_{\mathbf{ECa}} = ([ECa_1 - ECa_2]^2)^{1/2} = |ECa_1 - ECa_2| \quad (3.3)$$

$$NSI_{\mathbf{Elevation}} = ([Elv_1 - Elv_2]^2)^{1/2} = |Elv_1 - Elv_2| \quad (3.4)$$

$$NSI_{\mathbf{Slope}} = ([Slp_1 - Slp_2]^2)^{1/2} = |Slp_1 - Slp_2| \quad (3.5)$$

It is generally accepted that soils represent the end product of the influence of relief (elevation, orientation, and slope of terrain), biotic (organisms) and abiotic (climate) elements while differing in terms of its texture and chemical content among other characteristics (Heiniger *et al*., 2003). For the specific purpose of the present research, the approach used to create the Soil variable was the combination of the three variables (ECa, Elevation and Slope). For instance, ECa has been widely recognized in the literature as proxy for soil texture (Heiniger *et al*., 2003; Ferguson *et al*., 2002) and nutrient and organic matter content (Kitchen *et al*., 2003; Kravchenko *et al*., 2003), while Elevation and Slope are determinants of erosion and/or deposition of the soil particles, nutrients and chemical properties of the high and low areas of the field (Tiessen *et al*., 2008; Kravchenko *et al*., 2003; Kravchenko and Bullock, 2000).

Following the approach described above to determine similar soil zones, the equation derived from the Euclidean distance concept is expressed as follows:

$$D = ([X_1 - X_2]^2 + [Y_1 - Y_2]^2 + [Z_1 - Z_2]^2)^{1/2} \qquad (3.6)$$

Where the 1 and 2 suffixes refer to each points for which the distance is calculated.

Substituting the equations (3.3, 3.4 and 3.5) into (3.6) the nearest neighbour equation for the soil can be written as:

$$NSI_{\mathbf{Soil}} = ([ECa_1 - ECa_2]^2 + [Elv_1 - Elv_2]^2 + [Slp_1 - Slp_2]^2)^{1/2} \qquad (3.7)$$

Once the NSI for each parameter was calculated, the results were then compared to the $NSI_{\mathbf{Ref}}$. The purpose of this comparison is to analyze the influence of NSI on the N variability through the field. At the same time each NSI was divided into two, three and four classes in order to determine the class that could be used to define the reference plots locations. Selected statistical methods according to the research needs were used to analyze the relationship among all the variables and its influence on the N variability throughout the fields.

The validation process was performed only using the data from the variable(s) that best describe the variability of N throughout the fields. The same methodological approach described above was applied to a set of data that represent the potential zones (suitable locations) in order to compare the results with the ones obtained from the variable(s) selected as good indicators of N variability. The latter was adopted as a validation tool for the methodology applied in the analysis of the influence of the variables on the N spatial distribution, since the results of processing data were not able to be validated with ground truth.

3.6 Histogram threshold to determine classes

The classes for the variables ECa, Elevation, Slope were determined using the histogram segmentation method of Otsu (Tremblay et al., 2010) in order to find the thresholds that minimize the weighted within-class variance, maximizing the between-class variance (Otsu, 1979). In order to facilitate the simplest explanation of differences that maybe found between NDVI within the identified class thresholds, the number of classes for each variable (ECa, Elevation, Slope) that represented the majority of modes in the multimodal distribution was selected for further analysis in the calculation of the $NSI_{\mathbf{Ref}}$ and the selection of the suitable locations for saturated plots. The minimum number of class groups were chosen for analysis as doing so meets the objective of maintaining operational manageability of fertilizer applications.

As a result from this statistical procedure, each variable was classified into two, three and four classes which were considered in the analysis for their influence on $NSI_{\mathbf{Ref}}$. The numbers of class were also selected based on the range of the values and the spatial distribution.

3.7 Statistical analysis

The aim of this work is to create a relative vegetation index (NSI) that depends on soil nitrogen (or N status). Thus this index needs to be independent of the spatial variability of ECa, ELE and SLP. As the original NSI (with large saturated strips, called nearest neighbour or NSI_nn) is not efficient to use in practice, we here propose alternative ways for calculating NSI with limited areas of saturation in nitrogen fertilizer. Therefore, all calculations for the NSI for each variable (called alternative NSIs) were performed using data from the saturated plots (N rich). The next step in the analysis was to determine the statistical significance of each of the alternative NSI ($NSI_{\mathbf{ECa}}$, $NSI_{\mathbf{Elevation}}$, $NSI_{\mathbf{Slope}}$ and $NSI_{\mathbf{Soil}}$) on the NDVI in the non-saturated areas of the fields.

Averages of $NDVI_{\mathbf{RichN}}$ were calculated for each variable (ECa, Ele, Slp and Soil) and compared. The significant differences between the NSI for each variable class calculated based on $NDVI_{\mathbf{RichN}}$ were analyzed using a T-test in order to determine if they were or not significantly different. The T-value is related to the size of the difference between the means of the samples to be compared. The larger the T-value is, the larger the difference. In the particular case of the present study the statistical significance was set at $p < 0.01$.

The analysis of variance (ANOVA) was performed using General Linear Model (GLM) procedure of SAS software (SAS Institute, Cary, NC). ANOVA was used to assess the effect of the spatially variable properties of the field, represented by ECa, ELE and SLP, on the various alternative NSIs proposed, as compared with NDVI and original NSI_nn. Thus, for each field (each year), each way to compute alternative NSIs (i.e. from several classes of ECa, or ELE) an ANOVA is applied to assess the importance of the effect of field properties (ECa, ELE and SLP) on NSI versions. The less affected NSI by field variability is the most sensitive to nitrogen status. Finally, the Pearson correlation coefficient (R) was used to analyze the relationship between the alternative NSIs in order to understand their influence on the N variability throughout the fields.

3.8 Summary

This chapter contains a description of the study site and the techniques used to collect the data for further processing and analysis. The variables were acquired over four years (2005, 2006, 2007 and 2008) in four corn fields in St-Valentin (Quebec). NDVI was collected using GreenSeeker tractor mounted sensor; ECa measurements were derived from the VERIS 3100 while terrain data was acquired by using Differential GPS (DGPS). NSI indices were calculated for each field and all variables ($NSI_{\mathbf{Ref}}$, $NSI_{\mathbf{ECa}}$, $NSI_{\mathbf{Elevation}}$, $NSI_{\mathbf{Slope}}$ and $NSI_{\mathbf{Soil}}$). Finally, the statistical procedures used were described. In the next chapter (Chapter 4), the results will be presented and discussed.

4. Results and Discussion

In this chapter, the NSI reference (NSI_{Ref}) and the alternative NSI for each variable (ECa, Elevation, Slope and Soil) are calculated. Also, the NSI reference (NSI_{Ref}) capacity to predict N stress is analyzed, and the output maps are compared with the NDVI maps. Each variable is reclassified on an ordinal scale from low to high in order to assess which classes better predict N variability through the fields. Discrete classes are used to be consistent with the delineation of fertilizer management zones. Finally, new saturated zones are identified and a validation procedure examines the accuracy of the new zones for predicting N variability throughout the fields. It is noted here that due to issues of spatial autocorrelation, the R^2 and significance are both inflated.

4.1 Analysis of the Spatial Fields Variability

The spatial variability of ECa, Elevation and Slope for each field is presented in this section. Nitrogen availability throughout fields has been proven to be influenced by soil type and terrain features (Shanahan *et al*., 2008; Krachenko *et al*., 2003). Several studies have described ECa as a potentially useful surrogate variable to successfully predict soil texture, nutrient availability and soil organic matter (Bausch and Brodahl, 2012; Shanner *et al*., 2008; Heiniger *et al.*, 2003). Elevation and slope have also been identified as terrain features that play important roles in the distribution of nutrients throughout fields (Krachenko and Bullock, 2000).

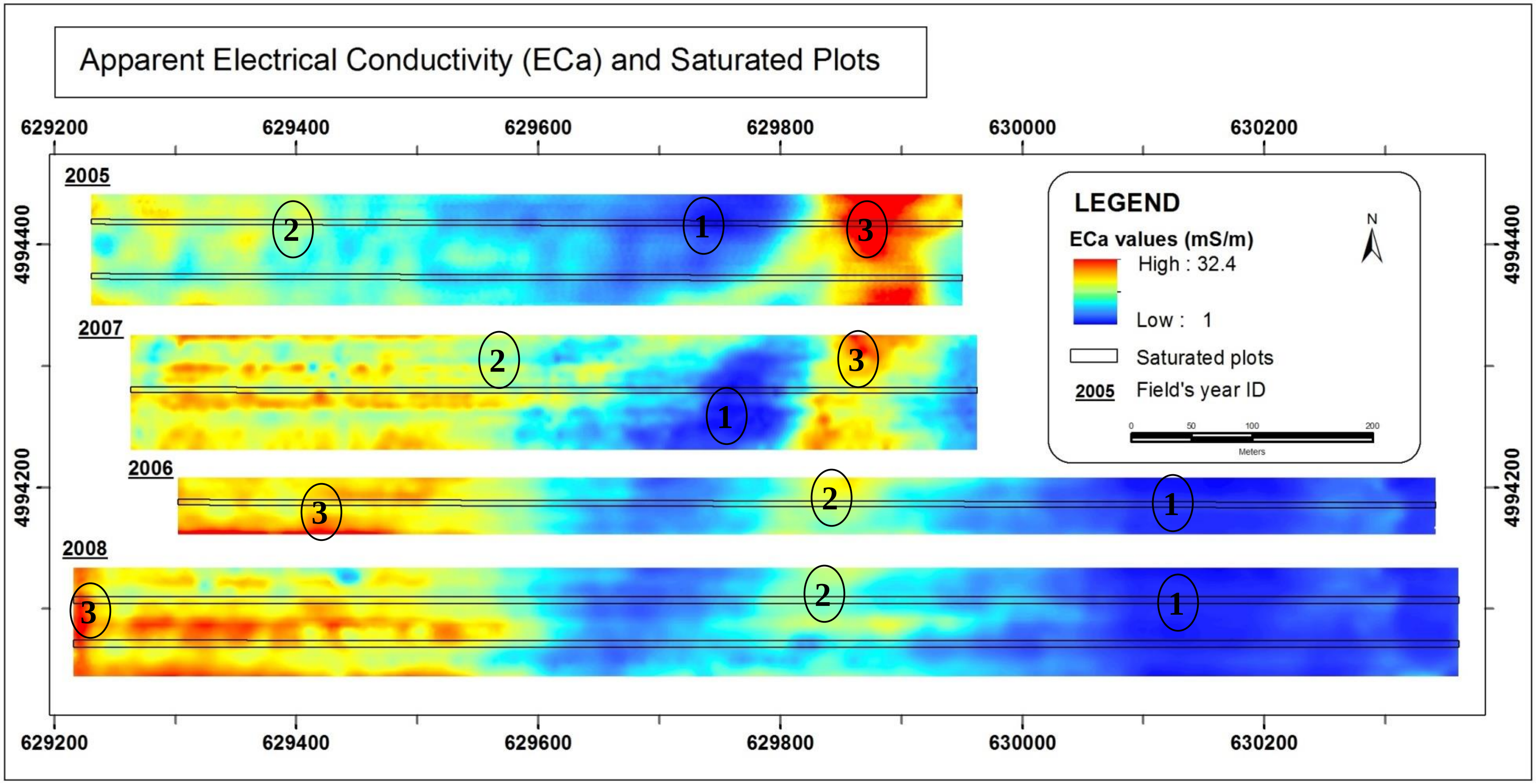


Figure 4.1. ECa maps for each field generated from the measurements obtained from 5 GreenSeeker sensors mounted on a trailer, where 1, 2 and 3 indicate areas with low, medium and high ECa values, respectively.

4.1.1 Analysis of the variable ECa

Figure 4.1 shows the ECa maps for all the fields with values that vary between 1 and 32.4 mS/m, representing the largest range of values among all the analyzed variables. On one hand, fields 2006 and 2008 showed larger areas with low ECa values (areas marked with the number 1). On the other hand, fields 2005 and 2007 showed larger areas with high ECa values (areas marked with the number 3). Meanwhile, field 2005 exhibited a noticeable concentration of very high ECa values among all fields. The areas with medium ECa values did not present a predominant pattern for any of the fields in particular.

As described in Chapter 2, ECa has been used as a surrogate variable to analyze soil texture. Soil texture plays an important role in soil characteristics and its potential uses in agriculture. Clay texture zones, which also result in more humid zones within fields, can be linked to high ECa values (more than 25 mS/m), since humidity promotes electrical conductivity. These zones are generally considered good for crop growth; nevertheless, high-density clay soils are also linked to flooded areas due to their low infiltration rates and reduced pore space, which both contribute to low permeability affecting cultivars and yields as well as agricultural procedures. ECa values between 5 and 20 mS/m have been described in correlation with topsoil (silty) characteristics and are optimal soils for crop growth and higher yields. Such soils present more balanced physical and chemical characteristics while maintaining stable humidity and nutrient content, key elements for full plant development. Very low ECa values (close to 1 mS/m) are linked with sandy texture, which is known for its low capacity to retain water and nutrients.

4.1.2 Analysis of the variable Elevation

The spatial variability of Elevation within the fields was marked by a range of values that varied from 2 to 3 m. As depicted in Figure 4.2, in fields 2006 and 2008, the highest zones (areas marked with the number 3) were located toward the eastern portion of each field, whereas for fields 2005 and 2007 such areas were concentrated in north and central locations, respectively. The zones with low elevation values (areas marked with the number 1) were found in eastern locations for most of the fields, except for field 2005, in which those areas showed a clear

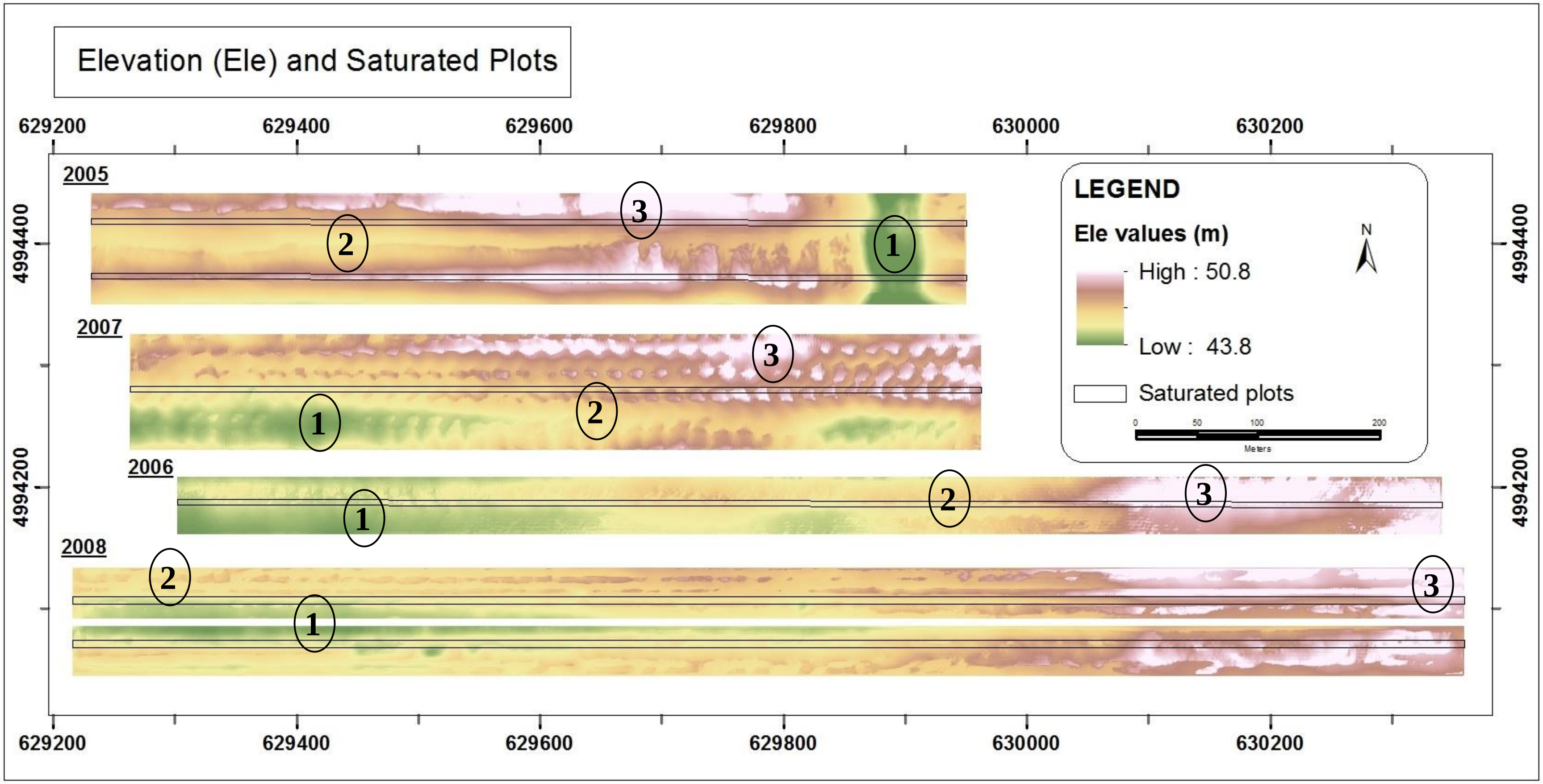


Figure 4.2. Elevation maps for each field generated from the DGPS transect measurements throughout the fields, where 1, 2 and 3 indicate areas with low, medium and high Elevation values, respectively.

valley shape on the western side of the field. Medium elevation areas presented the greatest extent for most of the fields, with less representation in field 2007.

4.1.3 Analysis of the variable Slope

Slope values were between 0 and 12 degrees, with most values less than 6 degrees. Slope is known to be related to transportation and deposition of material and nutrients. In the particular case of the fields under study, the spatial variability of slope differs from the variability of the two other variables previously analyzed. Most areas throughout all the fields showed low slope values (under 6 degrees), and higher values were localized at specific points throughout all four fields, showing a clear spatial relationship with elevation zones. As mentioned above, the major influence of slope in agriculture is to control the movement of materials and nutrients from higher to lower areas of fields. Therefore, taking into account its distribution patterns can help to develop understanding of nutrient availability throughout fields.

4.1.4 Relationship between the variables

In the case of the relationship between Elevation and ECa, the locations with high ECa values were found to be spatially linked to low elevation zones, while the higher elevation zones were linked to low ECa values (Figure 4.2). This behaviour has been described in previous research (Kravchenko *et al*., 2003) as being due to the fact that soil water content migrates (influenced by slope patterns) from higher to lower elevation zones, creating high water concentration, which increases electrical conductivity. Conversely, high elevation areas are prone to accumulating less water, so their electrical conductivity is low. In the eastern portion of field 2005, high ECa value areas were spatially distributed throughout low elevation zones of the field. Similar spatial distribution patterns linked high elevation areas to low ECa value zones for fields 2006 and 2008, due to the lack of soil water content for higher areas of the fields.

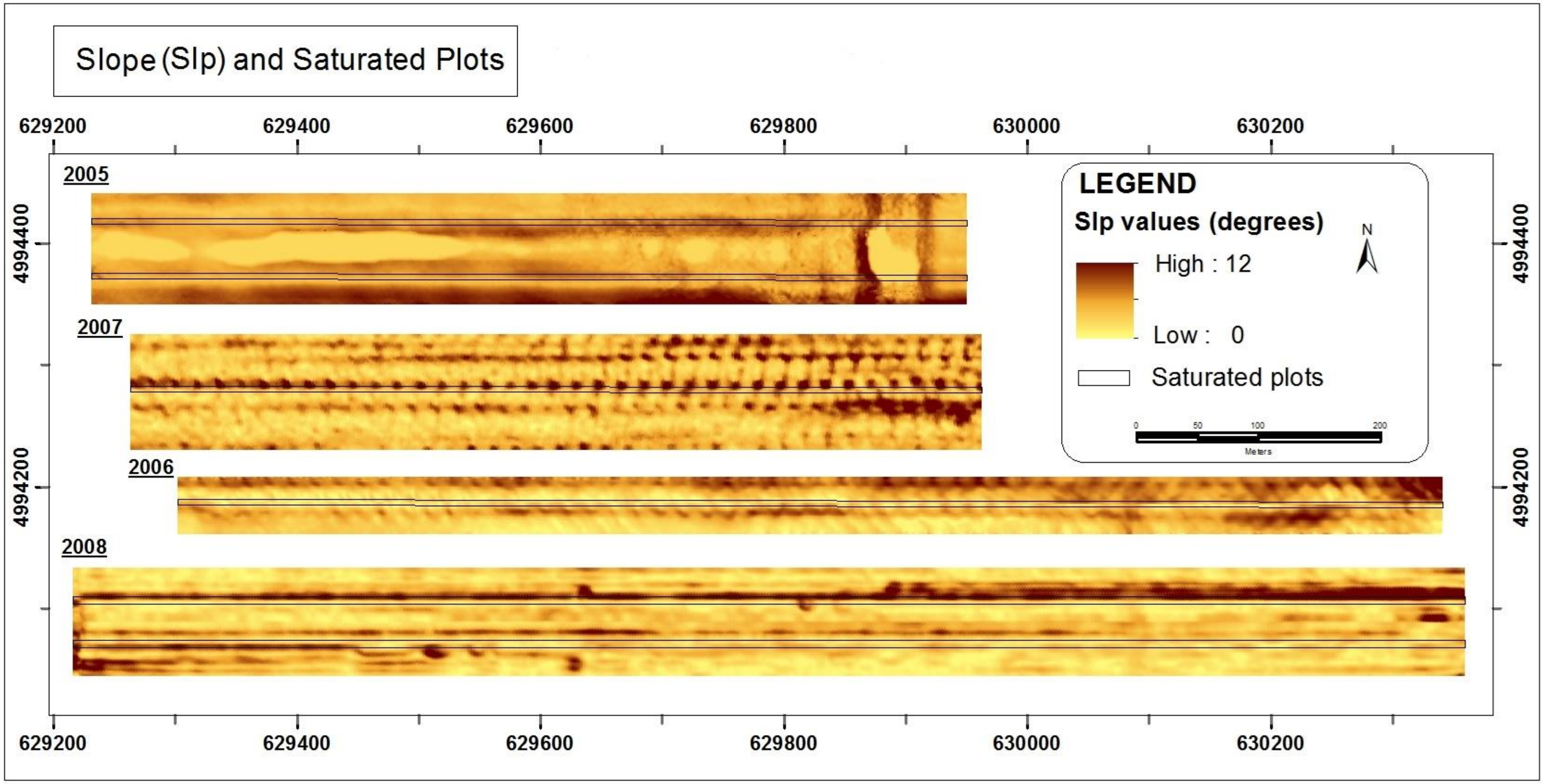


Figure 4.3. Slope maps for each field derived from the elevation points generated from the DGPS transect measurements throughout the fields.

As depicted in Figures 4.1 and 4.2, and as previously discussed in the Methodology chapter, saturated (N-rich) plots covered areas throughout all the fields, strategically representing the spatial variability of the variables under analysis. According to Shanaban *et al*. (2008), without N-rich reference plot data, N fertilization recommendations are difficult to prescribe. More research is needed to determine the optimal locations for N-rich plots by examining and understanding within-field soil variability. Thus, evaluations based on the analysis of field soil variation can potentially improve recommendations in the present research, since the data associated with the saturated plots cover all types of ECa values (recognized as a proxy variable for soil descriptors).

4.2 Normalized Difference Vegetation Index versus Nitrogen Sufficiency Indices

Through canopy reading, vegetation indices have proven to be a useful tool to estimate N status and its spatial variability in fields. The accuracy of this estimation is a key factor when deciding which of those indices better assesses N stress for fertilization applications. As discussed in the literature review, NSI improves the performance of NDVI due to the tendency of the latter to be affected by environmental noise (e.g., soil background). In this section, these indices are compared to each other in order to analyze their capacity to assess the spatial variability of N stress throughout the fields.

The NDVI values obtained from the GreenSeeker mounted sensor ranged from 0.08 to 0.81, where low values were linked with bare soil or little plant biomass and high values corresponded to high crop density (biomass). According to Bannari *et al.*, 1991, the average error in NDVI readings because of the influence of soil background is between 15-20%. Therefore, it is important to take into consideration that in the particular case of this research the areas with NDVI values under 0.2 likley indicate very low or no crop cover.

Taking into account the limitations of NDVI, and analyzing the output maps in Figure 4.3, it is possible to locate zones with low crop cover (biomass) where N might be a growth-limiting factor (areas marked with the number 1). Field 2005 showed larger areas with low NDVI values, followed by field 2008. In most cases, these areas of the fields were spatially linked with lower

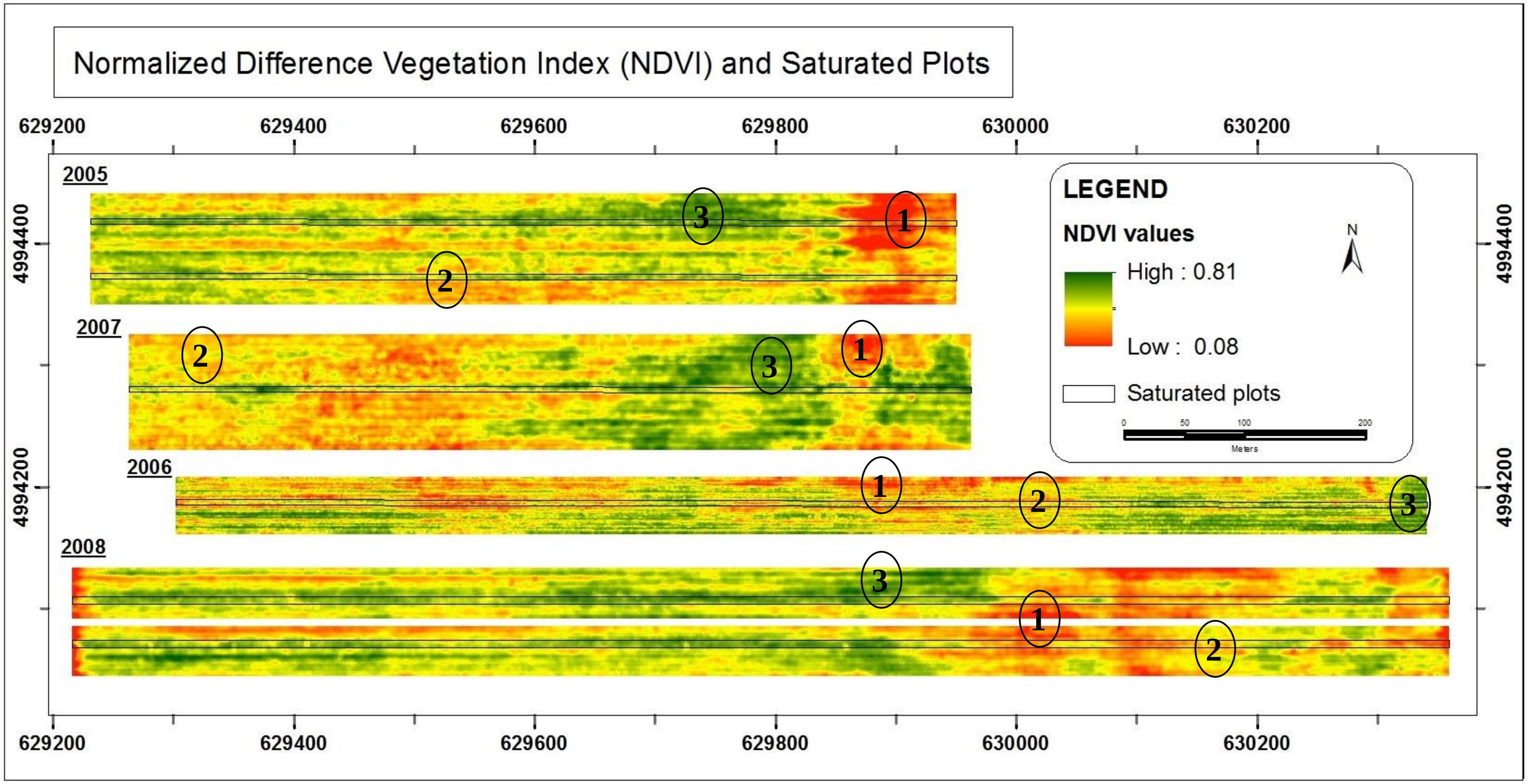


Figure 4.4. Normalized Difference Vegetation Index (NDVI) maps for each field generated from the measurements from 5 GreenSeeker sensors mounted on a trailer, where 1, 2 and 3 indicate areas with low, medium and high NDVI values, respectively.

elevation and high ECa, which, as described before, are portions of the field where soil water content is high, leading to losses of N due to the leaching processes. Conversely, the zones of the fields in green were linked with higher crop cover; thus, high crop biomass was spatially connected to lower ECa values and higher elevations.

The $NSI_{\mathbf{Ref}}$ maps show an apparent reduction of the areas associated with higher N availability (green colour) for all the fields. These areas are represented in Figure 4.4 with colours from light yellow-green to dark green. The output maps from both vegetation indices identify the same areas under N stress (areas marked with the number 1). This result demonstrates the relationship between NDVI and NSI when describing crop biomass status, but, with the second normalization applied to the NDVI in the equation to calculate NSI, the latter is capable of reducing the confounding effect the soils exert on NDVI measurements.

Comparing visually the NDVI and NSI ($NSI_{\mathbf{Ref}}$) maps for all the fields, it is possible to see that one of the main differences between the two indices outputs is that the NDVI maps show relatively more dark red areas (marked with number 1) which are associated with low NDVI values and greater N stress. Although, it is possible to identify locations in all fields where these areas persist despite the calculation made based on the new index ($NSI_{\mathbf{Ref}}$), it is evident that there is a reduction of the amount of area under N stress in the $NSI_{\mathbf{Ref}}$ maps. For instance, the zones under N stress in the western portion of fields 2005 and 2008 in the NDVI maps show a significant reduction compared to the same locations in the $NSI_{\mathbf{Ref}}$ maps. Fields 2006 and 2007 show a more modest improvement regarding reduction of stressed areas, and in the specific case of the field 2006 more zones in red colour appear in the NSI output. Nevertheless, this situation is associated with the differences between the mathematical definitions of each index. For NDVI dense vegetation canopy will tend to positive values (0.3 to 0.8) and soil background rather small positive values (0.1 to 0.2) while in the case of the NSI only the values under 0.95 (95%) are considered linked to areas of crop with N deficiency (Peterson *et al.*, 1993). Table 4.1 shows a comparison between the percentages of areas under N stress (according to the previous analysis) from the NDVI and the NSI maps. For most of the fields except for 2006 the percentage (bold) of areas under stress decreased when analysing the NSI.

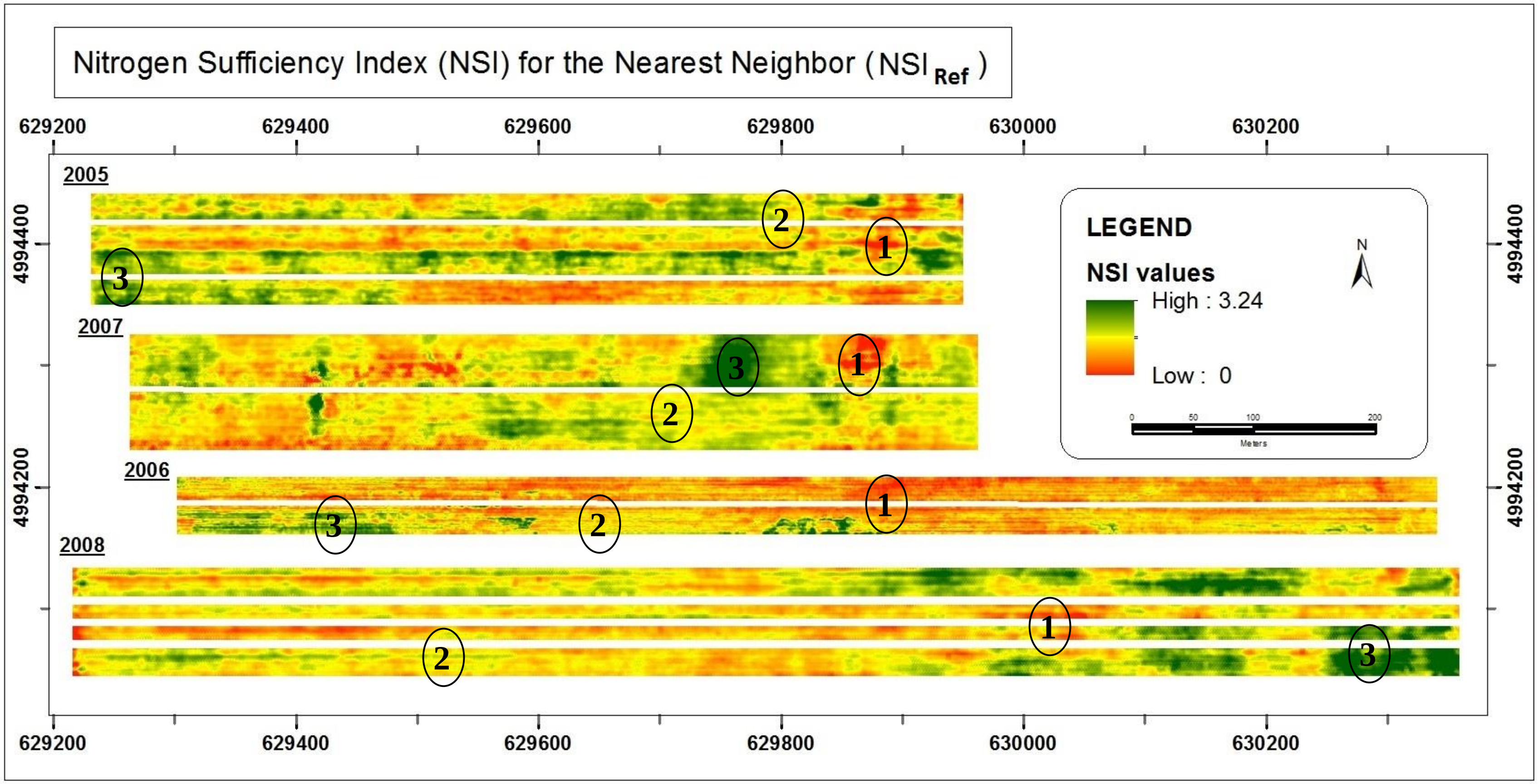


Figure 4.5. Nitrogen Sufficiency Index reference (NSI_{Ref}) maps calculated from both the NDVI data from the saturated plots (N-Rich) and the NDVI data from the rest of the field, where 1,2 and 3 indicate areas with low, medium and high NSI values, respectively.

Table 4.1. Percentages of areas under N stress from the NDVI and the NSI maps.

Fields / Indices	2005	2006	2007	2008
NSI <0.95 (%)	**55.4**	50.7	**62.5**	**47.0**
NSI >0.95 (%)	44.6	49.3	37.5	53.0
NDVI <0.5	71.9	**41.0**	68.4	66.5
NDVI >0.5	28.1	59.0	31.6	33.5

The NSI output maps demonstrated that the uses of such index (NSI) to determine the spatial variability of N stress can improve the outputs coming from the analysis of the NDVI maps. These results are in agree with the previous studies (Bouroubi *et al.*, 2013 and Tremblay *et at.*, 2010) and could contribute as a reference for future studies investigating and predicting crop N status through the analysis of canopy reflectance. Nevertheless, the NSI analysis by itself does not completely explain the availability of N throughout the fields due to the influence of other variables (terrain and soils). Therefore, as previous research has observed, it is necessary to combine crop status data with a fields natural characteristics in order to better access the factors affecting the spatial availability of N.

4.3 Determination of the Classes for each Variable

In order to analyze whether NDVI and NSI are dependent on the field variability in Elevation, ECa, and Slope, the univariate distributions of the latter three variables were plotted and examined. If the univariate distributions of Elevation, ECa or Slope exhibit a multimodal character, then critical thresholds within the corresponding histogram were determined using Otsu's method (Otsu, 1979) in order to reclassify Elevation, ECa and Slope variables on a Low to High Scale. Given that the objective of precision farming is to judiciously apply fertilizer treatments where they are most needed, a farmer can make improved application decisions with information on how fertilizer requirements vary within a field according to different levels of

ECa, Elevation or Slope. However, and at the same time, true dynamic application is unrealistic with today's farming technologies; that is to say, prescribing different amounts of fertilizer application for every point in a field is unrealistic in practice. For example, dividing a field into three or four classes of Elevation or ECa, and prescribing different amounts of fertilizer for each range of the variables therein may be manageable but presenting many more will likely mean that the farmer will not adopt the precision practice. Therefore, there is a necessary trade-off between identifying where changes in the amount of fertilizer applied is needed and minimizing the efforts required making those different applications throughout a field.

Given the above optimization goals, the purpose of this section is to examine the variability of Elevation, ECa and Slope and divide these variables into classes to see if crop needs requirements differ among those classes as measured by NSI and NDVI. Class breaks in Elevation, ECa, and Slope throughout the fields were determined using Otsu's methodology (Tremblay *et. al*., 2010), whereby, each variable is subdivided into classes that minimize the intra-class variance. The number of classes is chosen a priori and these classes are used as grouping factors to extract their associated NDVI and NSI values within each class grouping. From each of these defined class groups, average NDVI values were determined for the non-saturated areas of the fields, as well as for the values of NDVI from the saturated plots. These values were analyzed using ANOVA in order to determine if significant differences exist between the averages of NDVI values in the fields that were grouped according to Elevation, ECa or Slope class groups.

The histograms obtained for ECa, Elevation and Slope using Otsu's methodology presented multimodal distributions. As discussed in Chapter 3 this thresholding method (Otsu's) is capable of finding thresholds that minimizes the weighted within-class variance, maximizing the between-class variance (Otsu, 1979). In order to facilitate the simplest explanation of differences that maybe found between NDVI within the identified class thresholds, the number of classes for each variable (ECa, Elevation, Slope) that represented the majority of modes in the multimodal distribution was selected for further analysis in the calculation of the $NSI_{\mathbf{Ref}}$ and the selection of the suitable locations for saturated plots. The minimum number of class groups were chosen for analysis as doing so meets the objective of maintaining operational manageability of fertilizer applications.

4.3.1 Apparent Electrical Conductivity (ECa) Classes Determination

The histogram showing class thresholds for ECa values for field 2005 is shown in Figure 4.5. ECa divided using three classes (Table 4.2) to approximate high, medium and low values was selected to determine whether differences in average NDVIsat and NSI values by class existed in the saturated zones. Analysing the histogram frequency distribution is possible to determine that the ECa grouped into three classes (Also referred as "ECa class Three" in tables, graphics and maps) was the smallest number of classes that captured the majority of modes. For the rest of the fields the ECa grouped into three classes also captured the modes in their respective histograms (See threshold tables and histograms in Appendix). Therefore, the ECa grouped into three classes will be used to determine NDVIsat values to calculate $NSI_{\mathbf{Ref}}$ and in the selection of the suitable locations for saturated plots.

Table 4.2. Threshold for ECa grouped into three classes and the threshold ECa values for each class.

Fields	**Class thresholds**		**Low ECa**	**Med ECa**	**High ECa**
2005	9.07	14.54	6.83	11.18	17.99
2006	7.80	15.09	4.30	11.18	19.37
2007	9.50	16.20	5.87	13.36	18.93
2008	6.29	13.67	4.10	9.28	17.84

Table 4.2 shows the threshold values of ECa grouped into three classes as well as the average NDVIsat values for each of the section class. The values in Table 4.3 show the average NDVI for all the class sections and are statistically analyzed using the t-test in order to check if there is any significant difference between the average NDVIsat values of each class. For the specific purposes of the present research, the p values were set at 0.01. For values of $p>0.01$ the

hypothesis was considered null and no significant difference is found, while for $p<0.01$ there was a significant difference between the NDVIsat values of each class.

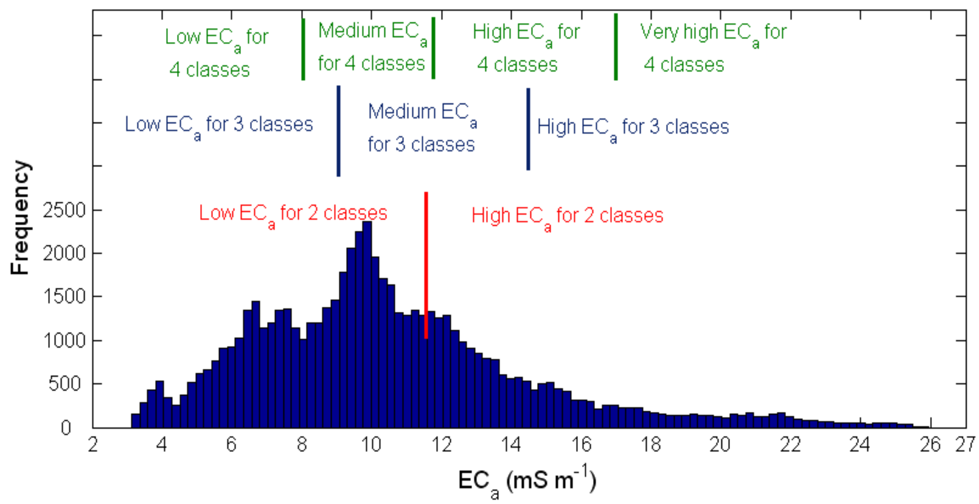


Figure 4.6. Histogram threshold and section class for the Apparent Electrical Conductivity (ECa) for the field 2005.

Table 4.3. Averages of NDVIsat for ECa section class

	ECa class Two		**ECa class Three**			**ECa class Four**			
2005	0.47	0.44	0.51	0.50	**0.37**	0.53	0.48	0.51	**0.32**
2006	0.49	**0.38**	0.59	0.52	0.56	0.62	0.59	0.44	0.55
2007	0.44	0.49	0.50	0.50	**0.37**	0.53	0.45	0.48	**0.30**
2008	0.50	0.49	0.44	0.53	0.48	**0.37**	0.50	0.49	0.51

In Table 4.3, low (<40) average NDVI values for the saturated zones are shown in the high class sections (number in bold) of ECa grouped into two classes (Also referred as “ECa class Two” in tables) and ECa grouped into three classes. The same low values for average NDVI are present in the very high class sections for ECa grouped into four classes (Also referred as “ECa class Four” in tables and maps) for all the fields. The outputs demonstrated that areas with high ECa values were linked to low density crops areas. Kravchenko *et al.*, 2003 found similar behaviour of ECa and stated that it is negatively correlated with plant growth.

Table 4.4. T-test results for the comparison of the NDVI values between all classes for the variable ECa (NDVI values are significantly different if P< 0.01). Where VHigh=Very High

Fields / Classes	2005	2006	2007	2008
Two				
Low-High	H=0; P= 0.2158	H=0; P= 0.0680	H = 0; P=0.0855	H =0; P =0.8235
Three				
Low-Medium	H =0; P =0.5901	H =0; P =0.0716	H =0; P =0.8810	H =1; P =0.0284
Low –High	H =1; P =4.9e-7	H =0; P =0.3515	H =1; P =9.8e-7	H =0; P =0.2129
Medium-High	H =1; P =3.7e-6	H =0; P =0.4561	H =1; P =7.6e-5	H =0; P =0.2392
Four				
Low-Medium	H =0; P =0.1049	H =0; P =0.4416	H =1; P =0.0474	H =1; P =0.6e-4
Low –High	H =0; P =0.4846	H =1; P =1.9e-5	H =0; P =0.1090	H =1; P =0.4e-4
Low –Vhigh	H =0; P =0.2980	H =1; P =1.9e-5	H =0; P =0.0083	H =0; P =0.7883
Medium-High	H =1; P =1.6e-7	H =0; P =0.0569	H =1; P =2.3e-8	H =1; P =0.4e-5
Medium-VHigh	H =1; P =5.4e-5	H =0; P =0.3028	H =1; P =9.7e-4	H =0; P =0.8280
High-VHigh	H =1; P =7.4e-7	H =1; P =0.3028	H =1; P =3.1e-6	H =0; P =0.5686

**No corrections created for multiple testing*

For all the fields, the ECa grouped into two classes T-test results (Table 4.4) showed that the NDVIsat are not significantly different from each other. Thus, using NDVI values from two class grouping does not yield accurate results to describe N variability within fields. In the case of ECa grouped into three classes, all fields presented at least two classes with NDVIsat significantly different from each other. For both fields 2005 and 2007, significant differences were shown between the low-medium and medium-high classes. In fields 2006 and 2008, a significant difference was found between the low and medium classes. The same test for ECa grouped into four classes yielded more than two class sections showing significant differences between them within all classes for all the fields. The results from the t-test demonstrated that ECa grouped into three classes accounted for the NDVI differences in the saturated zones and validated its selection for the posterior analysis of the influence of ECa on NSI variability throughout the fields.

4.3.2 Elevation Classes Determination

Figure 4.6 depicts the histogram class threshold for Elevation values for field 2008. In the graphic it is possible to see the distribution of the data for each of the classes and thresholds. The Elevation grouped into four classes (Also referred as “Elevation class Four” in tables, graphics and maps), shows that is the one that better represent the major number of modes derived from the frequency distribution, while Elevation grouped into two classes (Also referred as “Elevation class Two” in tables, graphics and maps) and Elevation grouped into three classes (Also referred as “Elevation class Three” in tables, graphics and maps) are associated with a more imbalanced representation of the histogram modes. Therefore, Elevation grouped into four classes (Table 4.6) was selected as the most representative of the Elevation classes, and analyses were performed to evaluate the relationship between NSI and Elevation in the saturated zones.

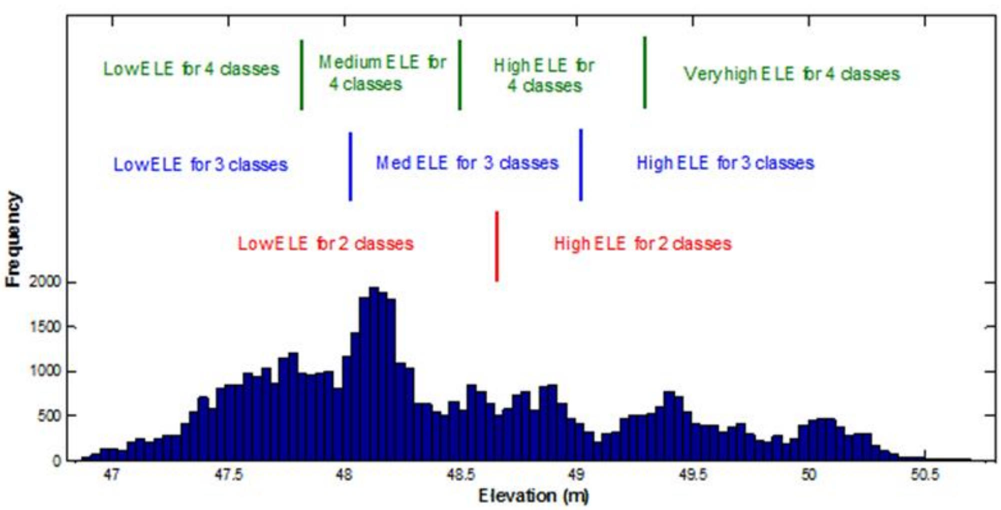


Figure 4.7. Histogram threshold and class section for the Elevation of field 2008

Table 4.5. Thresholds for four classes' segmentation of Elevation and the central Elevation value for each class.

Fields	Thresholds			Low ECa	Medium ECa	High ECa	Very High ECa
2005	44.30	44.50	44.80	44.00	44.35	44.60	44.95
2006	44.30	45.00	45.60	44.10	44.65	45.25	45.80
2007	44.00	44.30	44.50	43.85	44.20	44.35	44.70
2008	47.80	48.50	49.30	47.20	48.15	49.1	51.05

Table 4.5 shows the threshold values of Elevation grouped into four classes and their average NDVIsat values for each of the class sections. The average NDVI values for all the class sections are shown in Table 4.6 and were analyzed using the t-test in order to check if there was a significant difference between the average NDVIsat values of each class. For the Elevation section classes, the NDVIsat for the low values (<40) followed different patterns compared to the ECa section class results. Fields 2006 and 2007 showed no low average NDVIsat values for any of the Elevation classes. In field 2005, low values were found in Elevation grouped into three and four classes, while for field 2008 these values were linked to the high and very high class sections for Elevation grouped into three and four classes.

The results for field 2005 could have been influenced because the lower portion of the field received more than sufficient water arriving from neighbouring higher locations, which can cause an increase of N losses due to the leaching process (Krachenko and Bullock, 2000). High elevation in field 2008 (the highest values among all the fields) could be associated with the loss of water and nutrients affecting crop growth (Jiang and Thelen, 2004).

Table 4.6. Averages of NDVIsat for Elevation section class

	Elevation classes Two		**Elevation classes Three**			**Elevation classes Four**			
2005	0.42	0.47	**0.33**	0.49	0.48	**0.32**	**0.33**	0.48	0.52
2006	0.46	0.46	0.54	0.50	0.62	0.63	0.42	0.55	0.53
2007	0.44	0.50	0.53	0.50	0.57	0.54	0.43	0.50	0.48
2008	0.56	0.40	0.55	0.44	**0.35**	0.50	0.50	0.40	**0.38**

For all the fields in Elevation grouped into two classes, t-test results (Table 4.7) showed that NDVIsat values were not significantly different from each other, except for field 2008. Elevation grouped into three classes for fields 2005, 2006 and 2008 presented at least one class section with NDVIsat significantly different from the others, while for field 2007 no significant results were found. The analysis of the Elevation grouped into four classes showed that between 4 and 5 groups of section class showed significant differences from each other for fields 2005, 2006 and 2008, while only the low-medium classes were found to be significantly different for field 2007. According to these results, Elevation grouped into four classes could account for the NDVI difference in the saturated zones; thus, it was selected for analysis of the influence of Elevation on NSI variability throughout the fields.

4.3.3 Slope Classes' Determination

In the histogram (Figure 4.7), Slope is unimodal so no reclassification was warranted as a means of exploring NDVI or $NSI_{\mathbf{Ref}}$ relationship in the saturated zones. Imposing a reclassification scheme on this variable did not elucidate any significant relationships with NDVI or NSI. The tables and results from the t-test and ANOVA (not shown see Annex C) did not yield significant information that validates the uses of this variable to determine $NSI_{\mathbf{Ref}}$ and the selection of the suitable locations for saturated plots. Although slope mainly influences the movement of nutrients and water throughout the field, in the particular case of this research, the spatial distribution of slope was not significant linked with that of the other variables and calculated indices.

Table 4.7. T-test results for the comparison of the NDVI values between all classes for variable Elevation (NDVI values are significantly different if P< 0.01). Where VHigh=Very High

Classes \ Fields	2005	2006	2007	2008
Two				
Low-High	H=0; P=0.073	H=0; P=0.950	H=0; P=0.421	H=1; P=1.1e
Three				
Low-Medium	H=1; P=1e-9	H=0; P=0.389	H=0; P=0.299	H=1; P=0.006
Low –High	H=1; P=3e-8	H=0; P=0.115	H=0; P=0.732	H=1; P=3.84e
Medium-High	H=0; P= 0.960	H=1; P= 0.013	H=0; P= 0.107	H=1; P= 0.041
Four				
Low-Medium	H=0; P=0.689	H=1; P=4.6e	H=1; P=0.011	H=0; P=0.827
Low –High	H=1; P=3.e-7	H=1; P=0.035	H=0; P=0.414	H=1; P=5.0e
Low –Vhigh	H=1; P=1e-7	H=1; P=8.3e	H=0; P=0.055	H=1; P=0.004
Medium-High	H=1; P=6e-11	H=1; P= 0.03	H=0; P= 0.185	H=1; P= 0.001
Medium-VHigh	H=1; P=5e-13	H=1; P=0.009	H=0; P=0.181	H=1; P=0.009
High-VHigh	H=0; P=0.052	H=0; P=0.775	H=0; P=0.572	H=0; P=0.565

**No corrections created for multiple testing*

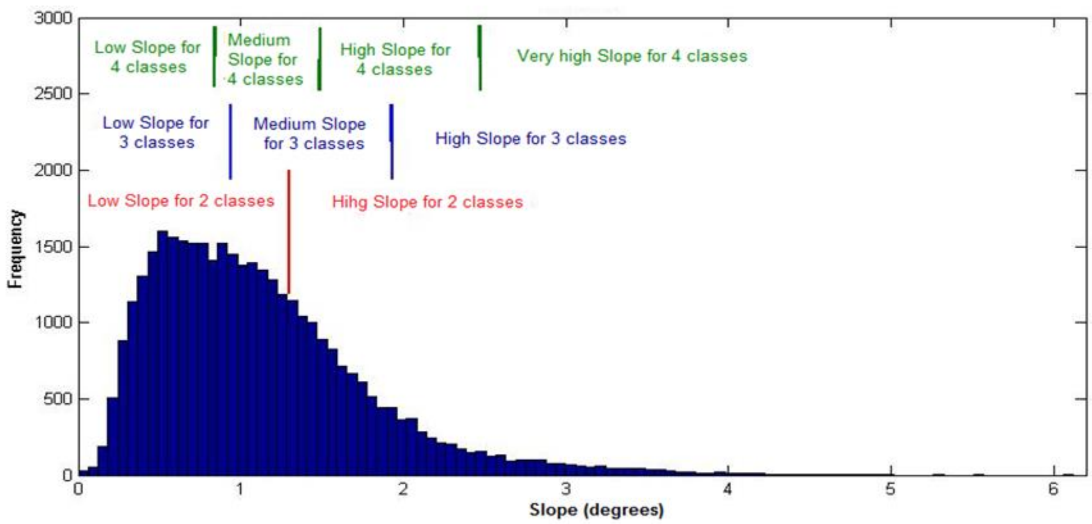


Figure 4.8. Histogram threshold and class section for the Slope of field 2007.

4.4 Analysis of the spatial relationship between selected classes and the alternative NSIs.

After the analysis of the variables' class determinations, the next step was to evaluate the influence of each variable on the NDVI in the non-saturated areas of each field in relation to the alternative NSIs. The analysis of the influence of each variable was based on the results from the ANOVA test, where the F test values determined how statistically significant the relationship was between the source and dependent variables. The aim of this test was to identify the dependent variable with the lowest value (F) relative to the source (e.g., the ECa class with the lower ECa value). Finally, correlation analysis was performed to evaluate the relationship between the alternative NSIs calculated from the three ECa classes and the NSI reference ($NSI_{\mathbf{Ref}}$).

4.4.1 Spatial relationship between ECa grouped into three classes and the alternative NSIs

After the analysis outlined in the previous section, ECa grouped into three classes was found to be the best variable class to represent N spatial variability in the fields. Table 4.8 shows the results for the ANOVA test. For all the fields (except 2005), the NSI calculated from ECa grouped into three classes shows the best results, improving the values of the dependent variables with respect to the source variables. The NDVI shows the highest values (green) compared to the rest of the dependent variables, due to problems with soil background issues described in the VIs sections. The NSI calculated from the nearest neighbour (NSI_nn) generally improves this problem related to NDVI.

NSI calculated from the nearest ECa for three classes (NSI_3eca) is the dependent variable that best performs and shows the lowest values for all fields (bold). The analysis of this table combined with the analysis of the histogram threshold justifies the selection of ECa grouped into three classes as the best variable to describe the relationship between the NDVI and ECa in the saturated strips. One of the possible reasons why the results of field 2005 were affected were the high ECa values located in the eastern portion. Due to the data distribution by class section in ECa grouped into four classes that portion of the field with high ECa values was separated for the analysis into high and very high classes.

Table 4.8. Results of F test values from ANOVA for each alternative NSIs calculated based on ECa classes for all the fields. Where 2, 3 and 4 represent each ECa class; neca and nn stand for near ECa and nearest neighbour, respectively.

Source	**Dependent variables**					
2005						
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
ECA	**2005.64**	*250.62*	21.52	100.86	105.46	**13.94**
ELE	**508.30**	*0.22*	269.81	945.90	755.40	23.49
SLP	**71.74**	*28.45*	36.33	79.07	32.78	38.67
2006						
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
ECA	**3856.99**	*22047.7*	17539.2	7524.97	**397.20**	1093.99
ELE	**2517.17**	*54.22*	0.45	3583.37	530.41	113.42
SLP	**3922.46**	*2649.90*	4469.70	3043.96	3659.39	3582.00
2007						
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
ECA	**3261.44**	*1414.44*	1837.20	764.64	**206.38**	923.74
ELE	**49.47**	*141.47*	4.26	24.78	2.96	6.45
SLP	**0.45**	*10.74*	1.25	0.06	0.29	1.02
2008						
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
ECA	**742.51**	*2471.22*	743.13	1077.96	**28.80**	4484.42
ELE	**232.86**	*3285.16*	1190.85	203.31	16.73	199.96
SLP	**121.33**	*118.06*	246.26	122.17	206.71	205.71

**No corrections created for multiple testing*

The ANOVA served to quantify differences between all NSIs calculated from ECa classes. Overall, the F-value results showed that the NSIs calculated from the different combinations of

ECa values increased the accuracy of the calculation of NSIs compared to estimations based on NDVI, especially the NSI obtained from ECa grouped into three classes (NSI_3eca). Moreover, the ECa demonstrated that it was capable of minimizing the effects on NSI better than the rest of the variables evaluated.

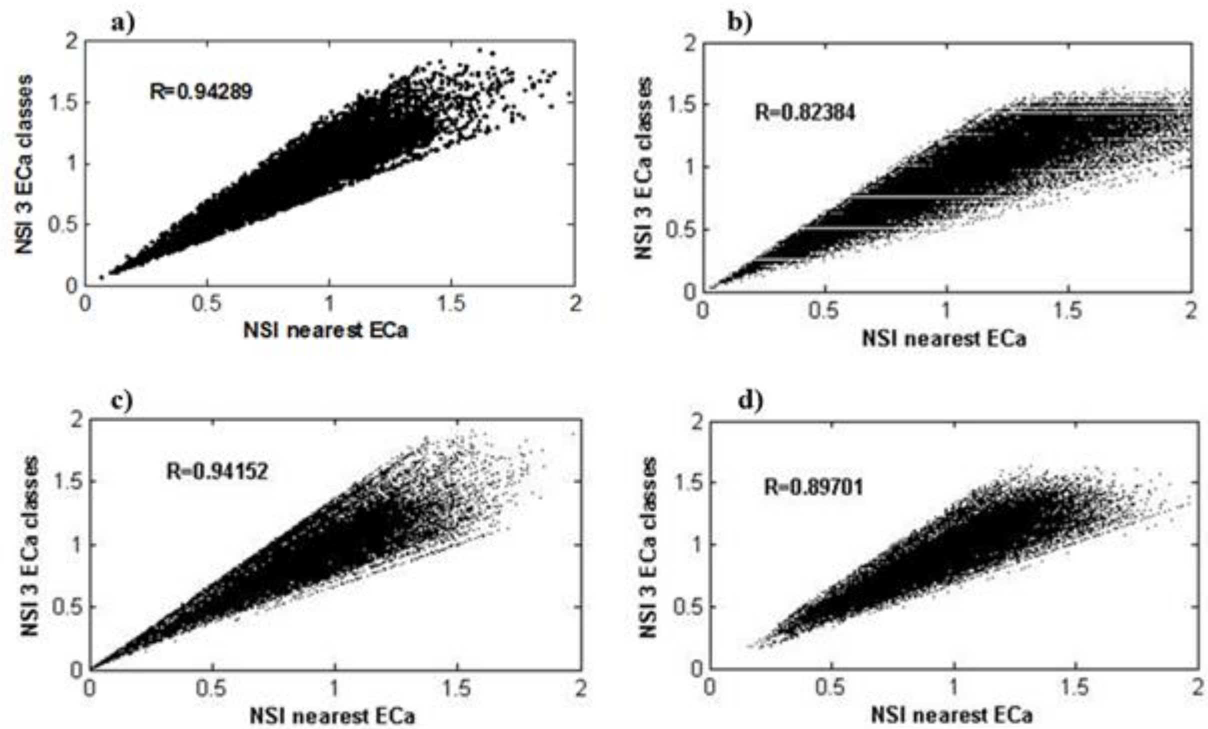


Figure 4.9. Correlation results between the NSI calculated from the nearest ECa points and the NSI calculated from the three ECa classes (NSI_{3ECa}). (where R is the Pearson Correlation Coefficient; a), b), c) and d) represent fields 2005, 2006, 2007 and 2008, respectively)

A correlation (R) analysis was performed between the NSI calculated based on the three ECa classes (NSI_3eca), the $NSI_{\mathbf{Ref}}$, and the NSI calculated based on the nearest ECa (NSI_neca) in order to evaluate their relationship. Since the graphics for the correlation between NSI_3eca and $NSI_{\mathbf{Ref}}$ were not produced, an analysis was done comparing the numerical results from their correlation with the graphic of the correlation between NSI_3eca and NSI_neca (Figure 4.7). The correlation between NSI_3eca and NSI_neca values (derived from the same variable) was, as expected, very high for all the fields with values between 0.82< R <0.94. The highest correlation coefficients were associated with fields 2005 and 2007. Meanwhile, the correlation between the nearest neighbour NSI and the NSI calculated from ECa grouped into three classes showed a reduction in the strength of their relationship. Nevertheless, NSI_3eca correlation values were consistently significant in relation to the NSI reference, with an average of R=0.79 for all the fields. The highest coefficient was detected for field 2007, with R=0.89, whereas the lowest values were associated with field 2006 (R=0.67).

Table 4.9. Results of F test values from ANOVA for each alternative NSIs calculated based on Elevation classes for all the fields. Where 2, 3 and 4 represent each Elevation class; nele and nn stand for near Elevation and nearest neighbour, respectively

Source	**Dependent variable**					
			2005			
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**
ECA	2005.64	*250.62*	2051.35	2370.17	1404.71	2697.91
ELE	508.30	*0.22*	1256.47	**61.41**	114.05	5495.96
SLP	71.74	*28.45*	90.55	103.38	36.56	128.54
			2006			
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**
ECA	3856.99	*22047.7*	17566.5	4165.17	94.29	24363.1
ELE	2517.17	*54.22*	31.38	2762.98	1401.10	**461.93**
SLP	3922.46	*2649.90*	1394.75	3903.67	4796.31	4587.57
			2007			
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**
ECA	4563.81	*2298.58*	3910.86	3164.93	4444.98	5451.64
ELE	55.03	*130.91*	5.45	159.57	**11.02**	242.40
SLP	0.45	*16.30*	4.54	2.28	0.26	3.77
			2008			
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**
ECA	742.51	*2471.22*	3272.56	3675.47	4062.16	1981.81
ELE	232.86	*3285.16*	2989.82	2176.29	3762.36	**1209.97**
SLP	121.33	*118.06*	97.98	145.60	1.03	101.47

**No corrections created for multiple testing*

Overall, the results from the performance of the ECa grouped into three classes influence on the alternative NSIs showed the robustness of the class for predicting the variability of N throughout the fields. Consequently, it was used to elaborate the NSI maps for the fields, which reflect a more realistic distribution of N availability throughout the fields versus the NDVI maps. These results are in agreement with previous findings, where ECa accounted for within-field N variability (Tiessen *et. al*., 2008; Kravchenko *et. al*., 2003; Heiniger *et. al*., 2003; Kravchenko and Bullock, 2000). Finally, these maps serve as a reference in comparing the maps obtained from the proposed saturated zones, in order to validate the uses of the new areas replacing the long rich strips.

4.4.2 Spatial relationship between Elevation grouped into four classes and the alternative NSIs

The ANOVA outputs for Elevation are shown in Table 4.9. For two of the fields (2008 and 2006), the NSI calculated from Elevation grouped into four classes showed lower F values, but only in field 2006 did it improve the values of the dependent variables with respect to the source variables. The other fields (2005 and 2007) showed lower values for the NSI for Elevation classes Two and Three, respectively. Furthermore, The F values for these two fields failed to improve the values of the dependent variables with respect to the source variables. Therefore, little evidence was found to suggest that the NSI calculated from the different combinations of Elevation classes could accurately account for the within-field N variability. The correlation results between the NSI calculated from the Elevation grouped into four classes (NSI_4ELE), the $NSI_{\mathbf{Ref}}$, and the NSI calculated from the nearest Elevation (NSI_nELE) yielded a weaker relationship among all indices when compared to the ECa outputs. Following the same comparison approach, Figure 4.8 shows the correlation rates between NSI_4ELE and NSI_nELE (high values were expected due to the fact that they were derived from the same variable).

Nevertheless, the values were relatively low for most of the fields with values between $0.46 < R < 0.61$. Only field 2005 showed a high correlation coefficient, with R=0.88. Meanwhile, the correlation between the $NSI_{\mathbf{Ref}}$ and the NSI from Elevation grouped into four classes showed no improvement in the strength of their relationship, with average values of R=0.55 for all the fields. The highest coefficient was detected for field 2007, with R=0.70, whereas the lowest values were associated with field 2006 (R=0.40).

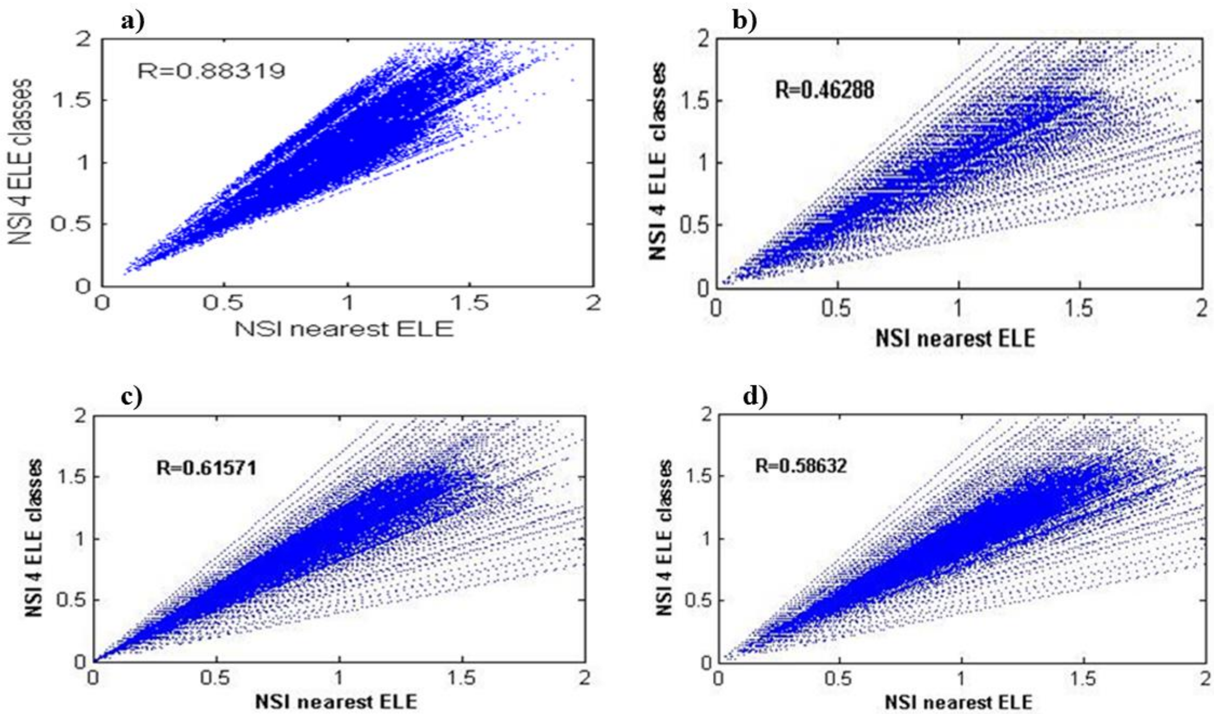


Figure 4.10. Relationship between the NSI calculated from the nearest Elevation points and the NSI calculated from Elevation class Four (NSI_{4ELE}). (where R is the Pearson Correlation Coefficient; a), b), c) and d) represent fields 2005, 2006, 2007 and 2008, respectively)

In general, the results from the performance of the selected Elevation class in relation to the alternative NSIs showed its limitations in predicting the variability of N throughout the fields. Thus, it was not used to elaborate the NSI maps for the fields, since it failed to predict the distribution of N availability throughout the fields versus the NDVI maps. Elevation has been described in previous research as having an influence on yields and plant growth (Jiang et. al., 2004; Kravchenko *et. al.*, 2003; Kravchenko and Bullock, 2000). Nevertheless, those earlier findings refer to this variable behaviour throughout the whole extent of the fields, not to localized areas such as saturated plots.

4.4.3 Spatial relationship between selected Soil classes and the alternative NSIs

Because of the procedure followed to obtain the Soil variable, only one class was determined. Thus, correlation analysis was not performed, leaving the ANOVA as the unique statistical procedure to use for the evaluation of the Soil variable's relationship with alternative NSIs. The ANOVA outputs for the Soil variable were found not to be significant (data not shown). Therefore, no evidence suggests that the NSI calculated from Soil class could accurately account for within-field N variability.

4.5 Calculating and comparing NSI calculated using ECa grouped into three classes.

After the analysis of the performance of each variable class and its influence on NSI variability throughout the fields, it was concluded that the best and most accurate results were obtained from ECa grouped into three classes. The next step in the analysis was to determine new areas (proposed zones) using the central values of ECa grouped into three classes (Table 4.2). A group of points from neighbourhood values of ECa grouped into three classes central values were selected. They covered determined areas of the saturated plots that were selected and mapped out as the new saturated plots that were proposed to replace the long strips (Figure 4.10).

The ECa data from the new plots were processed using the ANOVA, following the same methodological approach previously applied. The test results for the new areas proposed for saturated zones (scenarios) are shown in Table 4.10. They show that the new zone values (bold) continued to improve the values of the dependent variables with respect to the source variables for all the fields and that in general they were close to the values of ECa grouped into three classes (lower for the 2006 Area_1). Thus, the proposed zone (scenario) data was used to elaborate NSI maps (maps not shown) for all the fields, which were then compared to the NSI map elaborated based on ECa grouped into three classes, in order to validate the accuracy of the new data while describing N variability throughout the fields.

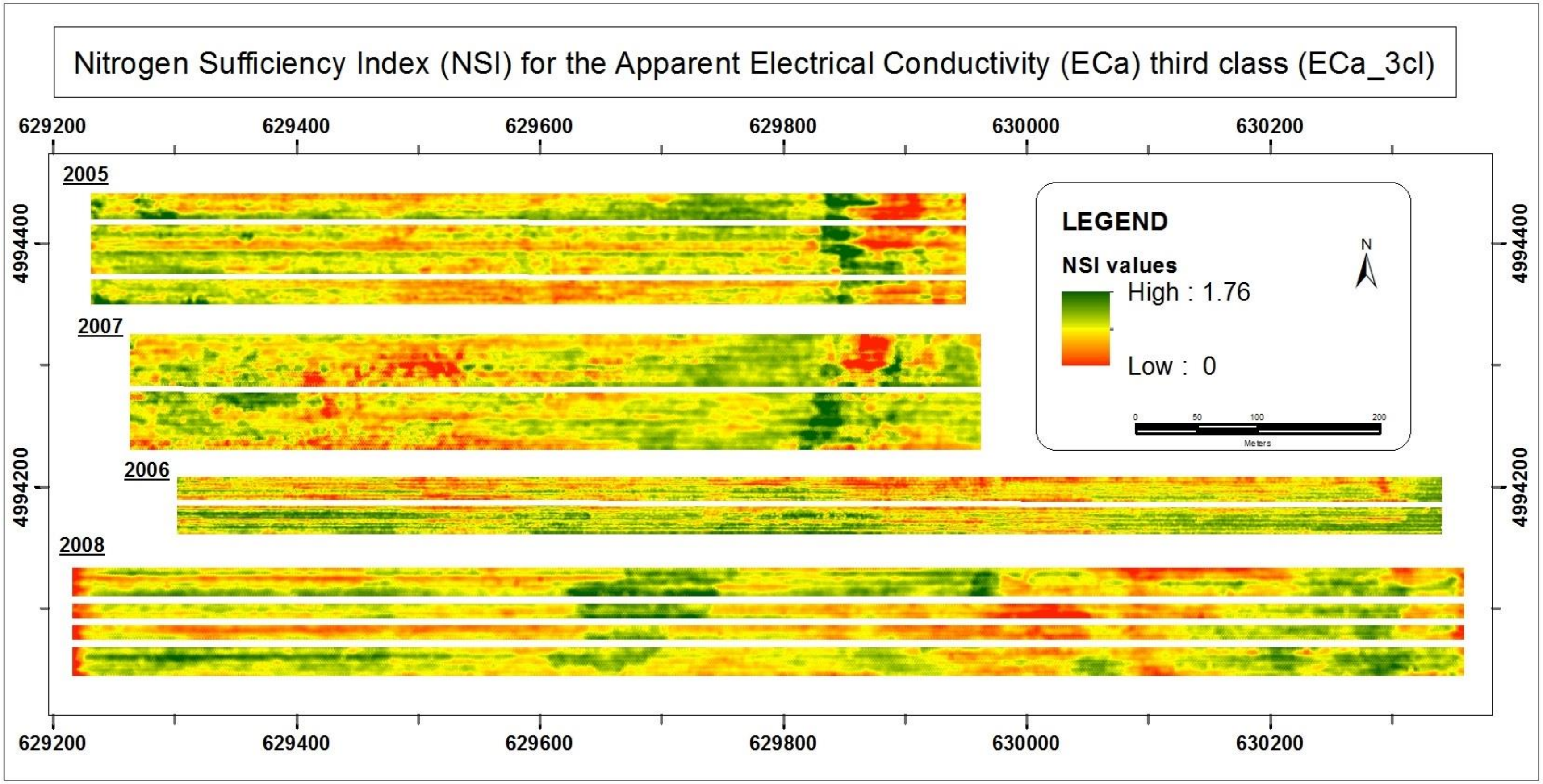


Figure 4.11. Nitrogen Sufficiency Index (NSI) maps calculated from ECa grouped into three classes (3ECa class).

By comparing Figure 4.3 and Figure 4.9, it is possible to see that the NDVI maps show high levels of N stress in several zones of each field (for instance, the eastern portion of field 2005), while the maps elaborated from NSI data show a more realistic extent of the areas under N stress. The differences in the N assessment from the NDVI were due to this index being more affected by environmental noises than the NSI. These results demonstrated that NSI, as found in previous research (Tremblay *et. al*., 2010), showed more robustness than the row NDVI for better predicting within-field N variability.

Figure 4.10 shows the average values of $NDVI_{\mathbf{RichN}}$ in the rich strip in relation to ECa grouped into three classes for the two proposed scenarios. In the case of fields 2006 and 2007, there was no significant difference between the low, medium and high ECa classes, except for the medium class for field 2007, which showed a 0.05-unit difference between the two scenarios. In the case of field 2005, the low and medium ECa classes did not show clear differences between each scenario, while the high class showed around a 0.1 unit difference between the two scenarios. Conversely, for field 2008, it was the low ECa class that had a significant difference (almost 0.1 units) from the other two classes, while the medium and high classes presented a small difference from each other. These results demonstrated the variability of the N availability throughout the fields due to soil properties, since N availability in the rich strips was not a limiting factor.

The ECa grouped into three classes areas of scenario 1 were then used to elaborate the map for $NSI_{\mathbf{3ecaAreas}}$. The new map shows almost the same patterns as the map elaborated based on $NSI_{3\mathbf{ecaCl}}$, with less spatial extension of zones under high N stress compared to the raw NDVI maps. Indeed, $NSI_{\mathbf{3ecaAreas}}$, like $NSI_{\mathbf{3ecaCl}}$, was also characterized by the exposure of more areas of the fields under less N stress. The $NSI_{\mathbf{3ecaAreas}}$ values ranged from 0.10 to 1.72, very close to the values of the $NSI_{\mathbf{Ref}}$, for which rates were between 0.11 and 1.73, with a similar spatial distribution ($NSI_{\mathbf{3ecaAreas}}$ map not shown). These NSI maps provide producers (farmers) with accurate data related to the crops' N status (needed or not) throughout the fields. Lower NSI areas mean that higher N rates are necessary, while in areas of NSI equal or higher to 1, no nitrogen is needed (Peterson *et.al.*, 1993).

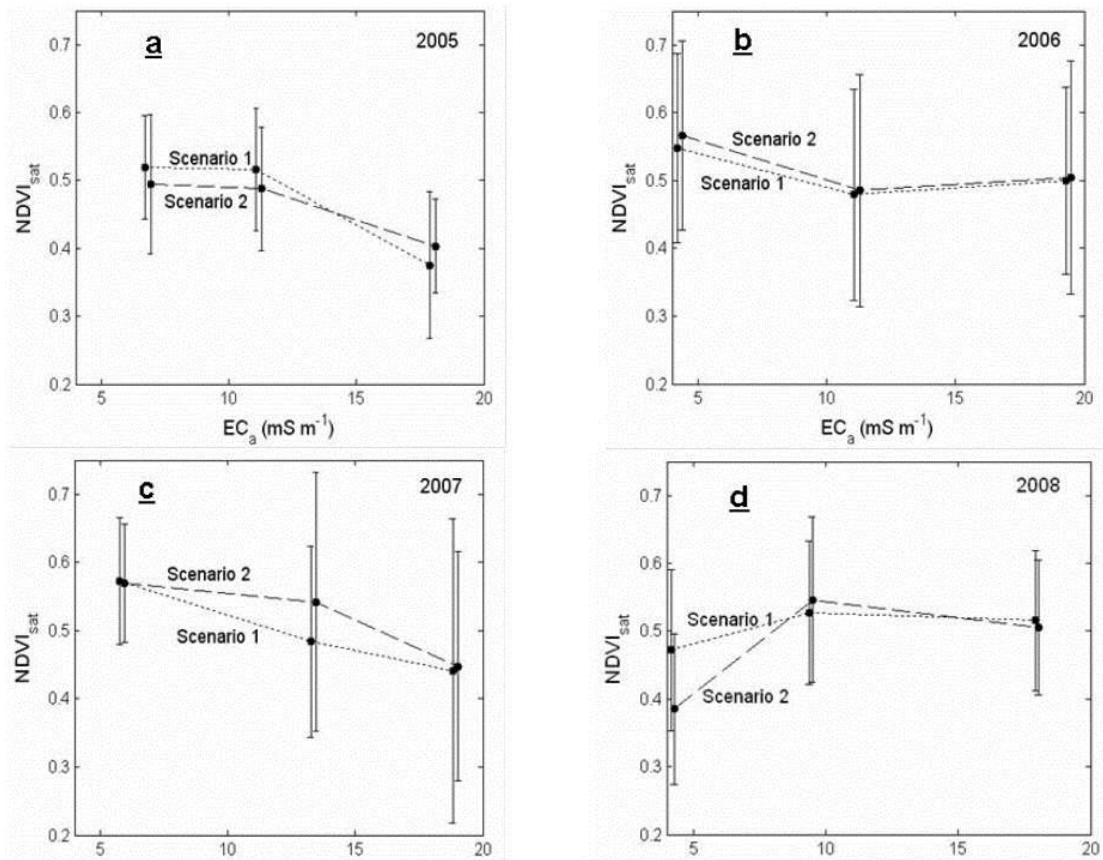


Figure 4.12. NDVIsat vs. ECa for various ECa areas (2005 (a), 2006 (b), 2007 (c) and 2008 (d): Scenario 1 and Scenario 2.

One of the main issues that motivated the present research was the situation involving the intensive use of N in saturated plots. These areas of a field are often placed across the whole length of the field, and because of the role of such plots as a reference for fertilization application, they receive 250 kg/ha of N fertilizer on average. This amount is known to be more than enough N for plant growth; thus, N is not a limiting factor for plants located in these artificially fertile zones. As previously discussed, up to 45% of this excess N amount is lost via leaching, passing on to lower layers of the soil and to nearby bodies of water, with subsequent impact on the environment.

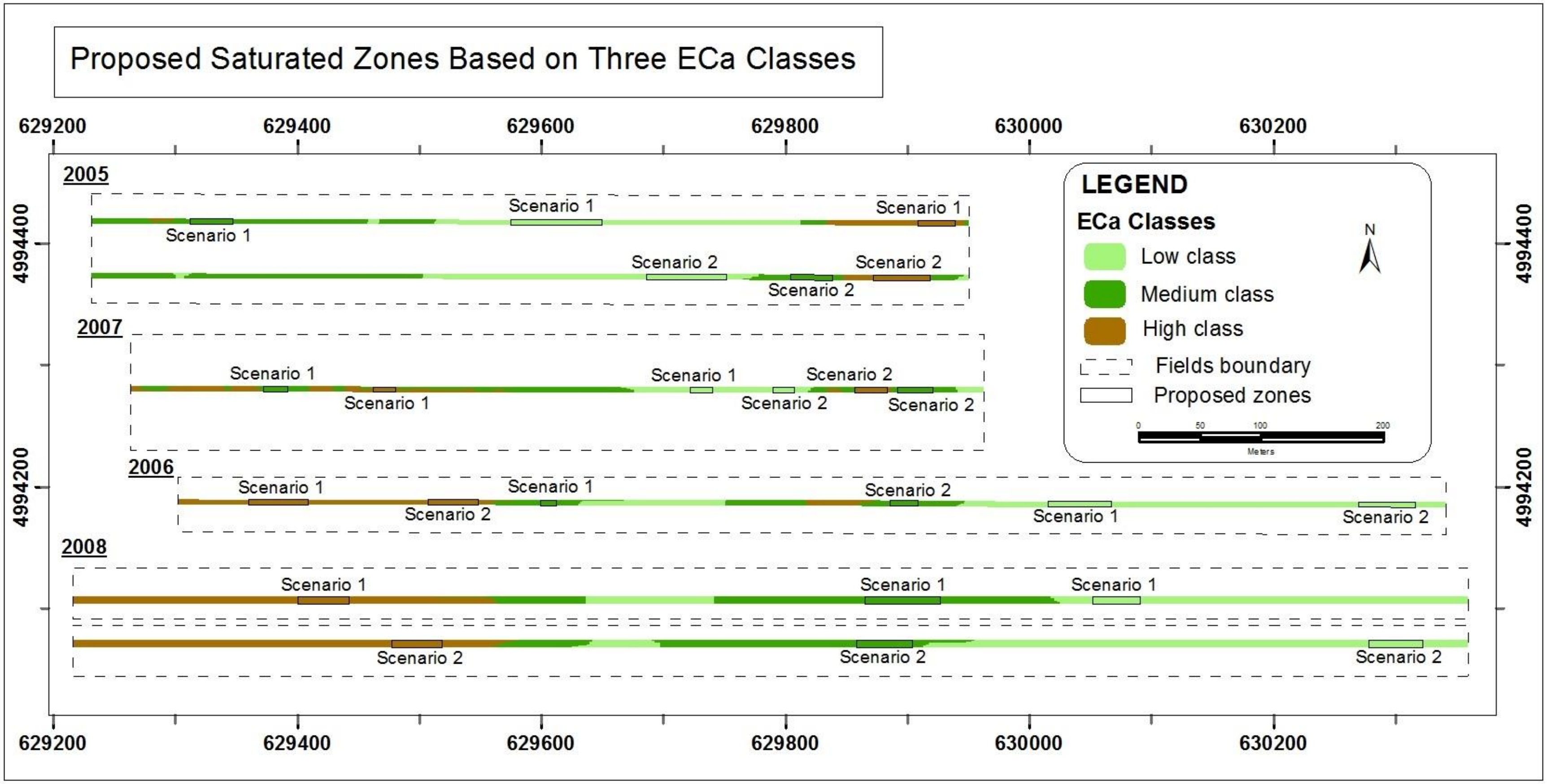


Figure 4.13. Proposed saturated zones determined by NSI values calculated based on ECa grouped into three classes (3ECa class)

Table 4.10. Results from F test values from ANOVA for each alternative NSIs calculated based on ECa grouped into three classes for all the fields. Where 3 represents the ECa class; neca and nn stand for near ECa and nearest neighbour, respectively; Areas_1 and 2 represent Scenario 1 and 2, respectively.

Source			**Dependent variables**		
			2005		
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_3eca Areas_1**	**NSI_3eca Areas_2**
ECA	**2005.64**	*250.62*	21.52	**54.69**	**157.94**
ELE	**508.30**	*0.22*	269.81	785.25	658.29
SLP	**71.74**	*28.45*	36.33	30.13	47.33
			2006		
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_3eca Areas_1**	**NSI_3eca Areas_2**
ECA	**3856.99**	*22047.7*	17539.2	**349.53**	**518.09**
ELE	**2517.17**	*54.22*	0.45	1407.92	1185.76
SLP	**3922.46**	*2649.90*	4469.70	3609.50	3537.95
			2007		
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_3eca Areas_1**	**NSI_3eca Areas_2**
ECA	**3261.44**	*1414.44*	1837.20	**212.00**	**316.88**
ELE	**49.47**	*141.47*	4.26	20.00	6.86
SLP	**0.45**	*10.74*	1.25	0.00	0.12
			2008		
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_3eca Areas_1**	**NSI_3eca Areas_2**
ECA	**742.51**	*2471.22*	743.13	**56.58**	**151.87**
ELE	**232.86**	*3285.16*	1190.85	141.73	0.13
SLP	**121.33**	*118.06*	246.26	147.18	203.17

**No corrections created for multiple testing*

By reducing the areas exposed to such high levels of N without compromising yield goals, producers can not only save money but also contribute to mitigating the negative impacts of fertilization application on the environment. Table 4.12 shows a comparison between the amounts of N applied to the saturated plots using the original N-rich strips (across the whole fields) and the amounts that would be applied if the proposed saturated plots were assumed. The N amount differences between fields were 65 and 272.5 kg/ha, the larger amounts being related to fields 2005 and 2008 due to the fact that they had two N-rich strips compared to one strip in each of fields 2006 and 2007. With the introduction of new zones, both the areas and the N amounts to be applied can be reduced by 77%.

Table 4.11. Comparison between the amounts of N applied in Saturated plots (N-rich) vs. Proposed zones.

Fields	Saturated plot (SP) area (ha)	Proposed zones (PZ) area (ha)	N applied in SP (Kg/ha)	N applied in PZ (Kg/ha)	ΔN (Kg)
2005	0.63	0.18	157.5	45	112.5
2006	0.47	0.15	117.5	37.5	80
2007	0.32	0.06	80	15	65
2008	1.33	0.24	332.5	60	272.5

4.6 Summary

The analysis of the variables spatial distribution showed an inverse relationship between low and high values of ECa and Elevation, mainly determined by the influence of elevation values on soil water content. Slope values showed a localized distribution and showed little influence on the spatial variability of ECa. The establishment of N-rich strips across the extent of all the fields allowed them to account for the spatial variability of all variables, especially ECa and Elevation. Thus, N-strips can ultimately serve as an accurate reference for understanding N availability throughout the fields. The analysis of the variables' class determinations demonstrated that ECa grouped into three classes showed the most robust performance among all of the variable classes. ECa grouped into three classes not only accounted for the variability of ECa values, but also accounted for the NDVI values in the saturated plots.

Although it was less robust than ECa grouped into three classes in predicting NDVI variability for all the fields, Elevation grouped into four classes showed some potential to understand within-field N variability. Slope classes showed a modest capability to predict NDVI variability throughout the fields. The maps elaborated from the NSI for ECa grouped into three classes showed a high level of accuracy. Furthermore, new saturated plots were proposed in order to replace the existing ones across the fields. The new N-rich zones not only can contribute to mitigating the environmental impact of agricultural practices but also can be an accurate source of data for the analysis of NSI and within-field N variability.

5. Conclusions and Recommendations

This chapter contains a summary of the thesis findings as well as the contributions made to the research on improving fertilization application techniques based on readings from a mounted sensor on-the-go and the use of N-saturated strips. As well, recommendations have been made in order to improve further research.

5.1 Summary and Conclusions

Use of NSI is an improvement over NDVI due to the tendency of the latter to be affected by environmental noise (e.g., soil background). NDVI maps show more areas within fields with low values and, therefore, increased regions of N stress. Although such areas persist within $NSI_{\mathbf{Ref}}$ maps, there is a reduction in the extent of total area under N stress using NSI. For instance, the zones under N stress in the western portion of fields 2005 and 2008 in the NDVI maps are significantly reduced at the same locations in the $NSI_{\mathbf{Ref}}$ maps. This finding demonstrates that NSI is a more accurate method for estimating N deficiency when prescribing fertilization applications.

The analysis of the spatial distribution of each variable showed an inverse relationship between ECa and Elevation, where low ECa values were generally found in areas of the field with high elevation and vice versa. This inverse relation was mainly determined by the influence of high elevation zones on the reduction of soil water content due to water in a soil tends to move downward due gravity. Conversely, Slope values showed a localized distribution and therefore had little influence on the spatial variability of ECa. Since N-rich strips were established across the extent of all the fields, they accounted for the spatial variability of the variables, especially ECa and Elevation. Thus, N-strips can ultimately serve as an accurate reference for understanding N availability throughout the fields.

The use of Otsu's method for reclassifying ECa, Elevation and Slope was successful in representing the spatial variability of NSI in the saturated zones. Based on the significant differences between the NDVI values for each of the ECa, Elevation and Slope classes, t-test outputs demonstrated that ECa grouped into three classes accounted for the NDVI difference in the saturated zones and validated its selection for the posterior analysis of the influence of ECa on NSI variability throughout the fields, whereas, for the variable Elevation, Elevation grouped into four classes was selected as the most representative, accounting for the relationship between NSI and Elevation in the saturated zones. No significant differences were found for the classes of the Slope variable; therefore, it was not used in posterior analysis.

The influence of selected variable classes on NDVI in the unsaturated areas of the fields, as well as its relationship with the alternative NSIs, was analyzed using ANOVA, with the aim of determining the statistical significance of the relationship between the source and the dependent variables. Overall, the F-value results showed that the NSI calculated from ECa grouped into three classes (NSI_3eca) was capable of minimizing the effects on NDVI better than the rest of the evaluated variables. Despite Elevation grouped into four classes having been selected in previous sections, the ANOVA outputs for the class were not statistically significant. Finally, correlation analysis was performed to evaluate the relationship between the alternative NSIs calculated from the selected classes and the NSI reference ($NSI_{\mathbf{Ref}}$). Correlation coefficients (R) between NSI_3eca and NSI_neca values were as expected (derived from the same variable) and were very high for all the fields with values between $0.82 < R < 0.94$, with the highest coefficients associated with fields 2005 and 2007. Meanwhile, NSI_3eca coefficients were consistently significant in relation to the NSI reference, with an average of R=0.79 for all the fields. The highest coefficient was detected for field 2007, with R=0.89, whereas the lowest values were associated with field 2006 (R=0.67). In the case of Elevation grouped into four classes, the correlation results were not statistically significant, with overall average values of $R<0.70$.

The analysis of the variables' class determinations demonstrated that ECa grouped into three classes showed the most robust performance. This ECa three-class grouping accounted not only for the variability among ECa values, but also for the NDVI values in the saturated plots. Although it showed less robustness than ECa grouped into three classes in predicting NDVI variability for all the fields, Elevation grouped into four classes showed some potential for understanding within-field N variability. Slope classes showed a modest capability to predict NDVI variability throughout the fields. The maps of NSI for ECa grouped into three classes showed a high level of accuracy compared to the $NSI_{\mathbf{Ref}}$ map. Therefore, new saturated plots were proposed in order to replace the existing ones across the fields. The new N-rich zones not only can contribute to mitigating the environmental impact of agricultural practices (reducing 77% of N inputs) but can also be an accurate source of data for the analysis of NSI and within-field N variability.

5.2 Recommendations for further research

A better understanding and quantification of N distribution and variability within fields is a key element in improving current issues in precision farming with regard to fertilization application techniques. Accounting for the variability of all factors affecting crop growth, such as soil properties and terrain features, will contribute to a more accurate estimation of N availability throughout fields. Achieving such goals will require precise collection of ground data and improved measurements extracted from remotely sensed data.

Remote sensing precision represents another issue in the data collection task, since it is considered one of the most promising tools for measuring within-field variation in crop growth based on analysis of crop canopy reflectance. Spectral indices derived from the reflectance spectra need more research in order to improve association with crops N status, since the use of remote sensing techniques during the growth period enables farmers to identify areas with different biomass development and nitrogen uptake. Moreover, the reflectance data have to be agronomically calibrated to derive a fertilizer recommendation from these remotely sensed data.

Finally, more research is necessary to improve knowledge regarding the use of N-rich strips, since the establishment of N-saturated zones often tends to be problematic, leading to confusion and errors. Future research should focus on the analysis of the natural spatial variability in fields, considering that early-season N fertilizer applications may contribute to the creation of zones with more than adequate N for reference. Therefore, these areas could serve as N-rich strips once they can be correctly identified and quantified. Once N-rich strips can be effectively located, they can be used to improve the time consuming task of N-rich strip establishment for farmers while at the same time reducing N losses due to leaching and associated negative environmental impacts.

6. References

Adamchuk V. (2009) Economic and environmental benefits from canopy sensing for variable-rate nitrogen corn fertilization, American Society of Agricultural and Biological Engineers Annual International Meeting 2009. pp. 4774-4790.

Bakhsh, A., T. S. Colvin, D. B. Jaynes, and R. S. Kanwar, U. S. Tim. 2000. Using soil attributes and gis for interpretation of spatial variability in yield. American Society of Agricultural Engineers, Vol. 43(4): 819-828.

Bannari, A., D. Morin, and F. J. Bonn. 1995. A Review of Vegetation Indices. Remote Sensing Reviews, Vol. 13, pp. 95-120.

Bannari, A., D. Morin, G. B. Benie, and F. J. Bonn. 1995a. A theoretical review of different mathematical models of geometric corrections applied to remote sensing images. Remote Sensing Reviews, Volume 13, 27-47.

Baret, E., G. Guyot, and D. J. Major. 1989. TSAVI: A vegetation index which minimizes soil brightness effects on LAI and APAR estimation. Proceedings of the 12th Canadian Symposium on Remote Sensing, Vancouver, Canada, 1355-1358.

Bausch, W. C. and M. K. Brodahl. 2011. Strategies to evaluate goodness of reference strips for in-season, field scale, irrigated corn nitrogen sufficiency. Precision Agriculture. 13: 104-122

Bhatti A.U., Ali R., Ullah F., Khan M.J. (1998) Comparison of wheat yield under uniform and variable rates of fertilizer on spatially-eroded land. Commun soil sci plant anal 29:2855-2863.

Bouroubi, Y.; N. Tremblay; P. Vigneault; C. Belec and V. Adamchuk. 2013. Estimating Nitrogen Sufficiency Index Using A Natural Local Reference Approach. Agro-Geoinformatics (Agro-Geoinformatics), 2013 Second International Conference on. DOI: 10.1109/Argo-Geoinformatics.2013.6621882. 71-75 pp

Brisco, B., R.J. Brown, T. Hirose, H. McNairn, and K. Staenz. 1998. Precision agriculture and the role of remote sensing: a review. Canadian Journal of Remote Sensing, Vol. 24, No. 3, pp. 315–327.

Chen, P.-Y., R. Srinivasan, G. Fedosejevs, and J. R. Kiniry. 2003. Evaluating different NDVI composite techniques using NOAA-14 AVHRR data. International Journal of Remote Sensing, Vol. 24, No. 17, 3403–3412.

Clay, D. E., K. Kim, J. Chang, S. A. Clay, and K. Dalsted. 2006. Characterizing Water and Nitrogen Stress in Corn Using Remote Sensing. Agronomy Journal, 98:579–587.

Doerge, T. A. 2005. Nitrogen Measurement for Variable-Rate N Management in Maize. Communications in Soil Science and Plant Analysis. 36, 23-32.

ESRI, EUA, 2010

Ferguson, R. B., G. W. Hegert, J. S. Schepers, C. A. Gotway, J. E. Cahoon and T. A. Peterson. 2002. Site-Specific Nitrogen Management of Irrigated Maize: Yield and Soil Residual Nitrate Effects. Soil Science Society of America Journal. 66, 544-553.

Flowers M., Weisz R., Heiniger R., Tarleton B., Meijer A. (2003) Field validation of a remote sensing technique for early nitrogen application decisions in wheat. Agronomy Journal 95:167-176.

Gascho G.J., Lee R.D. (2002) Determining side-dress nitrogen requirements of corn following broiler litter in the Southern Coastal Plain. J plant nutr 25:2361-2371.

Gitelson, A., Y. Kaufman, and M. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment, 58:289–298.

Gitelson, A.A., A. Vina, T.J. Arkebauer, D.C. Rundquist, G. Keydan, and B. Leavitt. 2003. Remote estimation of leaf area index and green leaf biomass in maize canopies. Geophys. Res. Lett., 30(5), 1248.

GreenSeeker. http://www.ntechindustries.com/greenseeker-home.html

Haboudane, D., J. R. Millera, E. Patteyc, P. J. Zarco-Tejadad, and L. Dextrazec. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, 81:416–426.

Haboudane, D., J. R. Millera, N. Tremblay, P. J. Zarco-Tejadad, and I. B. Strachane. 2004. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sensing of Environment, 90:337– 352.

Haboudanea, D., J. R. Millera, E. Patteyc, P. J. Zarco-Tejadad, and L. Dextrazec. 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, 81:416–426.

Hansena, P.M, and J.K. Schjoerringb. 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. Remote Sensing of Environment, 86:542–553.

Hatfield, J. L., A. A. Gitelson, J. S. Schepers, and C. L. Walthall. 2008. Application of Spectral Remote Sensing for Agronomic Decisions. Agronomy Journal, 100:117–131.

Heiniger, R. W., R. G. McBridge and D. E. Clay. 2003. Using Soil Electrical Conductivity to Improve Nutrient Management. Agronomy Journal, 95:508–519.

Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25, 295–309.

Inman, D., R. Khosla, R. Reich, and D. G. Westfall. 2008. Normalized Difference Vegetation Index and Soil Color-Based Management Zones in Irrigated Maize. Agronomy Journal, 100:60–66.

Jiang, P., and K. D. Thelen. 2004. Effect of soil and topographic properties on crop yield in a North-Central corn–soybean cropping system. Agronomy Journal, 96:252–258.

Kaspar, T. C., D. J. Pulido, H. Butler, T. S. Colvin, D. L. Karlen, D. B. Jaynes, D. E. James, and D. W. Meek. 2003. Relationship between six years of corn yields and terrain attributes. Precision Agriculture, 4:87–101.

Kaspar, T. C., D. J. Pulido, T. E. Fenton, T. S. Colvin, D. L. Karlen, D. B. Jaynes, and D. W. Meek. 2004. Relationship of corn and soybean yield to soil and terrain properties. Agronomy Journal, 96:700–709.

Katsvairo, T. W., W. J. Cox, and H. M. Van Es. 2003. Spatial Growth and Nitrogen Uptake Variability of Corn at Two Nitrogen Levels. Agronomy Journal, 95:1000–1011.

Kitchen N.R., Shanahan J.F., Roberts D.F., Sudduth K.A., Scharf P.C., Ferguson R.B., Drummond S.T., Scharf P.C., Palm H.L., Roberts D.F., Vories E.D. (2010) Ground-based canopy reflectance sensing for variable-rate nitrogen corn fertilization. Agronomy Journal 102:71-84.

Kitchen, N. R., S. T. Drummond, E. D. Lund, K. A. Sudduth and G. W. Buchleiter. 2003. Soil electrical Conductivity and Topography Related to Yield for Three Contrasting Soil-Crop System. Agronomy Journal, 95:843–495.

Kravchenko, A. N., and D. G. Bullock. 2000. Correlation of Corn and Soybean Grain Yield with Topography and Soil Properties. Agronomy Journal, 92:75–83.

Kravchenko, A. N., K. D Thelen, N. R Miller and D. G. Bullock. 2003. Relationship Crop Grain Yield, Topography and Soil Electrical Conductivity Studied with Cross-Correlation. Agronomy Journal, 95:1132–1189.

LaRuffa J.M., Raun W.R., Phillips S.B., Solie J.B., Stone M.L., Johnson G.V. (2001) Optimum field element size for maximum yields in winter wheat, using variable nitrogen rates. Journal of Plant Nutrition 24:313-325.

Li, H., R. J. Lezcano, E. M. Barnes, J. Booker, L. T. Wilson, K. F. Bronson, and E. Segarra. 2001. Multispectral reflectance of cotton related to plant growth, soil water and texture, and site elevation. Agronomy Journal, 93:1327–1337.

Li, Y., Dhou SHI, Ci-fang WU, Hong-yi LI and Feng LI. 2008. Determination of Potential Management Zones from Soil Electrical Conductivity, Yield and Crop Data. Journal of Zhejiang University Science B, 9(1):68–76.

May W.E. (2009) Optical sensors have potential for determining nitrogen fertilizer topdressing requirements of canola in Saskatchewan. Canadian Journal of Plant Science 89:411-425.

Moran, M.S., T.R. Clarke, Y. Inoue, and A. Vidal. 1997. Estimating crop water-deficit using the relation between surface-air temperature and spectral vegetation index. Remote Sensing of Environment, 49:246–263.

Olfs, H.W., K. Blankenau, F. Brentrup, J. Jasper, A. Link, and J. Lammel. 2005. Soil and plant-based nitrogen fertilizer recommendations in arable forming. J. Plant Nutr. Soil Sci. 168:414–431

Otsu, N. 1979. "A threshold selection method from gray-level histograms". IEEE Trans. Sys., Man., Cyber. 9 (1): 62–66

Pagani, A., H. E. Echeverría, F. H. Andrade and H. R. Sainz Rozas. 2009. Characterization of Corn Nitrogen Status with a Greenness Index under Different Availability of Sulfur Agronomy Journal. 101: 2: 315-322

Paz J.O., Batchelor W.D., Babcock B.A., Colvin T.S., Logsdon S.D., Kaspar T.C., Karlen D.L. (1999) Model-based technique to determine variable rate nitrogen for corn. Agricultural Systems 61:69-75.

Pena-Yewtukhiw, E. M., G. J. Schwab, J. H. Grove, L. W. Murdock, and J. T. Johnson. 2008. Spatial analysis of early wheat canopy normalized difference vegetative index: determining appropriate observation scale. Agronomy Journal, 100:454–462.

Peterson T.A., Blackmer T.M., Francis D.D., Schepers J.S. (1993) Using a Chlorophyll Meter to Improve N Management. Coop. Ext. Serv., Univ. of Nebraska. NebGuide:1-4.

Pinter, Paul J., Jr., J. L. Hatfield, J. S. Schepers, E. M. Barnes, M. S. Moran, C. S.T. Daughtry, and D. R. Upchurch. 2003. Remote Sensing for Crop Management. Photogrammetric Engineering & Remote Sensing. Vol. 69, No. 6, pp. 647–664.

Pontailler, J. Y., G. J. Hymus, and B. G. Drake. 2003. Estimation of leaf area index using ground-based remote sensed NDVI measurements: validation and comparison with two indirect techniques. Canadian Journal of Remote Sensing, Vol. 29, No. 3, pp. 381–387

Raun W.R., Johnson G.V., Sembiring H., Lukina E.V., LaRuffa J.M., Thomason W.E., Phillips S.B., Solie J.B., Stone M.L., Whitney R.W. (1998) Indirect measures of plant nutrients. Communications in soil science and plant analysis (USA) 29:1571-1581.

Raun W.R., Solie J.B., Johnson G.V., Stone M.L., Mullen R.W., Freeman K.W., Thomason W.E., Lukina E.V. (2002) Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. Agronomy Journal 94:815-820.

Roberts D.F., Kitchen N.R., Scharf P.C., Sudduth K.A. (2010) Will variable-rate nitrogen fertilization using corn canopy reflectance sensing deliver environmental benefits? Agronomy Journal 102:85-95.

Samborski, S. M., N. Tremblay, and E. Fallon. Strategies to make use of plant sensors-based diagnostic information for nitrogen recommendations. 2009. Agronomy Journal, 101:800–816.

Scharf P.C., Lory J.A. (2002) Calibrating corn color from aerial photographs to predict sidedress nitrogen need. Agronomy Journal 94:397-404.

Scharf, P.C., Kitchen N.R., K.A. Sudduth, J.G. Davis, V.C Hubbard and J.A. Lory. 2005. Field-scale variability in economically-optimal N fertilizer rate for corn. Agron. J. 97:452-461.

Scharf, P.C., Kitchen N.R., and R.G. Hoeft . 2006. Chlorophyll meter readings can predict nitrogen need and yield response of corn in the North-Central USA. Agron. J. 98:655–665.

Schepers J.S. (1994) New Diagnostic Tools for Tissue Testing. Commun Soil Sci Plant Anal 25:817-826.

Schepers J.S., Blackmer T.M., Francis D.D. (1992) Predicting N fertilizer needs for corn in humid regions: using chlorophyll meters, in: B. R. Bock and K. R. Kelley (Eds.), Predicting N fertilizer needs for corn in humid regions. Bulletin Y-226, National Fertilizer and Environmental Research Center, Muscle Shoals, AL. pp. 105-114.

Schlemmer, M. R., D. D. Francis, J. F. Shanahan, and J. S. Schepers. 2005. Remotely Measuring Chlorophyll Content in Corn Leaves with Differing Nitrogen Levels and Relative Water Content. Agronomy Journal, 97:106–112.

Schmidt, John P., A. J. DeJoia, R. B. Ferguson, R. K. Taylor, R. K. Young, and J. L. Havlin. 2002. Corn Yield Response to Nitrogen at Multiple In-Field Locations. Agronomy Journal, 94:798–806.

Schroder J.J., Neeteson J.J., Oenema O., Struik P.C. (2000) Does the crop or the soil indicate how to save nitrogen in maize production? Reviewing the state of the art. Field Crops Research 66:151-164.

Shahandeh, H., A. L. Wright, F. M. Hons, and R. J. Lascano. 2005. Spatial and temporal variation of soil nitrogen parameters related to soil texture and corn yield Agronomy Journal, 97:772–782.

Shanahan J.F., Schepers J.S., Francis D.D., Varvel G.E., Wilhelm W.W., Tringe J.M., Schlemmer M.R., Major D.J. (2001) Use of remote-sensing imagery to estimate corn grain yield. Agronomy Journal 93:583-589.

Solari, F., J. Shanahan, R. Ferguson, J. Schepers, and A. Gitelson. 2008. Active sensor reflectance measurements of corn nitrogen status and yield potential. Agronomy Journal, Volume 100, Issue 3, 571–579.

Sripada, R. P., D. C. Farrer, R. Weisz, R. W. Heiniger, and J. G. White. 2007. Aerial color infrared photography to optimize in-season nitrogen fertilizer recommendations in winter wheat. Agronomy Journal, 99:1424–1435.

Tremblay, N., M. Y. Bouroubi, B. Panneton, S, Guillaume, P. Vigneault and C. Belec. 2010. Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features. Precision Agriculture 11(6): 621-635.

Tremblay, N., M. Y. Bouroubi, P. Vigneault, C. Belec . 2011. Guidelines for in-season nitrogen application for maize (Zea mays L.) based on soil and terrain properties. Field Crops Research 122: 273–283.

Van Leeuwen, W. J.D., B. J. Orr, S. E. Marsh, and S. M. Herrmann. 2006. Multi-sensor NDVI data continuity: Uncertainties and implications for vegetation monitoring applications. Remote Sensing of Environment, 100:67 – 81.

Varvel, G. E., W. W. Wilhelm, R. Ferguson, J. F. Shanaham, and J. S. Schepers. 2007. An algorithm for corn recommendations using chlorophyll meter based sufficiency index. Agronomy Journal, 99:701–706.

Veris model 3100. http://www.veristech.com

Weiss, M., and F. Baret. 2000. Use of remote sensing data for nitrogen management in precision farming. Authorized licensed use limited to: University of Ottawa. Downloaded on January 19, 2010 at 16:26 from IEEE Xplore.

Yu H., Tremblay N., Wang Z., Bélec C., Yang G., Grant C. (2010) Evaluation of nitrogen sources and application methods for nitrogen-rich reference plot establishment in corn. Agronomy Journal 102:23-30.

Zebarth B.J., Younie M., Paul J.W., Bittman S. (2002) Evaluation of leaf chlorophyll index for making fertilizer nitrogen recommendations for silage corn in a high fertility environment. Commun. Soil Sci. Plant Anal. 33:665-684.

Zillmann, E., S. Graeff, J. Link, W. D. Batchelor, and W. Claupein. Assessment of Cereal Nitrogen Requirements Derived by Optical On-the-Go Sensors on Heterogeneous Soils. 2006. Agronomy Journal, 98:682–690.

APPENDICES

APPENDIX I: PAPER PRESENTED AT THE 32ND CANADIAN SYMPOSIUM ON REMOTE SENSING AND 14TH CONGRESS OF THE AQT HELD IN SHERBROOKE, QUÉBEC, CANADA ON JUNE13-16 2011

Optimal Nitrogen Reference Plots Locations for Corn Using NDVI and Soil Apparent Electrical Conductivity

Eugenio Landeiro Reyes[1], Mohamed Yacine Bouroubi[2], Abdou Bannari[1] and Nicolas Tremblay[2]

1. *Remote Sensing and Geomatics of Environment Laboratory, Department of Geography, University of Ottawa, 60 University Str., Ottawa (ON) K1N 6N5*
2. *Horticultural R&D Centre, Agriculture and Agri-Food Canada, 430 Gouin Blvd, St-Jean-sur-Richelieu (QC) J3B 3E6*

ABSTRACT

Nitrogen (N) is the most important nutrient in agriculture since it is critical to achieve quantity and quality of harvest. However, excess of N fertilization is costly and can have negative impacts on crops and the environment. The NDVI can be used as a valuable indicator of crop performance and can be translated into a *Nitrogen Sufficiency Index* (NSI) which is a relative indicator, based on non-limiting N reference (N-rich) areas, to judge the fertilization requirements of the rest of the field. Soil *apparent electrical conductivity* (EC_a) has been used as a surrogate parameter providing great spatial details to important soil properties. The objective of this research was to identify zones that could substitute for field-long N-rich strips, based on the spatial analysis of the NSI-EC_a relationship. The data was acquired from 2005 to 2008 inclusive, over four adjacent corn fields in St-Valentin, Quebec. The NDVI values were acquired using tractor-mounted GreenSeeker sensors. The EC_a values were recorded using a Veris 3100 cart system. The NSI values–were first calculated from each NDVI point in the field and its nearest N-rich neighbour. A serie of alternative NSI_{ECa} were calculated using areas in the N-rich strip with comparable EC_a value in two, three or four different classes. Results show that NSI_{ECa} calculated from three EC_a classes has a better performance than the nearest neighbour NSI. It is therefore possible to use limited 'well selected' N-rich areas for NSI calculations representative of the different soil conditions present in the field for N application.

Key words: N rich plot, fertilizer management, optimal N use, NDVI, EC_a, NSI

INTRODUCTION

The use of fertilizer nitrogen is one of the main option by which farmers can improve the quantity and quality of their production. However, excess nitrogen fertilization could have negative impacts on the crops through increased sensitivity to lodging and pests, and on the environment through nitrate leaching and gases (N_2O and NH_3) emissions. Many current agricultural production methods do not take into account spatial variability within fields (xx). Yet, variation in soil fertility, type and terrain features (slope and elevation) are some of the parameters affecting crop productivity differently in the various fields locations (ix; i, vii) as well as the need for inputs such as nitrogen fertilizers. Farming with no considerations of the different requirements for inputs at different locations within fields contributes to a waste of resources and money, but also introduces an excessive amount of fertilizer (N surplus) that leads to a potential source of environmental pollution (xiii).
Precision farming requires a better understanding of the variability patterns in order to determine the cause-effect relationships (xxi). Normalized Difference Vegetation Index (NDVI) (xv) is one of the common sources of information to describe crops conditions–and productivity in

agriculture (vi). There is a strong relationship between NDVI and soils, topography, water and N availability. Soils attributes such as texture are key factors affecting availability of nutrients and water. Soils capable to retain sufficient nutrients, air and water will be more suitable for increasing crop biomass (which will be associated with higher values of NDVI) and ultimately, yield. In the last fifteen years, the Apparent Soil Electrical Conductivity (EC_a) has been used as variable to delineate soils maps and management zones because EC_a describes multiple soils properties (viii) such as texture, moisture, depth of the arable layer, salinity and nutrient content (iii, v, viii, x, xi). Low ECa values are often associated with better growing conditions and *vice versa* (viii, xviii).

According to (ii), one of the current variable N rate strategies is to monitor the N status in real time using canopy reflectance from tractor-mounted sensors as an option. GreenSeeker (iv) is one of such equipment on the market. The NDVI measurements it provides make it possible to calculate Nitrogen Sufficiency Index [NSI] (xiv) by comparison to non N-limiting strips. The NSI constitutes an improvement for the assessment of N as it helps to remove noises from soil influence, radiometric and sensor properties, etc, affecting raw VIs values (xvi). However, field-long strips supplied with "non-limiting" levels of N are potentially harmful to the environment and should ideally be substituted by a limited number of plots strategically positioned so as to provide the same reference information.

Therefore, the objective of this study is to identify EC_a zones in the fields that could be used as references areas for NSI calculation ($NSI_{\mathbf{ECa}}$) of equivalent quality to the original NSI ($NSI_{\mathbf{Ori}}$) calculation made from strips.

MATERIALS AND METHODS

Field sites and experimental design

The experiments were conducted in 2005, 2006, 2007 and 2008 on corn (*Zea mays* L.). The fields were adjacent to one another in St-Valentin, Montérégie, Quebec, Canada (45° 05' 21'' N, 73° 21' 03'' W). The soil were characterised by various textures, from heavy clay, loam and clay-loam to loam, sandy loam and loamy sand (xvii). Field descriptions are given in Table 1.

Table 1: Experimental fields description.

Year	**2005**	**2006**	**2007**	**2008**
Coordinates (UTM 18 T)	629589 E 4994395 N	629781 E 4994184 N	629598 E 4994275 N	629788 E 4994156 N
Field size (ha)	8.66	6.52	8.74	12.99
Sowing date	12 May	9 May	3 May	6 May
Early-season plant status observation (NDVI used to calculate NSI) and growth stage on the "V" scale	28 June V7	5 July V6-7	22 June V6	25 June V5-6

Apparent Electrical Conductivity (EC_a) measurement

EC_a was measured on bare soil in the spring prior to the corn crop (for 2005, 2006 and 2008) and after harvest 2007 using a VERIS model 3100 sensor cart system (xix) of which the 0-30 cm readings were extracted. Measurements were made along transects approximately 10 m apart as a simple mono-directional scan or a bidirectional scan depending on the complexity of the terrain features. Figure 1 shows the EC_a maps for each of the four fields, obtained through universal kriging. These maps reflect spatial heterogeneity of soil textures which vary from sandy soils for low EC_a values to clay soils for high EC_a values.

Histogram thresholding for EC_a

The EC_a classes were determined using the histogram segmentation method of Otsu (xii) based on the minimization of the intra-group variance and maximization of inter-group variance. As a result from this methodology EC_a was classified into two, three and four classes which will be considered for their effects on $NDVI_{RichN}$. The numbers of class were also selected based on the range of the EC_a values and the spatial distribution.

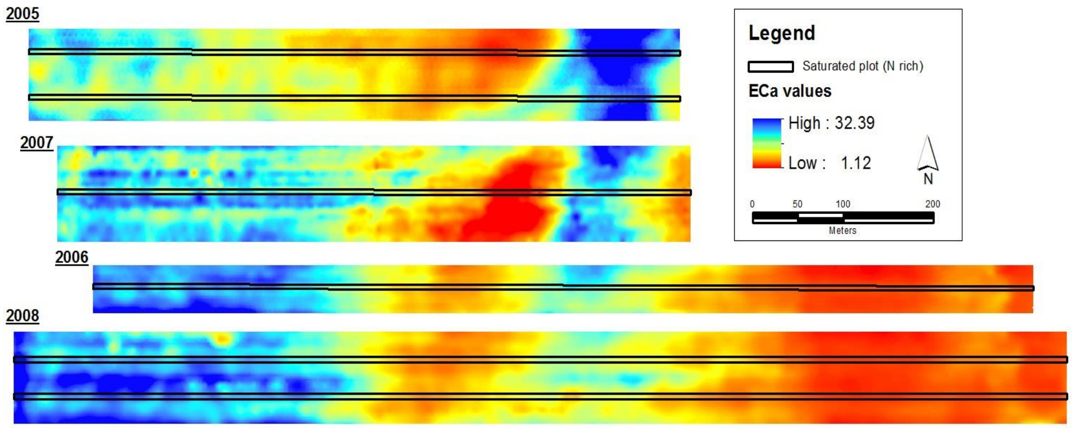


Figure 1: Soil Apparent Electrical Conductivity (EC_a*) for the experimental fields*

NDVI measurement and NSI calculation

The NDVI measurements (figure 2) were obtained before N application from 5 GreenSeeker sensors mounted on a trailer and pulled by a tractor. The NSI for every point was calculated from NDVI, using as a reference the NDVI from the rich N strips (defined as $NDVI_{RichN}$). This "original" NSI (NSI_{Ori}) was calculated from the average value of the 20 nearest neighbours in the rich-N strip (See equation).

$$NSI_{Ori} = NDVI \,/\, \text{nearest neighbours} \, [NDVI_{RichN}]$$

Then, alternative NSIs were calculated by taking into account EC_a. Three approaches were adopted: (1) NSI_{neca} was calculated for every point from the average value of the 20 points (distributed anywhere) in the N-rich strips having the closest EC_a; (2) NSI_{2ecaCl}, NSI_{3ecaCl} and NSI_{4ecaCl} was calculated from two, three and four EC_a classes. For each point, the average $NDVI_{RichN}$ (from points distributed anywhere) within the nearest EC_a class is used; and (3) $NSI_{3ecaAreas}$ calculated after defining actual areas representing three EC_a classes. Two scenarios (optimum areas) were chosen for each class in order to verify the independence of $NDVI_{RichN}$ from the choice of areas representing EC_a classes.

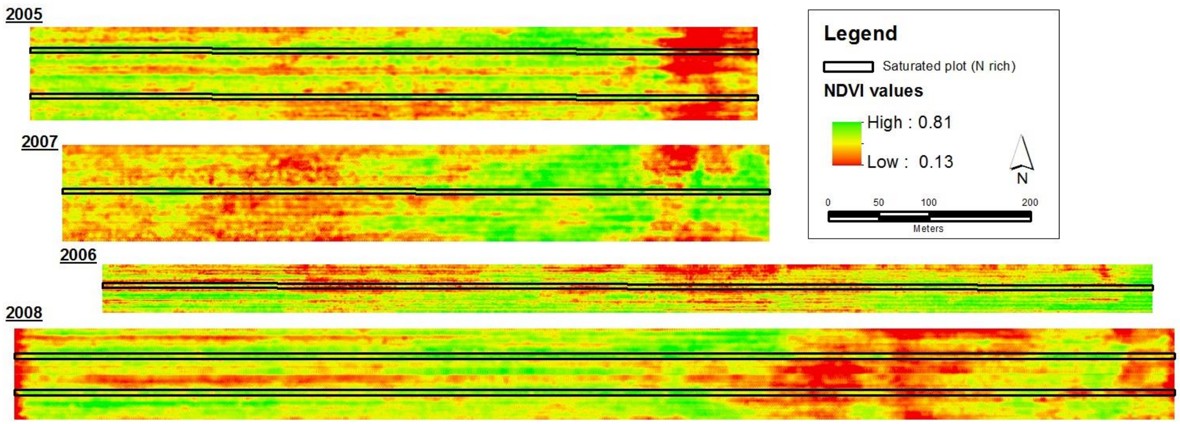


Figure 2: NDVI *maps from the experimental fields*

Statistical analysis

Averages of $NDVI_{\mathbf{RichN}}$ was calculated for EC_a classes and compared using a T-test to see if $NDVI_{RichN}$ is significantly different for EC_a classes.

ANOVA (GLM, SAS Institute, Cary, NC) was used to compare the effects of EC_a on the NDVI and on the different versions of NSI. The *F* value, which is the ratio between inter-group and intra-group mean of squares, was used to see if different variants of NSI are less affected by EC_a and to select the best way for the calculation of this NSI.

RESULTS AND DISCUSSION

EC_a classes determination

Figure 3 shows the 2005 EC_a histogram segmented for two, three and four classes. The averages of $NDVI_{RichN}$ for each EC_a class and each year are given in table 2. NDVI values are generally lower for highest EC_a values. For the two EC_a classes the $NDVI_{RichN}$ is not significantly different between any of the fields. With three EC_a classes, only the high class shows $NDVI_{\mathbf{RichN}}$ values significantly different from the two others classes. The four EC_a classes, showed the most significant difference in $NDVI_{RichN}$ values between each class. The three EC_a classes was then taken as the reference for the analysis due to that present the best balance between spatial and numerical variability.

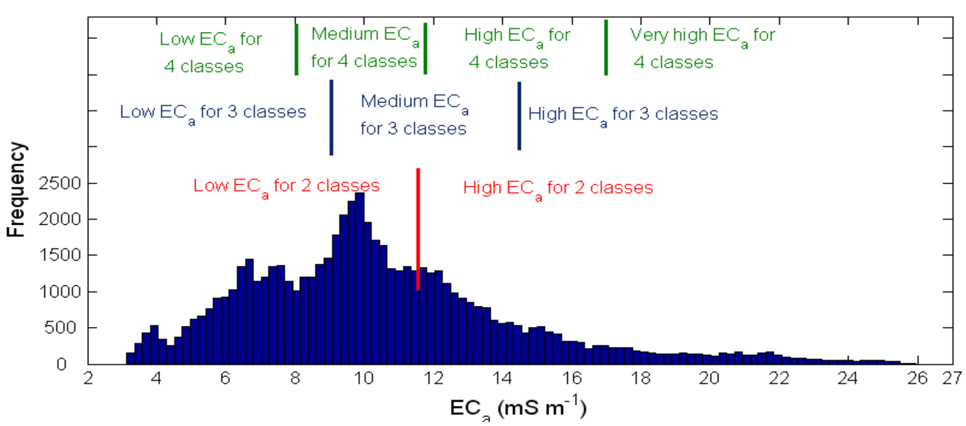


Figure 3: Histogram segmentation for EC_a *in 2005*

Table 2: Averages of $NDVI_{RichN}$ *for* EC_a *classes*

	Two EC_a classes (for NSI_{2ecaCl})		Three EC_a classes (for NSI_{3ecaCl})			Four EC_a classes (for NSI_{4ecaCl})			
	Low	High	Low	Medium	High	Low	Medium	High	Very high
2005	0.447	0.496	0.503	0.507	**0.373**	0.531	0.455	0.487	**0.303**
2006	0.495	**0.388**	0.597	0.519	0.559	**0.627**	0.597	0.445	0.553
2007	0.447	0.496	0.503	0.507	0.373	0.531	0.455	0.487	**0.303**
2008	0.507	0.499	0.440	0.529	0.487	**0.370**	0.504	0.495	0.511

Spatial selection of EC_a classes

Variances associated to NDVI were relatively high (Table 3). T-test results showed that the NSI calculated from the different combination of the EC_a values reduce the influence of the noises affecting raw NDVI. NSI calculated from three EC_a classes showed the best ability overall to reduce variances. On this basis, two scenarios were constituted for spatial areas in the N-rich strips representing these three EC_a classes. Figure 4 shows the areas scenario 1 and 2 selected to replace the strips.

Table 3: F-values from an ANOVA of EC_a *effect on* NDVI *and* NSI *versions*

Year	Dependent variable							
	NDVI	NSI_{Ori}	NSI_{neca}	NSI_{2ecaCl}	NSI_{3ecaCl}	NSI_{4ecaCl}	$NSI_{3ecaArea}$ Scenario 1	$NSI_{3ecaAreas}$ Scenario2
2005	**2005**	251	21	101	105	**14**	**55**	158
2006	**3856**	22047	17539	7525	**397**	1094	**349**	518
2007	**3261**	1414	1837	765	**206**	924	**212**	317
2008	**742**	2471	743	1078	**29**	4484	**56**	152

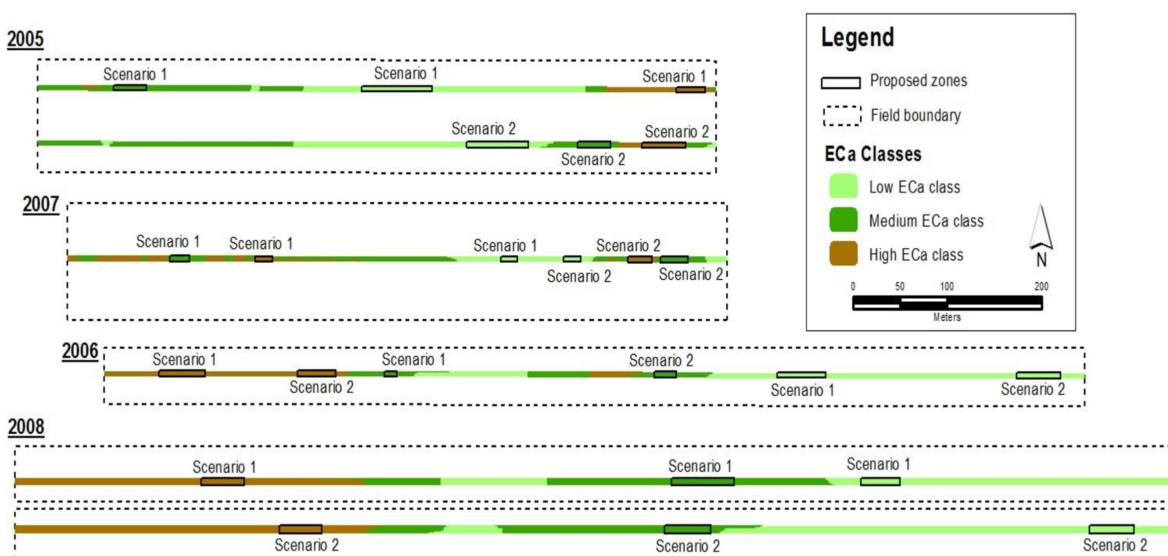


Figure 4: Proposed saturated zones based on three EC_a *classes.*

The $NSI_{3ecaAreas}$ calculated using these three EC_a areas are satisfying in term of EC_a influence for the two chosen scenarios (Table 3). The F-values are in general close to the values of the NSI_{3ecaCl} and in some cases lower.

The data from scenario 1 was used to produce a new NSI map (figure 5). Lower NSI areas mean that higher N rates are necessary, while in areas of NSI equal or higher to 1, less nitrogen is needed (Tremblay et al. 2010). Indeed, $NSI_{3ecaAreas}$ (figure 5) is characterised by a greater range (0.10 to 1.72) and therefore less extreme areas than raw NDVI (0.13 to 0.81; figure 2). The $NSI_{3ecaAreas}$ values range is also close to NSI_{Ori} (0.11 and 1.73) with a similar spatial distribution (data not shown).

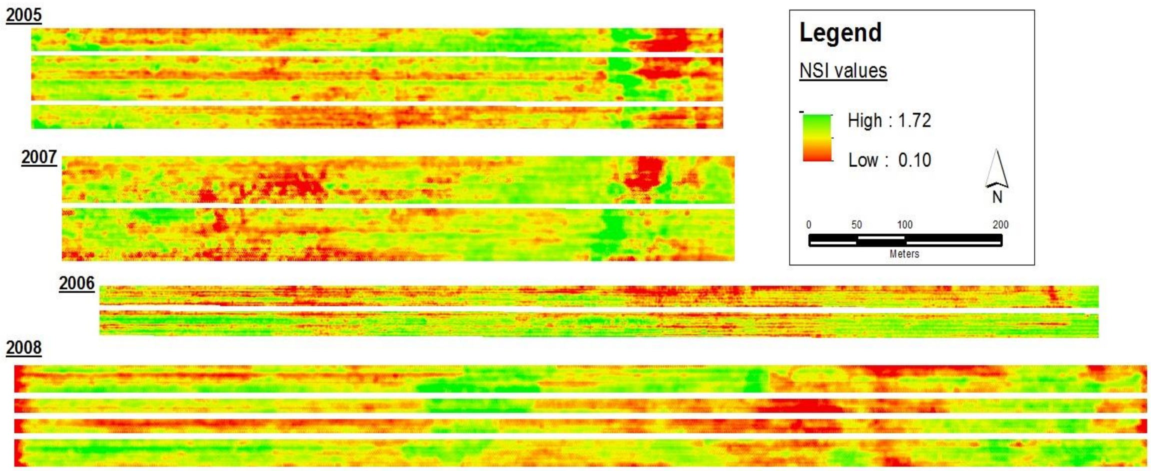


Figure 5: $NSI_{3ecaAreas}$ *calculated from the* EC_a *areas of scenario 1*

CONCLUSION

It is therefore possible to change long N-rich reference strips for a limited number of small areas based on EC_a without compromising accuracy in NSI calculations.

Although our results show the usefulness of EC_a to determine the appropriate locations of reference areas, other variables such as elevation and slope should be evaluated for the same purpose.

ACKNOWLEDGEMENTS

The authors would like to thank the University of Ottawa and the Horticultural R&D Centre, Agriculture and Agri-Food in St-Jean-sur-Richelieu for the data and financial support. We are grateful to all those who offered valuable comments and the research assistant staff which provided technical support.

REFERENCES

i. Bakhsh, A., T. S. Colvin, D. B. Jaynes, and R. S. Kanwar, U. S. Tim. 2000. Using soil attributes and GIS for interpretation of spatial variability in yield. *American Society of Agricultural Engineers* 43(4):819-828.

ii. Doerge, T. A. 2005. Nitrogen measurement for variable-rate N management in maize. *Communications in Soil Science and Plant Analysis* 36:23-32.

iii. Ferguson, R. B., G. W. Hegert, J. S. Schepers, C. A. Gotway, J. E. Cahoon and T. A. Peterson. 2002. Site-specific nitrogen management of irrigated maize: Yield and soil residual nitrate effects. *Soil Science Society of America Journal* 66:544-553.

iv. GreenSeeker. NTech Industries, Ukiah, CA. http://www.ntechindustries.com/greenseeker-home.html

v. Heiniger, R. W., R. G. McBridge and D. E. Clay. 2003. Using soil electrical conductivity to improve nutrient management. *Agronomy Journal* 95:508–519.

vi. Inman, D., R. Khosla, R. Reich, and D. G. Westfall. 2008. Normalized Difference Vegetation Index and soil color-based management zones in irrigated maize. *Agronomy Journal* 100:60–66.

vii. Kaspar, T. C., D. J. Pulido, H. Butler, T. S. Colvin, D. L. Karlen, D. B. Jaynes, D. E. James, and D. W. Meek. 2004. Relationship of Corn and Soybean Yield to Soil and Terrain Properties. *Agronomy Journal*. 96:700–709.

viii. Kitchen, N. R., S. T. Drummond, E. D. Lund, K. A. Sudduth and G. W. Buchleiter. 2003. Soil electrical conductivity and topography related to yield for three contrasting soil-crop system. *Agronomy Journal* 95:843–495.

ix. Kravchenko, A. N., and D. G. Bullock. 2000. Correlation of corn and soybean grain yield with topography and soil properties. *Agronomy Journal* 92:75–83.

x. Kravchenko, A. N., K. D Thelen, N. R Miller and D. G. Bullock. 2003. Relationship crop grain yield, topography and soil electrical conductivity studied with cross-correlation. *Agronomy Journal* 95:1132–1189.

xi. Li, Y., Dhou SHI, Ci-fang WU, Hong-yi LI and Feng LI. 2008. Determination of potential management zones from soil electrical conductivity, yield and crop data. *Journal of Zhejiang University Science B*, 9(1):68–76.

xii. Otsu, N. 1979. A threshold selection method from gray-level histogram. IEEE Trans. Systems, Man and Cybernetics, 9(1):62-66.

xiii. Pena-Yewtukhiw, E. M., G. J. Schwab, J. H. Grove, L. W. Murdock, and J. T. Johnson. 2008. Spatial analysis of early wheat canopy normalized difference vegetative index: determining appropriate observation scale. *Agronomy Journal* 100:454–462.

xiv. Peterson T. A., T. M. Blackmer, D. D. Francis and J. S. Schepers. 1993. Using chlorophyll meter to improve N management. *NebGuide G93-1171-A*. Cooperative Extension Institute of Agricultur and Natural Resources, University of Nebraska, Lincoln.

xv. Rouse, J.W., Jr., R.H. Haas, J.A. Schell, and D.W. Deering. 1974. Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. Prog. Rep. RSC 1978-1, Remote Sensing Center, Texas A&M Univ., College Station, 93 p.

xvi. Schmidt, John P., A. J. DeJoia, R. B. Ferguson, R. K. Taylor, R. K. Young, and J. L. Havlin. 2002. Corn yield response to nitrogen at multiple in-field locations*. Agronomy Journal* 94:798–806.

xvii. Tremblay, N., M. Y. Bouroubi, B. Panneton, S, Guillaume, P. Vigneault and C. Belec. 2010. Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features. *Precision Agriculture* 11(6): 621-635.

xviii. Tremblay, N., M. Y. Bouroubi, P. Vigneault, C. Belec . 2011. Guidelines for in-season nitrogen application for maize (*Zea mays* L.) based on soil and terrain properties. *Field Crops Research* 122: 273–283.

xix. Veris model 3100. http://www.veristech.com

xx. Weiss, M., and F. Baret. 2000. Use of remote sensing data for nitrogen management in precision farming. Authorized licensed use limited to: University of Ottawa. *Downloaded on January 19, 2010 at 16:26 from IEEE Xplore.*

xxi. Zillmann, E., S. Graeff, J. Link, W. D. Batchelor, and W. Claupein. Assessment of cereal nitrogen requirements derived by optical on-the-go sensors on heterogeneous soils. 2006. *Agronomy Journal* 98:682–690.

APPENDIX II: THRESHOLD AND AVERAGE NDVI, T-TEST RESULTS, CORRELATION RESULTS AND HISTOGRAM FOR THE VARIABLE APPARENT ELECTRICAL CONDUCTIVITY.

Threshold and Average NDVI.

ECa 2005 (3.14 – 25.95)		Average NDVI			
2 classes	12	0.47	0.44		
3 classes	9	0.51	0.50	0.37	
	14.5				
4 classes	8	0.53	0.48	0.51	0.32
	11.5				
	16.5				

ECa 2006 (1.12 – 31.5)		Average NDVI			
2 classes	11.50	0.49	0.39		
3 classes	8	0.59	0.52	0.56	
	15				
4 classes	5	0.62	0.59	0.44	0.55
	11				
	17				

ECa 2007 (1.12 – 29.06)		Average NDVI			
2 classes	12	0.44	0.49		
3 classes	9	0.50	0.50	0.37	
	16				
4 classes	8	0.53	0.45	0.49	0.30
	12				
	17				

ECa 2008 (1.02 – 27.39)		Average NDVI			
2 classes	11	0.50	0.50		
3 classes	6	0.44	0.53	0.48	
	13.5				
4 classes	6	0.37	0.50	0.49	0.51
	12				
	18				

2005

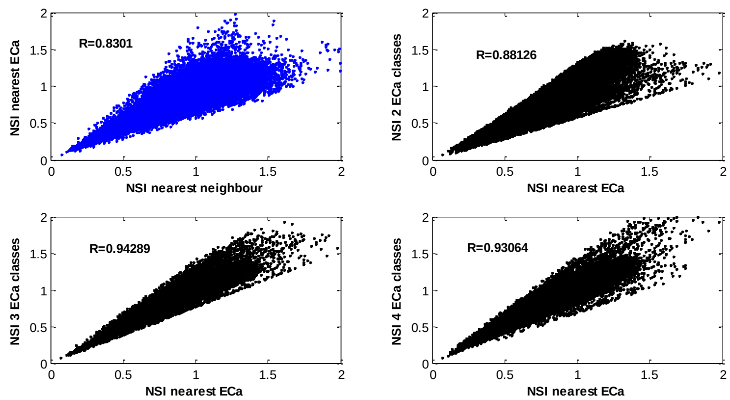
T-test

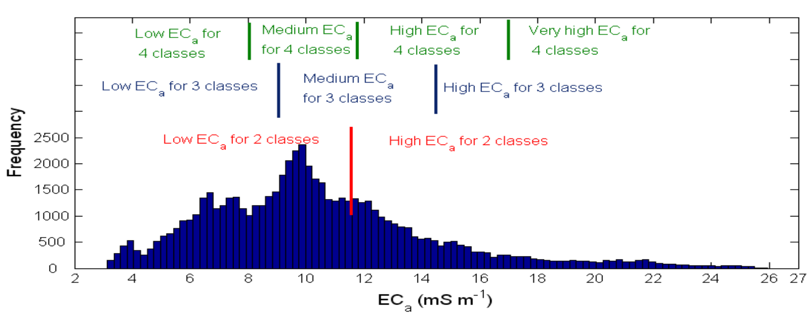
Low-high	H=0; P= 0.2158

Low-medium	H =0; P =0.5901
Low-high	H =1; P =4.9916e-7
Medium-high	H =1; P =3.7474e-6

Low-medium	H =0; P =0.1049
Low-high	H =0; P =0.4846
Low-vhigh	H =0; P =0.2980
Medium-high	H =1; P =1.63e-7
Medium-vhigh	H =1; P =5.44e-5
High-vhigh	H =1; P =7.46e-7

Correlation NSI nearest neighbour - NSI nearest ECa :	0.8301
Correlation NSI nearest neighbour - NSI 2 ECa classes :	0.8416
Correlation NSI nearest neighbour - NSI 3 ECa classes :	0.8205
Correlation NSI nearest neighbour - NSI 4 ECa classes :	0.8096
Correlation NSI nearest ECa - NSI 2 ECa classes :	0.9312
Correlation NSI nearest ECa - NSI 3 ECa classes :	0.9409
Correlation NSI nearest ECa - NSI 4 ECa classes :	0.9421





2006

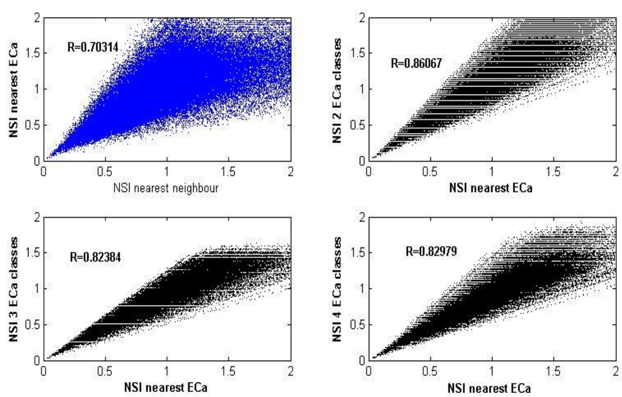
T-test

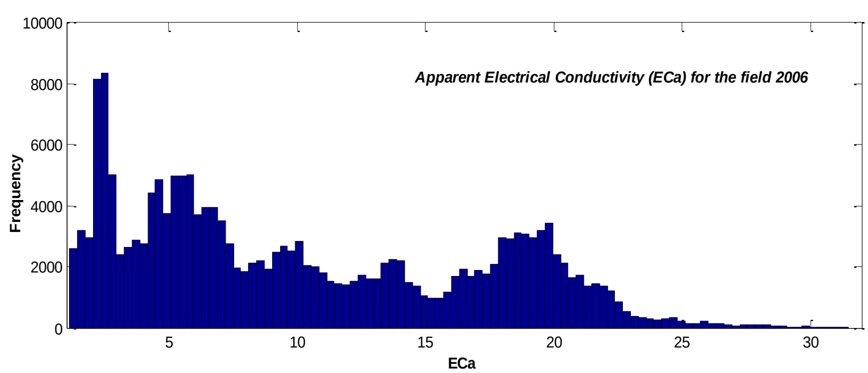
Low-high	H=0; P= 0.0680

Low-medium	H =0; P =0.0716
Low-high	H =0; P =0.3515
Medium-high	H =0; P =0.4561

Low-medium	H =0; P =0.4416
Low-high	H =1; P =1.9538e-005
Low-vhigh	H =1; P =1.9538e-005
Medium-high	H =0; P =0.0569
Medium-vhigh	H =0; P =0.3028
High-vhigh	H =1; P =0.3028

Correlation NSI nearest neighbour - NSI nearest ECa :	0.7031
Correlation NSI nearest neighbour - NSI 2 ECa classes :	0.7669
Correlation NSI nearest neighbour - NSI 3 ECa classes :	0.6732
Correlation NSI nearest neighbour - NSI 4 ECa classes :	0.6928
Correlation NSI nearest ECa - NSI 2 ECa classes :	0.8607
Correlation NSI nearest ECa - NSI 3 ECa classes :	0.8238
Correlation NSI nearest ECa - NSI 4 ECa classes :	0.8298





2007

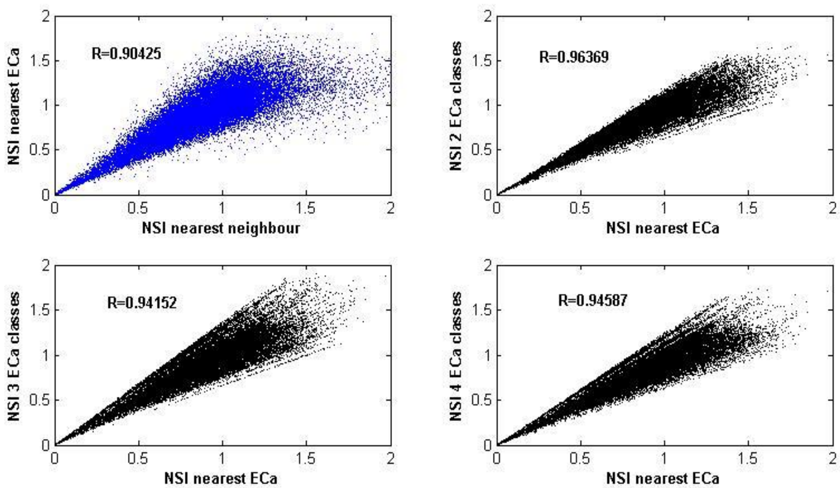
T-test

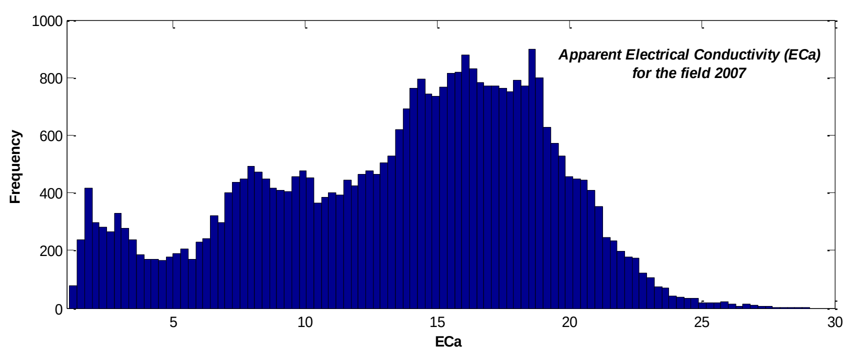
Low-high	H = 0; P =0. 0855

Low-medium	H =0; P =0.8810
Low-high	H =1; P =9.8397e-007
Medium-high	H =1; P =7.6443e-005

Low-medium	H =1; P =0. 0474
Low-high	H =0; P =0. 1090
Low-vhigh	H =0; P =0.0083
Medium-high	H =1; P =2.3221e-008
Medium-vhigh	H =1; P =9.7989e-004
High-vhigh	H =1; P =3.1488e-006

Correlation NSI nearest neighbour - NSI nearest ECa :	0.9043
Correlation NSI nearest neighbour - NSI 2 ECa classes :	0.9208
Correlation NSI nearest neighbour - NSI 3 ECa classes :	0.8953
Correlation NSI nearest neighbour - NSI 4 ECa classes :	0.9055
Correlation NSI nearest ECa - NSI 2 ECa classes :	0.9637
Correlation NSI nearest ECa - NSI 3 ECa classes :	0.9415
Correlation NSI nearest ECa - NSI 4 ECa classes :	0.9459





2008

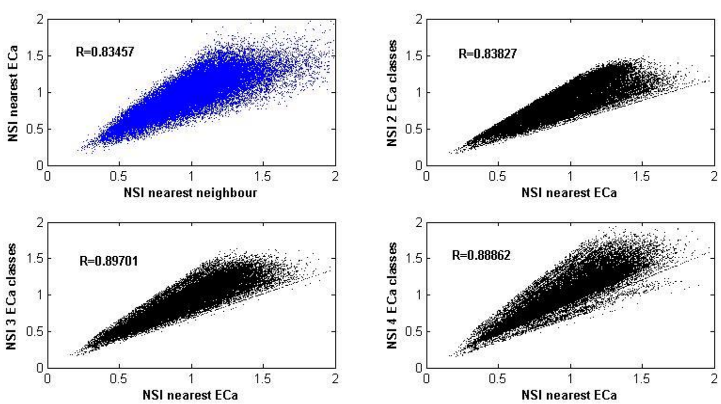
T-test

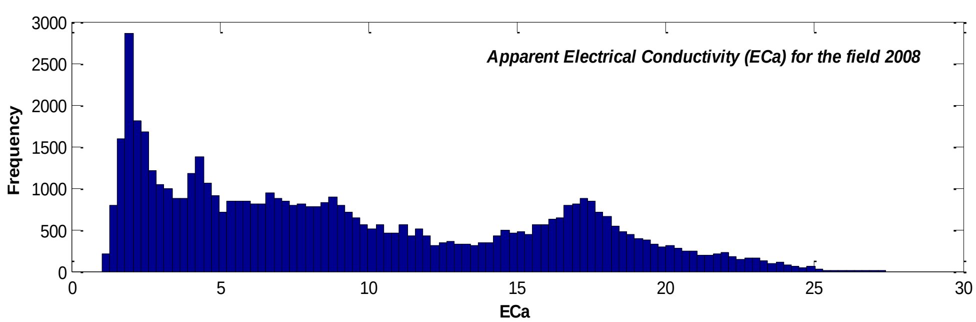
Low-high H =0; P =0.8235

Low-medium H =1; P =0.0284
Low-high H =0; P =0.2129
Medium-high H =0; P =0.2392

Low-medium H =1; P =0.6.6226e-004
Low-high H =1; P =0.4.3339e-004
Low-vhigh H =0; P =0.7883
Medium-high H =1; P =0. 4.2683e-005
Medium-vhigh H =0; P =0. 8280
High-vhigh H =0; P =0. 5686

Correlation NSI nearest neighbour - NSI nearest ECa : 0.8346
Correlation NSI nearest neighbour - NSI 2 ECa classes : 0.7290
Correlation NSI nearest neighbour - NSI 3 ECa classes : 0.7952
Correlation NSI nearest neighbour - NSI 4 ECa classes : 0.8089
Correlation NSI nearest ECa - NSI 2 ECa classes : 0.8383
Correlation NSI nearest ECa - NSI 3 ECa classes : 0.8970
Correlation NSI nearest ECa - NSI 4 ECa classes : 0.8886



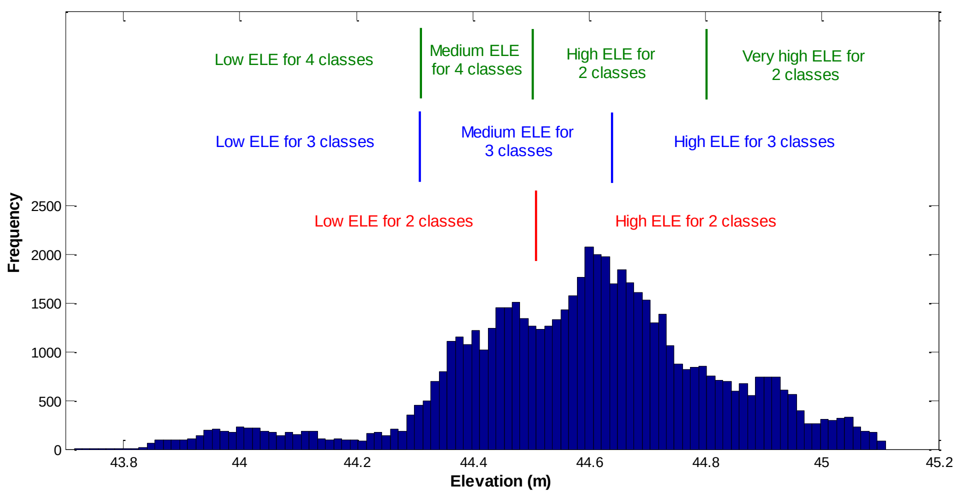


APPENDIX III: THRESHOLD AND AVERAGE NDVI, T-TEST RESULTS, CORRELATION RESULTS AND HISTOGRAM FOR THE VARIABLE ELEVATION.

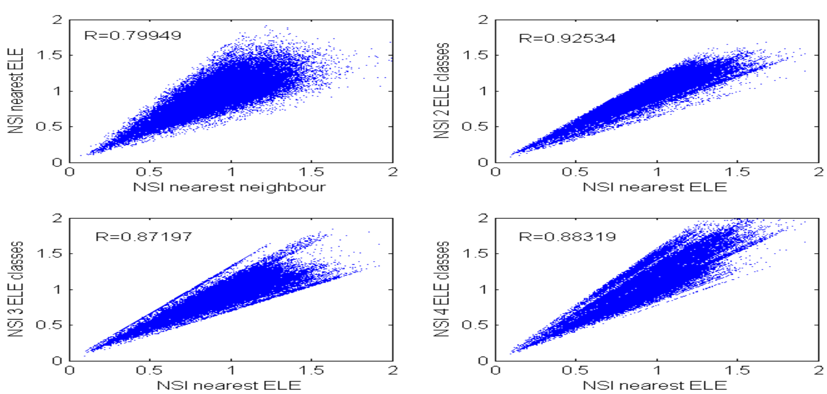
2005

Threshold and Average NDVI.

Elev 2006 (43.8 – 46.25 m)		Average NDVI			
2 classes	44.5	0.42	0.47		
3 classes	44.3	0.33	0.49	0.48	
	44.6				
4 classes	44.3	0.32	0.33	0.48	0.52
	44.5				
	44.8				



Correlation NSI nearest neighbour - NSI nearest ELE : 0.799
Correlation NSI nearest neighbour - NSI 2 ELE classes : 0.838
Correlation NSI nearest neighbour - NSI 3 ELE classes : 0.841
Correlation NSI nearest neighbour - NSI 4 ELE classes : 0.704
Correlation NSI nearest ELE - NSI 2 ELE classes : 0.925
Correlation NSI nearest ELE - NSI 3 ELE classes : 0.872
Correlation NSI nearest ELE - NSI 4 ELE classes : 0.883



2 classes:
Difference between NSI calculated by considering low and high ELE classes:
T-test gives: H=0?; P=0.0733; the difference depends on the choice of α.

3 classes:

	Low ELE	Medium ELE	High ELE
Low ELE	x	H=1; P=1.17e-8	H=1; P=3.06e-8
Medium ELE		x	H=0; P= 0.9606
High ELE			x

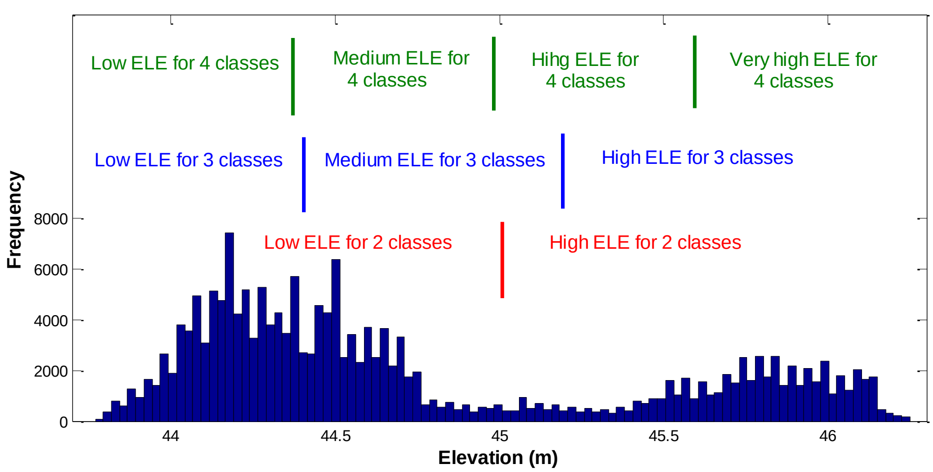
4 classes

	Low ELE	Medium ELE	High ELE	Very high ELE
Low ELE	x	H=0; P=0.6891	H=1; P=3.09e-7	H=1; P= 6.4e-11
Medium ELE		x	H=1; P=1.12e-7	H=1; P=5.1e-12
High ELE			x	H=0; P=0.0522
Very high ELE				x

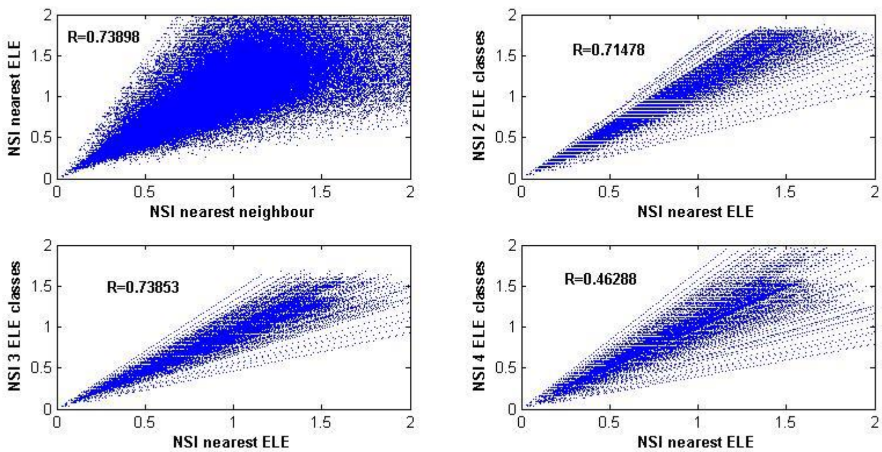
2006

Threshold and Average NDVI.

Elev 2006 (43.8 – 46.25 m)		Average NDVI			
2 classes	45	0.465	0.463		
3 classes	44.4	0.54	0.50	0.62	
	45.2				
4 classes	44.3	0.63	0.42	0.55	0.53
	45				
	45.6				



Correlation NSI nearest neighbour - NSI nearest ELE : 0.739
Correlation NSI nearest neighbour - NSI 2 ELE classes : 0.648
Correlation NSI nearest neighbour - NSI 3 ELE classes : 0.6757
Correlation NSI nearest neighbour - NSI 4 ELE classes : 0.402
Correlation NSI nearest ELE - NSI 2 ELE classes : 0.7148
Correlation NSI nearest ELE - NSI 3 ELE classes : 0.7385
Correlation NSI nearest ELE - NSI 4 ELE classes : 0.4629



2 classes:
Difference between NSI calculated by considering low and high ELE classes:
T-test gives: H=0?; P=0.9507; the difference depends on the choice of α.

3 classes:

	Low ELE	Medium ELE	High ELE
Low ELE	x	H=0; P=0.3894	H=0; P=0.1154
Medium ELE		x	H=1; P= 0.0136
High ELE			x

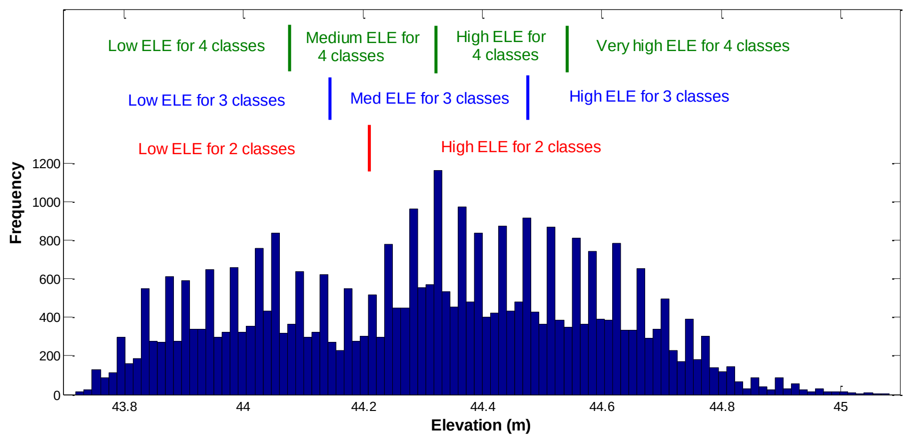
4 classes

	Low ELE	Medium ELE	High ELE	Very high ELE
Low ELE	x	H=1; P=4.6679e	H=1; P=0.0351	H=1; P= 0.039
Medium ELE		x	H=1; P=8.349e	H=1; P=0.0097
High ELE			x	H=0; P=0.7755
Very high ELE				x

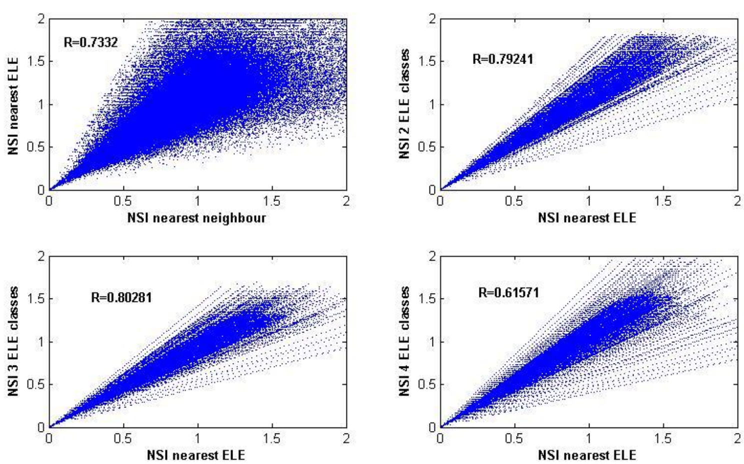
2007

Threshold and Average NDVI.

Elev 2007 (43.7 – 45 m)		Average NDVI			
2 classes	44.2	0.44	0.50		
3 classes	44.2	0.53	0.50	0.57	
	44.2				
4 classes	44	0.54	0.43	0.50	0.48
	44.3				
	44.5				



Correlation NSI nearest neighbour - NSI nearest ELE : 0.739
Correlation NSI nearest neighbour - NSI 2 ELE classes : 0.648
Correlation NSI nearest neighbour - NSI 3 ELE classes : 0.6757
Correlation NSI nearest neighbour - NSI 4 ELE classes : 0.402
Correlation NSI nearest ELE - NSI 2 ELE classes : 0.7148
Correlation NSI nearest ELE - NSI 3 ELE classes : 0.7385
Correlation NSI nearest ELE - NSI 4 ELE classes : 0.4629



2 classes:
Difference between NSI calculated by considering low and high ELE classes:
T-test gives: H=0?; P=0.4218; the difference depends on the choice of α.

3 classes:

	Low ELE	Medium ELE	High ELE
Low ELE	x	H=0; P=0.2996	H=0; P=0.7329
Medium ELE		x	H=0; P= 0.1071
High ELE			x

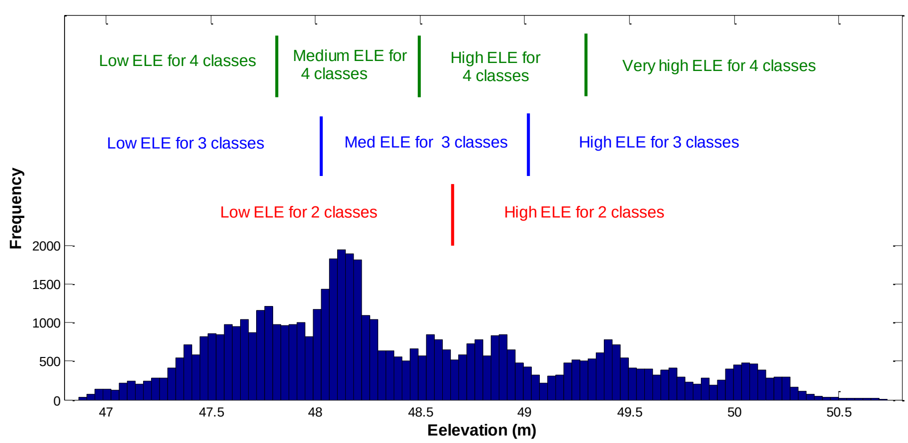
4 classes

	Low ELE	Medium ELE	High ELE	Very high ELE
Low ELE	x	H=1; P=0.0113	H=0; P=0.4143	H=0; P= 0.1852
Medium ELE		x	H=0; P=0.0559	H=0; P=0.1815
High ELE			x	H=0; P=0.5723
Very high ELE				x

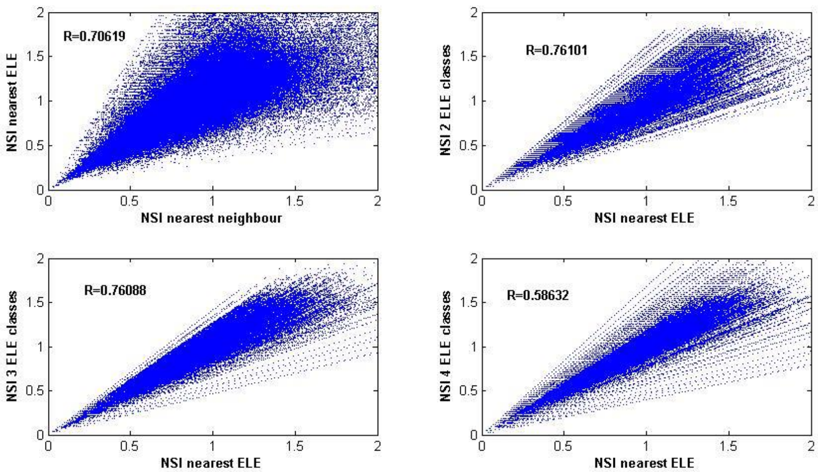
2008

Threshold and Average NDVI.

Elev 2008 (46.8 – 50.7 m)		Average NDVI			
2 classes	48.6	0.56	0.40		
3 classes	48	0.55	0.44	0.35	
	49				
4 classes	47.8	0.50	0.50	0.40	0.38
	48.5				
	49.3				



Correlation NSI nearest neighbour - NSI nearest ELE : 0.7062
Correlation NSI nearest neighbour - NSI 2 ELE classes : 0.6827
Correlation NSI nearest neighbour - NSI 3 ELE classes : 0.7201
Correlation NSI nearest neighbour - NSI 4 ELE classes : 0.5166
Correlation NSI nearest ELE - NSI 2 ELE classes : 0.761
Correlation NSI nearest ELE - NSI 3 ELE classes : 0.7609
Correlation NSI nearest ELE - NSI 4 ELE classes : 0.5863



2 classes:
Difference between NSI calculated by considering low and high ELE classes:
T-test gives: H=1?; P=1.1100e; the difference depends on the choice of α.

3 classes:

	Low ELE	Medium ELE	High ELE
Low ELE	x	H=1; P=0.006	H=1; P=3.8412e
Medium ELE		x	H=1; P= 0.0415
High ELE			x

4 classes

	Low ELE	Medium ELE	High ELE	Very high ELE
Low ELE	x	H=0; P=0.827	H=1; P=5.016e	H=1; P= 0.0015
Medium ELE		x	H=1; P=0.0045	H=1; P=0.0095
High ELE			x	H=0; P=0.5653
Very high ELE				x

APPENDIX IV: THRESHOLD AND AVERAGE NDVI, T-TEST RESULTS, CORRELATION RESULTS AND HISTOGRAM FOR THE VARIABLE SLOPE.

Threshold and Average NSI.

Slope 2005 (0 – 4.12)		Average NSI			
2 classes	0.90	0.51	0.45		
3 classes	0.57	0.41	0.46	0.44	
	1.40				
4 classes	0.41	0.34	0.51	0.53	0.44
	0.90				
	1.56				

Slope 2006 (0 – 3.93)		Average NSI			
2 classes	1.02	0.54	0.65		
3 classes	0.78	0.58	0.66	0.64	
	1.50				
4 classes	0.63	0.59	0.72	0.60	0.64
	1.18				
	1.73				

Slope 2007 (0 – 6.12)		Average NSI			
2 classes	1.34	0.50	0.46		
3 classes	0.98	0.50	0.50	0.53	
	1.96				
4 classes	0.85	0.41	0.48	0.57	0.53
	1.47				
	2.44				

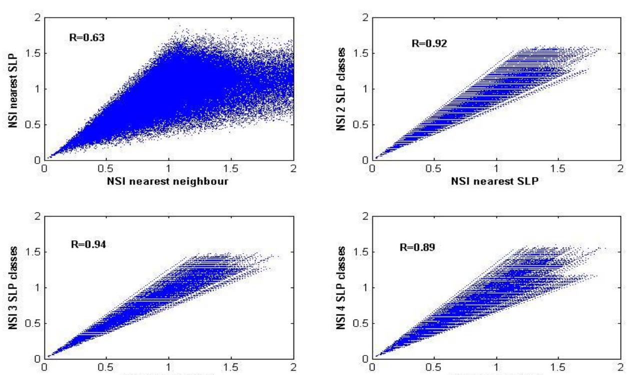
Slope 2008 (0 – 10.00)		Average NSI			
2 classes	3.80	0.49	0.48		
3 classes	2.40	0.45	0.47	0.47	
	5.60				
4 classes	1.80	0.46	0.43	0.51	0.43
	3.80				
	6.60				

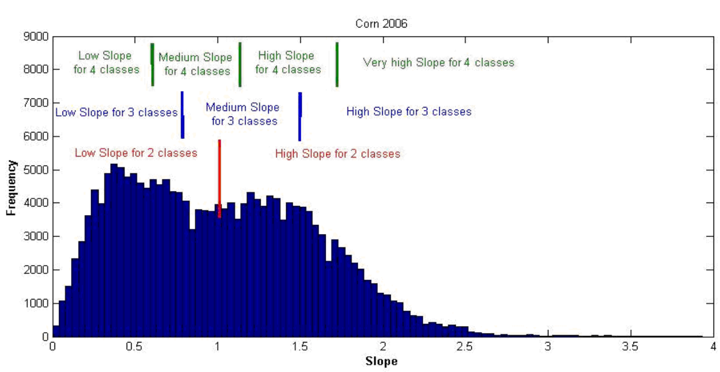
2006

Correlation NSI nearest neighbour - NSI nearest SLP : 0.6316
Correlation NSI nearest neighbour - NSI 2 SLP classes : 0.6576
Correlation NSI nearest neighbour - NSI 3 SLP classes : 0.6532
Correlation NSI nearest neighbour - NSI 4 SLP classes : 0.5929
Correlation NSI nearest SLP - NSI 2 SLP classes : 0.9251
Correlation NSI nearest SLP - NSI 3 SLP classes : 0.9383
Correlation NSI nearest SLP - NSI 4 SLP classes : 0.8922

T-test

Low-high	H =1; P =0.0035
Low-medium	H =1; P =0.0291
Low-high	H =0; P =0.1564
Medium-high	H =0; P =0.6150
Low-medium	H =1; P =6.0858e-006
Low-high	H =0; P =0.1499
Low-vhigh	H =1; P =0.0405
Medium-high	H =1; P =1.1869e-004
Medium-vhigh	H =1; P =0.0262
High-vhigh	H =0; P =0.3699





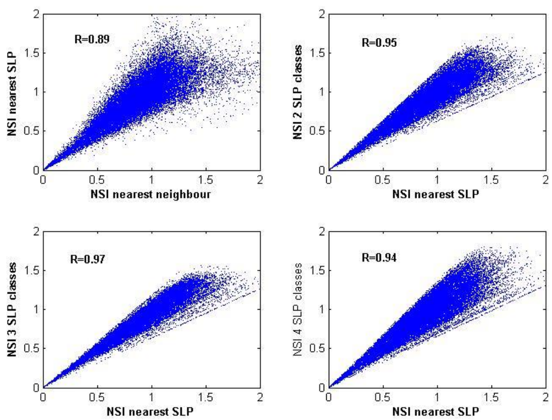
2007

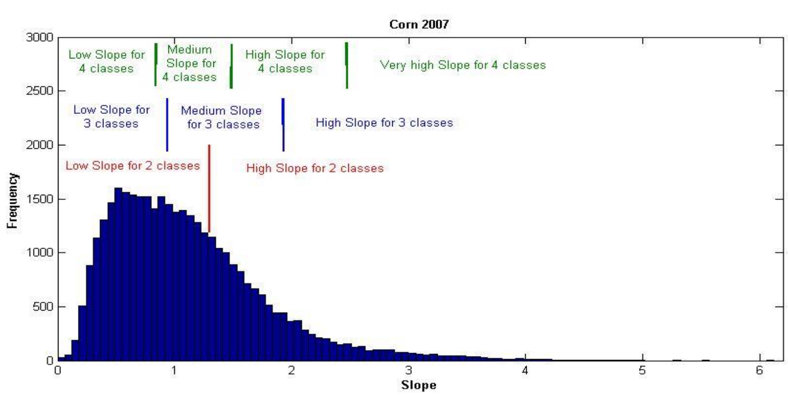
Correlation NSI nearest neighbour - NSI nearest SLP : 0.8957
Correlation NSI nearest neighbour - NSI 2 SLP classes : 0.9190
Correlation NSI nearest neighbour - NSI 3 SLP classes : 0.9240
Correlation NSI nearest neighbour - NSI 4 SLP classes : 0.8926
Correlation NSI nearest SLP - NSI 2 SLP classes : 0.9563
Correlation NSI nearest SLP - NSI 3 SLP classes : 0.9717
Correlation NSI nearest SLP - NSI 4 SLP classes : 0.9433

T-test
Low-high H = 0; P =0.4129

Low-medium H =0; P =0.9225
Low-high H =0; P =0.5566
Medium-high H =0; P =0.5504

Low-medium H =0; P =0.1429
Low-high H =1; P =0.0014
Low-vhigh H =1; P =0.0083
Medium-high H =1; P =0.0478
Medium-vhigh H =0; P =0.2210
High-vhigh H =0; P = 0.3362



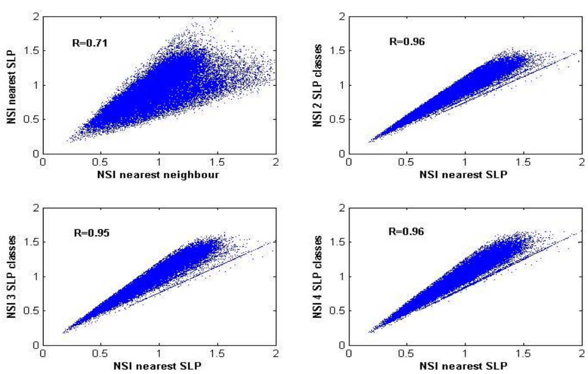


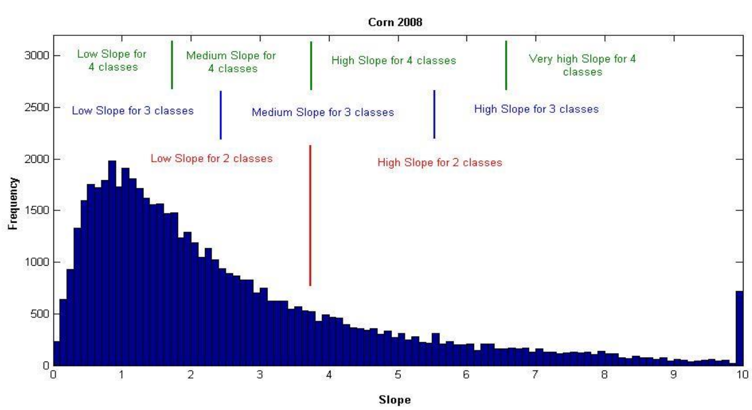
2008

Correlation NSI nearest neighbour - NSI nearest SLP : 0.71
Correlation NSI nearest neighbour - NSI 2 SLP classes : 0.73
Correlation NSI nearest neighbour - NSI 3 SLP classes : 0.73
Correlation NSI nearest neighbour - NSI 4 SLP classes : 0.72
Correlation NSI nearest SLP - NSI 2 SLP classes : 0.96
Correlation NSI nearest SLP - NSI 3 SLP classes : 0.95
Correlation NSI nearest SLP - NSI 4 SLP classes : 0.96

T-test

Low-high	H =0; P =0.8609
Low-medium	H =0; P =0.6423
Low-high	H =0; P =0.5154
Medium-high	H =0; P =0.8703
Low-medium	H =0; P =0.4938
Low-high	H =0; P =0.1422
Low-vhigh	H =0; P =0.5024
Medium-high	H =1; P =0.0302
Medium-vhigh	H =0; P =0.9889
High-vhigh	H =1; P =0.0312





APPENDIX V: ANOVA TABLES FOR ALL VARIABLES.

ECa

Source	Dependent variable (Fisher values from ANOVA)					
						2005
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
N rate	438.71	*756.86*	367.47	470.34	409.89	338.92
ECA	2005.64	*250.62*	21.52	100.86	105.46	**13.94**
ELE	508.30	*0.22*	269.81	945.90	755.40	23.49
SLP	71.74	*28.45*	36.33	79.07	32.78	38.67
						2006
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
N rate	1055.22	*476.02*	980.26	1180.09	**1137.83**	829.02
ECA	3856.99	*22047.7*	17539.2	7524.97	**397.20**	1093.99
ELE	2517.17	*54.22*	0.45	3583.37	530.41	113.42
SLP	3922.46	*2649.90*	4469.70	3043.96	3659.39	3582.00
						2007
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
N rate	27.34	*0.98*	1.97	3.57	2.92	6.29
ECA	4563.81	*1414.44*	1837.20	764.64	**206.38**	923.74
ELE	55.03	*141.47*	4.26	24.78	2.96	6.45
SLP	0.45	*10.74*	1.25	0.06	0.29	1.02
						2008
	NDVI	**NSI_nn**	**NSI_neca**	**NSI_2eca**	**NSI_3eca**	**NSI_4eca**
N rate	458.25	*153.94*	318.11	457.71	475.45	483.61
ECA	742.51	*2471.22*	743.13	1077.96	**28.80**	4484.42
ELE	232.86	*3285.16*	1190.85	203.31	16.73	199.96
SLP	121.33	*118.06*	246.26	122.17	206.71	205.71

Elevation

Source	Dependent variable							
								2005
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	438.71	756.86	267.67	343.47	535.29	218.79		
ECA	2005.64	250.62	2051.35	2370.17	1404.71	2697.91		
ELE	508.30	0.22	1256.47	**61.41**	114.05	5495.96		
SLP	71.74	28.45	90.55	103.38	36.56	128.54		
								2006
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	1055.22	476.02	1264.98	1050.38	1084.96	407.30		
ECA	3856.99	22047.7	17566.5	4165.17	94.29	24363.1		
ELE	2517.17	54.22	31.38	2762.98	1401.10	**461.93**		
SLP	3922.46	2649.90	1394.75	3903.67	4796.31	4587.57		
								2007
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	27.34	1.56	4.55	21.41	35.03	22.40		
ECA	4563.81	2298.58	3910.86	3164.93	4444.98	5451.64		
ELE	55.03	130.91	5.45	159.57	**11.02**	242.40		
SLP	0.45	16.30	4.54	2.28	0.26	3.77		
								2008
	NDVI	**NSI_nn**	**NSI_nele**	**NSI_2ele**	**NSI_3ele**	**NSI_4ele**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	458.25	153.94	365.76	245.80	575.96	353.44		
ECA	742.51	2471.22	3272.56	3675.47	4062.16	1981.81		
ELE	232.86	3285.16	2989.82	2176.29	3762.36	**1209.97**		
SLP	121.33	118.06	97.98	145.60	1.03	101.47		

Slope

Source	Dependent variable							
	2005							
	NDVI	NSI_nn	NSI_nslp	NSI_2slp	NSI_3slp	NSI_4slp	NSI_ Areas_1	NSI_ Areas_2
N rate	438.71	756.86	194.00	484.54	332.14	97.93		
ECA	2005.64	250.62	5533.58	2143.79	2392.49	3665.16		
ELE	508.30	0.22	1534.95	382.69	235.76	382.04		
SLP	71.74	28.45	10320.1	**1092.88**	1358.71	7809.00		
	2006							
	NDVI	NSI_nn	NSI_nslp	NSI_2slp	NSI_3slp	NSI_4slp	NSI_ Areas_1	NSI_ Areas_2
N rate	1055.22	476.02	783.89	600.10	1122.46	1630.59		
ECA	3856.99	22047.7	2373.14	669.37	2014.79	3647.33		
ELE	2517.17	54.22	1720.52	1005.30	1302.85	418.45		
SLP	3922.46	2649.90	8960.49	27488.9	13171.9	**11367.6**		
	2007							
	NDVI	NSI_nn	NSI_nslp	NSI_2slp	NSI_3slp	NSI_4slp	NSI_ Areas_1	NSI_ Areas_2
N rate	27.34	1.56	17.56	43.21	21.49	0.04		
ECA	4563.81	2298.58	4171.83	4645.65	4497.17	4025.24		
ELE	55.03	130.91	11.89	125.66	32.23	27.26		
SLP	0.45	16.30	185.30	176.11	**40.91**	1643.43		
	2008							
	NDVI	NSI_nn	NSI_nslp	NSI_2slp	NSI_3slp	NSI_4slp	NSI_ Areas_1	NSI_ Areas_2
N rate	458.25	153.94	583.96	475.20	403.97	491.67		
ECA	742.51	2471.22	433.93	770.31	673.01	467.94		
ELE	232.86	3285.16	85.58	229.68	227.61	199.39		
SLP	121.33	118.06	255.32	216.29	**14.08**	42.84		

Soil

Source						Dependent variable
						2005
	NDVI	**NSI_nn**	**NSI_nsoil**	**NSI_nSoilC**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	438.71	877.45	624.48	393.26		
ECA	2005.64	602.56	975.74	1164.83		
ELE	508.30	0.18	1054.59	678.95		
SLP	71.74	28.45	920.01	561.60		
						2006
	NDVI	**NSI_nn**	**NSI_nsoil**	**NSI_nSoilC**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	1055.22	476.02	1924.59	1202.83		
ECA	3856.99	22047.7	9278.83	1658.45		
ELE	2517.17	54.22	125.95	3.90		
SLP	3922.46	2649.90	3979.15	4455.05		
						2007
	NDVI	**NSI_nn**	**NSI_nsoil**	**NSI_nSoilC**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	27.34	1.56	6.01	11.79		
ECA	4563.81	2298.58	2111.14	2188.62		
ELE	55.03	130.91	7.91	13.92		
SLP	0.45	16.30	30.79	60.73		
						2008
	NDVI	**NSI_nn**	**NSI_nsoil**	**NSI_nSoilC**	**NSI_ Areas_1**	**NSI_ Areas_2**
N rate	458.25	153.94	565.81	325.46		
ECA	742.51	2471.22	2115.86	1022.74		
ELE	232.86	3285.16	1559.77	946.50		
SLP	121.33	118.06	522.29	208.66		