Evaluating the Economic Value of Variable Rate Nitrogen Application in Corn Production

by

Yida Zhang

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ABSTRACT

EVALUATING THE ECONOMIC VALUE OF VARIABLE RATE NITROGEN APPLICATION IN CORN PRODUCTION

Yida Zhang
University of Guelph, 2020

Advisor(s):
Dr. Alfons Weersink

The use of precision agriculture technologies has been heralded as a means to increase farm profitability and reduce its environmental footprint by targeting inputs to spatial and temporal differences in production. While certain precision agriculture technologies, such as guidance systems and data gathering platforms, are widely used in crop production, the adoption rates for variable rate technologies are much lower. The slow uptake of variable rate application methods is inconsistent with the perception of the value to its ability to tailor input application to match the differing needs across a field. This thesis examines the difference in payoff between uniform rate nitrogen application, which is the standard approach, and variable rate nitrogen application in corn production using farm-level data from Southern Ontario. The results indicate that variable rate nitrogen application is modestly more profitable than uniform rate nitrogen application in corn production.

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LIST OF SYMBOLS, ABBREVIATIONS OR NOMENCLATURE

AIC – Akaike Information Criterion

GPS – Global Positioning Systems

GIS – Geographic Information Systems

IR95 – Input Range 95

LM – Lagrange Multiplier

N – Nitrogen

NDVI – Normalized Difference Vegetation Index

OLS – Ordinary Least Squares

PA – Precision Agriculture

SAR – Spatial Autoregressive Model

SEM – Spatial Error Model

SEC – Soil Electrical Conductivity

UAV – Unmanned Aerial Vehicle

URA – Uniform Rate Application

URNA – Uniform Rate Nitrogen Application

VRA – Variable Rate Application

VRNA – Variable Rate Nitrogen Application

VRT – Variable Rate Technology

YPI – Yield Potential Ind

1 Introduction

1.1 Precision agriculture

Precision agriculture (PA) is a modern farming practice that makes production more efficient. Precision agriculture seeks to improve crop yields and profitability while reducing the level of inputs needed to grow crops. Traditional crop production tends to treat the entire field homogeneously and so inputs are applied uniformly on a field at a single rate based either on farmers' previous experience or simply their retailers' recommendations. The traditional uniform approach ignores the potential spatial variation in the field whereas PA recognizes the variability and adjusts the rate for different zones within the field.

Precision agriculture is a farm management concept that based on observing, measuring, and responding to spatial variability in the field as well as temporal variability across years. The goal of precision agriculture is to lower production costs and increase profitability sustainably by reducing resource waste through increasing productivity and efficiency.

In the context of precision agriculture, intra-field spatial variability can be observed. Multiple layers of data such as previous yields, application rates, normalized digital vegetation indices (NDVI), and soil nutrient contents can be recorded by the combine or collected from soil sampling, or other tests. Farmers can recognize the heterogeneity of yields and field characteristics from the collected data and to adjust input management decisions accordingly. The availability of precision agriculture technologies such as Global Navigation Satellite System (GNSS), Geographic Information Systems (GIS) and autonomous vehicles allows farmers to react to heterogeneity and manage their field on a much smaller scale (Weersink *et al*, 2018).

Site-specific input management is the practice of managing different regions in one field separately. Each region is recognized as a management zone that is delineated via certain decision criteria. The criteria to delineate zones are typically based on yields in prior years but could also depend on other field characteristics such as soil electrical conductivity and soil sampling test results. Farmers could make heterogeneous input management decisions for each management zone, such as applying different rates of fertilizer to different locations. The purpose of doing site-specific management is to optimize the inputs used in each zone in order to earn a better payoff.

Once the management zones in a field are identified using information technology and guidance systems, Variable Rate Technology (VRT) allows for input rates to differ for each zone. VRT refers to any combination of technologies that enables the variable application of seed, fertilizer, chemical, lime, irrigation water and other inputs, and allows farmers to control the amount of inputs they apply in a specific location. Two types of VRA, which is map-based control and real-time control, can be used to deal with spatial variability. Map-based control is the most common approach. Prescription maps for input rates are usually generated using GIS, for the field, prior to the application of the input. The Global Navigation Satellite System (GNSS) allows farmers to interpret the map. Farmers do not have to manually change the target rate setting on the applicator or make multiple passes over an area. Real-time control is an "on-the-go" approach that is specifically designed for certain chemicals. Input rate decisions are made using information collected during the operation.

1.2 Adoption and profitability of precision agriculture technologies

The adoption rates of precision agricultural technologies vary depending on the type of technology and sector. For example, Mitchell *et al*. (2018) found, in a survey of agri-input

suppliers, that almost all were using GPS guidance systems in their application of inputs on fields. GPS guidance systems reduce overlap and, thus, input use, while ensuring complete coverage and easing the strain on drivers of the application equipment. The benefits are greater than the costs and so GPS is now standard equipment. Similarly, mapping services, including yield maps from drone and UAV imagery, tend to have high adoption rates (Erickson & Widmar 2015; Griffin *et al*. 2017; Mitchell *et al*. 2018). Maps, which can be generated at relatively low cost, give farmers a comprehensive view of their previous performance and help farmers to monitor their field.

The adoption rate for variable rate application is significantly lower than for other general forms of precision agriculture. This is closely related to its limited ability to generate additional benefit compared to a traditional application method. Precision crop production technologies with a high adoption rate are either simplifying farmers' work (e.g., auto-steering systems) or passively generating valuable information during operation (e.g., yield monitors). GPS technologies are embodied-knowledge technologies where no additional skills are required to capture their value (Weersink *et al*., 2018). In contrast, variable-rate technologies involve a complex decision support system, where each step towards the application requires data management and data analytic skills. Variable-rate technologies require intensive information from the farm to support decision making and to reap the benefits (Griffin *et al*. 2017). In addition, the value of the information may be limited due to a relatively flat payoff function, which means there can be a large range in fertilizer application rates for which the difference in net returns is minimal (Weersink *et al*., 2018).

1.3 Research problem

Previous research has argued that the difference in payoff between variable rate application (VRA) and uniform rate application (URA) is positive but small. Anselin *et al*. (2004) stated that VRA in corn production can hardly break-even; Maine *et al*. (2009) found that VRNA is modestly more profitable than URNA. Other research argued the VRA of different inputs have limited ability to boost yield. Griffin and Hollis (2017) found that the yield benefits bought by VRA over URA is small; and Kempenaar *et al*. (2018) stated that VRA nitrogen and fungicide has a positive cost-benefit ratio but the size is small. The question arises whether site-specific nitrogen management will yield a better payoff than traditional uniform nitrogen management in corn production and whether the benefit of VRA is underestimated. Also, this raises questions whether the improvement in payoff under VRA is sufficient to cover its cost is. The answer to this question will provide implications on the relationship between the input management scale and farm payoff.

The profitability of VRA depends on a variety of factors. One of these factors is the strategy used to define and delineate management zones. Previous studies have used different criterion to delineate management zones. Maine *et al*. (2009) used a previous 3-year yield map; Anselin *et al*. (2004) used landforms, a measure of relative elevation. Others used more complex criteria including modified partition entropy (MPE) and fuzzy performance index (FPI) (Metwally *et al*., 2019). VRA involves multiple steps including management zone delineation, input prescription, and operation. The economic return of using VRA can be heterogeneous and unique for every farmer since everyone can have their own strategies at any step of VRA. The field trial for the case study in this thesis used previous yields as the management zone

delineation criteria. Whether this particular zone delineation strategy will make VRNA more profitable than URNA is going to be explored in this thesis.

Another factor that influences the profitability of VRA is the extent of spatial variability within fields. If the degree of variability is high, the economic benefits of VRA are more significant, and vice versa. Swinton and Lownberg-DeBoer (1998) stated that VRA is more likely profitable in fields exhibiting high variability. Wang *et al*. (2003) found that greater variation in topsoil depth and soil pH resulted in higher profitability in VRA. Pannell, Gandofer, and Weersink (2019) stated that the benefits of precise input application depend on the variability of yields across different zones of the field. Greater yield variance means the optimal site-specific rates are more variable. The input rate adjustment makes a greater difference in payoff when the curvature of the payoff function is large (Pannell, Gandofer, & Weersink, 2019). They expressed that the flatness of the payoff function determines the profitability of conducting site-specific input management. This thesis will test whether the payoff function is flat, and whether variable rate nitrogen application is profitable with a flat payoff function. Maine *et al*. (2009) indicates that input and output prices will affect the profitability of VRA. Whether changes in nitrogen and corn prices affect VRNA profitability will also be examine in this thesis.

Previous research has indicated the problem of spatial autocorrelation may exist in field-level datasets and mentions the necessity of using spatial models in regression analysis. This thesis examines whether using spatial models in regression will lead to different estimations of yield response functions and whether different statistical models will lead to different economic conclusions on the profitability of VRA. It also examines whether the spatial scale of data will impact the issue of spatial autocorrelation.

1.4 Research gaps and contributions

Research regarding the profitability of URA versus VRA started in the late 90s but has not yet come to a consensus. Generally, this thesis is going to add more evidence regarding the profitability of URA and VRA. The data used in this thesis are collected from field trials that adopt VRNA in production. This dataset allows comparison between actual returns to VRNA as well as simulated optimal payoffs under URNA and VRNA.

Most previous VRA research had focused on profitability (Anselin *et al*. 2004; Maine *et al*. 2010; Griffin and Hollis. 2017; Kempenaar *et al*. 2018), but few previous studies give suggestions on how to appropriately conduct VRA. In fact, no research has suggested a universal way to create input prescriptions for VRA. This thesis incorporates the concept of flat payoff functions into the practice of VRA. The concept of flat payoff functions is used to evaluate the marginal payoff of inputs in each management zone and to provide farmers with guidance on input prescriptions.

The issue of spatial autocorrelation in field-level datasets was frequently mentioned and discussed in previous research regarding VRA and site-specific input management. Most of the research suggested using spatial models in estimating yield response functions (Lark and Wheeler. 2003; Anselin *et al*. 2004; Hurley *et al*. 2005; Lambert *et al*. 2006; Liu *et al*. 2006; Maine *et al*. 2009), but few carried the regression results into further economic simulation of VRA payoffs. This thesis is going to confirm whether the spatial autocorrelation problem exists in the dataset that is used in the case study. Also, this thesis will compare the economic simulation payoff of VRA between a typical OLS model and spatial models. Besides, this thesis will also examine the relationship between spatial autocorrelation and the spatial scale of the data. The results of this analysis will have implications on future field data collection methods.

In addition, by comparing the estimated yield response function using two scaled datasets, the value of information in VRA could be explained.

1.5 Purpose and objectives

The purpose of this thesis is to evaluate the returns of variable rate nitrogen application (VRNA) on corn compared to traditional uniform rate systems (URNA) using farm-level data. The specific objectives are:

1. To estimate the whole-field and site-specific yield response function using OLS models and spatial models.
2. To evaluate the impact of spatial autocorrelation on estimating yield response functions.
3. To simulate the nitrogen rate, yield, and net payoff under URNA and VRNA using coefficients estimated by OLS and spatial models.
4. To compare the net payoff between URNA and VRNA.
5. To examine the impacts of input/output price on the difference in payoff between URNA and VRNA
6. To explain the implications of flat payoff functions in variable-rate nitrogen application.
7. To evaluate the impact of spatial data scale on the issue of spatial autocorrelation.

1.6 Outline

This thesis contains 4 chapters. Chapter 1 has provided an introduction to the thesis including a brief background description of precision agriculture, and the need to understand why the adoption rate of variable rate technologies in crop production has lagged behind other

precision agriculture technologies. Chapter 2 discusses the concept of Big Data and its connection with precision agriculture. It also describes the opportunities and challenges of using Big Data in precision agriculture, especially for variable rate application, and outlines how the value of information is defined, particularly in the case of precision agriculture. Chapter 3 presents the results of the empirical analysis on the economic feasibility of variable rate nitrogen application in corn production. The case study uses farm trial data collected by OMAFRA in 2015. Chapter 4 concludes the thesis, describes the contributions made by the research, and provides suggestions and directions for future research.

2 Value of Information in Precision Agriculture

This chapter will discuss the roles of information in precision agriculture. The chapter opens with an introduction to Big Data followed by a more specific discussion about big data and precision agriculture. The third part of this chapter discusses the limitations of Big Data in precision agriculture applications. Followed by a general description of VRA. This chapter concludes with a discussion of the value of information and the factors that influence the value of information.

2.1 Big Data and precision agriculture

2.1.1 Defining Big Data

Big Data is a term that describes a large volume of complex structured data that inundates a business on a day-to-day basis. While the fast evolution of the "big data" concept has obstructed the development of a universal and formal definition of big data (De Mauro *et al*, 2016), the attributes of big data have reached a consensus. Laney (2001) denoted the most popular three-dimension definition of big data, which is volume, velocity and variety.

Volume refers to the amount of data generated through a variety of sources such as business transactions, equipment, social media, smart devices, and more. With the generation and collecting of massive data, data scale becomes increasingly huge (Chen *et al*., 2014). In the context of agriculture, data are generated through a variety of sources along the supply chain including production equipment, climate satellites, transaction records, and other devices. The volume of data at every point of the supply chain has different sizes. At the production stage, for example, yield data and application data are usually generated annually, and the data scale is small. Weather and climate data are generated either hourly or by the minute, which has a greater

scale. In contrast, on the other end of the supply chain, retailers and consumers contribute an insanely large amount, or volume, of data every hour or every minute.

Velocity is a measure of how fast the data is coming in. It means the timeliness of big data, especially collection and analysis. Receiving and responding to big data in a timely manner requires advanced computation technology since humans cannot rapidly process data with such a large volume. In the context of agriculture, some data arrives in real-time, whereas others come in at a slower pace. An example of a production practice based on real-time data is sensor-based variable rate chemical application. The sprayer will adjust the application rate base on the data collected during the operation.

Variety indicates the data have different forms, including structured, semi-structured, and unstructured (Chen *et al*., 2014). Data are collected from different places and delivered in different formats. Some are in a typical shape of typical database files, while others are presented in non-traditional forms such as audio, video, graphics, webpage, and text. Data generated along the agricultural supply chain also have a variety of forms. Data generated via monitoring devices such as UVAs, drones, and satellites are usually presented in a graphical form. Smart scouting equipment can collect a variety of data from the field and present them in either a video or a graphic form on a mobile device. Other examples include product information transmitted in the form of QR codes; consumer behaviour data is gathered and collected in various forms on the internet.

Besides the three consensus characteristics of big data, several authors added other features of big data along with the "3 Vs" model. Dijcks (2013) added the term "value" as another feature of big data. Big data are considered as an information asset and it has an identifiable entity that is independent of the field of application (De Mauro *et al*, 2016). The

value of big data could be recognized through a transformation that extracts the utility from the collected data. The transformation of "big data" to value requires the support of specific technologies and analytical methods. The transformation of big data or information into insights might create economic value for companies and society.

2.1.2 The use of Big Data in precision agriculture

Precision agriculture is generally defined as doing the right thing at the right time and location at the right intensity (Mulla & Khosla, 2016). This farm management concept is based on observing, measuring, and responding to spatial variability in the field as well as temporal variability across years. The goal of precision agriculture is to increase productivity and efficiency while lowering the input cost to improve payoff and preserve resources. To achieve this goal, big data plays a critical role along with the whole supply chain in precision agriculture. Big data can support different precision agriculture applications by extracting value and discovering insights from collected data to solve potential problems involved in production and inspire farming decisions.

Production equipment, smart devices, climate satellites and other information and communication technologies (ICT) generate an enormous amount of data during operation. For example, combines collect yield data for a particular area; UAVs or drones take images of crops; sprayers record the application rate of different chemicals; satellites collect regional weather data; soil sampling collects soil data, etc. Real-time and historical data are collected in either a structured or an unstructured format and stored in a database. With the support of farm management software, lab tests, and other analytical tools, data can be transformed into a "big data" format that is easier for farmers to understand. When data is presented in a more explicit form, farmers will have a better and a more precise view of what is happening in their field. For

instance, GIS software can transform georeferenced crop data into yield performance maps for a growing year. Scouting software can generate daily logs based on the data collected by the UAVs and sensors that give farmers a comprehensive view of weed populations, crop plant diseases, soil humidity, and crop growing conditions. This transformation of raw data into "big data" provides farmers with opportunities to have better control over their land and information about its use.

Precision agriculture technologies and applications rely on the input of big data. The data extraction enables farmers to come up with more accurate decisions regarding their production and farm management. The most widely adopted precision agriculture technology, GPS auto-steer, relies on data from the GPS. It was first purposed by Larsen *et al*. (1994), O'Conner *et al*. (2015) pioneered the use of real-time kinematic (RTK) GPS for automatic steering of a tractor along straight lines. The GPS receiver collects the real-time latitude and longitude of the farm machinery to navigate them and keep them correctly following the desired trajectory. Besides GPS auto-steer, real-time control on input application also relies on data collection and rapid data processing during the operation. In comparison, site-specific input management relies less on real-time data but more on historical data that are accumulated every year. One common site-specific input management is variable rate application (VRA). It refers to the application of certain inputs, in which the rate of application is based on the characteristics of the area that the inputs are being applied to. Variable-rate application requires a beforehand recognition of spatial variability in the field. Then farmers can decide the right inputs at the right place at the right intensity. Precision agriculture leverages big data and analytics tools to achieve optimal productivity and reduce costs.

2.1.3 Limitations of Big Data in precision agriculture applications

The value of Big Data in general is remarkable; however, some of the following issues seem to be the main challenges of adopting Big Data in precision agriculture applications. The value of Big Data in agriculture depends on a sufficient amount of information contributed by farmers. The aggregation of information gives it robust predictive power (Coble *et al*., 2016). The value of Big Data is different among farmers. The value of Big Data for a single farmer is small compared to the value of Big Data enjoyed by a group of farmers. A group of farmers could share information and the volume of data accessed by each farmer is greater.

The first limitation of Big Data is that the volume of data that can be accessed by a single farmer might be insufficient for any valuable analysis. The factors behind this limitation include the nature of slow data accumulation, limited internet connectivity, and data ownership and confidentiality concerns (Coble *et al*., 2016). Using yield data as an example, a cash crop farmer can only collect yield data once a year, not to mention that most farmers use crop rotations. To recognize spatial variability using annual yield maps, a farmer needs to compare the yield maps for that cash crop across years. Since the spatial variability in yield for any kind of crops is not constant across years, it might take as long as ten years to get a reliable conclusion from observing spatial variability. The implementation of input management strategies based on what is observed will become an extremely slow process that discourages the continuity of data collection. Besides the factor of slow data accumulation, the absence or limited availability of broadband connectivity in some production regions has restricted the benefit of Big Data in precision agriculture applications (Coble *et al*., 2016). Upload and download speed restrictions impede the adoption of some. In addition, data ownership concerns could make farmers willingly stop collecting data and slowly adopt precision agriculture technology (Mitchell *et al*., 2017). In

many cases, farmers will send their data to a precision agriculture retailer for data processing services. Their retailer might sell back the value-added products to the farmers who provided the data. Besides, farmers who have limited capability to store data would need to use other databases. Without a formal data privacy agreement, the owner of the database might take advantage of the data owner. Mitchell *et al*. (2017) stated in the Ontario Precision Agriculture Retailers Survey Report that only 50 percent of the survey respondents reported that their companies have customer data privacy agreement and/or a data terms and conditions agreement.

The second limitation of Big Data in precision agriculture applications is that the benefit of data management is low relative to its potential cost. Since the implementation of precision agriculture applications using Big Data is slow, the economic benefit will not be realized in the short term. The cost of data management and purchasing necessary equipment and devices can hardly be recovered in the short run. This is the reason that, while data collection and transmission are available on agriculture equipment, many farmers still use equipment without such capabilities (Coble *et al*., 2016). They are just not sure whether it is worth spending so much money and time on such things.

The third limitation is that farmers lack the ability to transform data into valuable information. Besides, even when farmers receive valuable information from someone who helps them with the data processing, they might not have enough confidence to respond to the information.

2.1.4 Big Data and site-specific management

The advances in automation hardware and software technology have made the concept of spatially variable, prescription, and site-specific crop production possible (Schueller, 1991). Site-specific management (SSM) is a crop management practice at a smaller scale than that of the

whole field (Plant, 2001). It is used to observe and measure the spatial variability within fields, record the variability at specific locations and then use the collected information to guide changes in crop or input management decisions. Instead of using the same management on the entire field, SSM treats areas within fields differently. The areas with relatively similar and homogeneous factors that affect crop yield should be put into a management zone so that a different uniform input recommendation can be made for each zone (Mulla, 1991). SSM relies on information about locations within fields to delineate the management zone. Information can be collected by using monitoring devices such as a yield monitor, soil electrical conductivity sensors, remote imagery, etc., or by soil sampling. Plant (2001) stated three potential criteria that must be satisfied for SSM to be justified. First, there exists significant within-field spatial variability in factors that influence crop yield. Second, what causes spatial variability is observable and measurable. Third, the information obtained from the measurements can be used to improve input management practices to increase profit or decrease environmental impact.

2.1.5 Variable rate technology and variable rate application

Variable rate technology is the way to achieve SSM within fields. It allows variously known inputs to be applied at a different rate across a field without manually changing rate settings on the equipment. Inputs available for VRA include fertilizers, manure, and irrigation water as liquid materials, and anhydrous ammonia, seed, and planter-based starter fertilizer as dry materials. Variable rate application equipment can be as large as a commercial fertilizer applicator or as personal as a variable-rate seeder (Franzen, 2018). There are two types of variable rate technology available for SSM, including map-based control VRA and sensor-based control VRA (Ahmad & Mahdi, 2017). The map-based VRA requires farmers to produce a prescription map prior to the operation. The prescription map is a geo-referenced map that

includes application rate information so that the variable rate controller on the equipment can apply the appropriate amount of input at the appropriate location. Sensor based VRA uses real-time information collected during operation and creating a prescription map "on-the-go". It is currently a much less common way of conducting VRA since it requires fast data collection speed, strong data processing power, as well as high internet upload and download speed.

The practice of variable rate application is heterogeneous among farmers. Two crucial steps in VRA are management zone delineation and creating prescription maps. The definition of the management zone did not reach a consensus among previous literature. Mulla (1991) offers the first definition that the management zone should include the portion of the field with similar soil fertility. Doerge (1999) modified this concept by defining management zones as "the sub-region of a field that expresses a homogenous combination of yield-limiting factors for which a single crop input is appropriate". Farmers have their own understanding of the management zone and it will affect their decision on how to delineate the them within fields. Khosla *et al*. (2010) summarized an extensive literature for management zone delineation in precision agriculture. The most common method of management zone delineation was based on soil characteristics such as soil texture or soil nutrients content. Using sensing technologies to construct a soil electrical conductivity map for delineating management zone is another common approach (Khosla *et al*. 2010). Other less common approaches for delineating management zones include yield mapping and land elevation differences (Khosla *et al*. 2010). More recent studies introduced a clustering approach that uses more than one factor as the delineating criterion. Among all approaches, none of them was identified as the optimal approach by existing scientific literature. The second crucial step of VRA, prescription maps, can also be heterogeneous among farmers. There is not a universal approach to creating input prescriptions.

Farmers can create a prescription for a single input or for a combination of different inputs. Besides, farmers could decide which zone receives more inputs and which receives less.

2.1.6 Value of VRA and value of information

A typical way of evaluating the value of a precision agriculture technology is to compare the net returns before and after the adoption of that technology. Its value gets realized when the benefit of using it exceed the cost. The value of VRA is ambiguous among different kinds of crops and different kinds of input combinations. Swinton and Lowenberg-DeBoer (1998) stated that VRA is more profitable when crops are of high value or input-intensive. Kempenaar *et al*. (2018) concluded that the investment in VRNA in potato production in the Netherlands will payoff under practical conditions. Maine *et al*. (2010) stated VRNA in corn production yields modestly more profit than URNA; Anselin *et al*. (2004) founded that VRNA can hardly break-even; Lowenberg-DeBoer *et al*. (2008) said that the VRA of nitrogen and phosphorus has an insignificant improvement in profit margin compared to URA. The degree of spatial variability also influences the profitability of VRA. Roberts *et al*. (2004) stated that applying inputs according to soil needs using PA technologies might lead to an increase in input-use efficiency in fields with extensive variability. However, previous research always ignored the influence of people in VRA. The research regarding the profitability of VRA does not separately discuss the influence of human decisions from the influences caused by other factors. The value of VRA does not solely depend on its capability to accomplish the context of site-specific input management but also depends on the people who use the technology. Kachanoski and Miller (1992) said that "the technical ability to vary management within the field will be presented, the important missing link in the knowledge base to decide what kind of management should be done at each point in the field". VRA involves human decisions in every step toward the

operation. Different strategies on delineating management zones and creating prescriptions will lead to completely different results. The payoff of VRA could be different from farmer to farmer, even when other factors are assumed to the same. It is possible that, for VRA, the knowledge base still has not caught up with the technology.

2.2 Value of information in variable rate application

The Big Data/information involved in variable rate application affects its value. The amount of information that farmers use could reduce uncertainty, thereby determining the value of the information. Under the scenario of perfect information, farmers will know all the possible situations they may face. There will be no uncertainty since everything is predictable and controllable; therefore, farmers can optimize their choice to maximize the return. In the real world, perfect information is challenging to achieve. Conditions of uncertainty will reduce the expected result. Input management decisions made by farmers take place under conditions of uncertainty. Farmers normally rely on their own experiences or others' suggestions when facing input management problems. In this context, the level of information involved in input management is limited. Limited information reflects a higher degree of uncertainty. Isik and Khanna (2002) stated that the payoff for farmers using variable rate nitrogen applications will increase as the degree of uncertainty decreases. Farmers could choose to gather additional information if the expected outcome can be improved. The additional information will only have value when it is likely to alter the original decision. A posterior decision given additional information might lead to a different outcome compare with a prior arrangement with limit information. The production decisions made by farmers with different levels of information, including no information, little information, and perfect information, could be compared. Information value can be calculated as the difference between the returns of a farmer after he

receives additional information and returns before he receives additional information. The difference in returns indicates the marginal value of information. The improvement in outcomes is not always positive which indicates the value of information could be negative. Information gathering requires investment of money and time. By the time the information is obtained, the situation may have changed, which make the information useless, and the cost of collecting information will not be recovered. In the context of variable rate nitrogen application in corn production, the value of site-specific information can be showed as the difference between the payoffs under different levels of information. If the price of corn is P_c, the price of nitrogen fertilizer is P_n, and all other costs are generalized to 0, the payoff of a traditional uniform rate application is:

$$\pi = \sum_{i=1}^{i}[P_c f(N_i, Z_i) - P_n N_i] \quad [1]$$

The yield response function f can have different curvature and shape under different levels of information. i refers to the management zones within the field, and it is equals to 1 under uniform rate application. When a farmer has access to perfect information and applies N at an economically optimum rate, N_i^*, the payoff, π^*, is maximized. However, in general, it is not attainable because access perfect information is impossible. Assuming the cost of access to information is C. The intrinsic value of information V_t is:

$$V_t = \pi^* - \pi - C \quad [2]$$

This is the theoretical value of information assuming a farmer can transfer one hundred percent intrinsic value of information into payoff. Practically, the real value of information that can be observed is less than or equal to the intrinsic value of information. The intrinsic value of information determines its upper limit of value. How the information is used determines the

actual value of information. The situation may happen that the intrinsic value of information is great, but the marginal value of information is zero or negative.

Suppose a farmer collects site-specific information and uses variable rate nitrogen application in corn production. The payoff is:

$$\pi_s = \sum_{i=1}^{i}[P_c f(N_{i,} Z_i) - P_n N_i] \quad [3]$$

where i is greater than one since there is more than one management zone within the field, Z is a vector of factors that influence the yield. The value of site-specific information is the difference between π and π_s minus the cost of collecting site-specific information. The maximum value of site-specific information is achieved under the scenario of perfect site-specific information. It is the difference between π and π_s^* less the cost of perfect information. In general, it is hard to capture the maximum value of site-specific information, but the value of site-specific information under certain levels of information can be found through comparing the payoffs between variable rate application and uniform rate application. The difference in payoff indicates the actual value of information extracted.

2.3 Summary

In the context of modern agriculture, collecting data and information becomes a common practice. The accumulation of historical and real-time information helps farmers to increase production efficiency and to improve farming payoffs. Big Data plays an important role in different precision agriculture applications. Variable-rate technology, an example of an information-intensive precision agriculture technology, relies on spatial and temporal information to achieve site-specific input management. The value of variable rate technology and variable rate applications depends on the amount and quality of site-specific information being

used. The value of site-specific information can be observed by comparing the payoff under variable rate application and the payoff under uniform rate application at a certain level of information. In chapter 3, a case study was conducted to measure the value of information via evaluating the profitability of variable rate nitrogen application in corn production.

3 Financial Feasibility of Uniform vs Variable Rate Nitrogen Application in Corn Production

3.1 Introduction

While several considerations are part of the decision to adopt any new technology by agricultural producers, increased profitability is one of the major determinants (Larson *et al*. 2008, Miller *et al.* 2017, Watcharaanantapong *et al*. 2014). There are significant differences in the adoption rates of precision agriculture technologies suggesting that there are differences in their profitability. For example, several surveys have found crop producers have been quick to use GPS technologies such as auto-steer and yield monitors but the uptake of variable rate technologies (VRT) lags (Schimmelpfennig and Ebel. & 2016; Erickson *et al*. 2017; Griffin *et al*. 2017; and Mitchell *et al*. 2018).

The low adoption rate for VRT is inconsistent with the perception of the value of its ability to tailor input application to match differing needs across a field (Larson *et al*. 2008). Fields often have large degrees of heterogeneity and VRT provides the ability to observe this variability and to match inputs accordingly. Mechanization, hybrid seeds and low-cost fertilizer all led to an evolution since WWII in which entire farms were treated as a single unit and managed uniformly (Sonka, 2016). In contrast, VRT allows for much smaller-scale management. The use of VRT is of particular interest for nitrogen fertilizer in crop production since, in contrast to the use of a single rate across the whole field, it can increase yields in areas that are under-fertilized and can avoid crop damage and reduce excess nutrient loadings in areas that are over-fertilized. However, the value of being able to adjust the fertilizer rate spatially must be able to cover the cost of VRT to encourage its widespread adoption.

The additional value from variable rate nitrogen application (VRNA) has been questioned by Pannell (2006) who finds that there is a large range of fertilizer application that result in a similar payoff so the cost of under or over applying is small. In a specific profitability comparison, Ferguson *et al.* (2002) found neither uniform rate nitrogen application nor variable rate nitrogen application had consistently higher yields. However, Koch *et al.* (2004) found VRNA increased per acre profit by $18.21 to $29.57 compared to the traditional uniform application (URNA) method. Anselin *et al.* (2004) also found ex post higher profit from VRNA but the profits changed greatly depending on the simulation model used. Similarly, Basso *et al.* (2016) found, using a validated crop simulation, higher profit and lower fertilizer use per acre could be achieved with a VRNA compared to an URNA rate. However, Boyer *et al.* (2011) studied VRA using on board sensors to detect N requirements but did not find VRNA to enhance profits relative to a homogeneous rate. The findings of profitability are ambiguous and often rely on simulated models.

The issue of spatial autocorrelation was always mentioned in the previous VRA research. An important driver of using spatial econometric techniques is the need to handle spatial data. This has been simulated by the widespread of geographic information systems (GIS) and the availability of geocoded data (Anselin, 2001). The presence of spatial autocorrelation is commonplace in geographic (cross-sectional) datasets which contain the location of the observations. The spatial autocorrelation effect that typically ignored by traditional econometrics are important in applied econometric analysis (Anselin, 1988). Ignoring the spatial autocorrelation will make OLS estimates inefficient and will biased the standard errors, t-test statistics and measure of fit (Anselin, 1988). Fail to properly incorporate the spatial structure of the data will influence the estimation of yield response function as well as profitability analysis

(Anselin *et al*. 2004). Hurley *et al.* (2005); Anselin *et al*. (2007); and Maine *et al.* (2009) also stated the potential problem that might caused by spatial autocorrelation when applying OLS regression and suggested the use of spatial models in yield response function estimation. The motivation of using spatial models in this thesis includes (1) accounts the effect of spatial autocorrelation in order to yield more efficient estimates; (2) focuses on measuring and comparing the difference in profitability analysis results between the OLS model and spatial modes based on partial budgeting. The relationship between data grid size and the presence of spatial autocorrelation will also be examined.

The purpose of this paper is to compare the returns of variable rate nitrogen application (VRNA) on corn with the traditional uniform rate system (URNA). This study uses a unique field-level dataset from a farm in Ontario, Canada. This data is used to calculate specific yield response functions given different fertilizer strategies on the same field, that are then used to simulate the profit of VRNA versus URNA. The paper begins by explaining the framework used to calculate profit, this is followed by an examination of the data and the estimation of the yield response functions using different statistical models. The paper closes with the results of the simulation and then a discussion of the implications of the results.

3.2 Conceptual model

The financial feasibility of variable rate nitrogen application (VRNA) on corn is evaluated by comparing its payoff to the returns with the uniform rate nitrogen (URNA). The comparison assumes that the ex-post profit maximizing rate is applied in both approaches and this section defines that rate.

A general payoff for zone i per unit of land area (π_i) from applying nitrogen at a rate of N_i is

$$\pi_i = P_Y\ F_i\ (N_i, Z_i) - P_N\ N_i \qquad i=1,2, \ldots K \qquad [1]$$

where P_Y is the price of the crop per metric ton, $F_i(N_i,)$ is the yield response function relating the nitrogen application rate to the quantity of crop produced per unit of land area ($Y_i = F_i\ (N_i, Z_i)$), Z_i is a vector of geophysical characteristics of area i such as organic matter content, P_N is the unit price of nitrogen, and K is the total number of distinct land regions or management zones. At this stage, nitrogen application costs of the different management systems are not considered as these will influence the financial feasibility of the alternative application methods but not the optimal application rate of nitrogen fertilizer.

The optimal rate of nitrogen within a given management zone, N^*_i, maximizes the payoff function given by [1] for that zone. The maximum payoff occurs where the marginal value product of nitrogen is equal to the price of nitrogen or

$$P_Y\ (\partial F_i(N_i, Z_i))/\ \partial N_i) = P_N \qquad i=1,2, \ldots K \qquad [2]$$

The optimal rate N^*_i for each site i is found by solving the above first order condition explicitly for N using the yield response function for that zone ($F_i(N_i, Z_i)$). The optimal uniform rate, $N^{U}*$, is based on a yield response function for the whole field, $F(N,Z)$, rather than for each individual management zone.

The profit maximizing rate for URNA, $N^{U}*$, and rates for each zone i in the VRNA, N^*_i, are inserted into the payoff for each zone given by [1]. The actual payoff to applying the optimal uniform rate of $N^{U}*$ within each region when each zone potentially can have a different yield function is thus

$$\pi_i^{U}* = P_Y\ F_i\ (N^{U}*, Z_i) - P_N\, N^{U}* \qquad i=1,2, \ldots K, \qquad [3]$$

whereas the value of the payoff from applying the optimal rate in each region i is

$$\pi_i{}^* = P_Y\ F_i\,(N^*_i, Z_i) - P_N\ N^*_i \qquad i=1,2,\ldots K \qquad [4]$$

The whole field has an area A_T, which is the sum of the area of the K individual zones within the field. The share of the field in management zone, i, as denoted by, S_i, is thus the area of zone (A_i) divided by the total area in the field, $S_i = A_i/A_T$. The total profit per area for the field (π) is found by adding the profit for each management zone of the field, which is the profit per area given by [1] multiplied by the share of the area in that zone (S_i).

$$\pi^* = \pi_1 \times S_1 + \pi_2 \times S_2 + \ldots + \pi_K \times S_K \qquad [5]$$

Substituting the payoffs to each management zone under URNA from [3] and VRNA from [4] into [5], results in the payoff to the whole field from each strategy.

It is hypothesized that the payoff from VRNA using the optimal rate of N in each zone, π^*, is greater than using the optimal uniform rate across the field, $\pi^{U}*$. The benefits of adjusting input rates spatially arise because different parts of a field have different payoff functions, resulting in different optimal input rates. While π^* may be greater than $\pi^{U}*$, it must cover the difference in application costs for VRNA to be financially feasible compared to URNA.

In addition to ex post optimal rates and corresponding payoffs to variable and uniform application methods, the returns are also compared to ex ante rates. One is the rate recommended by the Ontario Ministry of Agriculture Food and Rural Affairs through its N calculator, which is based on yield potential and prices. The other is the actual rate used by the farmer in the field trial.

3.2.1 Data

The data used in this study were collected by the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) and Niagara College. The purpose of the project was to study

zone prescription and the profitability of variable rate application of seed for corn, soybeans and wheat, and the variable application of nitrogen fertilizer on corn and wheat. The data is based on the actual rates and VRA methods used by farmers on their normal scaled fields. This contrasts with other studies employing field trial plots (Ferguson, 2002) or simulations based on experimental data (Basso, 2016).

Data from a farm near Exeter, Ontario are used for the analysis in this study based on the quality of the collected information. The field is 32.4 hectares and made up of Perth Clay Loam, Huron Clay Loam, and Harriston Silt Loam soils. The average organic matter for the field was 3.7% with a standard deviation of 0.9. Average phosphorus and potassium levels were 30.3 ppm and 134 ppm respectively, so these nutrients were not limiting. Information on Soil Electrical Conductivity (SEC), which is an indicator of soil health, was also collected. It was distributed normally in the field (see Figure 1) with a range from 4 to 26.

There are several different data layers collected on the field and the unit size differed across the attribute being measured. The raw dataset layers are illustrated in Figure 2 for corn yield (upper right), N applied (upper left), soil properties (lower left). The number of observations in each data layer is different since the data in each layer was collected and recorded by a different method and by different equipment. The data in each layer was interpolated into uniform size grids (4m x 4m) using inverse distance weighting. Inverse distance weighting assumes things that are close to one another are more alike than those that are further apart. New observations for the unmeasured location were predicted using the measured values surrounding the unmeasured location. The processed data after interpolation contain 11,360 observations in each layer, which are illustrated in Figure 3. The three blank lines on the geo-maps in figure 3 are the observations that have a nitrogen target rate equal to zero. These

observations are removed from the dataset during data processing. This action will influence the estimation of the yield response function, especially for the downside, but will not affect the reliability of estimation since the number of observations remaining are abundant. An additional dataset was prepared at a larger spatial scale (20m x 20m), to address issues surrounding the size of the data cell. This dataset has the same data layers as the 4 meters by 4 meters dataset, but the total number of data points are at 458.

3.2.1.1 Management zones

The management zones in a field receiving individual treatment can be delineated using different criterion including yield, soil type, and/or topography. The farmers in this study used yield to define management zones. Previous years' yield data are converted into a yield performance index (YPI). Farmers use the YPI to create prescription maps of nitrogen fertilizer application for each management zone. The YPI for a management unit is found by comparing the annual average yield for the whole field to the yield for that management unit. If that management unit obtains a yield that is higher than the annual average yield for the whole field, its YPI will increase by 1.

The Exeter field has 7 years of historical yield data, which means the YPI for each management unit could range from 0 to 7. The field was delineated into three management zones on the basis of the following criterion: (1) a YPI between 0-3 was the low zone; (2) a YPI between 4-5 was the medium zone; (3) a YPI between 6-7 was the high zone. The amount of nitrogen applied increased with the yield potential of the management zone.

3.2.1.2 Yield

Corn yield was measured and recorded by the commercial yield monitor on the combine. Yield data points, shown in Figure 1, were recorded roughly every 30-40 feet (9-12m) depending on the speed of the tractor and given the width of the combine is approximately 20 feet meters, each yield observation point is around 650 square feet. Yield is reported as dry yield and yield data was corrected to 14.5% corn grain moisture. Average corn yield (14.5% moisture) was 13,988 kilograms per hectare (208 bushels per acre) with a standard deviation of 1,676 kg/ha. Yields in the 4m by 4 m grids ranged from 3,766 to 20,108 kilograms per hectare (56 to 299 bushels per acre). The distribution of the corn yield is illustrated in the upper quadrant of Figure 1 and indicates that yield is negatively skewed, but yield is relatively homogeneous for this field.

3.2.1.3 Nitrogen rate

There were two data layers associated with nitrogen: target rate set by the farmer and the actual rate recorded by the application equipment. A base amount of N (34 kg/ha) was applied uniformly to the whole field at planting and the remainder applied via side dressing in June.

The dataset recorded both actual and target fertilizer application rates reported by the application equipment. The averaged targeted rates were 112 kg/ha (24 gallons per acre) for the low zone, 146 kg/ha (31 gallons per acre) for the medium zone, and 185 kg/ha (37 gallons per acre) for the high management zone. The distribution of the target rates and the three peaks are illustrated in the lower left panel of Figure 3. The reason that the target rates are not illustrated simply as three vertical lines is that the interpolation process creates more grid cells that fall in between the original management units. These new grid cells have a target rate that is the weighted average of adjacent grid cells. For example, an interpolated grid cell that locates

between two grid cells with a target rate of 30 gallons per acre and a target rate of 40 gallons per acre will receive a target rate of 35 gallons per acre.

The distribution of the actual nitrogen application rate is illustrated in Figure 3. The distribution has a similar shape with the distribution of the target nitrogen rate, though the third peak is slightly sharper than the one indicated in the target nitrogen rate distribution. The correlation between the target nitrogen rate and the actual nitrogen rate is 0.88

3.2.1.4 Soil electrical conductivity

Soil Electrical Conductivity (SEC) is a potential indicator of soil health that affects the availability of plant nutrients, moisture and crop yield. SEC has been used to measure a list of soil properties including salt concentration, organic matter, cation-exchange capacity, soil texture, soil thickness, nutrients, and water-holding capacity (USDA, 2011). For this case study, a Dual EM instrument was used to measure the ability of the soil to conduct electricity. A low EC score indicates that the amount of moisture held by soil particles is low, which means the soil is sandy. Silt soil has a higher conductivity than sandy soil, and clay soil has a higher conductivity than silt soil. Average SEC was 14.4 with a range from 4 to 26. SEC was distributed normally as illustrated in the upper right panel of Figure 3. According to the distribution in Figure 3, the soil texture has little variation since few observations locate at the tails of the distribution. The SEC in this dataset can be considered unitless and a relative variation in soil electrical conductivity, which is often a proxy for soil texture.

3.3 Empirical Model

3.3.1 Yield response function

Measuring the returns to nitrogen management strategies requires estimating the yield response functions for the whole field and management zones based on data provided by the farmer. A quadratic functional form is used for each scenario based on a review of alternative corn yield response functions to nitrogen by Cerrato and Blackmer (1990). A single yield-maximizing nitrogen rate for each management zone can be calculated with the quadratic functional form, and this rate can be used for validation and comparison purposes. It has also been used by other Ontario studies examining the response of corn yield to nitrogen (Cabas *et al.* 2010; Gandorfer and Rajsic 2008; Rajsic and Weersink 2008).

The whole-field quadratic yield response function estimated is

$$Y = \beta_0 + \beta_1 N + \beta_2 N^2 + \beta_3 \text{SEC} + \beta_4 Z_l + \beta_5 Z_h + \varepsilon \qquad [6]$$

where *Y* is corn yield in kg per ha, *N* is the amount of nitrogen in kg per ha, *SEC* is the soil electrical conductivity index, Z is the management zone of the observation (l=low and h=high), and β's are the estimated parameters. The profit maximizing rate associate with this response function is

$$N^{U}* = [(P_N/P_Y) - \beta_1]\ (1/2*\beta_2) \qquad [7]$$

It is a single rate for the whole field and yield can vary across the field even with the single rate through differences in the SEC and management zones, by location.

The site-specific yield response function given by [8] has a similar form to the whole field function [6] but includes linear and quadratic interaction terms between management zone dummies and nitrogen

$$Y = \beta_0 + \beta_1 N + \beta_2 N^2 + \beta_3 \text{SEC} + \beta_4 Z_l + \beta_5 Z_h + \beta_6 N Z_l + \beta_7 N Z_h + \beta_8 (N Z_l)^2 + \beta_9 (N Z_h)^2 \qquad [8]$$

The optimal nitrogen rate for each zone is thus

$$N_i^* = \frac{\frac{P_N}{P_Y} - \beta_1 - \beta_6}{2(\beta_2 + \beta_8)} \text{ for low,}$$

$$N_m^* = \frac{\frac{P_N}{P_Y} - \beta_1}{2\beta_2} \text{ for medium, and}$$

$$N_h^* = \frac{\frac{P_N}{P_Y} - \beta_1 - \beta_7}{2(\beta_2 + \beta_9)} \text{ for high.} \quad [9]$$

3.3.2 Estimation method

The yield response functions are estimated using Ordinary Least Squares (OLS)

$$Y = X\beta + \varepsilon \quad [10]$$

where Y is a $n \times 1$ vector of observations on corn yield, X represents an $n \times k$ matrix of observations on the k explanatory variables (i.e. nitrogen rate, management zone), β is a $k \times 1$ vector of regression coefficients, and ε is the error term with a mean of 0 and a constant variance. The assumption of OLS that that observations of the error term are uncorrelated is often violated when modeling natural resources including the spatial heterogeneity of soil nutrients.

Early studies on site-specific nitrogen management considered the issue of spatial autocorrelation with yield data. Anselin (1988) stated that ignoring the spatial autocorrelation will yield inefficient estimates and will bias the standard errors. Hurley *et al.* (2005) and Maine *et al.* (2009) found spatial econometric models outperformed standard OLS models in estimating site-and-year-specific response functions. Liu *et al*. (2006) and Anselin *et al.* (2007) found the coefficient standard errors were significantly reduced by using spatial models. Since econometric results for the yield response function can differ between non-spatial and spatial models, so too can the economic results, but the impacts vary. Anselin *et al.* (2004) found using

spatial econometrics raised the value of variable rate application, but Maine *et al.* (2009) found the opposite that the OLS model overestimated profit for the variable rate application.

Three most common spatial models are estimated: (1) the spatial autoregressive error model (SEM); (2) the spatial autoregressive lag model (SAR); and (3) the spatial Durbin model. The first two have been used previously in site-specific studies in crop production.

The spatial autoregressive error model (SEM) can be expressed as:

$$Y = X\beta + \varepsilon \qquad \text{with } \varepsilon = \lambda W u + u \qquad [11]$$

where the error term ε is expressed as the sum of an uncorrelated error term u and a spatial lagged error, Wu. The spatial lagged error is a weighted average error in the neighboring area, which, in this study, is determined by the distance between two data points. $\boldsymbol{\lambda}$ is the spatial autoregressive parameter that indicates the degree of spatial dependency between the own error term and neighbouring area's error term.

The spatial autoregressive lag model (SAR), which assumes the spatial autocorrelation is captured by the dependent variable and non-spatial correlation with the error term, can be expressed as:

$$Y = \rho W y + X\beta + \varepsilon \qquad [12]$$

where Wy is the spatial lag term in the dependent variable and ρ is the spatial autoregressive parameter that indicates the degree that the neighbour's value in y influences the own dependent variable's value.

The spatial Durbin model is a mixed spatial autoregressive model that assumes the spatial dependency exists in the dependent variable as well as the explanatory variables. The dependent variable for each region is affected by its own region's factors plus the same weighted average factors from its neighbour regions. A spatial Durbin model can be expressed as:

$$Y = \rho Wy + X\beta + WX\theta + \varepsilon \quad [13]$$

It has a similar structure as the spatial lag model but with the addition of the term $WX\theta$, which describes the exogenous interaction effect caused by explanatory variables in the neighbour area. This model also addresses the issue of omitted variables (Liu, Griffin, & Kirkpatrick, 2014).

All three models can be estimated by either maximum likelihood (ML) or general method of moments (GM). The classic measures of fit, such as R^2, are no longer valid since the regression does not use a linear model so either a maximum log likelihood or an AIC should be used instead (Anselin, 1988).

Two set of tests are used to determine whether a spatial model should be used and to decide which spatial model is more appropriate. The Moran's I test, which was mentioned by Anselin (1988), is the most common test for the existence of spatial autocorrelation. It has the follow structure:

$$\mathrm{I} = \frac{n}{S_0}\frac{x'Wx'}{x'x} \quad [14]$$

where **x** is an $n \times 1$ vector of a random variable, **W** is an $n \times n$ spatial weights matrix, and S_0 is the sum of the elements of **W** (Anselin, 1988). The result of the Moran's I test returns five values: observed Moran I Index, Expected Index, variance, z-score, and p-value. A positive Moran I Index value means the values in the dataset tend to cluster spatially (high values cluster near other high values), while a negative Moran I Index value means high values tend to be near low values. The Moran I Index values are then compared to the expected Index value and the null hypothesis that the data is randomly distributed among the features in the study area.

Although Moran's I test detects the existence of spatial autocorrelation, it does not guide researchers in the selection of the best alternative spatial model. The five Lagrange Multiplier (LM) tests for spatial autocorrelation diagnostics using OLS residuals are conducted to determine

the appropriate spatial model for the regression analysis. The five LM tests include LM error, LM lag, Robust LM error, Robust LM lag, and LM spatial autoregressive moving average (SARMA). The LM test with the lowest p-value between the LM lag and LM error indicates the more appropriate spatial model.

Two spatial weights matrices are considered in this study: (1) Rook shape, and (2) Queen shape. The spatial weights matrix, which is expressed as $\boldsymbol{W}$ in the above spatial models, quantifies the connection between regions. The spatial connection among data points for the two options for $\boldsymbol{W}$ are illustrated in Figure 4. The "Rook" shape matrix, which is shown in the left panel of Figure 4, counts the adjacent four data points as neighbours. In contrast, the "queen" shape matrix, which is illustrated in right panel of Figure 4, counts the adjacent eight data points as a neighbour. Both spatial weights matrices will be used in the estimation to permit a comparison of the regression coefficients under different degrees of spatial dependency.

3.3.3 Simulation of returns

The corresponding yields under different optimal nitrogen rates are computed by inserting the optimal nitrogen rates from equation [7] and [9], into the estimated yield response functions in equation [6] and [8]. Given the price of nitrogen fertilizer and corn, the payoff can be found via inserting the optimal nitrogen rate and its corresponding yield into the payoff function. The payoff for the different nitrogen application strategies are compared, and the results will provide insight into the profitability of variable rate application and the value of information. The payoff for the four different nitrogen application rates is illustrated below:

$$\pi = P_Y Y\ (N_{OMAFRA}, Z) - P_N N_{OMAFRA} \quad [15]$$

$$\pi_{actual} = P_Y Y\ (N_{actual}, Z) - P_N N_{actual} \quad [16]$$

$$\pi^*_{URA} = P_Y Y\ (N^*_U, Z) - P_N N^*_U \quad [17]$$

$$\pi^*_{VRA} = \sum_{i=1} P_Y Y_i\,(N_i^*, Z_i) - P_N N_i^* \qquad i = l, m, h \qquad [18]$$

Equation [15] shows the payoff when the nitrogen application rate is derived from the OMAFRA nitrogen calculator. Equation [16] shows the payoff under the actual nitrogen application rate. Equation [17] shows the payoff when applied at an optimal uniform nitrogen rate. Equation [18] shows the aggregate payoff when an optimal nitrogen rate is applied in each management zone. The hypothesis is that the return should be:

$$\pi^*_{VRA} > \pi_{actual} > \pi^*_{URA} > \pi_{OMAFRA}$$

3.3.4 Sensitivity analysis

The payoff for each application approach is influenced by the price assumptions of nitrogen fertilizer and corn. The size of the difference in payoff between uniform rate application and variable rate application will change as the price assumptions change. Thus, sensitivity analyses are essential for monitoring the change in payoff among different approaches under different nitrogen fertilizer prices and corn prices.

3.4 Results

3.4.1 Yield response under OLS model

The regression results of the whole-field and site-specific yield response functions are reported Table 1. The overall fit, as measured by the adjusted R^2 of 0.4 for both models, is good considering the cross-sectional nature of the data. The signs of the regression coefficients are generally as expected and are statistically significant. For the whole-field response function, increases in nitrogen rate increase corn yield, but at a decreasing rate, as illustrated in Figure 6 with yield maximized at 13481 kg per hectare for an application rate of 184.74 kg per hectare. Higher SEC (salinity) levels have a negative effect on yield also as expected. All else constant in

the whole field model, yields are 12.3 bushels per acre lower (11.3 bushels per acre higher) in the low (high) management zone compared to the medium management zone.

The impact of nitrogen on corn yield in the site-specific response function is illustrated, by management zone, in Figure 6. Increases in nitrogen increase corn yield at a decreasing rate but the impact varies by management zone. Yield is maximized at 12,097 kg per hectare at a N rate of 157.1 kg per hectare in the low zone, 13,879 kg per hectare at a N rate of 181 kg per hectare in medium zone, and 14,157 kg per hectare at a N rate of 197.3 kg per hectare in the high zone.

Yield is more responsive to nitrogen in the medium zone than either of the two other regions (Figure 6). The output elasticity of nitrogen, which is the percentage change in yield for a 1% change in the nitrogen rate, is 0.40 in the medium zone at an application rate of 100 lbs per acre. In contrast, it is only 0.13 in the low management zone and 0.17 in the high management zone. The output elasticity of nitrogen for the whole field is 0.22, which is close to a weighted average of the three management zones. Besides the output elasticity of input, the Input Range 95 indicator can be used to measure the flatness of a function. This technique measures the range of input levels for which of the payoff is at least 95% as large as the maximum payoff (Pannell, Gandorfer & Weersink, 2019). The indicator has the follow structure:

$$IR95 = \frac{x_u - x_d}{x^*} \qquad [19]$$

Where IR95 stands for the Input Range 95, x_u is the upper limit of the range of inputs levels that has a payoff of 95 percent of maximum payoff, x_d is the downside limit of the range, and x^* is the input level where the payoff is maximized (Pannell, Gandorfer & Weersink, 2019). Figure 7 shows an example of how the IR 95 works. The flatter the payoff function, the greater the distance between x_u and x_d, and the greater the IR95 score.

Scaling up the yield response function using the input and output prices will get the corresponding payoff function. The whole field payoff function has an IR95 of 0.699, meaning that the range of input rates that leads to profits at least 95% of the optimal uniform rate is around 69.9%. The payoff function for low zone has an IR95 of 0.884; the payoff function for medium zone has an IR95 of 0.456; the payoff function for high zone has an IR95 of 0.898. The IR95 results are consistent with the results of the output elasticity of inputs. The medium zone payoff function has the greatest curvature, while the high zone payoff function is the flattest one. The relatively flat response functions for the two extreme management zones and for the whole field have implications for the financial feasibility of VRA as discussed later in section 3.5.

3.4.2 Yield response under spatial models

The null hypothesis of no spatial correlation in the residuals of the OLS regression are rejected for both the whole field and site-specific yield response functions with either of the two spatial weight matrices according to the Moran's I test as reported in Table 2. The five LM tests used to determine which of the two spatial weighting matrices to use with each of the three spatial models are reported in Table 3. The results suggest that any of the spatial models will increase the fit compared to a classic OLS model. Thus, all three spatial models are estimated, and their AIC compared to determine which model's regression coefficients are to be used for the economic analysis.

The regression coefficients for the whole-field yield response function under the three spatial models are given in Table 4. Spatial coefficients ρ and λ measure the strength of spatial dependency. They have the same sign, are of a similar magnitude, and statistically significant across all three models suggesting the spatial dependency is strong and positive. The magnitude

of spatial dependency is relatively smaller under a “Rook” shape matrix compared to a “Queen” shape spatial weights matrix.

The signs of the regression coefficients associated with the N rate in the three spatial models are all opposite to what appears in the standard OLS model, but most are generally statistically insignificant. However, among the three spatial models, only the coefficients for the spatial autoregressive error (SEM) model can be interpreted as the marginal effect of explanatory variables on yield in the same way as the OLS regression estimates. The interpretations of the parameter estimates in the spatial autoregressive lag model (SAR) or spatial Durbin model (Durbin) are different from a conventional least squares interpretation (Pace and LeSage, 2014). Any change to the explanatory variable in a single observation can affect the yield in its own region as well as its neighbouring regions. The spatial spillover will pass through the neighbour regions and back to its own region.

The direct, indirect, and total marginal effect of the explanatory variables as developed by Pace and LeSage (2014) are presented in Table 5 for the spatial autoregressive lag (SAR) model and spatial Durbin model. Nitrogen fertilizer in the SAR model continues to have the opposite impact as expected on yield (decreases yield at an increasing rate), but the magnitude of the impact is much smaller. In contrast, the total marginal effect of the main variables in the spatial Durbin model shows the same signs as the OLS model. Regardless of the spatial weighting matrix, the indirect effect represents a much larger share of the total marginal effect than the direct effect. Yield is influenced more by the yield (dependent variable) as well as nitrogen and other factors (explanatory variables) at neighbouring regions than from those factors at its own location. In contrast to the “Queen” shape, the sign of the regression coefficients for the whole-field yield response function under the three spatial models with Rook

spatial weighting matrix are the same as in the OLS model, although not generally significant. Compared to the OLS coefficients, the estimated impacts of the nitrogen variables are smaller for both the spatial lag and spatial Durbin models with the Rook shape matrix but only slightly so for the latter model.

The estimated coefficients for the site-specific yield response function under the three spatial models assuming a "Queen" and a "Rook" shape spatial weights matrix are listed in Table 6. All three models fit the data better compared to the OLS model based on their lower AIC value. In contrast to the results for the whole field response function, the signs of the main regression coefficients for the site-specific functions are the same as in the OLS model for both weighting matrices except for the last column in Table 6. The main coefficients for the spatial Durbin model with a queen shape weighting matrix has the reverse signs. The magnitude of the total marginal effect of the explanatory variables tends to be larger for the spatial lag and spatial Durbin models compared to the OLS for both the Queen shape and Rook shape spatial weighting matrices (Table 7). As for the whole field estimates, the indirect marginal effects are much larger than the direct impacts.

There are several implications from the results of the spatial analysis as compared to the OLS results. First, when an observation has more "neighbours", the level of spatial dependency is higher. The spatial parameters are always higher under a "Queen" shape compared to under a "Rook" shape spatial weights matrix for all three spatial models. This finding confirms the existence of spatial autocorrelation. The spatial dependency under two different spatial weights matrix would be very close if each observation is spatially independent.

Second, when spatial autocorrelation is captured by either only the dependent variable or only the error term, while at the same time the spatial dependency is high, the marginal effect of

nitrogen on yield is close to zero, since an observation's yield is either heavily affected by neighbours' yield or by neighbours' residual. However, if the spatial autocorrelation is also captured by explanatory variable(s), the marginal effect of nitrogen on yield is similar to that from the OLS model. The total marginal effect of nitrogen on yield under the spatial autoregressive lag model is smaller than what appears under the spatial Durbin model, but the latter results are like those from OLS.

Third, the shape of the yield response function changes as the degree of spatial dependency changes. Figure 6 shows the whole-field and site-specific yield response curves estimated using coefficients from three spatial models with two weighting matrices. The whole-field and site-specific yield response functions have a typical concave shape when there is no spatial dependency. Figure 6 shows the typical shape of a yield response curve. When the degree of spatial dependency is around 0.8 as estimated by the Rook shaped spatial weighting matrix, the yield response curves on the left side of figure 8 remain a concave shape except for the yield curve for the high zone in the SAR model. But its shape becomes convex as the spatial dependency increases beyond 0.9 for the Queen shaped matrix. On the right side of the figure 8, more yield curves turn into a convex shape.

The marginal effect of nitrogen on yield is overridden by the marginal effect of the neighbour region's yield under the SAR model. Similar effects happen under SEM and the spatial Durbin model. The marginal effect is overridden by the effect of the neighbour region's residuals in the SEM model; and the marginal effect is overridden by the effect of the neighbour region's yield and explanatory variables. Overall, when the spatial dependency increases, the marginal effects of the main variables in the own region becomes weaker.

Since R^2 is no longer an available measure of the goodness of fit for spatial models, it can not used to compare the model fit among the OLS and the spatial models. Akaike (1974) introduced AIC that is designed to pick the model that produces a probability distribution with the smallest discrepancy from the true distribution. All three spatial models show better fit compared to the OLS model as their AIC is smaller than OLS's AIC. Among the three spatial models, the spatial Durbin model has the best model fit since it has the lowest AIC. Comparing the model fit between spatial weighting matrices, regressions with queen shape weighting matrices always have the better model fit.

3.4.3 Simulated nitrogen rates

The simulated nitrogen application rates and associated yield under different application approaches are reported in Table 8. The optimal nitrogen rates are found for the uniform-rate application as well as the variable-rate application. The N-calculator recommended rate is 187kg per hectare and the associated yield is 13,480 kg per hectare (214 bushels/acre). The optimal uniform rate is 168 kg per hectare and the associated yield is 13,430 kg per hectare (214 bushels/acre). The uniform nitrogen rate that maximized the yield is 185 kg per hectare and the associated yield is 13,481 kg per hectare (215 bushels/acre). The yield difference among these three application rates is very small.

Under the variable rate application approach, the actual nitrogen rate is 94 kg per hectare in low yielding zone, 122 kg per hectare in medium yielding zone, and 147 kg per hectare in high yielding zone. The associated yield for the three zones is 11,216, 12,942, and 14,028 kg per hectare (180, 203, and 222 bushels/acre) in sequence. The optimal nitrogen rate for the low zone is 147 kg per hectare and the associated yield is 12027 kg per hectare (192 bushels/acre). The optimal nitrogen rate for the medium zone is 171 kg per hectare and the associated yield is

13,848 kg per hectare (221 bushels/acre). The optimal nitrogen rate for the high zone is 160 kg per hectare and the associated yield is 14,039 kg per hectare (224 bushels/acre). The optimal nitrogen rate that maximize the payoff for each management zone is higher than the actual applied nitrogen rate, but the difference in yield is relatively small. The optimal uniform nitrogen rate is higher than the optimal rate in the low management zone, but lower than the optimal rate in medium and high management zones. Besides, the nitrogen rate that maximizes the yield in each management zone is higher than the profit maximizing nitrogen rate in each management zone.

Optimal nitrogen rates are also simulated under three spatial models with two weighting matrices. The fifth column of the Table 9 shows the simulated rates under different decision rules. Since some of the estimated yield response curves have a convex shape, the simulation of optimal nitrogen rates that maximize the payoff lead to some corner solutions. A "zero" optimal nitrogen rate indicates that adding more nitrogen decreases the payoff since it decreases the yield. Among the simulated nitrogen rates, the spatial error model (SEM) with a Rook shape weighting matrix provides the most reasonable results that the whole-field optimal nitrogen rate is somewhere between the optimal nitrogen rates for the three management zones. All other combinations of spatial models and weighting matrices have at least one zero optimal nitrogen rate.

The total amount of nitrogen fertilizer used under different nitrogen application rates is calculated under the OLS and the spatial models. The fifth column of Table 10 shows the total nitrogen use under different application strategies, simulated using OLS coefficients. Among the four application rates, the actual variable-rate scenario leads to the least use of nitrogen fertilizer, while the yield maximizing variable-rate scenario leads to the most use of nitrogen fertilizer.

Besides, less nitrogen fertilizer is used under the optimal variable rate scenario compared to optimal uniform rate scenario. It is consistent with the results found by Kempenaar *et al* (2018), where variable rate application has a nitrogen reduction effect compared to uniform rate application. They argued that variable rate application reduced pesticide and nitrogen fertilizer use by 25% in potato production, in the Netherlands.

The fifth column of Table 11 shows the total nitrogen use under different application strategies, simulated using the spatial models' coefficients. Among all combinations of spatial models and weighting matrices, only the simulated total nitrogen rate under the spatial error model (SEM) with a Rook shape weighting matrix confirmed the nitrogen reduction effect for variable rate nitrogen application. Since all other combinations have at least one "zero" nitrogen application rate, the total nitrogen use does not make sense from an agronomic sense.

3.4.4 Simulated payoff under OLS model

Payoffs under different nitrogen rates are shown in Table 10. Payoffs are calculated on a per hectare base. The ranking of the payoff performance under the four application strategies (π^*_{VRA}, π_{actual}, π^*_{URA}, π_{OMAFRA}) is as expected. Among all nitrogen rates, the nitrogen rate recommended by the N calculator has the worse payoff at around $1,011 per hectare, and the optimal variable rate has the best payoff at around $1,221 per hectare. The optimal uniform rate yields a payoff around $1,140 per hectare, which is about $129 better than the payoff under the nitrogen rate suggested by the N calculator. The payoff under the actual variable rate is higher than the payoff under the uniform rate suggested by the N calculator. This indicates that the actual site-specific nitrogen management in the field trial leads to a better payoff than a traditional uniform rate. The difference in payoff between the optimal uniform rate and the optimal variable rate is at around $80 per hectare. In this sense, the improvement in payoff for

site-specific application compared to a uniform application is around 7%. This finding is consistent with the results found by Anselin *et al*. (2004) and Maine *et al*. (2009). Despite the positive improvement in payoff under variable rate application, the size of the improvement is small. The financial feasibility of variable rate nitrogen application is uncertain in general as it might influence by other factors such as farm size, cost of equipment, and externalities.

3.4.5 Simulated payoff under spatial models

Table 11 shows the simulated optimal payoffs under different decision rules using coefficient estimates from spatial regressions with two weighting matrices. Among all the simulated results, only the spatial error model (SEM) with a Rook shape weighting matrix has results close to the simulated payoff corresponding to the OLS model. The optimal payoff under uniform rate application is $889.12 per hectare and the optimal payoff under variable rate application is at $970.13 per hectare. The difference in payoff is $81 per hectare. This is consistent with the results in Table 10, although the size of the difference is smaller. The improvement in payoff for site-specific application compared to a uniform application is around 9%. Although the spatial Durbin model with a queen shape weighting matrix has the best model fit among all combinations of spatial models and weighting matrices, it might not provide reasonable results from either an economic or an agronomic perspective. The SEM model dose have better statistical measures for goodness-of-fit compared to the OLS model. Besides, it provides reasonable economic results.

3.4.6 Flatness of payoff function

The flatness of the payoff function indicates the size of difference in the payoff when the production decisions are deviated from the optimal case. Pannell (2006) has shown that the

existence of flat payoff functions in agriculture is common. The implication of a flat payoff function is that the value of being precise on input decisions based on the collected information is low. In other words, decision makers always have a wide margin for error in their production decisions.

In this study, a whole-field payoff function is constructed to check whether nitrogen application decisions have a large impact on the overall payoff of corn production. Figure 9 shows the whole-field payoff curve with the vertical axis representing the payoff in dollars per acre, and the horizontal axis representing the amount of nitrogen fertilizer applied in pounds per acre. The two horizontal lines indicate the level of payoff that is 95 percent of the maximum payoff. These two points of the 95% of maximum payoff occur for application rates of around 110 pounds per acre and 173 pounds per acre. Although a 150 pounds per acre nitrogen rate gives the maximum payoff, any rate between 110 (27% less than 150) and 173 (15% greater than 150) and the payoff would be within 5% of the maximum.

This finding indicates that this specific field has a flat payoff function and explains the result that variable-rate nitrogen application is not that much more profitable than the uniform-rate nitrogen application approach. Input rate decisions are less sensitive to the payoff since the response function is smooth rather than sharply curved. The flatness of the function depends on biological, technical, and human factors. The biological characteristics of a field, including soil properties or topographical characteristics, determine the sensitivity of yield to nitrogen fertilizer and its spatial variability. The field analysed is relatively uniform and the value of VRA increases with the extent of the variability in the field. Technical factors such as the quality of information and the accuracy of the prescription map can also influence the potential value of VRA. Human factors involve farmers' risk attitudes and their understanding of the collected

information. Regardless the optimal input suggestion, risk averse farmers tend to apply more than the recommend rate (Rajsic and Weersink, 2009).

3.4.7 Sensitivity analysis

Aside from the factors that lead to a flat payoff function, input and output prices also affect the financial feasibility of variable rate nitrogen application in corn production. The lower the corn price, the lower the optimal rate of application, whereas the higher the corn price, the greater the value of output generated from a unit of fertilizer and the greater the application rate. Thus, a sensitivity analysis was conducted to determine the influence of relative prices on the financial viability of variable rate nitrogen application in corn production.

The changes in payoffs under the optimal uniform nitrogen rate and the optimal variable nitrogen rate for a change in corn price are given in Table 12, and for a change in nitrogen fertilizer price in Table 13. As the nitrogen price increases, the returns to both fertilizer management systems decrease as costs go up but the difference in payoffs between URNA and VRNA increases. The value of applying less fertilizer, overall, under VRNA boosts its relative returns. As corn prices increase, variable rate application becomes more profitable. The value of increased yield from more appropriate fertilizer application increases the relative value of VRNA. Though the price of corn and nitrogen fertilizer influences the profitability of variable rate application in the same direction, the change in fertilizer price has a larger impact on the difference in payoff between URNA and VRNA

3.4.8 Testing the issue of spatial autocorrelation at a larger spatial scale

This section explores whether using less points on a larger data scale in regression will overcome the problem of spatial autocorrelation. Data are integrated into 20 meters by 20 meters

size using the 4 meters by 4 meters dataset. The number of data points decreases to 458. Whole-field and site-specific yield response functions were estimated using the integrated dataset.

Table 14 shows the regression results for whole-field and site-specific yield response functions for the two different grid size patterns. The main coefficients for the whole-field yield response function have the inverse signs compared to what is shown when the 4 meters by 4 meters dataset is used. The whole-field yield response function, as well as the site-specific yield response function for the low and medium zones have a convex shape as opposed to the expected concave response function. In addition, the main coefficients, regardless of which function, are not statistically significant.

A Moran's I test is used to check whether there is spatial autocorrelation in the residual of the OLS regression. Table 15 shows that regardless of which spatial weighting matrices are used, the null hypothesis that there is no spatial autocorrelation in the residual of the OLS regression is rejected for both whole-field and site-specific regression. The analysis indicates that the issue of spatial autocorrelation will not disappear at a larger data scale. However, collecting finer data points makes the estimation of the yield response function more stable and reliable. The value of information is reflected in the way of more reliable estimation of the yield function. Also, more information will help farmers to have a better understanding of their field and help them to reap the benefit of VRA.

3.5 Discussion and Conclusions

Based on the results obtained in this case study, variable rate application yields small additional financial benefits compared to the uniform rate application, which is consistent with the majority of the literature. The outcome of using variable rate application is always varied due to the uniqueness of farm characteristics, geographical and biological factors. These factors

cause the nonuniformity in crop yield across farms. Thus, the result of a sole regional case study is unlikely to provide sufficient evidence about the financial feasibility of VRA. More farm-level studies are necessary, along with an assessment of the factors that determine relative profitability to make a more general assessment.

Aside from the degree of spatial variability and prices, there are other factors which are not fully considered in this study that could also affect the profitability of variable rate application and lead to different conclusions. Thrikawala *et al*. (1999) and Isik and Khanna (2002) claimed that farm size and technology cost have an impact on the profitability of variable rate application. The cost of purchasing variable rate technology equipment and creating prescriptions involve a heavy capital outlay. The average fixed costs of the technology can be lowered by increasing the size of the number of acres on which VRA would be used and thus its relative net payoff. Larger farms can achieve these economies of size. The greater the area on which variable rate application is used, the larger the margin between the payoff of the two application strategies (Maine *et al*., 2009). However, variable rate application will become more profitable and feasible as the technology and prescription services become more affordable.

The result of this study also suggests that variable rate application has environmental benefits since less nitrogen was used in corn production compared to a uniform rate application. The environmental benefit was not included in the partial budget since it is difficult to quantify. If the nitrogen reduction effect is consistent across place and across time, from an environmental point of view, there is incentive to adopt the technology even with low incremental profit.

The profitability of variable rate application not only depends on the variable rate technology, but also the on the value of information that is used in the variable rate application. Variable rate application relies on information and data intensively. Spatial and temporal

information are critical for analysis and decision making. They are usually collected from the field or other credible sources such as soil sampling tests or weather stations. The quality of information could influence farmers' strategies and choices in every step of variable rate application. Low quality information could inaccurately reflect the field and weather conditions, and eventually lead to an inferior nitrogen recommendation. This will diminish the economic value of variable rate application.

Statistical or economic analysis could have different results when the amount of information involved in the analysis is different. In this study, all estimations are based on spatial information from a single year, and no temporal information is involved. Ex-post optimal rates were found for each management zone under variable rate application without considering future weather conditions. Thus, using this ex-post optimal rate as the target application rate for each management zone in the following growing season is a doubtful decision. Niemeyer (2019) argued that the estimated yield response function for the same field is different every year, and the differences in yield response are significant when the weather differences are dramatic. The optimal rate corresponding with last year's yield response function might not be the optimal rate for this year. Since temporal variability may dominate spatial variability, including weather information in any estimation is crucial.

The value of information also depends on how farmers act based on the information. Farmers' strategies on every essential step of the variable rate application will make the outcome varied even with the same type of equipment. One crucial step before the actual application is management zone delineation. In this case study, farmers used overlapping yield maps for the previous 7 years as the reference to delineate management zones. Although this approach was used in some previous case studies, no evidence supports that previous yield maps are the best

reference for management zone delineation in variable rate application. Topographical characteristics, such as elevation or landform, or soil physical and chemical properties, such as electrical conductivity, are potential available options with at least equal validity. A variety of approaches were developed for management zone delineation and some of them are not based solely on field characteristics. For example, clustering algorithm approaches based on multiple soil physical and chemical characteristics were developed for management zone delineation (Janrao *et al*. 2019). Variable rate application under different management zone delineation approaches could lead to different input prescriptions and eventually influence the outcome of the application. Besides, the number of management zones that farmers decide to have in the field could influence the outcome as well. A typical three-management zone strategy was used in most of the previous trials or experiments, as in this study. The effect of the number of management zones on variable rate application outcomes was rarely tested in previous studies. This has implications on how input management scale could affect the payoff of the technology. As more approaches are proposed, experiments should be conducted to find out the superior options.

Generating input prescription maps is another essential step before actual application. The way that farmers match input rates to each management zone is heavily dependant on farmers' understanding of variable rate application. In this study, more nitrogen was applied at high yield potential zones, and less was applied at low yield potential zones. Reverse prescription could happen if one tries to lower the yield gap among each management zone. The effect of different prescription types on variable rate application outcomes remains unexplored.

Future research should consider variable rate application as a complex system that involves many human decisions, rather than a simple technology cost-effectiveness problem.

Control groups are necessary for testing the effects of strategies involved in every step of variable rate application on the payoff. The payoff simulation for variable rate application in this study assumed that an optimal nitrogen rate is applied for every management zone. However, practically, it is difficult for farmers to find and apply at the exact optimal rate, and they might be unable to achieve the optimal payoff. Thus, there is a gap between the payoff under the actual and the optimal variable rate. The payoff simulated using the actual variable rate is lower than the payoff simulated using a uniform nitrogen rate suggested by the Nitrogen calculator. Whether variable rate application is still more profitable compared to a uniform rate application when both are applying at a non-optimal condition is questionable. This needs to be checked across time and space. Also, the cost-effectiveness of finding and applying the exact optimal variable rate should be discovered in future research. So far, most research focuses on cost-effectiveness of variable rate technology. Aside from this technology, few have investigated the 'human practice' in the variable rate application. It possible that our current knowledge reserve on nitrogen management is not enough to draw fully out the potential of variable rate application.

4 Conclusion

4.1 Summary

The main purpose this thesis is to evaluate the financial feasibility of variable rate nitrogen application in corn production through comparing the simulated payoff between variable and uniform rate nitrogen application. Some minor objectives include using different models to estimated yield response functions, simulating payoffs using coefficients estimated by different models, and examining the factors that influence the profitability of variable rate nitrogen application. The estimation of yield response functions also uses spatial models aside from OLS models. The reason for using spatial models is to address the issue of spatial autocorrelation that exists in the field level dataset.

The main regression coefficients of the OLS models have the expected signs, including a positive sign on the linear term and a negative sign on the quadratic term. The whole-field and site-specific yield response functions have a concave shape. The medium zone response function has the greatest curvature; the high zone response function has the smallest curvature; and the curvature of the whole-field response function is somewhere in between three site-specific yield response functions. In contrast, the estimated yield response functions under the spatial models are less reliable. Most estimated yield response functions have a convex shape, especially when assuming a higher level of spatial dependency among observations. Among all combinations of spatial models and spatial weighting matrices, only the spatial error model together with a Rook shape weighting matrix presents a concave shape for the whole-field and site-specific response functions.

The results of the economic simulations indicate that variable-rate nitrogen application can have a considerable advantage in payoff compared to a traditional input application strategy.

The payoff of variable rate nitrogen application is greater than the payoff of uniform rate nitrogen rate application after deducting the cost of generating a prescription map when both are assumed to apply at an economic optimum nitrogen rate. The difference in payoff between VRNA and URNA is $222 per hectare when the results are simulated using OLS regression coefficients. However, the simulated payoff under the actual variable nitrogen rate is lower but still better than the payoff under the uniform rate application. The simulated results using coefficients of the spatial error model are consistent with what appears under the OLS model. The environmental benefit of variable rate application is confirmed under the OLS model as well as the spatial error model.

The spatial variability and input and output price will influence the profitability of variable rate nitrogen application. The higher the spatial variability within fields, the greater the incentive to use variable rate nitrogen application. Input and output price are both positively correlated with the profitability of variable rate nitrogen application. The issue of spatial autocorrelation may persist regardless of the size of the spatial scale of the data collected.

4.2 Contributions and implications of research

The contribution of this research is that it adds more evidence of the profitability of variable-rate application. This study proves that variable rate nitrogen application in corn production under this particular zone delineation strategy is financially viable. Besides, although the environmental benefit is not included in the partial budget, the nitrogen reduction effect of using variable rate application in production is confirmed. This provides incentives for agricultural ministries to encourage the adoption of variable rate application. Instead of just considering variable rate application as a payoff booster, policy makers should consider this input management application as a way to preserve the environment and to encourage

sustainable farming practice. The sensitivity analysis provides farmers a guideline of whether to adopt variable rate application under certain price conditions. Besides, the flat payoff function shows the sensitivity of the change in payoff when the input level changes. It provides farmers practical implications of input prescriptions. Instead of applying more input in the zone where has better yield performance in the past, farmers should apply more input in the management zone that has the highest input sensitivity. The test of spatial autocorrelation provides implications to future researchers that spatial autocorrelation should always be considered, regardless of the scale of the data. The more data points collected in the field, the better the estimated yield response function reflects the actual condition of the field.

4.3 Suggestions for the future research

As is common with VRA research, the biggest limitation of this study is that only one field in a single year was studied, which raises concerns about generalizing the results across regions and years. If the farm trial was conducted on different regions with different soil properties, nutrient contents, and other field characteristics, the conclusion on whether VRA is profitable would be more comprehensive. Future research should conduct trials in different fields but should have the same crops planted. This enables the comparison of VRA profitability under different field characteristics. A comparison in the profitability of site-specific management for different inputs including seed, chemical, and irrigation water will provide a better guideline for VRA adoption. Future research should also evaluate the profitability of VRA for not only a single input but also a combination of inputs. In addition, using VRA on a single input, for example, nitrogen fertilizer, can yield different payoff when planting different crops. Future

research should conduct VRA trials for more crops to find the relationship between the crop's return and the feasibility of VRA.

The single-year cross-sectional dataset used in this thesis does not allow weather conditions to be included in the analysis. The temporal variability caused by weather could shift the estimated yield response function and lead to a different conclusion on VRA profitability for the same crop in the same field. Future VRA research should account for weather conditions as one of the main variables in estimating the yield response function. It can help to observe the payoff of VRA under different weather conditions and provide more comprehensive suggestions on the adoption of VRA. Thus, the experimental design for future VRA research should have a longer time horizon that enables the collecting of panel data. Besides, future research should also investigate the method of data collecting. Determining the most appropriate scale of data collection for different layers of field data would help future VRA analysis.

The strategies used in defining the management zones and creating input prescriptions also determine the value of VRA. The value of different management zone delineation strategies and input prescription strategies in VRA cannot be examined in this study since a comparison cannot be made with only one dataset. Future research should evaluate the value of zone delineation and prescription strategies separately. This requires designing a VRA field trial including multiple control groups at the zone definition and prescription creation stages. Moreover, exploring the relationship between the number of management zones within a field and the profitability of VRA will provide implications on whether being more precise in management will provide a better payoff.

In addition, other factors such as farm size and social externalities that can potentially affect the economic value of VRA should be discussed in the future research. Overall, all

suggestions for future research work toward one goal: to have a universal recommendation on what conditions are suitable for the use of VRA. A meta-analysis is necessary to integrate all existing VRA studies and determine the future path of VRA research.

5 Tables

Table 1: OLS Regression Results for Whole-field and Site-specific Yield Response Function

	Dependent variable:	
	Yield	
	(Whole-field)	(Site-Specific)
N	1.244***	2.003***
	(0.125)	(0.196)
Nsqr	−0.004***	−0.006***
	(0.001)	(0.001)
SoilEC	−0.427***	−0.348***
	(0.066)	(0.066)
lowzone	−12.330***	69.861***
	(0.695)	(17.433)
highzone	11.332***	114.944***
	(0.459)	(24.036)
lzintN		−1.162***
		(0.322)
lzintNsqr		0.003**
		(0.001)
hzintN		−1.420***
		(0.385)
hzintNsqr		0.005***
		(0.002)
Constant	119.270***	64.206***
	(7.491)	(11.682)
Observations	11,360	11,360
R^2	0.401	0.406
Adjusted R^2	0.401	0.406
Residual Std. Error	15.810 (df = 11354)	15.742 (df = 11350)
F Statistic	1,519.415*** (df = 5; 11354)	862.759*** (df = 9; 11350)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2: Global Moran's I test for the OLS model residual under both spatial weighting matrix

Yield response function	Spatial weights matrix	Observed Moran I Index	Expected Index	p-value
Whole field	Rook	0.761	-0.00042	2.2e-16
Whole field	Queen	0.747	-0.00041	2.2e-16
Site-specific	Rook	0.757	-0.00057	2.2e-16
Site-specific	Queen	0.744	-0.00058	2.2e-16

Table 3: Lagrange multiplier tests for the OLS model residual

Test	Result	
	"Queen" shape matrix	"Rook" shape matrix
LM lag	Significant	Significant
LM error	Significant	Significant
LM lag robust	Significant	Significant
LM error robust	Significant	Significant
SARMA	Significant	Significant

Table 4: Regression results for whole-field Yield Response Function under spatial models

	Dependent variable:						
	Yield						
Spatial Weights Matrix			Rook Shape			Queen Shape	
	(OLS)	(SAR)	(SEM)	(Durbin)	(SAR)	(SEM)	(Durbin)
N	1.244***	0.874	0.508***	0.174**	−0.0004	−0.0001	−0.14*
	(0.125)	(N/A)	(0.083)	(0.086)	(0.056)	(0.008)	(0.082)
Nsqr	−0.004***	−0.002	−0.001***	−0.0003	0.0002***	0.0002	0.0006*
	(0.001)	(N/A)	(0.0003)	(0.0003)	(0.00003)	(0.0003)	(0.0003)
SoilEC	−0.427***	−0.404	0.198*	0.261**	−0.003	0.136	0.154
	(0.066)	(N/A)	(0.106)	(0.114)	(0.003)	(0.113)	(0.116)
lowzone	−12.330***	−11.293	−2.390***	−0.651	−0.953***	−1.355**	−0.756
	(0.695)	(N/A)	(0.624)	(0.644)	(0.262)	(0.592)	(0.603)
highzone	11.332***	11.659	1.839***	0.077	0.955***	0.553	−0.199
	(0.459)	(N/A)	(0.445)	(0.461)	(0.213)	(0.430)	(0.439)
lag.N				−0.016			0.256**
				(0.111)			(0.117)
lag.Nsqr				−0.0001			−0.001**
				(0.0005)			(0.0004)
lag.SoilEC				−0.356***			−0.202*
				(0.117)			(0.120)
lag.lowzone				−1.547**			0.001
				(0.750)			(0.740)
lag.highzone				2.400***			1.539***
				(0.525)			(0.523)
ρ		0.847***		0.843***	0.924***		0.922***
		(0.004)		(0.005)	(0.004)		(0.004)
λ			0.877***			0.947***	
			(0.004)			(0.003)	
Constant	119.270***	20.61	161.320***	21.482***	13.756***	201.150***	8.108
	(7.491)	(7.491)	(5.657)	(5.278)	(1.002)	(5.710)	(5.276)
Observations	11,360	11,360	11,360	11,360	11,360	11,360	11,360
AIC	94874	81600	81948	81577	78929	79091	78919

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Summary Measure of the impacts of explanatory variable for the spatial lag and spatial Durbin model--whole field scale

Model	Spatial Lag (SAR)			Spatial Durbin		
Spatial weights matrix	Queen shape					
Impact	Direct[1]	Indirect[2]	**Total**	Direct	Indirect	**Total**
N	-0.00057	-0.00495	**-0.00553**	-0.08813	1.57419	**1.48605**
Nsqr	0.00022	0.00189	**0.00211**	0.00043	-0.00517	**-0.00474**
SoilEC	-0.04223	-0.36240	**-0.40470**	0.12949	-0.74559	**-0.61610**
Lowzone	-1.31892	-11.30044	**-12.61936**	-1.03902	-8.59038	**-9.62940**
Highzone	1.32111	11.31918	**12.64029**	0.35337	16.75557	**17.10894**
Spatial weights matrix	Rook shape					
Impact	Direct	Indirect	**Total**	Direct	Indirect	**Total**
N	0.18239	0.69122	**0.87361**	0.22950	0.78224	**1.01174**
Nsqr	-0.00039	-0.00148	**-0.00187**	-0.00054	-0.00264	**-0.00318**
SoilEC	-0.08443	-0.31996	**-0.40438**	0.20345	-0.81113	**-0.60768**
Lowzone	-2.35768	-8.93506	**-11.29274**	-1.55081	-12.58930	**-14.14012**
Highzone	2.43420	9.22505	**11.65925**	1.13587	14.80789	**17.10894**

[1] **Direct effect**: the marginal effect on yield for an observation that is caused by the explanatory variables from this observation.

[2] **Indirect effect**: the marginal effect on yield for an observation that is caused by the explanatory variables from the neighbour observations; which can also be recognized as the spillover effect.

Table 6: Regression results for site-specific yield response function under spatial models

	Dependent variable:						
	Yield						
Spatial Weights Matrix			Rook Shape			Queen Shape	
	(OLS)	(SAR)	(SEM)	(Durbin)	(SAR)	(SEM)	(Durbin)
N	2.003***	0.386***	0.734***	0.323***	0.192***	0.128	−0.027
	(0.196)	(0.090)	(0.112)	(0.118)	(0.029)	(0.106)	(0.110)
Nsqr	−0.006***	−0.001***	−0.002***	−0.001***	−0.0006***	−0.0003	0.00002
	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0004)	(0.0004)
SoilEC	−0.348***	−0.048	0.203*	0.264***	−0.021*	0.133	0.148
	(0.066)	(0.033)	(0.106)	(0.113)	(0.013)	(0.113)	(0.116)
lowzone	68.861***	21.088*	29.502***	15.767	16.227***	18.279*	13.341
	(17.433)	(12.795)	(10.781)	(11.033)	(6.075)	(10.268)	(10.459)
highzone	114.944***	27.805	−33.419**	−16.774	20.724*	−23.767	−18.315
	(24.036)	(20.327)	(15.399)	(15.599)	(10.777)	(14.937)	(15.103)
lztinN	−1.162***	−0.352	−0.496***	−0.268	−0.271**	−0.352*	−0.234
	(0.322)	(0.244)	(0.186)	(0.190)	(0.119)	(0.177)	(−0.180)
hzintN	−1.420***	0.002	−0.001	0.0004	−0.318*	0.269	0.162
	(0.385)	(0.001)	(0.0009)	(0.0009)	(0.170)	(0.228)	(0.231)
lztinNsqr	0.003**	0.001	0.002**	0.001	0.0009*	0.001	0.0009
	(0.459)	(0.001)	(0.0008)	(−0.0004)	(0.0006)	(0.0007)	(0.0007)
hzintNsqr	0.005***	0.002	−0.001	0.0004	0.0012*	−0.001	−0.00008
	(0.002)	(0.001)	(0.0009)	(0.0009)	(0.0006)	(0.0009)	(0.0009)
lag.N				0.036			0.395**
				(0.174)			(0.177)
lag.Nsqr				0.00003			0.001*
				(0.0007)			(0.0007)
lag.SoilEC				−0.335***			−0.181
				(0.117)			(0.121)
lag.lowzone				6.000			1.904
				(15.157)			(16.399)
lag.highzone				39.935			56.649**
				(20.720)			(22.055)
lag.lztinN				−0.078			0.002
				(0.272)			(0.298)
lag.hzintN				−0.329			−0.691
				(0.272)			(0.272)
lag.lztinNsqr				0.0005			−0.00003
				(0.001)			(0.001)
lag.hzintNsqr				0.0001			0.002
				(0.001)			(0.001)
ρ		0.846***		0.843***	0.923***		0.920***
		(0.004)		(0.005)	(0.004)		(0.004)
λ			0.876***			0.947***	
			(0.004)			(0.003)	
Constant	64.206***	4.673	147.680***	6.383	1.800	193.850***	−8.616
	(11.682)	(4.999)	(7.548)	(9.399)	(1.179)	(7.352)	(9.344)
Observations	11,360	11,360	11,360	11,360	11,360	11,360	11,360
AIC	94874	81591	81913	81533	78927	79077	78899
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 7: Summary Measure of the impacts of explanatory variable for the spatial lag and spatial Durbin model--site-specific scale

Model	**Spatial Lag (SAR)**			**Spatial Durbin**		
Spatial Weights Matrix	**Queen Shape**					
Impact	Direct	Indirect	**Total**	Direct	Indirect	**Total**
N	0.26553	2.25590	**2.52143**	0.12272	4.50208	**4.62480**
Nsqr	-0.00083	-0.00701	**-0.00785**	-0.00049	-0.01544	**-0.01593**
SoilEC	-0.02988	-0.25384	**-0.28371**	0.13011	-0.54464	**-0.41453**
Lowzone	22.42152	190.49154	**212.91306**	19.07158	172.45467	**191.52626**
Highzone	28.63545	243.38465	**271.92011**	-2.23671	483.84083	**481.60412**
Lz*N	-0.37482	-3.18443	**-3.55924**	-0.31277	-2.37080	**-2.68357**
Hz*N	-0.43985	-3.73695	**-4.17680**	-0.05681	-6.58549	**-6.64430**
$Lz*N^2$	0.00136	0.01156	**0.01293**	0.00112	0.00608	**0.00720**
$Hz*N^2$	0.00175	0.01483	**0.01657**	0.00066	0.02221	**0.02287**
Spatial Weights Matrix	**Rook Shape**					
Impact	Direct	Indirect	**Total**	Direct	Indirect	**Total**
N	0.52715	1.98342	**2.51057**	0.45538	1.83828	**2.29366**
Nsqr	-0.00172	-0.00645	**-0.00817**	-0.00150	-0.00542	**-0.00692**
SoilEC	-0.06580	-0.24757	**-0.31337**	0.21598	-0.66673	**-0.45075**
Lowzone	28.80096	108.36463	**137.16559**	24.00433	114.79610	**138.80043**
Highzone	37.97495	142.88210	**180.85704**	-5.76220	153.45248	**147.69028**
Lz*N	-0.48138	-1.81121	**-2.29259**	-0.39818	-1.80940	**-2.20757**
Hz*N	-0.56089	-2.11037	**-2.67126**	0.00060	-1.43854	**-1.43794**
$Lz*N^2$	0.00168	0.00633	**0.00802**	0.00142	0.00546	**0.00688**
$Hz*N^2$	0.00217	0.00818	**0.01035**	0.00048	0.00220	**0.00269**

Table 8: Simulated Nitrogen Rates and Corresponding Yield under different Decision Rules under (OLS)

Application Method	Scale	Decision Rule	N Rate (kg/ha)	Yield (kg/ha)
Uniform Rate	Whole Field	N calculator	187.21	13,480.49
		Yield Max	184.74	13,481.74
		Profit Max	**168.25**	13,430.27
Variable Rate	Low zone	Actual	94.63	11,216.11
		Yield Max	157.13	12,097.66
		Profit Max	**147.08**	12,027.99
	Medium zone	Actual	122.18	12,942.14
		Yield Max	181.01	13,879.70
		Profit Max	**170.98**	13,848.95
	High zone	Actual	147.24	14,028.61
		Yield Max	197.28	14,157.15
		Profit Max	**159.70**	14,039.77

*Shares of management zones are 0.12 for low, 0.50 for medium and 0.38 for high

Table 9: Simulate Nitrogen Rates and Corresponding Yield under different Decision Rules (Spatial models)

Application Method	Scale	Model	Spatial weights	N rate (kg/ha)	Yield (kg/ha)
Uniform rate	Whole field	SAR	Rook	228.63	7,211.45
			Queen	27.76	573.42
		SEM	**Rook**	**222.42**	**14,256.24**
			Queen	0	12,697.74
		Durbin	Rook	158.59	7,063.49
			Queen	163.94	7,756.99
Variable rate	Low zone	SAR	Rook	399.36	12,864.58
			Queen	0	13,222.50
		SEM	**Rook**	**173.44**	**12,999.68**
			Queen	0	13,434.66
		Durbin	Rook	0	10,465.64
			Queen	18.31	12,160.88
	Medium zone	SAR	Rook	165.02	12,663.90
			Queen	172.05	12,538.30
		SEM	**Rook**	**163.12**	**13,312.01**
			Queen	27.2	12,469.36
		Durbin	Rook	174.76	13,675.40
			Queen	159.10	20,185.82
	High zone	SAR	Rook	0	11,364.63
			Queen	0	16,926.37
		SEM	**Rook**	**268.10**	**17,588.21**
			Queen	178.02	13,328.66
		Durbin	Rook	99.15	13,708.83
			Queen	0	29,316.79

*Nitrogen rate is converted from lbs/acre to kgs/ha using a rate of 1.12
*Corn yield is converted from bushels/acre to kgs/ha using a rate of 62.77

Table 10: Payoff Under Different Nitrogen rates (OLS)

Application Method	Scale	Model	Decision Rule	Total N used (kgs)	Net Payoff ($/ha)
Uniform Rate	Whole-Field	OLS	N calculator	6,059.96	1,011.47
			Yield Max	5,981.02	1,028.56
			Profit Max	**5,447.13**	**1,140.75**
Variable Rate	Low zone	OLS	Actual	370.52	636.53
			Yield Max	663.84	895.85
			Profit Max	576.16	1,048.00
	Medium zone	OLS	Actual	1,976.78	911.67
			Yield Max	2,930.23	1,126.42
			Profit Max	2,767.72	1,194.67
	High zone	OLS	Actual	1,807.51	1,076.34
			Yield Max	2,420.63	1,055.95
			Profit Max	1,958.52	1,311.42
	Total	OLS	Actual	4,138.49	940.79
			Yield Max	6,014.70	1,071.84
			Profit Max	**5,303.38**	**1,221.17**

*Shares of management zones are 0.12 for low, 0.50 for medium and 0.38 for high

* Profit maximizing rates as based on a corn price (P_Y) of $0.177/kg and a nitrogen price (P_N) of $0.227/kg.

Table 11: Payoff Under Different Nitrogen rates (Spatial models)

Application Method	Scale	Model	Spatial weights	Total N use (kgs)	Net payoff ($/ha)
Uniform rate	Whole field	SAR	Rook	7,400.30	-403.44
			Queen	898.53	-102.47
		SEM	**Rook**	**7,199.29**	**889.12**
			Queen	0	2,244.31
		Durbin	Rook	5,133.24	84.99
			Queen	5,306.41	168.43
Variable rate	Low zone	SAR	Rook	1,564.10	-79.53
			Queen	0	283.19
		SEM	**Rook**	**679.28**	**122.44**
			Queen	0	287.73
		Durbin	Rook	0	224.14
			Queen	71.71	222.17
	Medium zone	SAR	Rook	2,670.69	514.51
			Queen	2,784.46	477.57
		SEM	**Rook**	**2,639.94**	**578.85**
			Queen	440.21	1,089.04
		Durbin	Rook	2,828.32	568.24
			Queen	2,574.88	1,201.95
	High zone	SAR	Rook	0	762.37
			Queen	0	1,135.47
		SEM	**Rook**	**3,288.91**	**268.84**
			Queen	2,183.85	350.96
		Durbin	Rook	1,166.76	654.77
			Queen	0	1,966.66
	Total	SAR	Rook	4,234.79	1,198.35
			Queen	2,784.46	1,896.23
		SEM	**Rook**	**6,608.13**	**970.13**
			Queen	440.21	1,727.73
		Durbin	Rook	3,995.08	1,447.15
			Queen	2,646.59	3,390.78

*Shares of management zones are 0.121 for low, 0.50 for medium and 0.379 for high

* Profit maximizing rates as based on a corn price (P_Y) of $0.177/kg and a nitrogen price (P_N) of $0.227/kg.

Table 12: Sensitivity analysis 1 (Corn price fixed)

	Corn price: $0.177/kg (Fixed)		
	Baseline	**-44%**	**+44%**
Nitrogen fertilizer price ($/kg)	0.227	0.127	0.327
Difference in payoff between URA and VRA ($/ha)	80	78.282	117

Table 13: Sensitivity analysis 2 (Nitrogen fertilizer price fixed)

	Nitrogen price: $0.227/kg (Fixed)		
	Baseline	**-44%**	**+44%**
Corn price ($/kg)	0.177	0.098	0.256
Difference in payoff between URA and VRA ($/ha)	80	67.773	91.741

Table 14: OLS Regression Results for Whole-field and Site-specific Yield Response Function using 20 meters by 20 meters size dataset

	Dependent variable:	
	Yield	
	(1)	(2)
N	−0.739	2.263
	(0.970)	(3.043)
Nsqr	0.005	−0.008
	(0.004)	(0.014)
SoilEC	−0.489	−0.387
	(0.316)	(0.321)
lowzone	−17.879***	483.196**
	(3.690)	(227.800)
highzone	9.707***	359.053
	(2.591)	(260.012)
lzintN		−9.881**
		(4.466)
lzintNsqr		0.049**
		(0.022)
hzintN		−5.541
		(4.450)
hzintNsqr		0.022
		(0.019)
Constant	234.350***	54.689
	(54.273)	(169.457)
Observations	457	457
R^2	0.410	0.423
Adjusted R^2	0.404	0.412
Residual Std. Error	15.230 (df = 451)	15.126 (df = 447)
F Statistic	62.704*** (df = 5; 451)	36.450*** (df = 9; 447)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 15: Global Moran's I test for the OLS model residual under both spatial weighting matrix (20 meters by 20 meters size data)

Yield response function	Spatial weights matrix	Observed Moran I Index	Expected Index	p-value
Whole field	Rook	0.232	-0.00777	4.311e-10
Whole field	Queen	0.268	-0.00729	2.2e-16
Site-specific	Rook	0.225	-0.00872	1.07e-10
Site-specific	Queen	0.268	-0.00805	2.2e-16

6 Figures

Figure 1: Density distribution of main variables

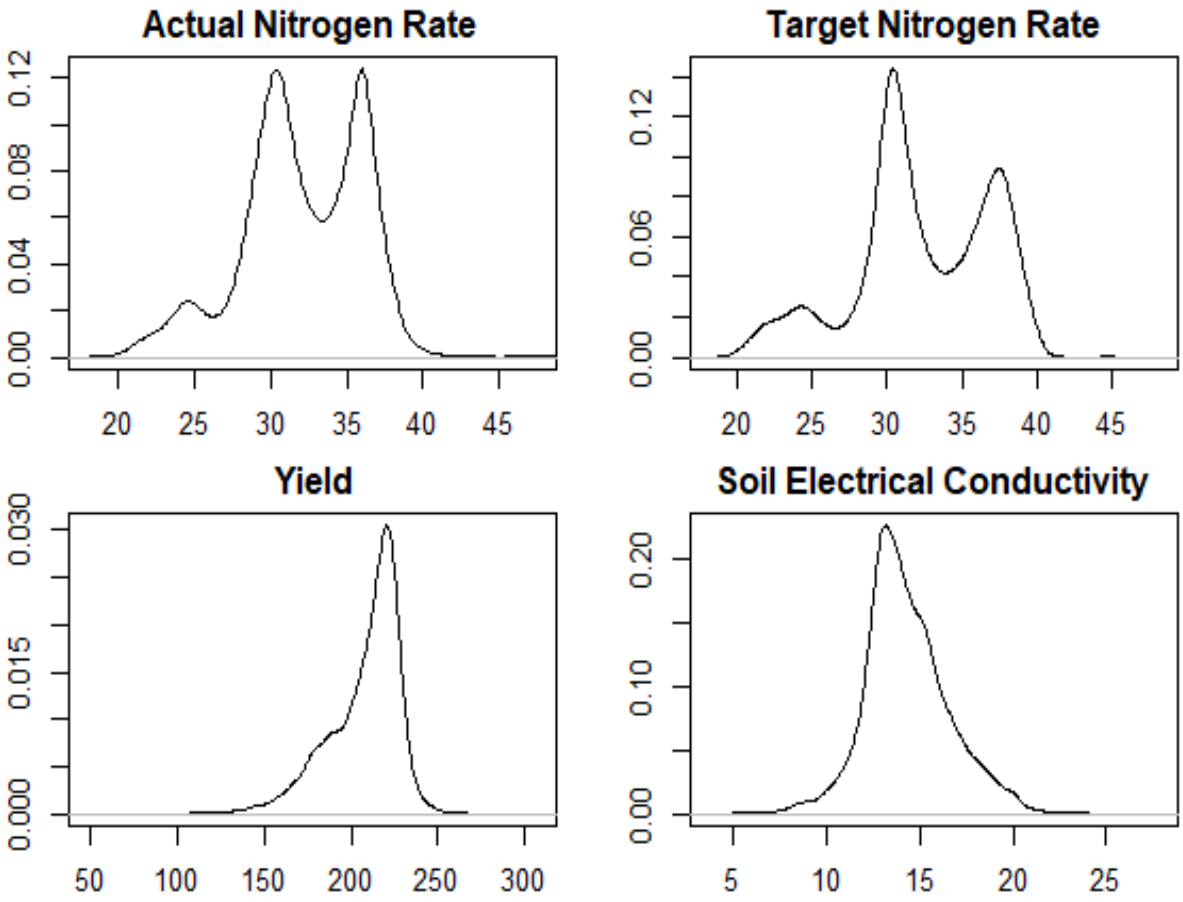
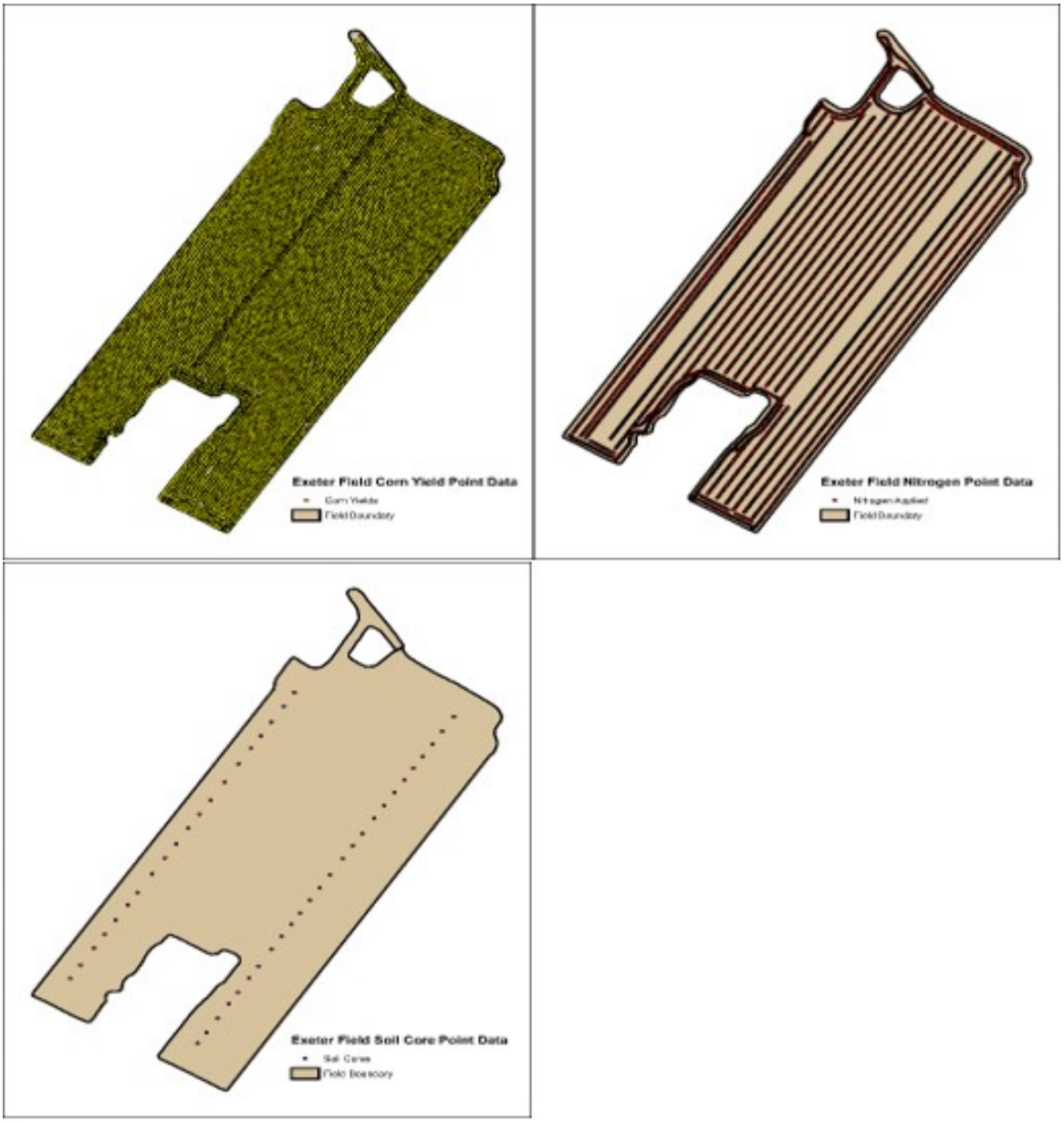


Figure 2: Geo Maps for each Data layers in raw dataset



Source: Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA)

Figure 3: Geo Maps for each Data layers after the process of interpolation

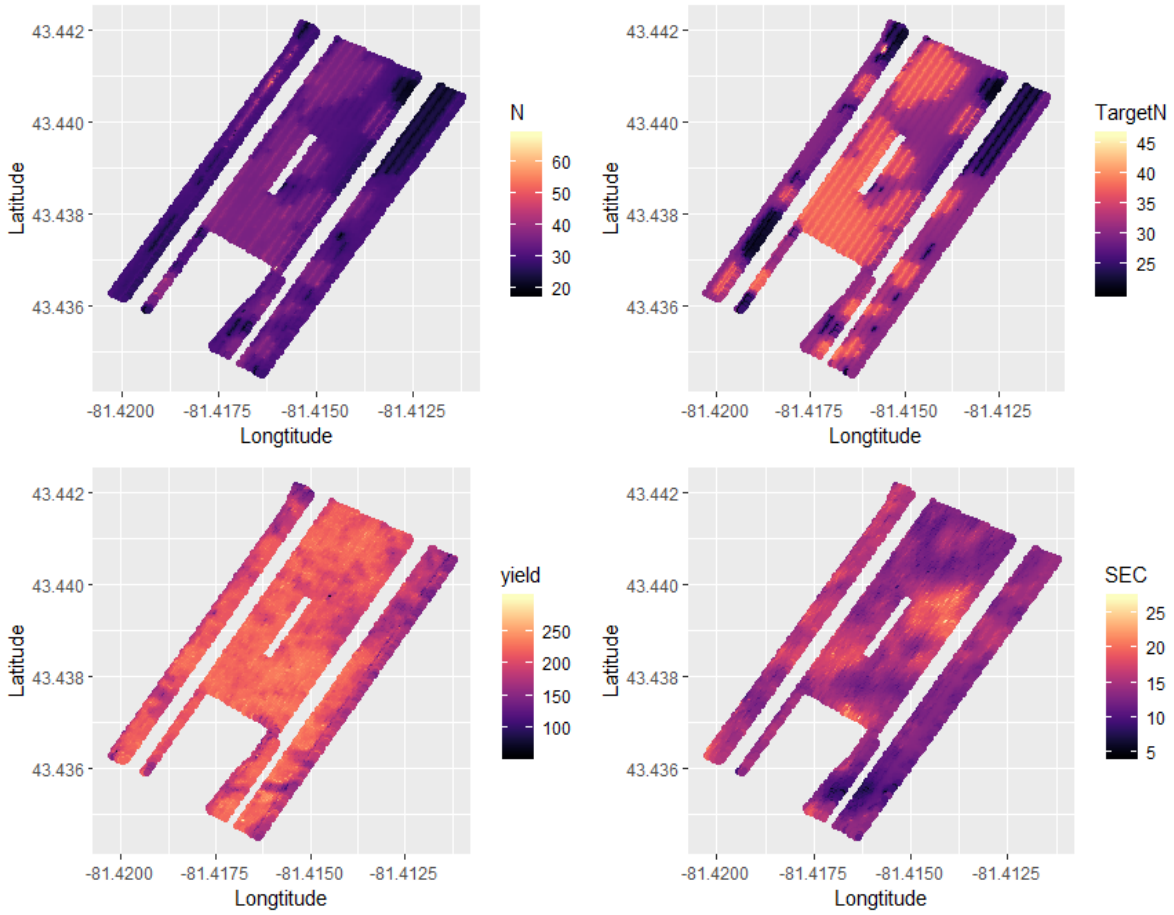


Figure 4: “Rook” and “Queen” shape spatial weights matrix

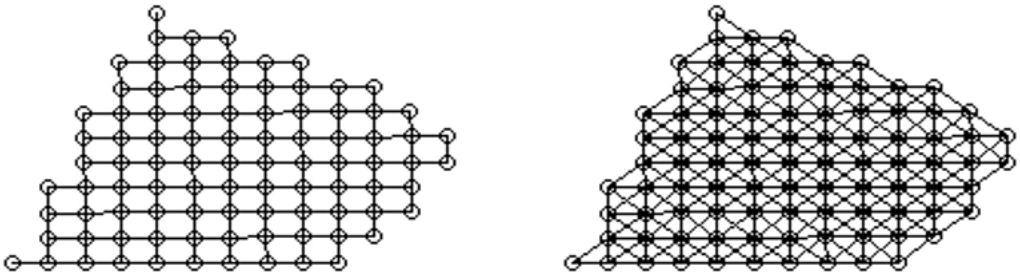


Figure 5: Whole-field and site-specific Yield Response Curve

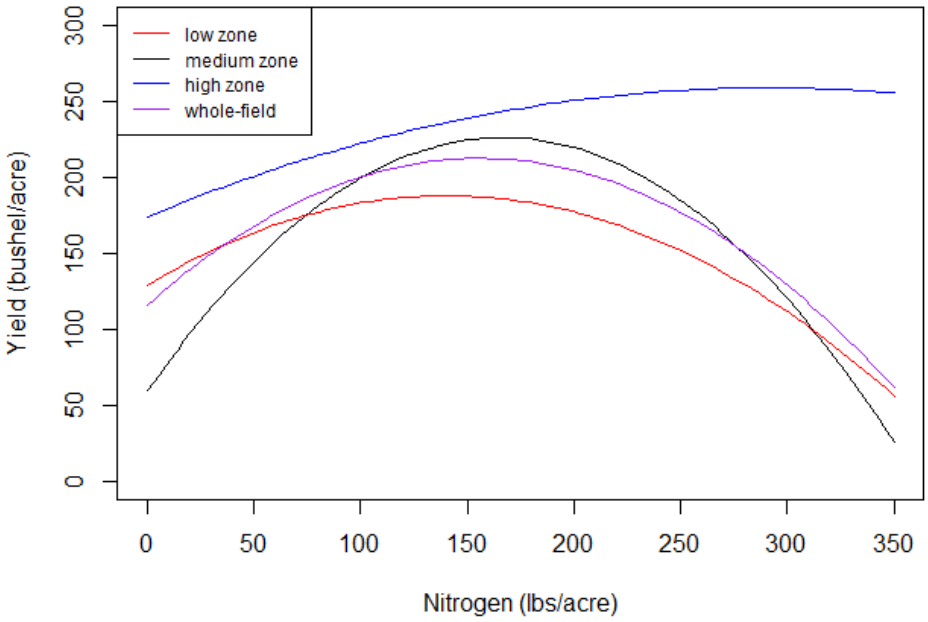
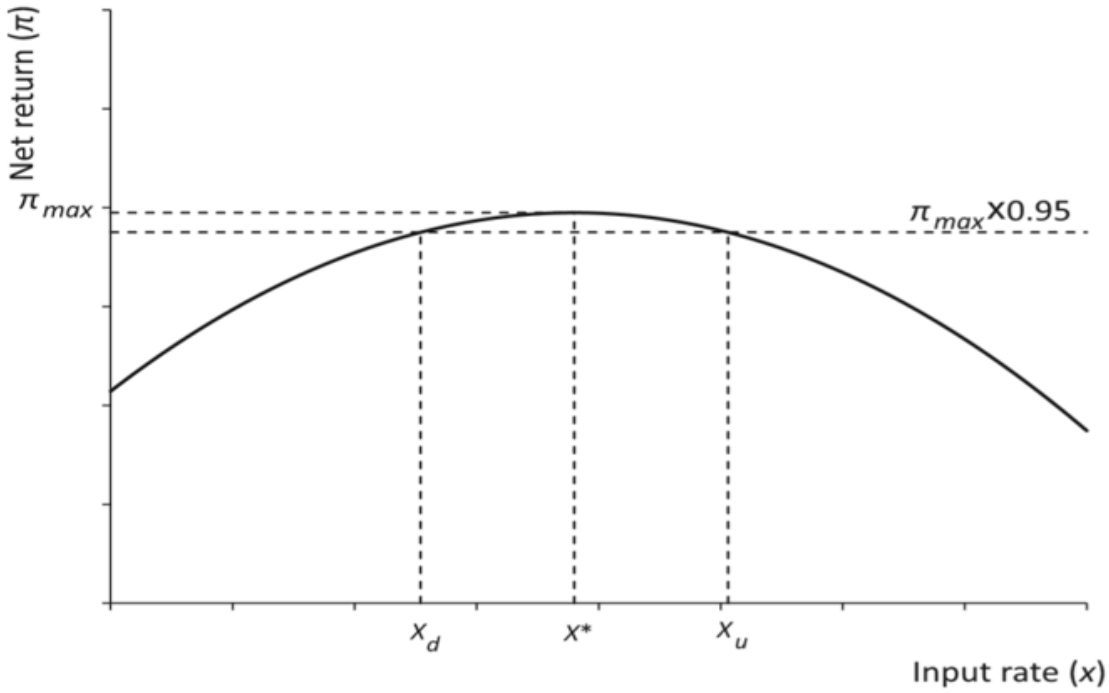


Figure 6: An example of payoff function showing the range of inputs levels giving a payoff at least 95 % of maximum payoff



Source: "How flat is flat? Measuring payoff functions and the implications for site-specific crop management"

Figure 7: Yield response function under three spatial models and two spatial weights matrices

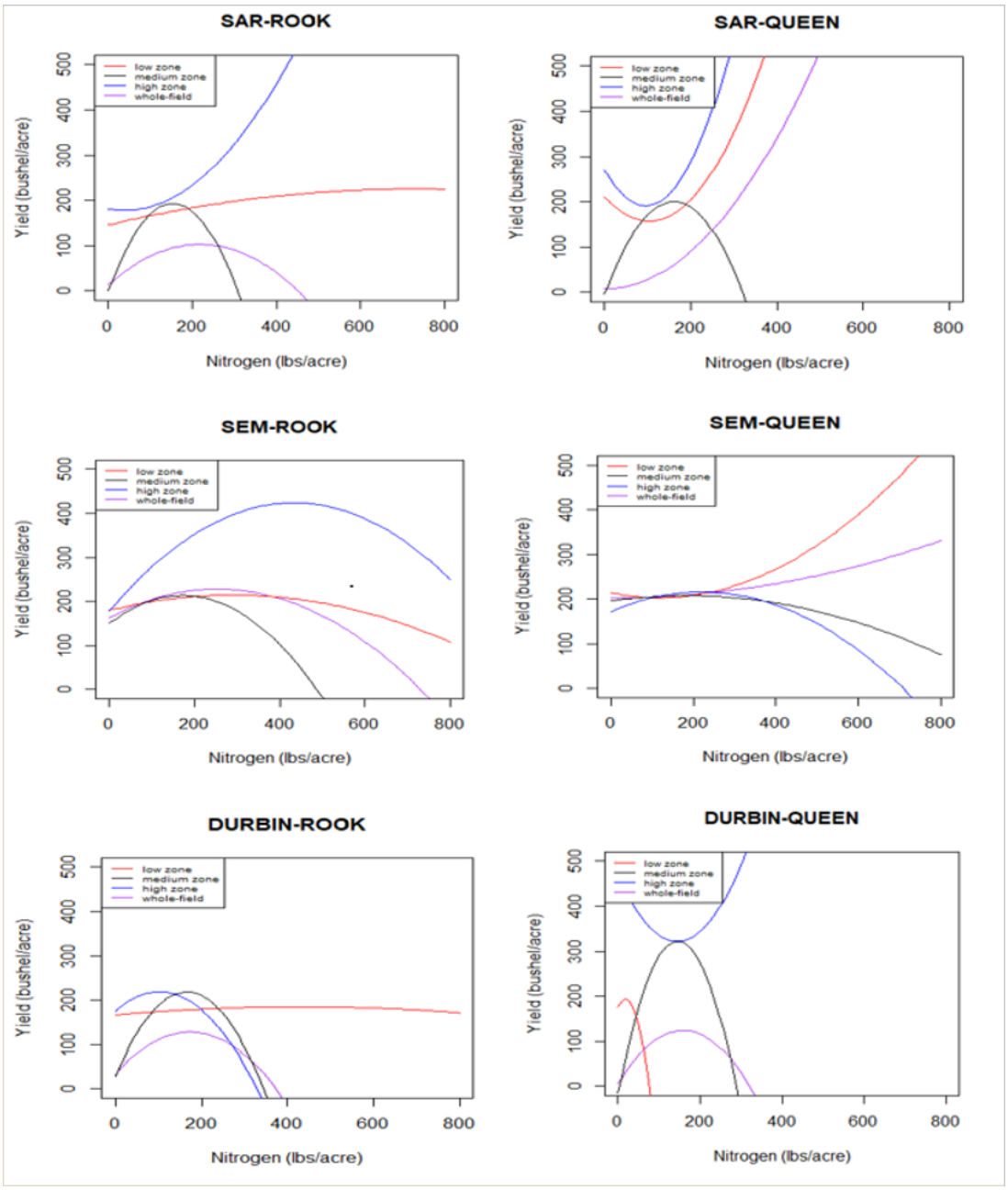
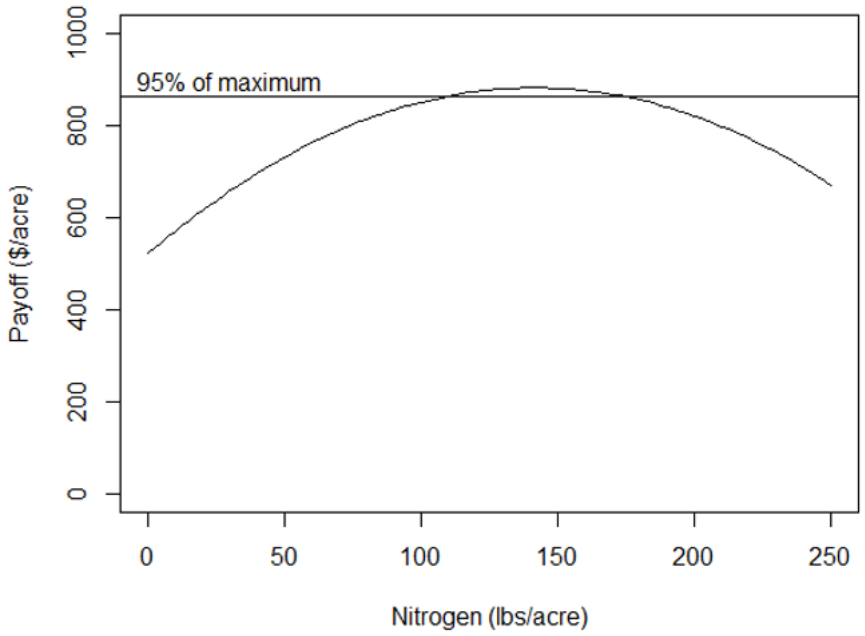


Figure 8: Payoff from corn production as a function of nitrogen fertilizer rate



References:

Akaike, H. 1974. "A new look at the statistical model identification," in IEEE Transactions on Automatic Control. 19 (6): 716-723.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht, Netherlands; Kluwer Academic Publishers.

Anselin, L., R. Bongiovanni, and J. Lowenberg-Deboer. 2004. "A Spatial Econometric Approach to the Economics of Site- Specific Nitrogen Management in Corn Production." *American Journal of Agricultural Economics* 86 (3): 675–687.

Anselin, L. 2007. "Spatial econometrics in RSUE: Retrospect and prospect." *Regional Science and Urban Economics* 37 (4): 450-456.

Ahmad, D., and M.S. Syed. 2017. *Satellite Farming: An Information and Technology Based Agriculture*. Springer, Cham.

Basso, B., B. Durmont, D. Cammarano, A. Pezzuolo, M. Francesco, and L. Sartori. 2016. "Environmental and Economic Benefits of Variable Rate Nitrogen Fertilization in a Nitrate Vulnerable Zone." *Society of the Total Environment* 546 (1): 227–235.

Boyer, C.N., B.W. Brorsen, J.B. Solie, and W.R. Raun. 2011. "Profitability of Variable Rate Nitrogen Application in Wheat Production." *Precision Agriculture* 12 (4): 473–487.

Cabas, J, A.Weersink, and E. Olale. 2010. "Crop yield response to economic, site and climatic variables". *Climatic Change* (Dordrecht).101(3):599–616.

Cerrato, M.E., and A.M. Blackmer. 1990. "Comparison of models for describing; corn yield response to nitrogen fertilizer." *Agronomy Journal* 82 (1): 138–143.

Chen, M., Y. Zhang, S. Mao, and V. Leung. 2014. *Big Data: Related Technologies, Challenges and Future Prospects.* Dordrecht, Netherlands; Kluwer Academic Publishers.

Coble, K., G. Terry, A. Mary, F. Shannon, S. Steve, and F. John. 2016. "Advancing U.S. Agricultural Competitiveness with Big Data and Agricultural Economic Market Information, Analysis, and Research." Council on Food, Agricultural, and Resource Economics Report (Report No. 249847).

De Mauro, A., M. Greco, M. Grimaldi. 2016. "A formal definition of Big Data based on its essential features." *Library Review* 65 (3): 122-135.

Dijcks, J. 2013. Oracle: Big data for the enterprise. Oracle White Paper. Redwood Shores, CA: Oracle DoeCorporation.

Doerge, A.T. 1999. "Yield Map Interpretation." *Journal of Production Agriculture*. 12 (1): 54-61.

Erickson, B., and Widmar, D. 2015. Precision agricultural services dealership survey results. Dep. of Agricultural Economics and Dep. of Agronomy, Purdue University., West Lafayette, IN.

Erickson, B., J.Lowenberg-DeBoer, and J. Bradford. 2017. Precision agriculture dealership survey. Departments of Agricultural Economics and Agronomy, Purdue University.

Ferguson, R.B., G.W. Hergert, 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* 66 (1): 544–553.

Franzen, D. 2018. "Site-specific Farming: Economics and the Environment." North Dakota State University, Fargo, North Dakota.

Gandorfer, M., and P.Rajsic. 2008. "Modeling Economic Optimum Nitrogen Rates for Winter Wheat When Inputs Affect Yield and Output-Price." *Agricultural Economics Review* 9 (2) 54–64.

Griffin, S., and J. Hollis. 2017. Plant growth regulators on winter wheat – yield benefits of variable rate application. Advances in Animal Biosciences. 8 (1): 233-237.

Griffin, T.W., N.J. Miller, J. Bergtold, A. Shanoyan, A. Sharda, and I.A. Ciampitti. 2017. "Farm's Sequence of Adoption of Information-intensive Precision Agricultural Technology." *Applied Engineering in Agriculture*. 33(4): 521-527.

Hurley, T., O. Kikuo, M. Gary. 2005. "Estimating the Potential Value of Variable Rate Nitrogen Applications: A Comparison of Spatial Econometric and Geostatistical Models." *Journal of Agricultural and Resource Economics.*30 (2): 231-249.

Isik, M., and K. Madhu. 2002. "Variable-Rate Nitrogen Application under Uncertainty: Implications for Profitability and Nitrogen Use." *Journal of Agricultural and Resource Economics.* 27 (1): 61-76.

Janrao, P. 2015. "Management Zone Delineation in Precision Agriculture Using Data Mining: A Review." *Conference: IEEE Conference ICIIECS 2015*.

Kachanoski, R.G., M.H. Miller, D.A. Lobb, E.G. Gregorich, R.D. Protz. M.H. Miller, D.A. Lobb, E.G. Gregorich, R.D. Protz. 1992. "Management of farm field variability: I. Quantification of soil loss in complex topography. II. Soil erosion processes on shoulder slope landscape positions." SWEEP/TED Report No. 38. University of Guelph.

Kempenaar, C., T.H. Been, J.A. Booij, F.van Evert, J.M.G.P. Michielsen, and C. Kocks. 2018. "Advances in Variable Rate Technology Application in Potato in The Netherlands." *Potato Research*. 60 (3).

Khosla, R., D. G. Westfall, R. M. Reich, J. S. Mahal, and W. J. Gangloff. 2010. Spatial variation and sitespecific management zones. In: M. A. Oliver (ed.), Geostatistical Applications for Precision Agriculture. Springer, Dordrecht, Netherlands.

Koch, B., R. Khosla, W. Frasier, D. Westfall, and D. Inman. 2004. "Economic Feasibility of Variable-Rate Nitrogen Application Utilizing Site- Specific Management Zones." *Agronomy Journal* 96 (6): 1572–1580.

Lambert, D. M., J. Lowenberg-Deboer, G. L. Malzer. 2006. "Economic analysis of spatial-temporal patterns in corn and soybean response to nitrogen and phosphorus." *Agronomy Journal*. 98(1): 43-54.

Laney, D. 2001. "3D Data Management: Controlling Data Volume, Velocity and Variety." *Journal of Data Analysis and Information Processing*. 3 (4).

Lark, R.M., and H.C. Wheeler. 2003. "A method to investigate within-field variation of the response of combinable crops to an input." *Agronomy Journal*. 95 (1):1093–1104.

Larsen, W.E., G.A. Nielson, D.A. Tyler. 1994. "Precision Navigation with GPS." *Computer and Electronics in Agriculture*. 11 (1): 85-95.

Larson, J.A., R.K. Roberts, B.C. English, S.L. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, and J.M. Reeves. 2008. "Factors Affecting Farmer Adoption of Remotely Sensed Imagery for Precision Management in Cotton Production." *Precision Agriculture* 9 (1): 195–208.

Liu, D., W. Zongming, Z. Bai, S. Kaishan, L. Xiaoyan, L. Jianping, L. Fang. (2006). "Spatial distribution of soil organic carbon and analysis of related factors in croplands of the black soil region, Northeast China." *Agriculture, Ecosystems & Environment*. 113 (1): 73-81.

Lowenberg-Deboer, J.M., T.W. Griffin, R.J.G.M. Florax. 2008. "Use of cross regression to model local spatial autocorrelation in precision agriculture." http://www.aragriculture.org/precisionag/research/Autocorrelation.pdf (Link tested July, 24, 2020).

Metwally, M.S., S.M. Shaddad, L. Manqiang, Y. Rongjiang, A.I. Abdo, L. Peng, J. Jiaoguo, C. Xiaoyun. "Soil properties spatial variability and delineation of site-specific management zones based on soil fertility using fuzzy clustering in a hilly field in Jianyang, Sichuan, China." *Sustainability.*

Miller, N., G. Terry, B. Jason, C. Ignacio, A. Sharda. 2017. "Farmers' Adoption Path of Precision Agriculture Technology." *Advances in Animal Biosciences*. 8: 708-712.

Mitchell, S., A. Weersink, and B. Erickson. 2018. "Adoption of precision agriculture technologies in Ontario crop production." *Canadian Journal of Plant Science*, 98 (6), 1384-1388.

Mulla, D. 1991. "Using Geostatistics and GIS to manage spatial patterns in soil fertility." *Automated Agriculture for the 21st Century*. (pp. 336-345).

Mulla, D., and R. Khosla. 2016. "Historical Evolution and Recent Advances in Precision Farming." *In Soil-Specific Farming Precision Agriculture.*

Niemeyer, C. 2019. "Improving corn nitrogen fertilizer recommendations for Ontario with rainfall effects on crop nitrogen demand."

O'Connor, M., T. Bell, G.H. Elkaim, and B.W. Parkinson. 2015. "Automatic Steering of Farm Vehicles Using GPS." *Precision Agriculture*. 767-777.

Pace, R.K., and J.P. Lesage. 2014. "Interpreting Spatial Econometric Models." *Handbook of Regional Science.*

Pannell, D. J. 2006. "Flat Earth Economics: The Far-reaching Consequences of Flat Payoff Functions in Economic Decision Making." *Review of Agricultural Economics* 28 (4): 553– 566.

Pannell, D.J., M. Gandorfer, A. Weersink. 2019. "How flat is flat? Measuring payoff functions and the implications for site-specific crop management." *Computers and Electronics in Agriculture.* 162: 459-465.

Plant, R.E. 2001. "Site-specific management: The application of information technology to crop production." *Computers and Electronics in Agriculture*. 30: 9-29.

Rajsic. P., and A. Weersink. 2008. "Do farmers waste fertilizer? A comparison of ex post optimal nitrogen rates and ex ante recommendations by model, site and year" *Agricultural Systems* 97 (1): 56–67.

Rajsic, P., A. Weersink, and M. Gandorfer. 2009. "Risk and Nitrogen Application Levels." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 57 (2): 223–239.

Roberts, R.K., B.C. English, J.A. Larson, R.L. Cochran, W.R. Goodman, S.L. Larkin, M.C. Marra, S.W. Martin, W.D. Shurley, and J.M. Reeves. "Adoption of Site-Specific Information and Variable-Rate Technologies in cotton Precision Farming." *Journal of Applied Agriculture Economics*. 36(2004):143-158.

Schueller, J. K. 1991. In-field site-specific crop production. In: Automated Agriculture for the 21st Century. ASAE Publication No. 1191 (ASAE, St. Joseph, MI, USA), p. 291–292.

Schimmelpfennig, D., and R. Ebel. 2016. "Sequential adoption and cost savings from precision agriculture." *Journal of Agricultural and Resource Economics* 41(1): 97-115.

Sonka, S. 2016. "Big Data: Fueling the Next Evolution of Agricultural Innovation." *Journal of Innovation Management*. 4 (2016): 114 - 136.

Swinton, S.M., and J. Lowenberg-DeBoer. 1998. "Evaluating the Profitability of Site Specific Farming." *Journal of Production Agriculture*. 11:439-446.

Thrikawala, S., A. Weersink, G. Kachanoski, and G. Fox. 1999. "Economic Feasibility of Variable-Rate Technology for Nitrogen on Corn." *American Journal of Agricultural Economics*. 81 (4):914-927.

Wang, D., T. Prato, Z. Qiu, N.R. Kitchen, and K.A. Sudduth. 2003. "Economic and Environmental Evaluation of Variable Rate Nitrogen and Lime Application for Claypan Soil Fields." *Precision Agriculture*. 4: 35-52.

Watcharaanantapong, P., R.K. Roberts, D.M. Lambert, J.A. Larson, M. Velendia, B.C. English, R.M. Rejesus, and C. Wang. 2014. "Timing of Precision Agriculture Technology Adoption in US Cotton Production." *Precision Agriculture* 15 (4): 427–446.

Weersink, A., E. Fraser, D. Pannell, E. Duncan, and S. Rotz. 2018. "Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis." *Annual Review of Resource Economics* 10 (1).

Appendix:

Table 16: SEM (Rook) Regression Results for Whole-field and Site-specific Yield Response Function using 20 meters by 20 meters size dataset

	Dependent variable:	
	Yield	
	(whole-field)	(site-specific)
N	−1.202	0.082
	(0.918)	(2.684)
Nsqr	0.0065	0.0028
	(0.0041)	(0.0119)
SoilEC	−0.2595	−0.133
	(0.4402)	(0.437)
lz	−3.442	284.991
	(3.561)	(205.183)
hz	5.736**	−99.903
	(2.447)	(223.085)
lzintN		−5.525
		(4.031)
hzintN		2.131
		(3.830)
lzintNsqr		0.026
		(0.019)
hzintNsqr		−0.010
		(0.016)
λ	0.481***	0.475***
	(0.006)	(0.057)
Constant	239.980***	161.775
	(52.145)	(150.269)
Observations	457	457
AIC	3741	3740
Note:	*p<0.1; **p<0.05; ***p<0.01	