Empirical Analysis and Modelling of Information and Communications Technology in Agriculture for Southern Ontario, Canada

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Information and communications technology (ICT) represents an important enabling technology for on-farm operations that helps to maximise yield and minimise on-farm inputs. This study investigates the adoption factors and coverage characteristics of ICT in Southern Ontario. A set of eight site and situation adoption factors were identified explaining 57% of the variation in agricultural high-speed Internet utilisation for Southern Ontario. ICT coverage was assessed through service carrier and band factors, and their presence in rural settlements. Findings of the research indicate that there exists a digital divide among settlements in Southern Ontario and recommendations for targeted policy and investment in infrastructure are proposed to bridge the gap.

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Term
AAFC	Agriculture and Agri-food Canada
AIC	Akaike Information Criterion
AICc	Akaike Information Criterion with Correction
ANOVA	Analysis of Variance
AWS	Advanced Wireless Services
BIA	Broadband Internet Access
BRS	Broadband Radio Service
CANSIM	Canadian Socio-Economic Information Management System
CAR	Census Agricultural Region
CD	Census Division
CMA	Census Metropolitan Area
COA	Census of Agriculture
CRTC	Canadian Radio-television and Telecommunications Commission
CSD	Census Subdivision
DC	Digital Canada
DEM	Digital Elevation Model
df	Degrees of Freedom
DSS	Decision Support System
FWA	Fixed Wireless Access
GLM	Generalised Linear Model
GP-GPU	General-Purpose Graphics-Processing Unit
GSM	Global System for Mobile Communications
GTHA	Greater Toronto and Hamilton area
GWPR	Geographically-Weighted Poisson Regression
GWR	Geographically-Weighted Regression
HIUS	Household Internet Usage Survey
HSPA+	High-Speed Packet Access Plus
ISP	Internet Service Provider
LIO	Land Information Ontario
LOS	Line-of-Sight
LTE	Long Term Elevation
Mbps	Megabits per Second
MLE	Maximum Likelihood Estimator
MSS	Mean Sum-of-Squares
NAICS	North American Industry Classification System
NLOS	Non-Line-of-Sight

OFA	Ontario Federation of Agriculture
OMAFRA	Ontario Ministry of Agriculture, Food, and Rural Affairs
PA	Precision Agriculture
PCA	Principal Component Analysis
pH	Power of Hydrogen
SS	Sum-of-Squares
SSM	Site-Specific Management
SWIFT	SouthWestern Integrated Fibre Technology
UAV	Unmanned Aerial Vehicle
VRT	Variable Rate Treatment
WAP	Wireless Access Point
WBS	Wireless Broadband Services
WCS	Wireless Communication Services
WiFi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WWW	World Wide Web

Chapter One: Introduction

1 Background

Demand for agricultural products will continue to increase as of 2050, with a projected population of 9 billion, driven mainly by large increases in developing countries, and slowing rates of growth in developed countries (Alexandratos & Bruinsma, 2012). The expected annual growth rate of agricultural production is projected to be lower at 1.1% from 2007 to 2050 compared to 2.2% over the past four decades. However, the level of intensification of agricultural production required to support increasing demand for aggregate agricultural output will be increasingly difficult to achieve (Alexandratos & Bruinsma, 2012). Land and water scarcity represent the most pressing issues in maintaining the growth rate in the future as soil degradation and erosion, salinisation of irrigated areas, and growing levels of competition from other uses for agricultural land places an increased demand on these agricultural resources (Alexandratos & Bruinsma, 2012).

2 Technology Innovation

Technological innovation has been a key in meeting increasing levels of agricultural product demand, helping farmers increase their productive capacity while reducing required land inputs. The application of innovative technology within agricultural systems has marked some of the most significant periods in human history, the most prominent example being the 17th-century agricultural revolution that led to an explosion in productivity caused by the diffusion of innovative crop management systems and mechanisation that allowed for increases in economies of scale, and reductions in the labour force (Sunding, Zilberman, & Hall, 1999). This revolution in agriculture was a precursor to the industrial revolution, a societal boom that was the dawn of

increased industrial production and migration of labour to cities due to the availability and societal need to seek employment alternatives away from the farm (Putterman, 2008). The study of how technological innovation can impact the many aspects of modern society warrants a discussion of technology diffusion in a more generalised context.

Technology diffusion describes the process by which innovations are adopted and is defined as the increase of ownership of technology and intensive use over time (Stoneman & Diederen, 1994). The diffusion of technological innovation was formalised by Everett Rogers in his seminal work 'Diffusion of Innovations' in which he laid out the foundational framework describing the topic. Central to the discussion of technological innovation is the interrelated ideas of information and uncertainty; a greater amount of information can help to reduce uncertainty within the problem-solving process that typically includes a cause and effect relationship between actions and consequences (Rogers, 1995). Information serves to facilitate a greater understanding of a system and hedge against unpredictability.

The process of diffusion consists of four elements: an innovation, communication channels, time, and the pool of potential adopters within a societal system - each influencing the rate that a technology is adopted (Rogers, 1995). Although each element within the diffusion process influences the general acceptance or rejection of an innovation, individual characteristics of the pool of potential adopters can heavily influence perceptions of the benefit of a technology. Independent of the specific technology innovation, five generalised groups of adopters have been identified: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1995); the individual affinities of each adopter group manifest into the willingness to adopt a technology.

The framework laid out by Rogers serves to describe the process and components of technology diffusion independent of geography. Adding to the work of Rogers, Hägerstrand (1967) established important theoretical linkages between space and technology diffusion in his early work entitled 'Innovation Diffusion as a Spatial Process'. His work defined a fundamental shift in researching how innovations are diffused not just based upon factors of the social system,

but how these factors can vary over space. Further, more contemporary studies beyond classical diffusion theory extend the theory to incorporate macro-level adoption characteristics alongside factors including technology class, interdependence, and network externalities (Katz & Shapiro, 1986).

The coupling of the components that comprise the technology diffusion process present a difficult challenge when constructing a theoretical model. A variety of quantitative approaches have been used to model complex systems including systems dynamics, Bayesian networks, coupled-component models, agent-based models, and expert systems (Kelly et al., 2013), however, the interaction-oriented nature of diffusion has seen the emergence of agent-based modelling as a predominant approach due to its ability to model individual agents and their interactions within a system (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007). The incorporation of spatial and temporal factors can further enhance the modelling capacity, allowing emergent aggregate behaviours to be seen from a set of simple agent properties and interactions (Matthews et al., 2007).

The theoretical framework of technology diffusion, as applied in the context of agricultural systems, has been used to assess a variety of paradigm-shifting innovations that have led to increases in productivity and yield. One of the largest factors influencing technology diffusion in agriculture is the individual characteristics and affinities of the on-farm decision-makers (Diederen, Meijl, & Wolters, 2003a). Technology innovation within agricultural systems has largely been broken down into two main categories: embodied and disembodied innovations. Embodied innovations describe capital assets or products, whereas disembodied innovations do not take a physical form, usually describing an idea or a greater understanding of the system itself (Sunding et al., 1999).

Modern innovation in the agricultural sector surrounds the concept of site-specific management (SSM) through the use of precision agriculture (PA) technologies. PA includes a broad range of technologies including information and communications technology (ICT), field

sensor and application technologies; the coupling of these technologies allow for the management of spatial and temporal variability of crops to increase economic returns and reduce the impact on the environment (Fountas, 2005).

The vast volume of information that is collected, stored and analysed through PA technologies relies heavily on the use of ICT technology to drive the decision-making process. ICT serves as an enabling technology that facilitates information-intensive processes within an agricultural system with the goal of helping the decision maker make more informed management choices (Fountas, Wulfsohn, Blackmore, Jacobsen, & Pedersen, 2006). The coupling of empirically-driven scientific, economic, and environmental information with the practical skills and knowledge of the on-farm decision-maker form the basis of information-intensive decision support systems (DSS; Cox, 1995). The utilisation of DSSs, when coupled with high-resolution spatiotemporal data collection techniques, can provide the farmer insight into their operations that are difficult to see or diagnose through more traditionally-expensive in situ means such as soil characteristics, water and crop stress, and overall crop health (Fountas, 2005; Fountas et al., 2006; Zhang, Wang, & Wang, 2002).

Fichman & Drive (1992) laid out a theoretical framework for classifying the study of information technology diffusion; the framework maps the locus of adoption against two broad classes of information technology. First, the locus of adoption describes two main types of adopters within the study of information technology: individual and organisational adopters. The individual adopter is measured in terms of binary adoption, non-adoption, time of adoption, and frequency of use; organisational adoption further adds an overall stage of implementation of the technology. Second, the class of the technology is differentiated into two types: Type 1 and Type 2. Type 1 is characterised by a lack of user interdependence and knowledge barriers; this class encompasses single-user hardware and software applications. Type 2 involves a higher knowledge barrier to entry and dependence on the user network to realise the full potential of the technology.

The classification of ICT applications through the capabilities and knowledge barriers allows for the important distinction to be drawn between traditional computing technology and information and communications technology. Computing technology, defined through Type 1, allows for an increased computational power without dependence on other users. Traditional computing can be represented through the classical definition of technology diffusion whereby the use of the technology is based on the direct benefits of each user adopting the technology. ICT is facilitated through a network infrastructure that connects computers together; in this way, a more contemporary approach must be taken to describe the diffusion of ICT. The dependence upon other users of ICT has been discussed as a 'network externality', whereby there exists a durable good (i.e. computing technology) and a complementary good or service (i.e. network infrastructure; Katz & Shapiro, 1986). The role of network externalities further allows the ICT to be used as an information dissemination tool that can facilitate the propagation of knowledge and ideas of other innovations (Harkin, 2005).

The study of ICT adoption in the agricultural sector has been applied in several geographic contexts, with distinct focus and direction towards understanding the intricacies of the technology. Largely situated within the larger field of rural development, the general theme of the research addresses the benefits and adoption characteristics in terms of aiding on-farm operations through the dissemination of knowledge and information to decision-makers. Although the major theme revolves around increasing the spread of innovation, two areas of focus emerge to have relative importance based on the geographic context: developing and developed countries.

The study of adoption ICT in the context of developing countries such as Africa (Maumbe & Okello, 2010; Munyua, Adera, & Jensen, 2009; Muriithi Gikandi Anthony, 2009) and India (Patil et al., 2008; Rao, 2007), present scenarios of adoption based on small-scale agricultural, and the use of ICT towards building productive capacity. Research centered on developed countries explore scenarios of relatively high rates of adoption of ICT, with a greater focus on the factors that impact the utilisation of the technology (Fountas, 2005; LaRose, Gregg, Strover, Straubhaar,

& Carpenter, 2007a) and the relative inequalities between those who do and do not have access to technologies explored through the topic of digital divide (Frieden, 2005; LaRose, Gregg, Strover, Straubhaar, & Carpenter, 2007b; Warren M.F, 2002). Independent of geographic context, the evolution of ICT research in agriculture has begun embracing the relevance of big data as the basis of information intensive-agriculture, contributing to the evolution of comprehensive farm management information systems (Sørensen et al., 2010).

Among the research focusing rural development, Canada serves as a nation of significant interest due to its large land mass that supports a vast and diverse landscape of agriculture and significant digital divide among urban and rural ICT usage. Several studies have been centred around the topic of contextualising factors that influence disparities among urban, rural, and remote communities. The investigation of Internet use in Canada has been well studied since the availability of several public datasets that summarise socioeconomic and demographic factors alongside Internet usage. Singh (2004), and Noce & McKeown (2008) and have each investigated the adoption factors of ICT with a specific focus on the concept of 'rurality' using Household Internet Use Survey (HIUS). Hambly, Fitzsimons, Pant, & Sykanda (2007) delve into the study of rural ICT from a capacity-development standpoint through the incorporation of several theoretical frameworks that used census data to summarise prevailing trends of rural development and their relation to broadband use. Finally, Sawada, Cossette, Wellar, & Kurt (2006) have interrogated the digital divide between urban and rural settlements in the promotion of terrestrial wireless deployment to propose an alternative solution that is more cost-effective than wired solutions for reaching lower density remote regions. The application of these studies within the context of rural agriculture situate Ontario as an important area of Canada in the study of digital divide, especially in light of its applicability to the agricultural sector to which we now turn.

3 Agriculture in Southern Ontario

Agricultural land use in the Province of Ontario, Canada, boasts a highly productive agricultural landscape consisting of 51,950 farms in total[1]. The province produces a diverse set of agricultural products spanning field crops, livestock and poultry, fruits and vegetables. Southern Ontario is characterised by long growing seasons, ranging from 170 to 190 days at the most southern point, making it highly productive compared to the rest of the province[2]. With a diverse range of agricultural products, Southern Ontario, represents an important agricultural producer for Canada - a world leading agri-food trading nation[3], and will be a major player in meeting future demand for agricultural products nationally and internationally.

Southern Ontario possesses a large urban population concentrated in metropolitan areas located in the south-most region of the province near the United States Border[4]. The concentration of population has led to the majority of ICT infrastructure to also be concentrated alongside the vast populations, significantly contributing to the on-going discussion of rural-urban digital divide. Digital divide describes the disparities that exist between users of a technology; in a report by the Federation of Canadian Municipalities (2014), urban-rural digital divide was found to pose a significant long-term challenge for the federal government, the private sector and communities themselves.

In the Telecom Regulatory Policy 2011-291 (Telecom Regulatory Authority of Canada, 2011) published in 2011, the Canadian Radio-television and Telecommunications Commission (CRTC) established a universal target speed for broadband (or high-speed) Internet access at 5 megabits per second (Mbps) download and 1 Mbps upload speeds; broadband Internet access

[1] http://www.omafra.gov.on.ca/english/stats/county/southern_ontario.htm (Accessed 2017-01-10)
[2] http://www.omafra.gov.on.ca/english/crops/facts/climzoneveg.htm(Accessed 2017-01-10)
[3] http://www.statcan.gc.ca/pub/11-402-x/2011000/chap/ag/ag-eng.htm (Accessed 2017-01-10)
[4] http://www.statcan.gc.ca/pub/91-003-x/2007001/4129908-eng.htm (Accessed 2017-01-10)

(BIA) refers to an always-on connection to the Internet through wired or wireless connection. Further distinctions of broadband speed in the Canadian context include high-speed access (typical broadband) and ultra-high-speed Internet describing fiber-optic connections that can attain speeds of 1000 Mbps[5]. The establishment of a universal speed is intended to provide a common measure among urban, rural, and remote areas; this target speed ensures sufficient transmission bandwidth to enable rural and remote communities with opportunities to participate in the digital world utilising e-commerce, high-resolution media, employment and educational opportunities. The Policy established a target for universal access to broadband Internet by the end of 2015 facilitated through a combination of market forces, targeted funding, and public-private partnerships at all levels of government (Telecom Regulatory Authority of Canada, 2011).

Initiatives to address the growing concern over access to BIA have prompted the creation of the Digital Canada 150 (DC150v1; Industry Canada, 2014) in 2014 and the updated Digital Canada 150 2.0 (DC150v2; Industry Canada, 2015) released in 2015. The plan sets forth five key pillars to aid in the growth of Canada in the digital age: connecting Canadians, protecting Canadians, economic opportunities, digital government, and the promotion of Canadian content. The rapid transition and update from DC150v1 to DC150v2 underscores the rapid change in the discussion ICT and the emphasis in positioning Canada in the digital world through increased access; all goals outlined in DC150v1 have been implemented or are in progress with 99.5% households having access to broadband Internet access. With the election of the Liberal government in October 2015, the Digital Canada plan has been replaced with the Innovation Agenda; the initiatives under the new agenda will be announced in Spring of 2017 and will potentially supersede, revamp, or prolong the initiatives outlined in the Digital Canada plan[6].

[5] http://swiftnetwork.ca/ (Accessed 2017-01-10)
[6] https://www.ic.gc.ca/eic/site/062.nsf/eng/h_00051.html (Accessed 2017-01-10)

The importance of BIA has been well established, spanning several sectors vital to the continued success in the Canadian economy. Studies in the field of adoption of ICT have laid the groundwork for a growing need to understand the factors of adoption and accessibility of technology to position future initiatives to close the digital divide that exists across Canada.

To access the factors of adoption and accessibility of broadband Internet access used in the agricultural sector in rural Ontario, public and private datasets will be used. The Census of Agriculture (COA) 2011 is a public dataset that summarises count data for farm and farm operators; the data will be used to assess the factors of adoption that influence the use of BIA used for on-farm work. The dataset consists of 41 distinct tables that describe characteristics of farms and farm operators aggregated at the Census Subdivision (CSD) level.

The dataset contains a table entitled ‘computers used for farm business’ that describes three distinct metrics of information technology usage for on-farm work: farms using computers for the farm business, farms using Internet for the farm business, and farms having high-speed Internet access (i.e. broadband). With the emphasis on respondents benefiting from network externalities, the distinction between ‘farms using Internet for the farm business’ and ‘farms having high-speed Internet access’ has a conditional relationship; farms that use Internet are subsequently asked whether their connection is high-speed. However, due to the nature of the COA, the definition of high-speed is self-reported by respondents and does not define a strict connection speed in megabits per second (Mbps; Statistics Canada, 2012). Further, the dataset describes the last available Census available based on five-year increments; in assessing the applicability of the study as of this writing, care should be taken in drawing conclusions based on more recent innovations since 2011. As such, consideration of these factors can situate the analysis of the forthcoming 2016 COA that will be available in 2017.

Table 1: Data source summary

Data	Source	Sector	Year
Census of Agriculture	Statistics Canada	Public	2011
Antennae	Loxcel Geomatics	Private	2016
Master List of Designated Educational Institutions	CanLearn	Public	2016
Digital Elevation Model (DEM) Ontario	Land Information Ontario	Public	2016
Registered Farm Implements Dealers	Land Information Ontario	Public	2015
Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA)	Land Information Ontario	Public	2015
Census Agricultural Regions Boundary	Statistics Canada	Public	2011
Census Subdivision Boundary	Statistics Canada	Public	2011

Alongside farm and farmer operator data, geographic locational data including the 'Master List of Designated Educational Institutions' (CanLearn), 'Registered Farm Implements Dealers' (Land Information Ontario), and 'Ontario Ministry of Agriculture, Food and Rural Affairs' (OMAFRA; Land Information Ontario) were used to allow the assessment of spatial factors of adoption, namely, how proximity to different institutions might impact the adoption of broadband Internet. A private dataset that includes the provider, location and wireless band and carrier provided by Loxcel Geomatics was used to assess how accessibility to wireless technology varies across rural agricultural regions of Ontario. Finally, boundary geographies allowed for spatial contextualisation over the Province of Ontario at the Census Subdivision (CSD) and Census Agricultural Region (CAR); the CSD describes a regional municipality and CAR describes a grouping of CSDs that share similar geographic, economic and environmental characteristics.

4 Motivation

Two dimensions of information and communications technology (ICT) will be investigated through the following chapters of this manuscript-style thesis. Chapter Two assesses site and situation factors that contribute to the adoption of technology. Chapter Three examines the accessibility of wireless ICT. Lastly, Chapter Four summarises key findings and provides future directions for research beyond this thesis.

Chapter Two: Factors of ICT Adoption

1 Introduction

Technological development and innovation have drastically changed agriculture over the past century. Information and communications technologies (ICT) has served as an important innovation that has been utilised by farmers to collect, manage, and analyse vast amounts of agriculture-related information to aid in on-farm decision-making (Plant, 2001). ICT facilitates access to a number of application areas including basic management information, specialised management information, e-commerce, information on outputs, and general applications including weather forecasting and online banking (Taragola & Van Lierde, 2010)

Technology adoption has been assessed in light of the foundational framework laid out by Rogers (1995) whereby the diffusion process has been broken down into its constituent components including the role of adopters, communication channels, innovation, and the societal construct which drive the adoption of the innovation. This framework has been applied to the diffusion ICT innovation in agriculture with specific focus on the role of the adopter and the communication channels that influence adoption in developed countries including Denmark (Fountas, 2005), Greece (Kutter, Tiemann, Siebert, & Fountas, 2011), Germany (Paustian & Theuvsen, 2016), the United States (Fountas, 2005; Isgin, Bilgic, Forster, & Batte, 2008) and Canada (V. Singh, 2004). The existing literature identifies two main factors of interest related to diffusion of technology innovation in agriculture: site and situational factors associated with a farm and farm operators.

Site factors describe socioeconomic and demographic (Diederen et al., 2003), biophysical (Bakker & van Doorn, 2009), and behavioural (Berger, 2001) characteristics of a farm operator, impacting the likelihood of adoption. The study of adoption has regarded socioeconomic and

demographic factors as an important predictor for ICT in developed countries (Isgin et al., 2008); many studies have found factors related to the skill, education, and age of farm operators to be dominant.

The interrelated factors describing the level of skill and education of a farm operator has been identified as having a positive impact on the level of adoption due to the highly specialised nature of ICT. The application of ICT in agriculture is regarded as highly technical in nature and requires specialised knowledge and skills (Fountas, 2005). Although there exists a number of ICT applications that range in technical complexity (Taragola & Van Lierde, 2010), highly skilled and educated farmers tend to be more effective in utilising technology to realise productivity gains (Adrian, Norwood, & Mask, 2005; Daberkow & McBride, 2003; Paustian & Theuvsen, 2016). Farmer age has also emerged out of the body of literature and typically describes behavioural factors of the farmer; younger farms have been regarded as more willing to adopt technologies (Daberkow & McBride, 2003; Fountas et al., 2006; Isgin et al., 2008; Warren, 2004).

Farm-related factors describe characteristics of the farm and its management. Farm size and type have been largely attributed as an important factor in the likelihood of adoption of ICT; notably, large farms have been associated with a greater likelihood of adoption (Ali & Kumar, 2011; Alvarez & Nuthall, 2006; Daberkow & McBride, 2003; Fountas, 2005). Farm management factors have also been found to play a role in adoption of ICT; full-time employment of the on-farm operators is associated with high adoption when compared to part-time employment (Isgin et al., 2008; Paustian & Theuvsen, 2016).

Situational factors describe channels of communication available to a farmer that influences their perception of the benefits of an innovation (Alvarez & Nuthall, 2006; Diederen, Meijl, & Wolters, 2003b). A central concept in consideration of situational factors of adoption extends back to theories proposed Hägerstrand (1967) that describes technology diffusion as a spatial process; the consideration of spatial factors in the literature surrounding agricultural innovation diffusion have served to bolster these findings. Diederen et al (2003) describe

participation within a cooperation network is an important factor in receiving external information, resulting in a positive association with being an early adaptor of innovation in agriculture. Communication within these networks has further been shown to be localised in nature; farmers participating in information and training events such as field days, exhibitions and trade fairs, and seminars and workshops have a greater opportunity to exchange knowledge, leading to a higher rate of adoption (Fountas et al., 2006; Kutter et al., 2011). Further, urban proximity (Kantor & Whalley, 2014; Woerter, 2009) and a farm's location within a state have also been shown to influence adoption of ICT (Isgin et al., 2008).

Literature that has assessed the site and situational factors that impact the adoption of ICT have generally focused on sampling techniques for the acquisition of data through mail surveys, focus groups, and personal interviews (Fountas, 2005; Isgin et al., 2008; Kutter et al., 2011); previous studies have identified small sample size and the potential for selection bias as limitations of sampling techniques (Paustian & Theuvsen, 2016). An alternative to sampling techniques is the use of national survey (e.g., a state-wide census; Chen & Song, 2008) to analyse data over an entire population; census data is typically aggregated at various geographic scales, then grouped into 'macro-regions' based upon the environmental or economic characteristics of the area (To & Id, 2012). The availability of census data can provide an opportunity to incorporate disparate variables into the analysis of factors of adoption; geographic aggregate groups can also be used to assess variation of adoption among different regions. Further, the availability of locational data can be used to introduce situational factors that influence a farm operators decision to adopt an innovation (Kantor & Whalley, 2014). Taken together, census and location data can be used to assess the site and situational factors that influence the adoption of ICT and how these factors vary over space.

The research presented in this chapter integrates site and situational factors to assess the likelihood of adoption of ICT for agricultural land use. To achieve this overarching goal, the presented research addresses three questions through spatial analysis. First, what are the spatial

patterns of ICT technology adoption in agriculture? Second, what are the site and situational factors driving the adoption of ICT technology in agriculture? Third, are there spatially localised patterns of adoption among the contributing factors? To answer these questions, a suite of spatial analysis approaches will be used including measures of spatial autocorrelation, local indicators of spatial association, and geographically weighted regression.

2 Methodology

2.1 Study Area

The presented research is situated within the Southern, Western, Central, and Eastern agricultural regions of Southern Ontario (Figure 1). These agricultural regions consist 326 Census subdivisions (CSD), with 286 representing agriculturally-significant populations, excluding highly urbanised areas and natural regions such as national parks. Southern Ontario agriculture in 2011 consisted of 17,094 farms spread across 1,549,113 hectares of land, representing 33% of the farms and 30% of the total area in Ontario[7]. With the small relative representation of land, the Southern Ontario region boasts a large portion of high gross income farm receipts, which represents approximately 50% of the farms in Ontario reporting over 2 million dollars.

[7] http://www.omafra.gov.on.ca/english/stats/county/southern_ontario.htm (Accessed 2017-01-10)

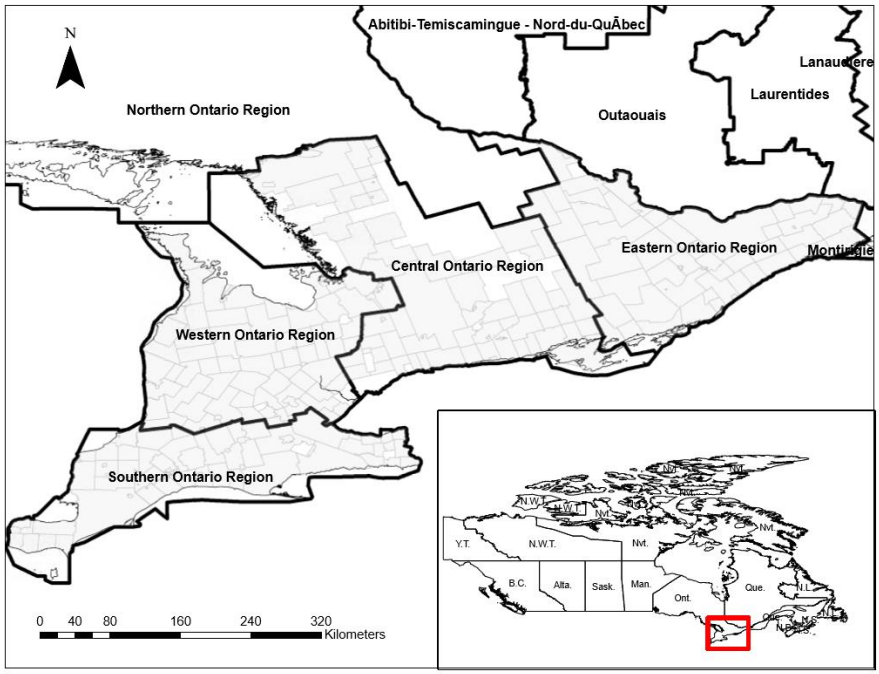

Figure 1: Study area: Southern Ontario, Canada – composed of the Southern, Western, Central, and Eastern agricultural regions

2.2 Data

A number of datasets including socioeconomic, demographic, and locational data were used to facilitate the study. Socioeconomic and demographic data were obtained from the Census of Agriculture (COA) for the year of 2011, available publicly through the Canadian Socio-Economic Information Management System (CANSIM) database published by Statistics Canada (Statistics Canada, 2011). The COA is a mandatory questionnaire, conducted every five years, and is distributed to persons who operate a farm and engage in agricultural operations including farms, ranches, or other operations that produce agricultural products for sale on the market (Statistics Canada, 2011). The Census data is presented at several geographic levels including Census Subdivision (CSD), Census Division (CD), Agricultural Region (AR), Provincial, and National scales. The assessment of ICT adoption was performed at the CSD geographic level, the smallest geographic scale available through the COA. Socioeconomic and demographic data were from the 'Farm and Farm Operator dataset' that included 43 tables that can be grouped into the

broad categories of products, operations, land, labour, and capital. Regions that did not have any respondents utilising computer usage were excluded from the study. Internet utilisation was described through the 'computers used for farm business'; three distinct metrics of information technology utilisation for on-farm work included: farms using computers for the farm business, farms using Internet for the farm business, and farms having high-speed Internet access

Locational data were used to quantify the situational adoption factors. Data acquired from Land Information Ontario (LIO)[8] provided locations of the Ontario Ministry of Agriculture, Food, and Rural Affairs (OMAFRA) research offices across Ontario and locations of 'Registered Farm Implements Dealers'. OMAFRA offices invest in the development of agricultural practices through regulation, economic development, and facilitating the dissemination of agricultural innovation and technology (Service Ontario, 2015). Farm implement dealers distribute agricultural suppliers and help facilitate the procurement of various types of technology used in agriculture, registered under the Farm Implements Act[9].

Additionally, the 'Master List of Designated Educational Institutions' provided by CanLearn was used to describe the geographic location of academic institutions and educational activities in Canada. The dataset included educational institutions categorised into private institutions, technical and vocational training institutes, and colleges and universities[10]. The data were geocoded using the address location to attain geographic coordinates of the institutions and then classified into technical and vocational institutions, and colleges and universities.

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[8] http://www.ontario.ca/page/land-information-ontario (Accessed 2017-01-10)

[9] http://www.omafra.gov.on.ca/english/engineer/fiap/dist_list.htm (Accessed 2017-01-10)

[10] http://tools.canlearn.ca/cslgs-scpse/cln-cln/reea-mdl/reea-mdl-1-eng.do?nom-name=ON (Accessed 2017-01-10)

2.3 Metrics of ICT Adoption

Three ICT metrics were used to assess the level of ICT adoption: standard Internet utilisation, high-speed Internet utilisation, and technology divide calculated using Eq. 1.

$$\textbf{(1)}\ \boldsymbol{Technology\ Divide = Standard - High\ Speed}$$

Technology divide was calculated to gauge differences amongst CSDs that utilise high-speed services and those who utilise standard Internet services for on-farm business. A common theme in the study of Internet utilisation in modern literature has focused on the urban context and sites the term 'digital divide' to address the increasing gap that exists between the 'haves' and 'have-nots', referring to the population that have access to a particular technology and those who do not (Boase, 2010; Frieden, 2005; LaRose et al., 2007b; Noce & McKeown, 2008). Recent literature in the context of agriculture has addressed the discrepancy that exists in having access to high-speed Internet to conduct farm-related work, citing the need for high-speed digital connectivity to turn data collected into actionable steps on the farm (McKinion et al., 2004).

2.4 Spatial Patterns of ICT

The assessment of the spatial characteristics of ICT utilisation can be used to identify CSDs that share statistically significant similarities or differences to their neighbours, which suggest underlying environmental, political, or proximity factors (Chen & Song, 2008; Lethiais & Cariou, 2007; Murthy, 2003). Spatial autocorrelation provides a quantitative method for assessing the degree to which an attribute of a spatial feature is associated with its neighbours over space (O'Sullivan & Unwin, 2010b). Global Moran's I was used to assess the degree of spatial autocorrelation of each ICT metric. The method reports value ranging from -1 to 1, that serves as an indication of the tendency of each metric to be clustered, or dispersed over space (O'Sullivan

& Unwin, 2010b). A value near -1 indicates that similar attributes are likely to be dispersed over the landscape, whereas a value near 1 indicates a tendency towards clustering.
A value near to 0 indicates that little autocorrelation is present in the landscape.

A localised measure of clustering (Getis-Ord Gi*) was applied to identify regional hotspots, areas of high values, and coldspots, areas of low values for each ICT metric. Clusters are identified by comparing the value of each CSD to its neighbours; a CSD is placed in a cluster when it shares a high similarity to its neighbours. Hotspots and coldspot clusters can serve to demarcate areas that share similar patterns of Internet utilisation. Anselin Local Moran's I was applied to the dataset to identify outliers of high-low or low-high ICT utilisation. High-low clusters identify an area that has an elevated level of utilisation when compared to adjacent areas, in contrast to low-high clusters that identify a depressed level of utilisation compared to adjacent areas.

2.5 Factors of ICT Adoption

2.5.1 Site Factors

The site factors of a farm encompass the socioeconomic, demographic, and biophysical characteristics that describe the likelihood of adoption. To identify site factors that impact ICT adoption, a number of variable reduction techniques were used. First, a set of variables were identified and selected based on a survey of adoption factors from existing literature (

Table 2). The survey was performed by first selecting a set of journals that reflect the topic ICT as it relates to agriculture. Three journals were selected based on direct association with the study of information technology in agriculture: Agricultural Systems, Precision Agriculture, and Computers and Electronics in Agriculture. For each journal, a full-text keyword search was performed using the Google Scholar to attain a listing of potentially relevant articles that have been published since 2005; the keywords that were used for the search were ‘adoption’, ‘factors’, and ‘information technology’. The keyword ‘communication’ was emitted to broaden the number of articles that generalise the use of Internet into the more common phrase ‘information technology’; articles were then assessed for relevance based on titles and abstracts.

The survey of literature resulted in a total of 38 articles for the Agricultural Systems, 46 for Precision Agriculture, and 100 articles for Computers and Electronics in Agriculture, based upon keywords only. Many of the articles were removed from consideration that do not directly relate to site factors or those that describe precision agriculture technologies that do not directly incorporate ICT (e.g. the factors of adoption of sensor technology and application technology only).

COA tables representing specific agricultural products (e.g. hay and field crops) were removed in favour of aggregate measures (e.g. farms classified by total farm area) to reduce the dataset and orient focus towards human-system factors of a farm (e.g. farm size). Further, the table classifying farms by the North American Industry Classification System (NAICS; Table 004-0200) was removed as it shares similarities with specific agricultural products tables (e.g. pigs on census day (Table 004-0223) and hog and pig farming (NAICS 1122; Table 004-0200)), and eliminate bias based specifically on farming products (See Appendix A: Census of Agriculture 2011 Farm and Farm Operator Data, for a comprehensive list of tables used in study).

Table 2: Summary of factors contributing to ICT utilisation in literature

Factor\Literature	*Kutter, Tiemann, Siebert, & Fountas, 2011*	*(Frey et al., 2012)*	(Isgin et al., 2008)	*(Alvarez & Nuthall, 2006)*	(Adrian et al., 2005)	(Paustian & Theuvsen, 2016)
Farm size	√	√	√	√	√	√
Farm Type	√	√				√
Age	√		√	√		
Education	√	√		√	√	√
Experience	√			√		
Application complexity	√			√		
Confidence					√	
Perception towards technology	√					
Finances			√			
Soil Quality			√			
Urban influences			√			

The factors identified from the survey of literature were used to select 23 tables from the COA yielding 207 relevant variables after removing superfluous duplicates (e.g. units representing same quantity). With a large number of variables, the chance of collinearity is likely to occur. Collinearity refers to the phenomenon where one or more variables within a model are highly correlated, potentially leading to an overspecified model (De Veaux, Velleman, Bock, Vukov, & Wong, 2011; Mela & Kopalle, 2002). An overspecified model introduces a great amount of complexity due to the increased number of variables, potentially leading to artificially-inflated predictive power when modelling a dependent variable (Allen, 1997). To reduce the likelihood of an overspecified model specified with the selected ICT factors, a method to cluster highly correlated variables and select a representative variable from the cluster was used.

Hierarchical clustering is a data consolidation method used to group together variables within a dataset that have strong correlations (Linoff & Berry, A., 2011). The method separates variables into individual discrete clusters and then combines with cluster variables that exhibit the

highest correlation. This process continues until only two clusters remain (Chavent, Kuentz, Liquet, & Saracco, 2012). For each cluster, a single synthetic variable was computed by performing a principal component analysis (PCA) among the correlated variables (Chavent et al., 2012). PCA is a dimension reduction technique that applies an orthogonal transformation to input variables to derive a set of linearly uncorrelated resultant variables (Jensen, 2005). The resultant variables represent the principal components of the input variables within each cluster; The first principal component represents the most variability among the input variables, with each subsequent principal component explaining the remaining variability (Jensen, 2005). Each cluster was assigned a synthetic variable based upon the first principal component to maximise variability among the correlated cluster variables.

As the last step in the variable reduction process, a stability analysis was used to set an optimal number of clusters. Stability refers to the ability for a cluster to be consistently reproduced given randomisation of the input variables (Ben-David, Luxburg, & Pál, 2006). The idea of stability is a core heuristic driving model selection when clustering variables, allowing for the determination of an optimal number of clusters (Chavent et al., 2012; Hubert & Arabie, 1985).

Each cluster was manually interpreted and assigned a name to describe the relationship between variables. Two reduction steps were taken to simplify clusters further. First, clusters of continuous quantitative ranges of values identified through hierarchical clustering were classified into qualitative categories (e.g. Farms classified by total farm area: small (under 130 acres), medium (130 – 1119 acres), large (over 1119 acres) farm size; Table 3). Second, a single representative variable was selected in cases where mutually exclusive variables (e.g. male and female) would result in confounding.

The result of the variable reduction process was a subset of sixty site variables that were identified as having a potential influence on ICT utilisation of farms in Southern Ontario (Table 3). To allow for a comparable evaluation of the relative impact of each of the identified variables,

each was standardised with a mean of zero and a standard deviation of one (Nakaya, Fotheringham, Brunsdon, & Charlton, 2005).

Table 3: Census of Agriculture variables selected for modelling high-speed adoption

Census Table	Exploratory Variable Name	Exploratory Variable Description
Farms classified by total farm area	**small201** **med201** **large201** (Percentage of farms)	Small-sized farms (under 130 acres) Medium-sized farms (130 – 1119 acres) Large-sized farms (over 1119 acres)
Land use	**croppas203** **sum203** (Average acres per farm)	Crop/pasture land use Summer fallow land use
Tenure of land owned, leased, rented, crop-shared, used through other arrangements or used by others	**owned204** **govleas204** **othlease204** **share204** **other204** (Average acres per farm)	Owned land Government leased land Rented or leased land Crop-shared land Other arrangements
Tillage practices used to prepare land for seeding	**notil205** **cropres205** (Average acres per farm)	No-till or zero-till seeding Incorporate crop residue
Land inputs in the year prior to the census	**herbfer206** **insect206** **fung206** **lime206** (Average acres per farm)	Herbicide/fertiliser application Insecticide application Fungicide application Lime application
Manure and manure application methods in the year prior to the census	**compnot207** **compinc207** (Percentage of farms)	Manure incorporated Manure not incorporated
Land practices and land features	**graz208** **crop208** (Percentage of farms)	Grazing-management practices Crop-management practices
Forms of weed control on summerfallow land	**chem209** **sumfal209** (Average acres per farm)	Chemical weed control used Summer Fallow weed control used

Irrigation in the year prior to the census	**past210** **crop210** (Average acres per farm)	Pasture irrigation Crop irrigation used
Farms classified by operating arrangements	**solepart230** **partwrit230** **family230** **nonfam230** **other230** (Percentage of farms)	Solo or partnership no agreement Written partnership Family Non-family Other arrangements
Farms classified by total farm capital	**u500k232** **o500k232** (Percentage of farms)	Under $500,000 total farm capital Over $500,000 total farm capital
Farms classified by total gross farm receipts in the year prior to the census	**totrecpt233** (Average gross farm receipts) **u25k233** **o25k233** (Percentage of farms)	Total farm receipts Farm receipts under $25,000 Farm receipts over $25,000
Farm capital (farm machinery and equipment, livestock and poultry, land and buildings)	**totland234** **smtrac234** **mdtrac234** **lgtrac234** **truck234** **harv234** **tilcul234** **irrig234** **other234** **livepoul234** (Percentage of farms)	Total land capital Small tractor capital Medium tractor capital Large tractor capital Truck capital Harvesting and small vehicle capital Tillage and cultivation capital Irrigation capital Other equipment capital Livestock and poultry capital
Farm business operating expenses in the year prior to the census	**past235** **other235** (Average dollars per farm)	Pasture supply expenses Other expenses
Paid agricultural work in the year prior to the census	**paidwork236** (Average employees per farm) **totweek236**	Paid yearly or seasonal work

	(Average weeks per farm	Total weeks paid work
Total number of farms and farm operators	**avgop237** (Average operators per farm)	Average number of operators
Number of farm operators per farm by sex	**maleop238** (Percentage male operators)	Total male operators
Number of farm operators per farm by age	**u35239** **u54239** **o54239** (Percentage of operators) **avgage239** (Average age of operators)	Farm operators under 35 years old Farm operators 35-54 years old Farm operators over 54 years old Average age of operators
Number of farm operators who lived on the farm at any time during the 12 months prior to the census	**onfarm240** (Percentage operators)	Farm operators living on farm
Number of farm operators by average number of hours per week worked for the agricultural operation in the calendar year prior to the census	**less40241** **over40241** (Percentage operators)	Hours work per week under 40 Hours work per week over 40
Number of farm operators by paid non-farm work in the calendar year prior to the census	**nononfarm242** **o40242** **l40242** (Percentage operators)	No non-farm work Under 40 hours non-farm work Over 40 hours non-farm work

Note: Exploratory variable names were specified with a short-name prefix based on the census cluster description and suffixed with the census table number

2.5.2 Situational Factors

Situational factors were used to investigate the influence of spatial proximity to collaboration partners on the propensity of a farm to adopt ICT. Several institutions were identified in the literature to have an association with on-farm operations including academic

institutions, government agencies, and commercial facilities (Ponds, van Oort, & Frenken, 2007; To & Id, 2012; Woerter, 2009).

Each collaboration partner and institution was used to select facilities within Ontario that serve an equivalent function. First, academic institutions encompassing comprehensive research facilities such as universities and colleges, and trade-oriented institutions such as technical and vocational institutions were selected to fulfil the role of academic institutions. Second, the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA)[11] was selected as the primary government agency that performs research in the field of agriculture, and these locations were used as the government research agency of interest. Third, dealers of farm equipment in Ontario registered under the Farm Implements Dealership program[12] were selected as the primary commercial facilities aiding on-farm operations. The minimum distance to each potential collaboration partner was calculated from the centroid of each CSD to attain a quantitative measure of proximity.

2.6 Modelling Technology Diffusion

A number of statistical modelling approaches have been used in the past to investigate the adoption of technology using count data (e.g., tobit/probit (Diederen et al., 2003a; Ghadim, Pannell, & Burton, 2005; Mrica, Adesina, & Baidu-forson, 1995), Poisson and negative binomial (Isgin et al., 2008; Plant, 2001)); few of these methods, however, incorporate the heterogeneity that exists across space. This heterogeneity adds a level of sophistication that suggests that the incorporation of localised characteristics of a region may be a better approach (To & Id, 2012). Geographically-weighted regression (GWR) is a statistical modelling method that allows parameter coefficients to vary over space (O'Sullivan & Unwin, 2010c). Variation in the coefficients typically enhances the predictive capabilities of the model due to the incorporation of

[11] http://www.omafra.gov.on.ca (Accessed 2017-01-10)

[12] http://www.omafra.gov.on.ca/english/engineer/fiap/fiap.htm (Accessed 2017-01-10)

localised and regional factors, compared to global models (Nakaya et al., 2005; Saefuddin, Saepudin, & Kusumaningrum, 2013; Weisent, Rohrbach, Dunn, & Odoi, 2012).

The computation of spatially-varying coefficients requires a GWR model to be calibrated for every areal unit of study, resulting in an exponential runtime complexity. To minimise the number of variables for importation into a GWR model, a global Poisson generalised linear model (GLM) was first applied to the dataset to identify statistically significant variables of interest. A Poisson distribution is commonly applied to count or rate data derived from a census (Nakaya et al., 2005; Rodriguez, 2007; Zeileis, Kleiber, & Jackman, 2007). The distribution has an error term that does not follow the traditional Gaussian standard error, but typically has a right-skewed orientation, with the assumption that the mean is equal to the variance (Rodriguez, 2007). A Poisson distribution probability density function (Eq. 2) measures the probability of a given number of events occurring when the likelihood is relatively small (De Veaux et al., 2011).

$$(2)\ Prob(x, \mu) = \frac{e^{-\mu}\mu^{x}}{x!}$$

where Prob (x, μ) is the probability of an event occurring, x is a non-negative integer value representing the number of events expected (utilisation rate), μ is the mean (average utilisation rate), and *e* is the natural logarithm.

High-speed Internet utilisation was used as the dependent variable of the Poisson model to capture the increasing importance of high-speed connections for on-farm operations such as precision agriculture, connectivity to the digital economy, and access to real-time information that aid in the decision-making process (Fountas, 2005; McKinion et al., 2004; Zhang et al., 2002). The distribution of high-speed Internet utilisation among CSDs is presented in Figure 2; the rate of farms utilising high-speed Internet are represented on the x-axis; the number of CSDs registering a high-speed utilisation rate is represented on the y-axis.

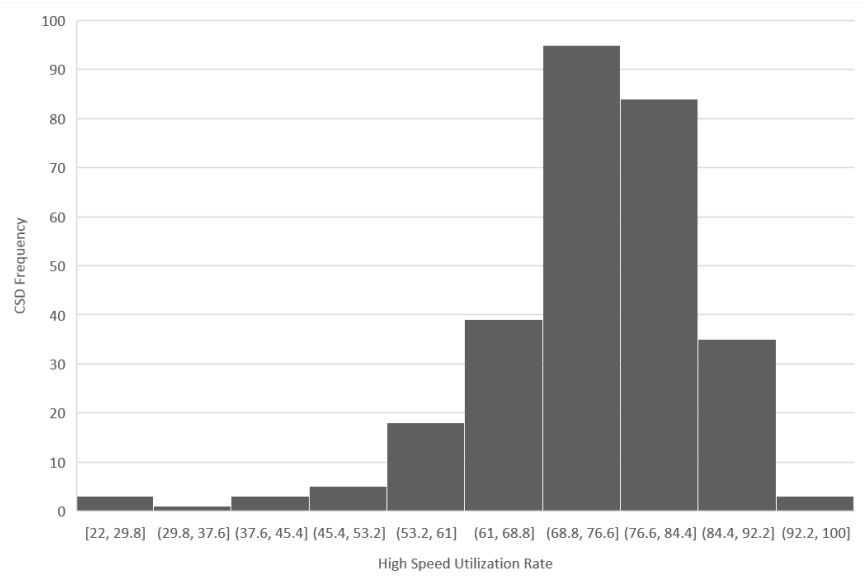

Figure 2: Frequency distribution of high-speed Internet utilisation

To ensure the assumptions of a Poisson model were met, the mean and variance of the high-speed Internet utilisation were calculated and compared. The summary statistics reported a mean of 73.5, and a variance of 123.1, which violates the assumption of the Poisson probability distribution that the mean must be equal to the variance (De Veaux et al., 2011). A model exhibiting properties of a vastly larger variance when compared to the mean is typical in count and rate data (Ver Hoef & Boveng, 2007), and represents overdispersion in the data. Overdispersion in a Poisson model violates underlying assumptions of the maximum likelihood estimator (MLE), whereby the data possesses a greater amount of variability than expected when modelled with a Poisson distribution; mismatches between data and model variability result in a model reporting reliable estimates for coefficients, but incorrect error terms for each coefficient estimate that impacts the assessment of statistical significance as determined through a t-test (Breslow, 1990).

To account for this violation in the Poisson model, a quasi-Poisson model was used to remove the stipulation that the mean must be equal to the variance. Using the quasi-Poisson model, a quasi-MLE was used to approximate the coefficient and error terms, robust to the

previous assumptions for a standard Poisson model, (Breslow, 1990; Ver Hoef & Boveng, 2007; Zeileis et al., 2007) and a t-test was performed to determine the statistical significance of each variable. A quasi-Poisson model is characterised by a dispersion parameter derived through the relationship between the mean and variance of the dataset, and does not have a defined distributional form (e.g. Poisson distribution), a key requirement of calculating a model comparison metric such as the Akaike Information Criterion (AIC; Ver Hoef & Boveng, 2007); a model comparison metric was not required since the quasi-Poisson model was used as a data reduction method.

Variation in the population size among CSDs was accounted for by introducing a Poisson offset; an offset allows for the modelling of count data as a rate. The standard Internet utilisation count was used as the offset for the modelling of high-speed Internet utilisation to target the population within each CSD that utilises some form of Internet (standard or high-speed). The quasi-Poisson GLM (Eq. 3) was specified with a log-link function relating the expected mean (high-speed Internet utilisation count) to the linear predictor of the model (Ver Hoef & Boveng, 2007; Zeileis et al., 2007).

$$(3)\ \log\frac{\mu}{t} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

where μ is the expected mean (average high-speed Internet utilisation count), t is an offset variable (standard Internet utilisation count), α is the intercept, x_n is the nth predictor variable, and β_n is the nth predictor coefficient

The quasi-Poisson model was parameterised using the site and situational factors identified above, and estimates for coefficients, error terms and associated t-values were computed. Statistically significant parameters from the quasi-Poisson model were selected at the 0.05 alpha level, representing a 95% confidence that the model is correctly specified (De Veaux

et al., 2011). This alpha level sets an appropriate statistical significance and reduces the occurrence of Type II errors related to being too restrictive with variable selection (De Veaux et al., 2011).

To assess that the quasi-Poisson model corrected for the overdispersion present in the traditional Poisson model, two methods were used. The first method compared the dispersion parameter of the model derived from the relationship between mean and variance with the scale factor. The scale factor assesses the residual deviance of the model in relation to the number of observations (Eq. 4).

$$(4)\ Scale\ Factor = \frac{Residual\ Deviance}{Degress\ of\ Freedom}$$

A properly specified model is expected to have a dispersion parameter approximately equal to the scale factor; over or underdispersion can be identified in the dispersion parameter, and scale factor have vastly different values (Zeileis et al., 2007).

The second method to assess the dispersion present in the model was to assess the pattern of the resulting residuals to identify potential violations of complete spatial randomness. A key assumption is that there are no underlying spatial patterns explaining the variation in the dependent variable (O'Sullivan & Unwin, 2010b). The Global Moran's I test for spatial autocorrelation was used to assess the spatial pattern of the residuals and indicate the presence of underlying spatial characteristics (De Smith, Longley, & Goodchild, 2014). Where there is significant spatial clustering (i.e. Moran's I value near 1), there is strong evidence of violating the assumption of complete spatial randomness, indicating that underlying spatial factors are at play and resulting in uncertainty when interpreting the results of the model (De Smith et al., 2014).

Using variables that were determined to be statistically significant in the quasi-Poisson model, a set of full and semi-parametric geographically-weighted Poisson regression (GWPR) models were specified to assess how the coefficients vary over space. The full and semi-

parametric GWPR models remove the constraint of the global Poisson model that the mean must be equal the variance, by calibrating the model using a geographically-weighted likelihood rather than a maximum-likelihood weighting (Nakaya et al., 2005). A global Poisson model was specified to establish a baseline to compare against each GWPR model.

Each full and parametric GWPR model was specified with a bandwidth that defines a neighbourhood for each CSD across the study area. Due to the non-homogeneity of the size and shape of each CSD in the study, an adaptive bi-squared nearest-neighbour approach was selected to account for spatial variation. The bi-squared approach allows the number of neighbours in the neighbourhood to be kept constant (Nakaya, Charlton, Lewis, Fotheringham, & Brunsdon, 2012).

The full GWPR, which allowed all variable coefficients to vary over space, was performed with a spatial variability test to identify variables that have a strong likelihood of geographic variation. The test allows each coefficient to vary with respect to the full GWPR model and computes the difference in criterion metrics (i.e. AIC; Tomoki Nakaya et al., 2012). Variables that reported a negative value in their difference of criterion and had a value less than negative 2 were found to exhibit variability in their coefficients across space (Nakaya et al., 2012). Semi-parametric GWPR allows only a subset of the variable coefficients to vary over space, modelling the rest of the variables with a fixed coefficient over space (Nakaya et al., 2005).

Each GWPR model was evaluated and compared using the computed Akaike Information Criterion (AIC; Akaike, 1973) with a correction (AICc; Eq. 5). AICc was used to compare models containing a different number of variables (*k*), given a fixed sample size (*n*; D. R. Anderson & Burnham, 2016).

$$(\mathbf{5})\ \boldsymbol{AICc} = \boldsymbol{AIC} + \frac{\mathbf{2}\boldsymbol{k}(\boldsymbol{k}+\mathbf{1})}{\boldsymbol{n}-\boldsymbol{k}-\mathbf{1}}$$

where k is the number of variables and n is the sample size

3 Results

3.1 Summary of ICT utilisation

The first research question looked to assess the spatial patterns of ICT utilisation in Southern Ontario agriculture; each ICT metric was first statistically summarised then spatial patterns were assessed through the use of global and localised measures of spatial autocorrelation. Each ICT metric was investigated individually, and the results will be discussed in turn.

Standard Internet utilisation had a minimum percent of 73% and the maximum of 100% of the population, with a range of 27%. The mean standard Internet utilisation was 94%, biased towards the maximum utilisation percentage, with a standard deviation of 4% (Table 4; Figure 3).

Table 4: Summary statistics for ICT metrics

	Standard Internet Utilisation	High-speed Internet Utilisation	Technology Divide
Minimum	73%	22%	0%
Maximum	100%	100%	75%
Mean	94%	73%	20%
Standard Deviation	4%	11%	9%

Measures of global and local spatial autocorrelation were used to identify clusters and outliers present across the landscape. The results of Global Moran's I (Table 5) reported a value of 0.26 with a P-value of approximately 0, indicating a statistically significant but relatively low to moderate level of positive spatial autocorrelation among CSDs for standard Internet utilisation.

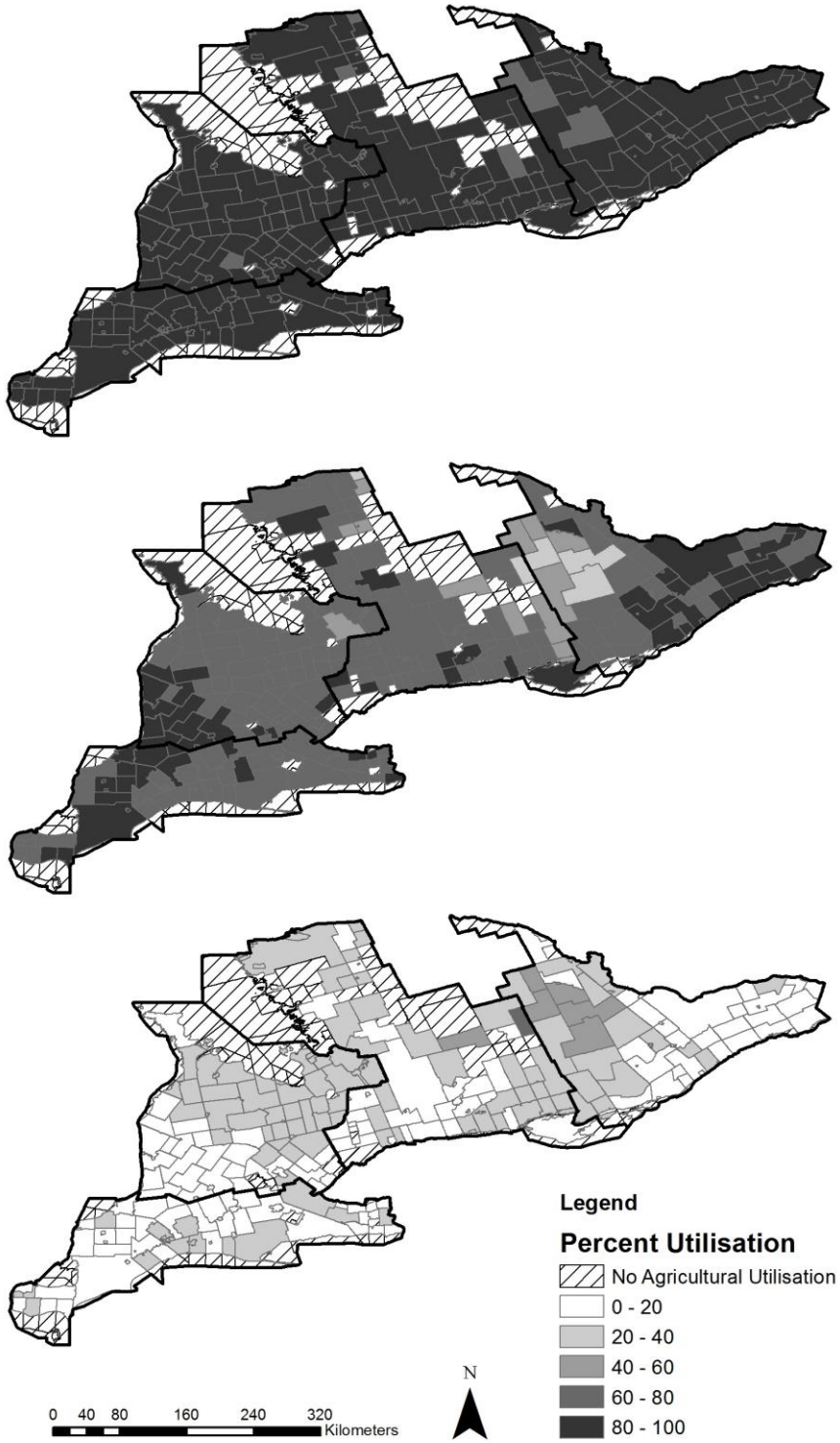

Figure 3: Spatial technology utilisation (percent) of standard Internet (top), high-speed Internet (middle), and technology divide (bottom)

Table 5: Moran's I report statistics for spatial autocorrelation of ICT utilisation

	Standard Internet	High-speed Internet	Technology Divide
Moran's Index (I)	0.26	0.50	0.44
Expected Index	-0.0035	-0.0035	-0.0035
Variance	0.0011	0.0011	0.0011
z-score	7.97	15.13	13.35
P-value	0.00	0.00	0.00

The results for the Getis-G Ord GI* test for spatial clusters in standard Internet utilisation (Figure 4) identified distinct hotspots and coldspots. Hotspots were found to be present in several areas including the Southern and Western agricultural regions surrounding Lake Huron and Georgian Bay water bodies, and one cluster in the Eastern agricultural region running along the St. Lawrence River. Coldspots were found mainly to the north of the study area located in the Central and Eastern agricultural regions surrounding Algonquin National Park and running southward towards the St. Lawrence River.

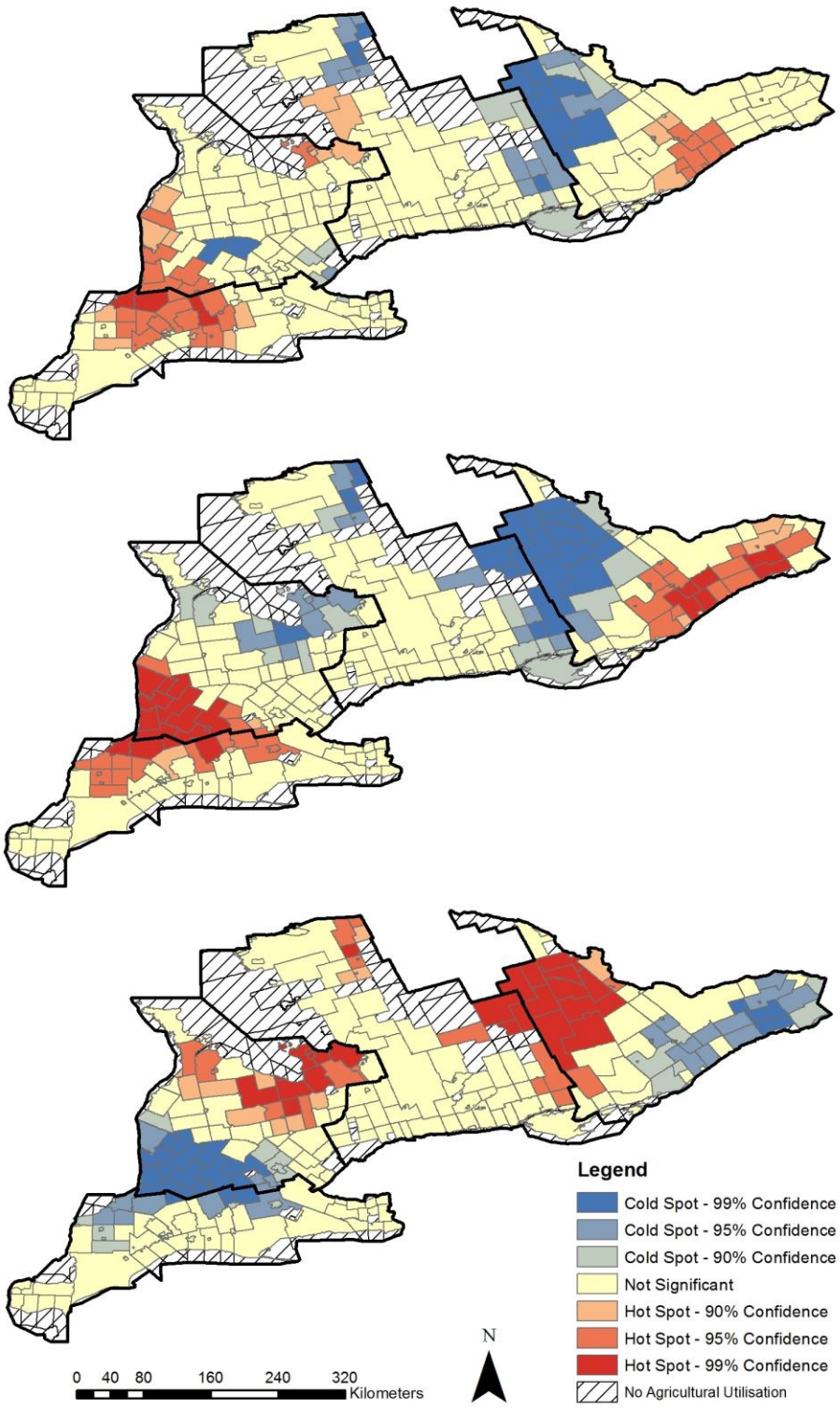

Figure 4: Getis-G Ord* spatial clustering analysis results of the utilisation of standard Internet (top), high-speed Internet (middle), and the technology divide (bottom); clusters are identified as hotspots (red) and coldspot (blue)

The results from Anselin Local Moran's I (Figure 5) were also used to facilitate the identification of localised regional outliers. Standard Internet utilisation identified a number of high-low outliers that mostly resided at the fringe of Algonquin National Park coldspot cluster as identified through Getis-G Ord GI* cluster analysis.

High-low outliers included the Machar, South River, Huntsville, Carlow/Mayo, North Algona Wilberforce, and Stone Mills CSDs, and are representative of regions that have a relatively high percentage of standard Internet utilisation when compared to adjacent CSDs. These high-low outlier CSDs represented utilisation of standard Internet close to 100%, 10 to 20% higher on average than their adjacent neighbouring CSDs. The Bancroft CSD located adjacent and west of the Carlow/Mayo high-low outlier was identified as a low-high outlier, exhibiting a 5 to 10% lower standard Internet utilisation when compared to adjacent CSDs.

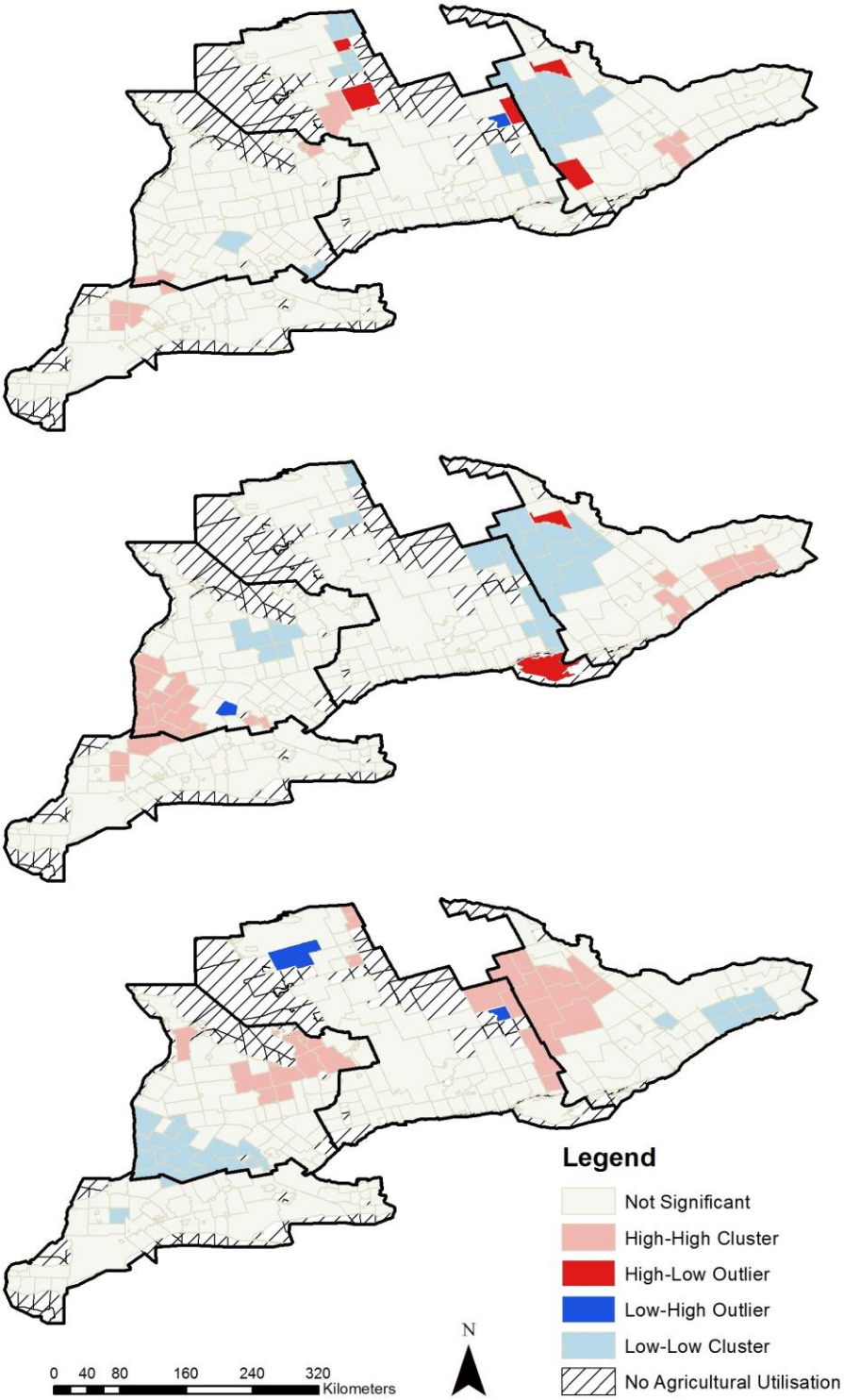

Figure 5: Ainselin's Local Moran's I outlier analysis results of utilisation of standard Internet (top left), high-speed Internet (top right), and technology divide

High-speed Internet utilisation (Table 4) exhibited a large range of 78% between minimum utilisation at 22% and the maximum utilisation at 100%. The mean of utilisation was 73% with a standard deviation of 11%, representing a large spread among the CSDs but a bias towards the maximum utilisation for this ICT metric.

Global Moran's I test for spatial autocorrelation (Table 5) for the high-speed Internet utilisation metrics reported a statistically significant value of 0.50, with a P-value close to 0. This Moran's I value indicates a moderate level of positive spatial autocorrelation for high-speed Internet utilisation. The moderate positive spatial autocorrelation implies a global tendency towards high-speed Internet utilisation being clustered together; this spatial pattern is evident across the landscape with distinct clusters of hotspots present in the Southern and Eastern agricultural regions, and coldspots in the Central agricultural region (Figure 3).

The results from the Getis-G Ord GI* (Figure 4) identified a number of localised spatial clusters of high-speed Internet utilisation. Hotspot clusters were identified surrounding Lake Huron in the Southern and Western agricultural regions, as well as in the Eastern agricultural region running along the St. Lawrence River, south of the metropolitan area of Ottawa. Areas of low high-speed Internet utilisation, represented as coldspot clusters, were identified for CSDs surrounding Algonquin National Park, extending southward to the St Lawrence River, as well as the area surrounding Georgian Bay.

Anselin Local Moran's I (Figure 5) for high-speed Internet utilisation found similar hotspot and coldspot regions as identified in the cluster analysis, presenting only three statistically significant CSD outliers. Prince Edward County and North Algona Wilberforce were identified as high-low outliers, both located at the fringe of the coldspot cluster in the Eastern agricultural region, extending from Algonquin National Park to the North and the St. Lawrence to the south. Each high-low outliers had a high-speed Internet utilisation of around 80% compared to adjacent CSDs that had a 10 to 40% lower rate. Wellesley, located in the Western agricultural region, was

identified as a low-high outlier having a stark difference in high-speed Internet utilisation of 62%, compared to adjacent areas that had a 20 to 35% greater rate.

Summary statistics for technology divide (Table 4) between standard and high-speed Internet utilisation had a minimum of 0% of the population, implying that one or more CSDs have their entire population utilising high-speed Internet. The maximum technology divide was 75%, representing CSDs that have a large percentage of their population that are only using standard Internet (75%) compared to the 25% remainder utilising high-speed Internet. Technology divide had a mean value of 20% with a standard deviation of 9%, representing a bias towards lower technology divide amongst the CSDs.

Measuring spatial autocorrelation for technology divide, Global Moran's I (Table 5) reported a statistically significant value of 0.44, with a P-value closely approximating 0. The reported I value indicates a moderate level of positive spatial autocorrelation representing a global tendency towards the clustering of technology divide. The assessment of spatial patterns of the digital divide (Figure 3) identified a number of distinct regional clusters in the Southern and Central agricultural regions, validating the interpretation of Moran's I value for technology divide.

The identification of hotspot and coldspots resulting from the Getis-G Ord GI* cluster analysis (Figure 4) identified a number of cluster regions. Coldspots were identified in regions surrounding Lake Huron in the Southern and Western agricultural regions and along the St. Lawrence River in the Eastern agricultural region, indicating a large percentage of the population in these clusters are utilising high-speed Internet. Hotspots were identified in areas surrounding Georgian Bay and Algonquin National Park in the Central agricultural region. These coldspots identify regions of high technology divide, indicating a small percentage of the population in these clusters are utilising high-speed Internet.

Anselin Local Moran's I outlier analysis (Figure 5) for technology divide identified two low-high outliers. The Whitestone CSD, located in the northern portion of the Central agricultural

region, had a 0% technology divide, signalling 100% utilisation of high-speed technology, compared to a 10 to 30% lower utilisation amongst adjacent CSDs. The Bancroft CSD, also located in the Central agricultural region, west of the hotspot cluster near Algonquin National Park, had a similar sign of low technology division at 10%, compared to 20 to 65% divisions in adjacent CSDs in the region.

3.2 Factors of Adoption

The second research question looks to assess the site and situational factors associated with high-speed utilisation. A quasi-Poisson model was specified using the sixty site factors plus four situational factors for each CSD to find the variables that have the strongest influence on high-speed Internet utilisation. The results from the quasi-Poisson model (Table 6) identified eight variables that were statistically significant (0.05 alpha value).

Table 6: Summary of statistically significant variables from quasi-Poisson regression

Variable	Description	Coefficient Estimate	Standard Error	t-value	p-value	Significance Code
(Intercept)	Intercept offset	-3.03E-01	6.93E-03	-43.70	2.0E-16	***
othlease204	Land area used through other arrangements	-2.28E-02	1.24E-02	-1.84	0.067	*
herbfer206	Herbicide and Commercial Fertiliser Application	7.82E-02	2.12E-02	3.69	0.000285	***
lime206	Lime Application	-3.30E-02	8.35E-03	-3.95	0.000105	***
partwrit230	Partnership with a written agreement	-2.03E-02	1.01E-02	-2.01	0.0461	**
over40241	Operators working more than 40 hours per week	-5.77E-02	1.88E-02	-3.07	0.00243	***
nononfarm242	Operators reporting no paid non-farm work	2.66E-02	1.54E-02	1.73	0.0854	*
Min_tech	Minimum distance to a technical or vocational school	2.21E-02	8.86E-03	2.49	0.0135	**
Min_univ	Minimum distance to a University	-5.47E-02	1.04E-02	-5.26	3.36E-07	***

Significance codes: 0.01 '*' 0.05 '**' 0.1 '*'**

The application of fertiliser or herbicide had a positive correlation with high-speed Internet utilisation; an increase in land input results in an increase in high-speed utilisation. Conversely, the application of lime resulted in a negative correlation to the high-speed utilisation.

The variable describing the use of land through other arrangements had a negative correlation with high-speed Internet utilisation; as the number of farms using land through other operating arrangements increases, the utilisation of high-speed Internet decreases. Similarly, farms with a written partnership also had a negative correlation with high-speed Internet utilisation; as the number of farms participating in this type of arrangement increases, high-speed Internet utilisation will decrease.

Operators working more than 40 hours a week had a negative correlation, indicating that as the number of operators working more than a typical workweek increases, the utilisation of high-speed Internet decreases. The number of operators reporting no off-farm work had a positive correlation; when farms report a greater number of no off-farm work, utilisation of high-speed Internet is likely to increase.

The variable representing the minimum distance to a university was negatively correlated, suggesting that as the distance between a CSD and a university increases, the utilisation of high-speed Internet is likely to decrease. The minimum distance to technical and vocational schools, however, shows a positive correlation; as the minimum distance to these facilities increases, high-speed Internet utilisation is likely to increase.

Evaluating the quasi-Poisson model's tendency towards over or underdispersion, the model dispersion parameter was determined to have a value of 0.57, with a computed scale factor of 0.587. Comparing these two values, the model was determined to show a slight tendency towards overdispersion in the variables, or a slightly higher variability in the dataset than expected by the model's distribution. Overdispersion was also evaluated using the Global Moran's I test for spatial autocorrelation, which reported a statistically significant value of 0.17 and indicated a low to moderate positive autocorrelation among residuals (based on a P-value close to 0; 0.1×10^{-5}). The presence of small amounts of spatial autocorrelation is typical of real-world data (De Smith et al., 2014). Given only a slight tendency of the model towards

overdispersion and low Moran's I value (i.e. Moran's I < 0.2) the data were satisfactory for ingestion into a GWR model (De Smith et al., 2014).

3.3 Spatially Localised Patterns of ICT

Statistically significant variables determined through the quasi-Poisson model were used to calibrate six GWPR models (Table 7). The global model (GLOB), representing a globally-defined set of coefficients over the study area, achieved an AICc value of 230, explaining 32% of the variation in high-speed Internet utilisation. A kernel mapping GWPR was used to assessed the impact of the intercept coefficient varying over space (KERN; Nakaya et al., 2005); the model described 52% of the variance and achieved a low relative AICc value of 182.

Table 7: Comparison of six full and semi-parametric GWPR models

Model	Bandwidth (km)	AICc	Variance
KERN	43	182.44	52%
GLOB	-	229.76	32%
F-GWPR	203	213.11	48%
SP-GWPR (herbfert, min_univ)	88	193.48	56%
SP-GWPR (min_univ)	64	186.47	57%
SP-GWPR (herbfert)	67	193.10	56%

A full GWPR model (F-GWPR) was specified that allowed all eight variables to vary over space, describing 48% of the variation in high-speed utilisation. The full GWPR received a relatively high AICc value of 213. A spatial variability test was run based on the full GWPR model to identify variables that show statistically significant indicators of their coefficients varying over space. From the set of eight variables tested (Table 8), the minimum distance from a university (i.e. min_univ), and the application of herbicide and fertiliser (i.e. herbfer), each

reported a difference of criterion that was less than negative two, representing a strong indication of spatial variability (Nakaya et al., 2005).

Table 8: Spatial variability test of independent variables

Variable	Difference of Criterion
Intercept	-7.39
othlease204	1.75
herbfer206	-5.93
lime206	1.29
partwrit230	3.25
over40241	1.47
nononfarm242	2.60
Min_tech	0.32
Min_univ	-4.83

The first semi-parametric GWPR specified a model with both variables varying over space (i.e. SP-GWPR(min_univ, herbfert)), explained 55% of the variance in the high-speed utilisation and a relatively low AICc value of 193. Two additional semi-parametric GWPR models were specified using each of the variables individually. Allowing only the minimum distance to a university variable to vary over space (i.e. SP-GWPR(min_univ)), the model explained 57% of the variance in the high-speed utilisation and a relatively low AICc of 186. Allowing the application of herbicide and fertiliser coefficients to vary over space (i.e. SP-GWPR(herbfert)), 55% of the variance in high-speed utilisation was explained, with a near identical AICc to SP-GWPR(min_univ, herbfert) of 193.

SP-GWPR(min_univ) was selected to be the optimal-performing model, based upon its high predictive power in describing the high-speed utilisation and low AICc value. Each model variable had a relatively high z-value (ratio of estimate to standard error) apart from the over40241 variable (Table 9). A high z-value indicates that the standard error for the coefficient estimate is negligible compared to the value of the estimate.

Table 9: Summary of SP-GWPR(min_univ) model

Variable	Coefficient Estimate	Standard Error	z-value (Estimate/SE)
othlease204	-0.036	0.012	-3.00
herbfer206	0.050	0.014	3.54
lime206	-0.023	0.0083	-2.76
partwrit230	-0.010	0.0088	-1.14
over40241	0.0017	0.011	0.15
nononfarm242	0.019	0.013	1.50
Min_tech	0.018	0.013	1.36

The spatially varying variables (i.e. intercept and min_univ; Table 10) had a similar range; However, the absolute value differed by approximately 0.23, with the intercept remaining negative through its varying coefficients; and the minimum distance to a university mostly remaining negative with few positive values across the study area.

Table 10: Summary statistics of spatially varying variables in SP-GWPR(min_univ) model

Variable	Intercept	Min_univ
Mean	-0.30	-0.048
STD	0.056	0.044
Min	-0.39	-0.16
Max	-0.20	0.028
Range	0.18	0.18
Lower Quartile	-0.35	-0.075
Median	-0.30	-0.044
Upper Quartile	-0.24	-0.021
Interquartile Range	0.11	0.054
R^2	0.082	0.040

The spatially-varying coefficients and error terms each show distinct regional patterns when visualised over the study area (Figure 6). CSDs in the Central, Eastern and Western agricultural regions exhibited a small negative correlation with the high-speed Internet utilisation. The Southern Agricultural region, in contrast, exhibited no correlation or small positive

correlation with high-speed Internet utilisation. Standard error terms associated with the minimum distance varied over space, with Eastern and Southern agricultural regions registering a lower error in the Western and Central regions. The difference in standard error for the minimum distance to a university variable (min_univ) indicates that the Eastern and Southern agricultural regions can more accurately describe variation in high-speed Internet utilisation when compared to the Western and Central agricultural regions.

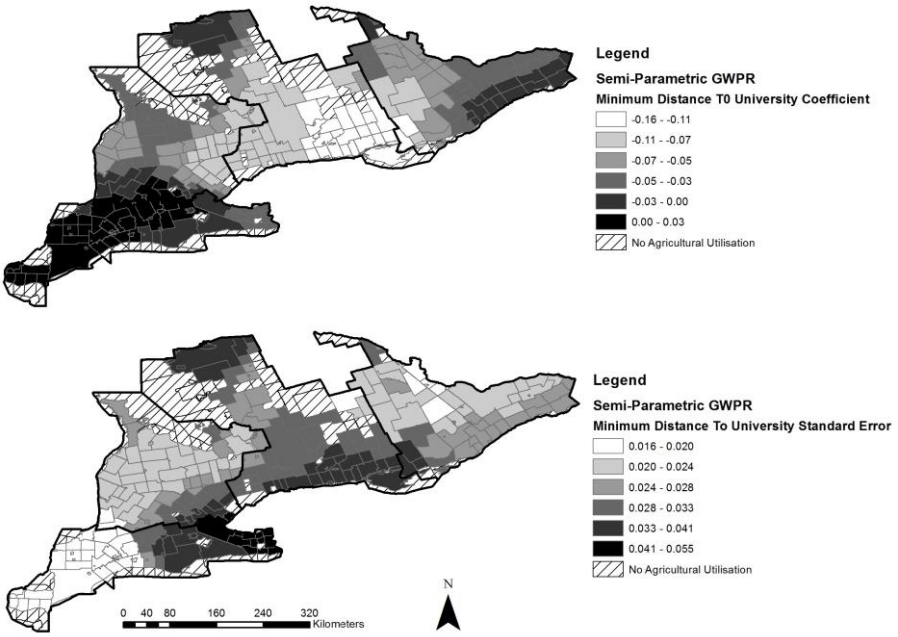

Figure 6: Spatial variation of minimum distance to university coefficient and standard error

4 Discussion

4.1 Where are farmers using ICT in Southern Ontario?

The spatial pattern of technology utilisation exhibited distinct hotspots and coldspots of standard and high-speed Internet utilisation. Areas that had a high percentage of utilisation of high-speed Internet had an associated low technology divide, indicating that if an area has a pronounced high-speed Internet utilisation, standard Internet utilisation will be high as well.

Areas with high-speed Internet utilisation generally exhibited a higher amount of clustering than either standard Internet utilisation or technology divide, but the regions running along the St. Lawrence River in the Eastern agricultural region and the region surrounding the Lake Huron water body each exhibited clusters of high utilisation for both standard and high-speed Internet and a low cluster for technology divide.

Areas surrounding Algonquin National Park had little clustering of standard and high-speed Internet utilisation; in contrast, areas surrounding Georgian Bay that had significant clustering for standard Internet utilisation, but relatively low clustering for high-speed Internet utilisation. Access to high-speed technology and regional governance initiatives in rural areas promoting innovate technology (LaRose et al., 2007a) could be potential descriptors for the spatial variation in the ICT utilisation not explained through the site and situation factors investigated in this study.

4.2 Farm Factors Impacting ICT Adoption

4.2.1 Site Factors

Farm and farm operator factors accounted for six out of eight variables identified as being statistically significant, at the 0.05 alpha level. The application of herbicide or fertiliser and the application of lime land inputs each had a p-value near 0 (0.01 alpha level), which are associated with high-speed Internet utilisation. The application of herbicide and fertiliser showed a positive correlation, whereas the application of lime had a negative correlation with high-speed technology adoption.

The association of herbicide and fertiliser land inputs with high-speed Internet utilisation are consistent with recent developments in variable rate application of land inputs that has become pronounced since the inception of precision agricultural (Fountas, 2005; Grenzdörffer, Engel, & Teichert, 2008; McKinion et al., 2004; Plant, 2001). Typically, these inputs are applied through variable rate treatments (VRT) based upon an assortment of data collected about field

variability including soil condition, crop health, topography, and other environmental factors (Plant, 2001; Zhang et al., 2002). The analysis of these data for an agricultural application generally requires a high-speed data path to a service provider to facilitate near real-time analysis and field-level prescription of inputs to be applied, allowing for optimal agricultural productivity (McKinion et al., 2004).

The application of lime, however, shows a negative correlation compared to fertiliser and herbicide. Lime is typically applied when the acidity is low and needs to be raised (N. P. Anderson et al., 2013; Brown, Koenig, Huggins, Harsh, & Rossi, 2008). The negative association between the application of lime and ICT adoption can largely be attributed to the composition of the soil in Southern Ontario. The soil is composed of dolomitic or calcitic limestone that is alkaline[13]; due to the high acidity of the soil, the application of lime is rarely needed. Based on the underlying composition of the soil of Southern Ontario, the association of the application of lime presents a factor of adoption that is strongly linked to the study area soil characteristics; this observation is substantiated by investigation of the COA that generally reported low levels of lime application across the study area.

Land area used through other arrangements had a negative association with high-speed Internet utilisation (0.1 alpha value). The Census of Agriculture describes land area used through other arrangements can be rented, leased or crop-shared, traded, or be offered rent-free to others (Statistics Canada, 2012). The lack of specificity presented within the census makes the interpretation of this factor difficult; however, all arrangement present a scenario whereby the respondent does not utilise the land directly for their own agricultural activities but allows another entity to operate upon it. Daskalopoulou & Petrou (2002) have discussed the factor of rented land on technology adoption through a typological framework that classifies farms into three categories: subsistence farms, survivalist farms and productivist farms. Each of these farm types

[13] http://www.plantstress.com/articles/toxicity_m/acidity_liming.htm (Accessed 2017-01-10)

were found to exhibit variation in the amount of rented land they possess. The survivalist farm is generally associated with high levels of rented land, and often engage in pluriactivity to generate income. With increasing levels of rented land, effective farm size becomes smaller, and it becomes difficult to realise the benefits of investment into modern innovations such as ICT (Kutter et al., 2011). Conversely, the productionist farm type is characterised by a large amount of rented land that facilitates an effective increase in overall farm size that can achieve economies of scale. Interpretation of these contrasting farm types can offer an explanation for the negative association of farm operating arrangements and ICT adoption.

Farms that had a partnership with a written agreement had a negative association with high-speed Internet utilisation (0.05 alpha value). In Ontario, approximately 30% of farms operate under a written partnership and are a result of family arrangements, or between farms and unrelated business partners[14]. Many of these partnerships offer an added benefit for both partners in question including tax benefits, income splitting mechanisms, and benefits similar to a small business without having to incorporate[6]. Kutter et al (2011) has addressed factors associated with the cooperation of partners identifying three major topics of interest: joint investment, agricultural contracting, and data outsourcing. In their study situated in Germany, findings found a similar negative association of investment in innovation and joint partnerships. These findings were attributed to the relatively high cost-of-learning the skills required to facilitate effective use of an innovation; further, joint investment, particularly for small farms, were viewed as uncommon in favour of outsourcing to a contractor when technology is not needed on a permanent basis. Applying the rational within the larger body of research could indicate farms participating in partnerships tend towards contracting out technology innovation, describing the negative association with high-speed Internet adoption.

[14] http://www.omafra.gov.on.ca/english/busdev/facts/11-019.htm (Accessed 2017-01-10)

Two factors related to on-farm labour were identified as having an impact on the adoption of ICT. Operators working more than 40 hours of off-farm work per week had a negative association with technology adoption (0.01 alpha value) and operators reporting no paid non-farm work had a positive correlation with high-speed technology adoption (0.1 alpha value). Each of these labour factors indicate similar findings when viewed in tandem due to their opposing associations with high-speed ICT utilisation. The negative association of ICT utilisation with operators working more than 40 hours off-farm gives strong indication that the operator is employed full-time, given the assumption of a standard 40-hour workweek; similarly, the positive association of high-speed utilisation with operators with no paid non-farm work gives a strong indication of full-time work.

These labour factors tend to line-up with literature in other developed countries such as Germany (Paustian & Theuvsen, 2016), the United States (Daberkow & McBride, 2003), and Greece (Daskalopoulou & Petrou, 2002), that found that full-time farming is positively associated with increasing levels of technology adoption. Daskalopoulou & Petrou (2002) further presented a typological framework that has been applied to classify the productive capacity of farms; productivist type farms strive to modernise and expand through active investment in labour and capital and thus support a full-time staff. Applying the typology to the labour factors that were identified in this study may indicate that large, progressive farms focused on growth are likely to adopt high-speed ICT.

4.2.2 Situational Factors

The proximity of a farm to potential collaboration partners accounted for two of the eight factors identified as being statistically significant. The minimum distance to a university had a negative association with the dependent variable, indicating that as the minimum distance to a university decreases, high-speed Internet utilisation increases (0.01 alpha level). In comparison, the minimum distance to technical and vocational schools was similarly found to have a low

alpha level (0.05 alpha level), but had an inverse relationship with high-speed Internet utilisation; as distance increases from these institutions, technology adoption increases.

Recent research shows that spatial proximity is paramount to the discussion of tacit and explicit knowledge transfer (Johnson, Lorenz, & Lundvall, 2002; Woerter, 2009). Whereas explicit knowledge can be articulated and disseminated efficiently and effectively, tacit knowledge is typically difficult to communicate and requires face-to-face contact, especially for cases where technical knowledge is being transferred (Kesidou & Szirmai, 2008; Yaremye, 2008). Literature discussing situational factors of adoption for ICT in agriculture noted that proximity to research and educational centres are important factors in spreading information through agricultural events, field days, exhibitions and trade fairs, and seminars and workshops (Kutter et al., 2011). The opposite association of technical and vocational schools with high-speed Internet adoption presents a contrasting association; availability of events that facilitate the transfer of knowledge might be lower in these areas surrounding technical and vocational schools. Although two situational factors were found to be statistically significant, educational institutions are generally located near urban centres (Woerter, 2009); investigation towards understanding the regional patterns of proximity could help contextualise situational factors and describe the likelihood of confounding these factors with urban proximity.

4.3 Regional Characteristics of Adoption

The eight factors that were selected to be modelled using geographically-weighted regression yielded only two statistically-significant spatially-varying factors: the minimum distance to a university (min_univ) and the application of herbicides and fertiliser (herbfert). Using these factors, semi-parametric GWPR models were specified, and the optimal model with the lowest AICc was found by only varying the minimum distance to a university coefficient over space. Having only a single quantity varying over space as the optimally-specified model offers insight into the global landscape, suggesting that many of the variables that were found to be

significant in describing high-speed Internet utilisation do not vary over space, but can be applied to the study area equally. However, the minimum distance to a university was found to vary over space.

Examining the spatial variation of the minimum distance to a university (Figure 6), regional patterns emerge and indicate a varying association with high-speed Internet utilisation. In the Eastern, Central, and Western Agricultural regions, the minimum distance to university matches the global trend with a negative association with high-speed internet utilisation; however, in the Southern agricultural region, the association is not present or becomes positive. The change in association with the global trend is further observed to have a relatively low standard error in the southern-most portion of the Southern agricultural region; the low standard error coupled with the coefficient value that changes from negative to positive indicates that this area might not follow the global trend. The universities present in this region are the University of Windsor and the University of Western Ontario (Figure 7); the near-zero coefficient provides a strong indication that CSDs surrounding these universities have no influence on the adoption of ICT.

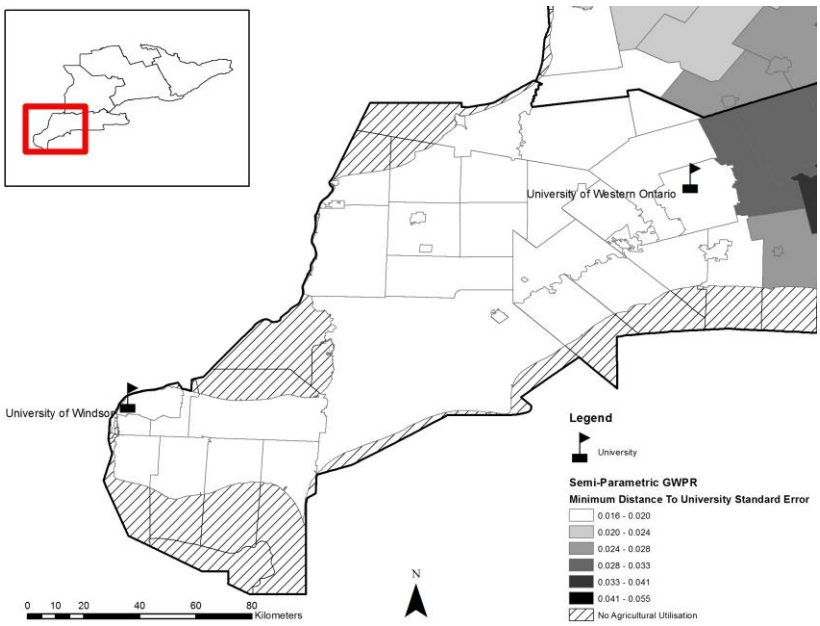

Figure 7: Southwestern Ontario standard error for minimum distance to university

The presence of the Ridgetown campus of the University of Guelph, located in south-east Chatham-Kent, Ontario, could offer an explanation for CSDs in this region having no association with high-speed adoption; the Ridgetown campus is located in between the university of Windsor and the University of Western Ontario, approximately 80 kilometres. Ridgetown offers a variety of programs centred around agriculture, environmental management, horticulture, and veterinary technology[15]; these programs serve to facilitate opportunities for education and innovation knowledge transfer. The presence of the Guelph Ridgetown campus could offer an explanation for the lack of association in the southern-most portion of the study area; further, the area with low standard error is centred around the Ridgetown campus that could demonstrate its importance as an influencer of ICT utilisation in this region.

4.4 Unexplained Variance in High-Speed Adoption

The semi-parametric model that allowed for the minimum distance to a university to vary over space was selected to be the optimal model based on the highest predictive power and lowest associated AICc indicator. Although the model explained approximately 57% of the variance in the utilisation of high-speed Internet, factors explaining the remaining 43% are unknown. The source of unexplained variance could allude to other factors such as the long-standing discussion of digital divide and availability of access to high-speed Internet technology (Boase, 2010; Frieden, 2005; LaRose et al., 2007b; Noce & McKeown, 2008). This observation could help to describe disparities in the investment into ICT infrastructure in rural agricultural areas, which does not describe an unwillingness to adopt high-speed Internet, but rather that the technology is not accessible through financial, connectivity, or educational-related factors. This issue of accessibility can provide further insight into the willingness for a farmer to adopt or not adopt

[15] http://www.ridgetownc.uoguelph.ca/future/programs.cfm (Accessed 2017-01-10)

based on not meeting accessibility requirements. This accessibility issue manifests into what has been previously defined as a situational factor, which could potentially act independently of site factors.

4.5 Limitations

This study investigated the site and situational factors of adoption of ICT in Southern Ontario, however, the results described a single case study of the agricultural adoption of this technology. The scale of this case study was based on the availability of data provided by the Census of Agriculture. These data used the largest scale available at the Census Subdivision (CSD) level, describing a distinct municipality within the province such as a city, town, or village. The use of the CSD as the basis of this study presents two interrelated problems associated with the analysis of spatial data: ecological fallacy and the modifiable areal unit problem (MAUP).

Ecological fallacy describes the problem that occurs when statistical relationships at one level of aggregation are assumed to hold true at another level (O'Sullivan & Unwin, 2010a). The fallacy imposes an important consideration when drawing conclusions based on the findings of this study; the relationship that was found to exist at the CSD level should not be assumed to be true for smaller geographies such as dissemination area, census tract, or parcel. Consideration of the ecological fallacy presents a limitation of scale when interpreting the findings presented within this research; CSDs represent an aggregate measure of population, and therefore conclusions about underlying population structure should not be assumed.

The arrangement and aggregation scheme of CSDs also presents an instance of the modifiable aerial unit problem (MAUP), which assumes that the selected boundaries are the most appropriate for grouping the populations in question (O'Sullivan & Unwin, 2010b). The existence of boundary and edge cases are another such limitation of this study. The region of Southern Ontario was defined as the Southern, Western, Central, and Eastern agricultural regions of Ontario;

however, for many of these regions, large portions of the border are shared with either water bodies, adjacent national or international regions.

Finally, the integration of situational factors presented within this study measured the proximity of a CSD to its closest collaboration partner. The centroid of each CSD was used to calculate a single central point that was used to facilitate the calculation of distance; however, CSD sizes and shapes exhibited variability. This variability among CSDs can largely be attributed to urban-rural gradient (Robinson, 2012), which describes that lot sizes generally increase as rurality increases.

4.6 Future Directions

The research in the paper proposed a framework for analysing ICT adoption in agriculture by assessing Internet utilisation through site and situational factors. This study took a static approach to analysing a snapshot in time of the study area. However, in addressing how these processes change over time, a static model can serve as an initial condition for a more dynamic analysis that might incorporate time-variant variables. A temporal analysis over consecutive censuses might offer a way to interrogate the influence of time on the factors of adoption; influences such as policy change (Stoneman & Diederen, 1994), commodity market volatility (Sunding et al., 1999), and climate change (Tey & Brindal, 2012) can be used to situate changes in technology adoption over time.

The limitations of this study presented through the discussion of ecological fallacy, MAUP, and CSD distance calculations offer an opportunity to explore the factors of adoption in different areal configurations. Areal interpolation describes a methodological approach to exploring substructures of populations, typically reported through census survey, through the integration of additional datasets at different areal scales and configurations (Goodchild, Anselin, & Deichmann, 1993). An extension of this study could incorporate smaller geographic areal units such as census tracts or land parcels, alongside landscape factors such as elevation and land-cover

type, to differentiate farm and non-farm parcels within a CSD. With the identified farm parcels and aggregate census count data from the COA, likely population substructures can be generated for each CSD through Monte-Carlo simulation (Fisher & Langford, 1995) and then modelled using the methodology presented in this chapter. Investigation of population substructure presents a challenge for agricultural data presented through the COA as the aggregation level represents large geographic regions, however, the integration of statistical techniques can aid in deriving likely population configurations that could mitigate the limitations presented within this chapter.

5 Conclusion

The utilisation of ICT has a pronounced presence in the southern portion of the Province of Ontario, indicating a relatively high level of adoption for application areas including access to digital markets, site-specific management, and information from weather to commodity prices. Each of these applications allows an enhanced operational capacity, enabling an increased level of efficiency through productivity gains. Through the research presented, a number of factors have been identified through spatial and statistical analysis, indicating that the adoption of ICT is generally linked with three main overarching farm characteristics: 1) the application of land inputs, 2) the operational management of the farm, and 3) the farm's proximity to research facilities. The two former categories serve to indicate that the management of land inputs and operations can be augmented through more precise and efficient practices, whereas the last category demonstrates that access to research and development can serve to either accelerate or hinder adoption based upon the research body's orientation and objectives. Although these three categories offer a generalised description of the likelihood of adoption over the study area, locational and localised situational factors also play a minor role in cases where naturally-endowed land efficiency in different areas are less likely to be dependent on proximity factors.

Chapter 3: Wireless ICT Coverage

1 Introduction

Connectivity to information and communications technology (ICT) infrastructure plays a critical role in the agricultural sector, enabling a farm to access markets through the digital economy and serving as an important tool for increasing on-farm productivity (Fountas et al., 2006). ICT connectivity to urban and rural settlements has been a longstanding point of discussion of technology adoption (Frieden, 2005; Ishmael, Bury, Pezaros, & Race, 2008; LaRose et al., 2007a; Zhang, Mingliu; Wolff, 2004). Increases in demand in rural and remote areas are adding pressure on service providers and policy makers to make high-speed ICT more accessible (Audirac, 2005; Noce & McKeown, 2008; Sawada et al., 2006).

Connectivity to ICT infrastructure can be classified into two categories: wired and wireless. Wired infrastructure includes a range of technologies that physically connect to an information network, generally utilising fibre and copper-based cabling. These wired connections form what is known as the backbone infrastructure of an ICT network, allowing for high-throughput of digital data with minimal degradation of the signal between interconnect facilities (Audirac, 2005).

Wireless infrastructure comes in a number of different forms, whereby the transmission of information is done through the propagation of electromagnetic waves at specific frequencies. Last mile connections, which typically have a lower bandwidth, connect end-users to backbone infrastructure, forming a hierarchical hub-and-spoke network of connections that make up the World Wide Web (WWW; Powell & Shade, 2006). Although alternative connectivity methods to standard wired and wireless infrastructure have been researched (e.g. powerline connectivity; Sarafi, Tsiropoulos, & Cottis, 2009), a growing number of connections in rural and remote

regions are being made through developments in wireless technologies (Banerji & Chowdhury, 2013; Kabir, Khan, & Hayat, 2012; Song & Issac, 2014).

Interconnections between wireless and wired technology have become an important infrastructural component toward obtaining ubiquity of Internet service over a variety of urban and rural landscapes; however, physical makeup of each of these landscapes makes utilisation of each type of infrastructure vary over space (Riaz, Nielsen, Pedersen, Prasad, & Madsen, 2010). Urban settlements typically utilise high-capacity wired infrastructure and interconnect with other cities that are capable of the transmission, storage, and processing of vast amounts of information (Audirac, 2005). In regions with high-density populations, such as urban metropolitan areas, incentives for Internet service providers (ISP) to commit to building infrastructure is high as initial investments can be easily recovered (Sawada et al., 2006).

Comparatively, while cost recovery is a priority in rural areas, it is more difficult due to a lower population density. The inability to recover capital costs has led to the adoption of wireless technologies as they are easier to deploy and maintain and allow wider access to a single installation point (Federation of Canadian Municipalities, 2014; Galperin, 2005). Wireless access points (WAP) act as a single point of installation, allowing for a maximum coverage of up to 50 kilometres (km) based on a number of landscape and transmission characteristics, and the location of the antenna installation (Kabir et al., 2012; Song & Issac, 2014).

Rural ICT usage in Southern Ontario has drastically changed over the past decade, with a 2004 report finding that rurality has a direct impact on the likelihood of households utilising Internet technology (Vik Singh, 2004). A number of initiatives to increase technological capability and market diversity through the expansion of infrastructure and market carriers have been employed to address disparities that exist among urban and rural settlements.

Industry Canada's Wireless Policy has been active in implementing initiatives to open the market to carriers through auctioning portions of the electromagnetic spectrum, allowing more companies to enter the market, and allowing for a greater choice to consumers of ICT services,

facilitating lower prices with an increased level of service and availability[16]. The SouthWestern Integrated Fibre Technology (SWIFT) project is an initiative to expand the rural ICT backbone network through the installation of high-speed fibre optics technology[17] across southwestern Ontario. SWIFT represents a joint effort by both government and industry to expand on existing infrastructure and address the economic and social disparities that exist between rural and urban settlements, emphasising the importance of the digital revolution to the prosperity of the region.

A 2015 unpublished survey of Internet and Telecommunications in agriculture was administered by the Ontario Federation of Agriculture (OFA), summarising ICT utilisation for 37,000 farm-family members (Sykanda, 2015). The survey indicated that 45% of all ICT connectivity used in rural agricultural settlements is through either cellular and fixed wireless technologies, the two highest-ranked categories, in comparison to farms that utilise strictly wired connections or farms that did not have any form of connectivity. Farms that utilise ICT identified the lack of product choice and carrier service providers as a concern.

The research presented in this paper builds upon previous studies of wireless ICT to facilitate a better understanding of the market and technological capabilities across rural settlements in Ontario. To achieve this objective, the research within this paper will address three research questions. First, what is the existing spatial coverage of wireless carriers and technologies of rural settlements in Ontario? Second, what are the compositional differences that exist among rural settlements? Third, how does spatial coverage vary among rural settlements? The three research questions will be addressed using advanced statistical and spatial methods, facilitated through advancements in parallel processing technologies.

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[16] http://www.ic.gc.ca/eic/site/ic-gc.nsf/eng/07389.html (Accessed 2017-01-10)

[17] http://swiftnetwork.ca (Accessed 2017-01-10)

2 Methodology

2.1 Study Area

The study area for the research presented in this chapter is composed of four agricultural regions of the Southern, Western, Central, and Eastern agricultural regions of Southern Ontario, Canada (Figure 1). The study area consisted of 286 Census Subdivisions (CSD) representing agricultural activity that excluded large urban metropolitan centres and areas that have a predominant presence of natural features such as natural parks. As of 2016, 1938 broadband antennas were in the Province of Ontario, supported by nine carrier companies: Bell, Freedom (formerly Wind), Inukshuk, Rogers, Silo Telus, Terrago, Videotron, and Xplornet.

2.2 Data

To assess the spatial coverage of wireless ICT and classify rural settlement types, administrative, environmental, and infrastructure datasets were utilised. Administrative datasets were used to segment the study area into regions of interest at different geographic scales. The first administrative boundary dataset was the municipal boundaries represented at the Census Subdivisions level (CSD). The second administrative boundary dataset used was the agricultural regions of Ontario, used to demarcate distinct agricultural zones within Southern Ontario.

Environmental data sets were utilised to analyse the spatial coverage of wireless ICT and classify rural settlement types. The first environmental dataset that was used was a digital elevation model (DEM) representing the elevation of terrain across the study area. The DEM was acquired from Land Information Ontario (LIO) for the year of 2015 at a pixel resolution of 30 meters. The second environmental dataset was a crop inventory map made available through Agriculture and Agri-food Canada (AAFC). The crop inventory was representative of the 2015 growing season at a pixel resolution of 30 meters. Each pixel represents a distinct land-cover type based upon the classification of visible, infrared, and radar imagery (Agriculture and Agri-Food

Canada (AAFC), 2016). Classification of these pixels are determined through a decision tree-based classification methodology, yielding an overall accuracy of 89.6% for agricultural land cover, and 71.8% for non-agricultural land cover (Agriculture and Agri-Food Canada (AAFC), 2016).

Finally, infrastructural data, describing man-made construction projects, were used to define carrier, band, and positional data used in the analysis of wireless ICT coverage. Loxcel Geomatics supplied a dataset representing wireless transmission towers across the study area[18] with a specified precision of 1/400th of a degree (250 meters). The dataset provided attributes defining the operator (carrier), operating frequency (band), and height for each antenna.

2.3 Factors of Wireless ICT Coverage

The assessment of wireless ICT coverage is complex and multi-faceted, including a number of factors that can each impact the maximum transmission distance of a wireless signal. Sawada et al. (2006) have summarised seven factors impacting the transmission and coverage of wireless signals:

1) Antenna height
2) Atmospheric scattering
3) Frequency
4) Foliage
5) Topography
6) Obstacles
7) Path

Of the seven factors that were identified, three distinct categories emerge related to transmitter, environmental, and human-related factors. Transmitter factors describe the

[18] https://www.loxcel.com (Accessed 2017-01-10)

characteristics of the antenna itself including the operating frequency, and the send/receive signal strength (or gain). Environmental factors describe naturally-occurring phenomenon including atmospheric scattering characteristics, foliage canopy cover, and topography such as the curvature of the earth, hills, and valleys. The last category describes human-related factors, including the construction of infrastructures such as buildings and roads, and the physical placement of the wireless antenna, including the decision of geographic location and height.

Human-related factors and environmental factors such as the construction of infrastructure can largely be ignored in rural areas due to the absence of large structures that serve to impede, reflect, or completely block the propagation of electromagnetic waves (Bölcskei, Paulraj, Hari, Nabar, & Lu, 2001; Ishmael et al.). This assumption allows for the exclusion of the added elevation of large structures, allowing the terrain DEM to suffice for analysing wireless coverage in rural landscapes.

The elimination of variables within the rural context and the simplification of transmitter variables into a range parameter define the analysis parameters that will be used in this study:

1) Antenna characteristics
    a. Range
    b. Height
    c. Location
2) Terrain elevation

2.4 Bands and Carriers

Mobile broadband and fixed wireless technologies including Long Term Evolution (LTE), WiMAX, HSPA+, and GSM (Fulle, Ronald, 2010) were selected for this study, capable of speeds greater than 5 Mbps for downloads and 1 Mbps for uploads (Canadian Radio-television and Telecommunications Commision, 2011; Table 11). Each wireless band operates in a distinct and

mutually exclusive segment of the electromagnetic spectrum ranging from 2100 MHz to 3700 MHz. The Innovation, Science and Economic Development Canada Organisation of Industry (ISED) Canada manages and regulates the operating arrangements of each band, segmenting for controlled use in different application domains; band names and frequencies for mobile broadband and wireless technologies were attained from the ISED website.

Table 11: Select wireless ICT bands[19]

Band name	Frequency
Advanced Wireless Services **AWS**	2100 MHz
Broadband Radio Service **BRS**	2500 MHz
Wireless Communication Services **WCS**	2300 MHz
Wireless Broadband Services **WBS**	3650 MHz
Fixed Wireless Access **FWA**	3475 MHz

Wireless antenna's range can vary depending on a signal's ability to travel through line-of-sight (LOS) and non-line-of-sight (NLOS) visibility (Sawada et al., 2006). LOS describes the maximum distance a frequency can be propagated between a transmitter and receiver before the signal is too low to be received. NLOS describes the transmission of signals that are fully or

[19] http://www.ic.gc.ca/eic/site/smt-gst.nsf/eng/h_sf01847.html (Accessed 2017-01-10)

partially obstructed, reducing the effective transmission power of a signal. Although there exists techniques for increasing the effective signal of NLOS waves, such as repeaters and redundant pathways for signal reinforcement, analysis of coverage can be difficult due to the increased number of parameters including transmission media, atmospheric conditions, and complex wave interference patterns (Sawada et al., 2006). For this study, a LOS scenario approach was adopted, reducing the computational complexity required to assess coverage of such a vast area.

Industry vendors report the operating distances of various technologies licensed to specific operating frequencies for both LOS and NLOS propagation patterns; theoretical LOS ranges from approximately 50 to 100 kilometres (km) have been cited (Eberle, 2011; N, Kusuma, & C, 2013; Talukder et al., 2013). Although these ranges could be attained in theory, a conservative distance of 32 kilometres (18 miles) LOS was used based upon a technology specification by BridgeMaxx[20] as the effective range that a wireless antenna could successfully propagate a signal in practice. WiMAX technology (representing BRS and WCS bands) operates on the 2300 and 2500 MHz frequencies, the median range of frequencies. The industry specification was selected to represent the average band frequency to standardise transmission distances; the conservative range defines a minimum distance that would provide sufficient performance criteria through the metrics of latency, bandwidth, and network consistency and availability (Kabir et al., 2012; Song & Issac, 2014).

2.5 Spatial ICT Coverage

To calculate the spatial coverage of wireless ICT, a viewshed analysis was performed, parameterised by the previously identified factors. Viewshed analysis is a technique used in a number of research areas to assess the geodesic spatial visibility of a set of observer points (Leusen, 1998; Figure 8). The use of viewshed analysis has been utilised extensively in the

[20] http://www.bridgemaxx.com/support/resources/specs.php (Accessed 2017-01-10)

calculation of coverage areas for communications towers due to the high precision in representing the real world LOS visibility (Dodd, 2001; Leusen, 1998; Sawada et al., 2006).

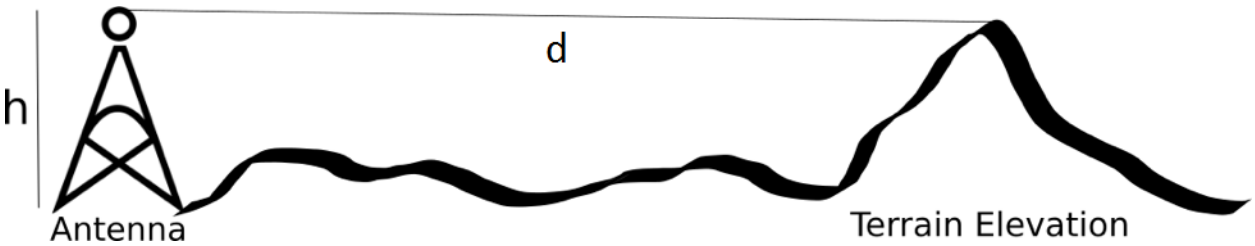

Figure 8: Viewshed sightline analysis; h represents the height of the antenna above ground and d represents the maximum transmission distance

The Viewshed 2 tool, developed by the Environmental Studies Research Institute (ESRI), was used to assess the spatial coverage of wireless antennas. The Viewshed 2[21] tool allows for the specification of analysis parameters including visibility radius, horizontal and vertical angle, and the capability to parallelise execution through the use of a general-purpose graphics-processing unit (GP-GPU; See Appendix D: Viewshed Analysis Processing).

Viewshed analysis was performed using the Southern Ontario DEM to define the topographic features of the study area; the DEM was cropped to a 32-km buffer extending outward from the study area to incorporate antennas lying outside the boundaries of the study area. The wireless antenna tower dataset was used to specify the set of observer points from which wireless signals can be propagated. Each tower was analysed individually based upon each wireless frequency (five bands), and the service provider (nine carriers).

For the specification of antenna-related parameters, the inner and outer radius of the potential coverage allowed the maximum potential transmission distance of each antenna to be bounded. An inner radius of 0 km and an outer radius of 32 km was specified, representing a coverage that extends from the base of the tower to the maximum transmission distance. A

[21] http://pro.arcgis.com/en/pro-app/tool-reference/3d-analyst/viewshed.htm (Accessed 2017-01-10)

horizontal range of 360° was specified for each tower, representing the angle that a wireless antenna can send and receive a wireless signal. Finally, the height of the antenna was added to the elevation of the terrain to attain the elevation of the antenna then specified as the observer elevation for the analysis.

Viewshed analysis was performed using the computationally-intensive analysis method that computes all possible sightlines for each transmission tower. This analysis method allows a high-level of precision of at the cost of increased computational processing time. The increased processing time was offset by the utilisation of parallel processing technologies facilitated through a GP-GPU. A number of parameters were left unspecified as they do not directly fall within the scope of the study or were deemed unnecessary due to previously made assumptions. An exhaustive list of all parameters used within the Viewshed 2 analysis tool is presented in Appendix B: Summary of Viewshed 2 Tool Analysis Parameters.

To minimise the complexity of sparsely arranged raster pixels while still retaining the coverage area of each calculated viewshed, a majority filter focal statistics method was employed to smooth and simplify wireless coverage. A majority filter was specified with a radius of 240 meters (8 pixels x 30-meter resolution) to account for the precision of the wireless transmission towers (250 meters). Each coverage raster was then converted to a representational set of polygons to aggregate areas of continuous coverage, and then borders were dissolved to attain the absolute spatial extent of each carrier and band.

Each carrier-band pair was then aggregated into groupings using a polygonal union tool and used for the interrogation of the market and technology-based factors of wireless ICT. Nine carrier-based aggregate groups were created for each of the carriers present in the study area; these groupings allowed for the analysis of the carrier market independent of the band. Five band-based aggregate groups were created representing each of the frequency bands identified in this study; these groupings allowed for the analysis of the wireless technology prevalence independent of the carrier. Each aggregate grouping was projected using the Canada Albers Equal Area Conic

projection to preserve area; summary statistics were then computed for each grouping's coverage area.

2.6 Technology Prevalence and Market Competition

The total number of available carriers and bands were used to evaluate market competition and technology prevalence across the study area. Market competition was used to evaluate the number of carriers that exists within a given area; calculated by summing the total number of carriers available and then used to identify regions of high and low levels of competition across the study area. Similarly, technology prevalence, calculated by summing the number of wireless bands, was used to identify regions of high and low wireless spectrum coverage. Market competition and technology prevalence were calculated by summing carrier and band coverage using binary addition for each pixel across the study area.

2.7 Rural Settlement Classification

The classification of urban and rural settlements are typically described by the underlying structure of natural resources and density of the human populations; on the one hand, urban settlements are identified through dense arrangements of human populations and built-up infrastructure in contrast to rural areas that are mostly composed of agricultural fields and pastures, and natural land such as forests, mountain and desserts (Ashley & Maxwell, 2002). The fundamental differences that exist between urban and rural settlements make traditional approaches to classification such as the analysis of population structure through socioeconomic and demographic factors (Kanagawa & Nakata, 2008; Long, Zou, & Liu, 2009) difficult to apply when populations are spread out over space.

Classification techniques for rural landscapes incorporate the regional distribution of different land cover types that make up the morphological characteristics of a settlement, alongside the wider geographic context to which the area belongs (Bibby & Shepherd, 2004).

Morphological characteristics are generally incorporated through the use of alternative data sources such as remote imaging extraction (Unsalan & Boyer, 2004), and the application of more advanced techniques through structured information (Gong & Howarth, 1990). In conjunction with the fundamental differences that describe urban and rural area, the assessment of wireless ICT coverage has largely been described as a spatial issue, dependent on the underlying geography that separates the deployment of a wireless antenna and the population being served (Prieger, 2003; Sawada et al., 2006).

To address the challenges presented in the classification of rural regions, a multi-level, hierarchal decision tree methodology was adopted (Ballas, Kalogeresis, & Labrianidis, 2003; Bibby & Shepherd, 2004) to classify settlements based upon the composition of land-cover types. A crop inventory supplied by the AAFC, broken down into 66 distinct land cover classifications for the Province of Ontario as identified through the Annual Crop Inventory – Data Product Specification (Agriculture and Agri-Food Canada (AAFC), 2016), was then used to classify overarching categories representing human-centric (urban and rural agricultural), and natural-centric (natural water and land) land-covers (excluding the class labeled 'cloud' that represents indeterminate land cover). Each raster pixel was reclassified into one of the four categories based on its coded-value description (See Appendix C: Crop Inventory Coded Land-Type Values for the list of values classified into each group).

The Grouping Analysis tool[22], developed by ESRI, was used to group CSDs based on the presence of human and natural land cover types. The Grouping Analysis Tool uses an unsupervised classification approach to cluster polygons based on a set of attributes. The tool uses a K-Means algorithm in order group polygons so that within-group variability is minimised, and between-group variability is maximised. The analysis was specified to differentiate six

[22] http://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/grouping-analysis.htm (Accessed 2017-01-10)

unique groups using Delaunay Triangulation, a geometric simplification technique based on each CSDs centroid, to account for variability in geometric properties amongst CSDs.

A two-tier hierarchical classification adopted from Bibby & Shepherd (2004) was then used to classify groups based on standardised values for each land-cover type. The standardised values represent the relative abundance or deficiency of land-cover types among groupings. The first classification was performed upon each group to rank the standardised values for natural-centric land-cover types (water and natural), split into two classes (3 groupings per class), and then designated a density classification (dense and not dense, representing the deficiency and abundance of natural-centric land-cover types). For the second classification, groups within each density class were then used to rank the standardised values for human-centric land-cover types (urban and agricultural), and then assigned a settlement classification (small town and fringe, village, dispersed settlements representing the largest to smallest abundance of human-centric land cover types; Figure 9; Bibby & Shepherd, 2004).

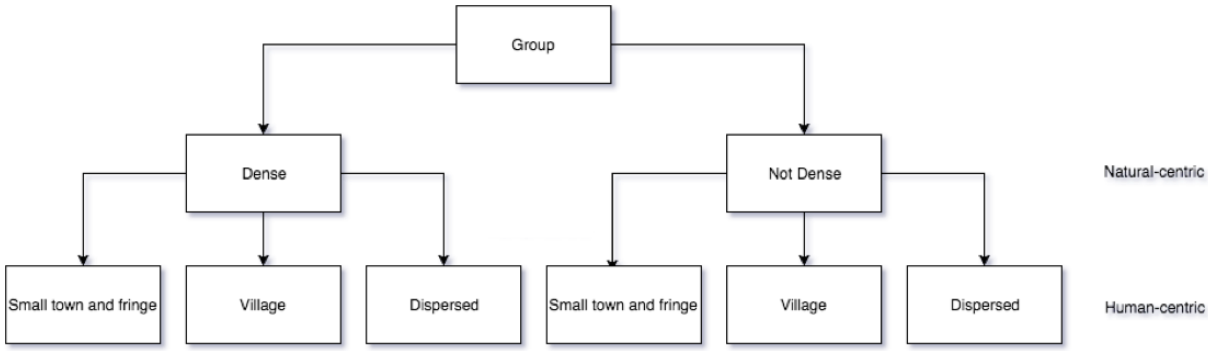

Figure 9: Hierarchical classification tree for rural settlements (adapted from Bibby & Shepherd, 2004)

2.8 Coverage Variance Across Rural Settlements

ICT coverage among wireless bands, carriers, and rural settlements was assessed through a two-way analysis of variance (ANOVA; De Veaux, Velleman, Bock, Vukov, & Wong, 2011). A two-way ANOVA is a two-dimensional extension of a one-way ANOVA that allows for the calculation of the variation in a response variable over several pairwise factor treatment levels; error terms are calculated for each treatment allowing a high degree of sensitivity in attributing the impact of each factor on the response variable. ANOVA reports the sum-of-squares (SS), degrees of freedom (df), and the mean sum-of-squares (MSS), calculated by dividing the sum-of-squares by the degrees of freedom for each factor. An F-statistic was then calculated for each pair of factors by dividing the mean sum-of-squares by the residual sum-of-squares for each factor *n*:

$$(1)\quad F = \frac{MSS_n}{df_n}$$

The F-statistic was then compared against the F-critical value to gauge the relative impact that each factor has on the response variable. An F-critical value was calculated for each factor from the F-distribution table incorporating (1) the degree of freedom, (2) the error degrees of freedom, and (3) the probability level (0.05) of the analysis (De Veaux et al., 2011). F-statistic values that possessed a value greater than the F-critical value and with a P-value less than .05 indicate that a factor has a statistically significant effect on the dependent variable.

ANOVA was applied twice to assess the variability of wireless factors (carrier and band) blocked by rural settlement classification; ICT coverage area was used as the response variable. The analysis was performed at a 0.05 alpha level, with a non-replication scheme that uses a single value for ICT coverage for each treatment level.

3 Results

3.1 Wireless ICT Coverage

Wireless coverage of ICT was assessed by looking at carrier and band factors. Among the wireless ICT carriers, significant variability existed across the study area (Figure 10). Rogers, Bell, and Xplornet each had coverage that spans the majority of the province. Each carrier exhibited distinct drops in coverage based on the rural settlement class; Rogers and Xplornet had low coverage in remote northern regions surrounding Algonquin National Park; Bell further had low coverage surrounding Lake Huron and Georgian Bay. Inukshuk and Freedom similarly possessed a wide area of coverage over the province, with some regional clustering around major urban centres, and a lower density in coverage across the study area. Finally, Silo and Terrago, Telus, and Videotron each represented a distinct regional coverage pattern, possessing a spatial concentration of service in one geographic metropolitan area (Hamilton, Windsor/Sarnia, and Ottawa, respectively)

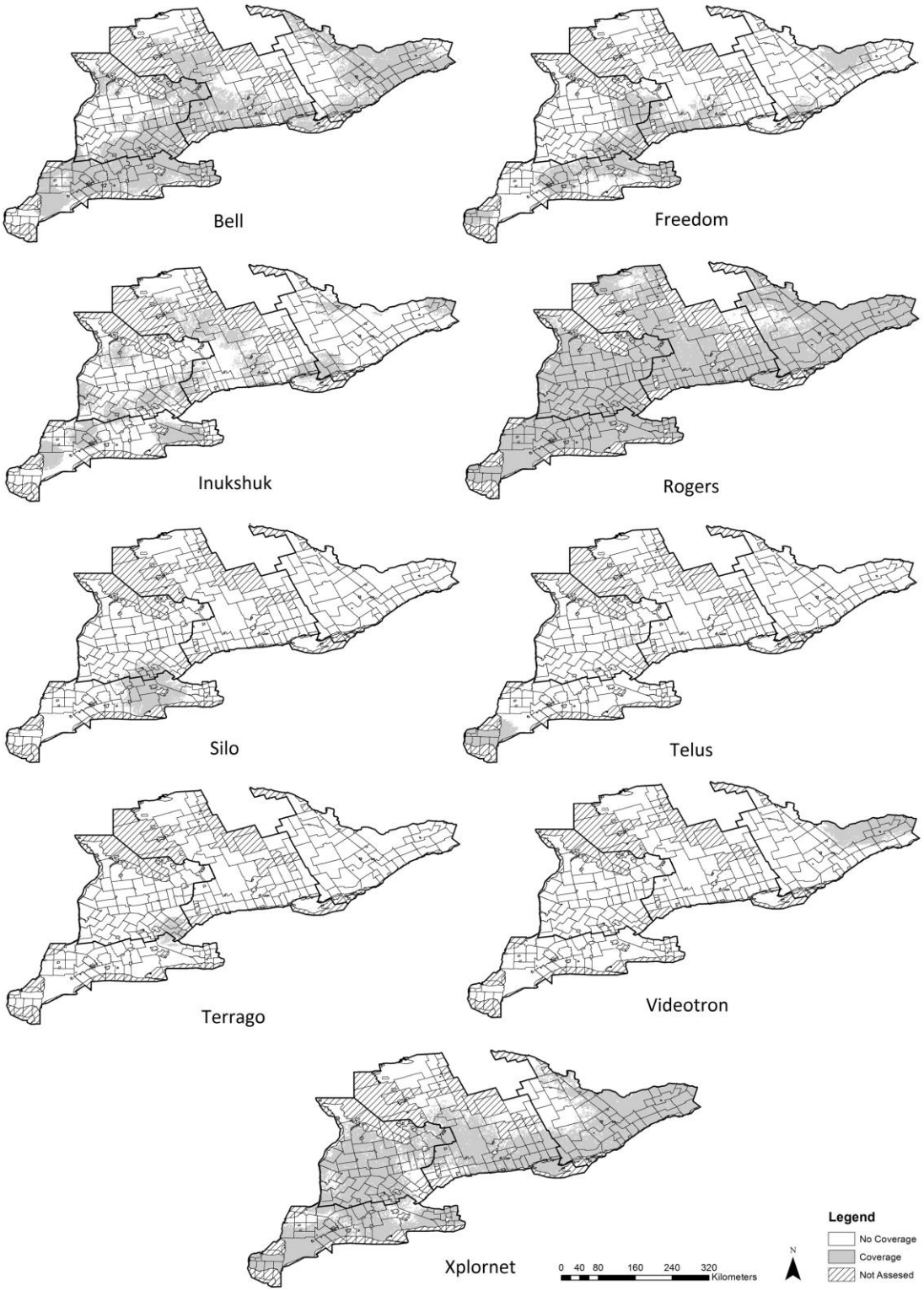

Figure 10: Spatial coverage of wireless ICT by carrier

Wireless coverage by band frequencies has a similar division in coverage compared to carriers, exhibiting distinct regional groupings over the study area. AWS was the most prevalent among the wireless bands, having only a small area in remote natural regions surrounding Algonquin National Park that exhibited no coverage. The FWA and BRS bands had a similar coverage pattern to AWS, however, the sparsity of coverage decreased in areas as the distance from metropolitan areas increased. WBS and WCS coverage was dispersed across the study area, with some clustering around metropolitan and agricultural regions.

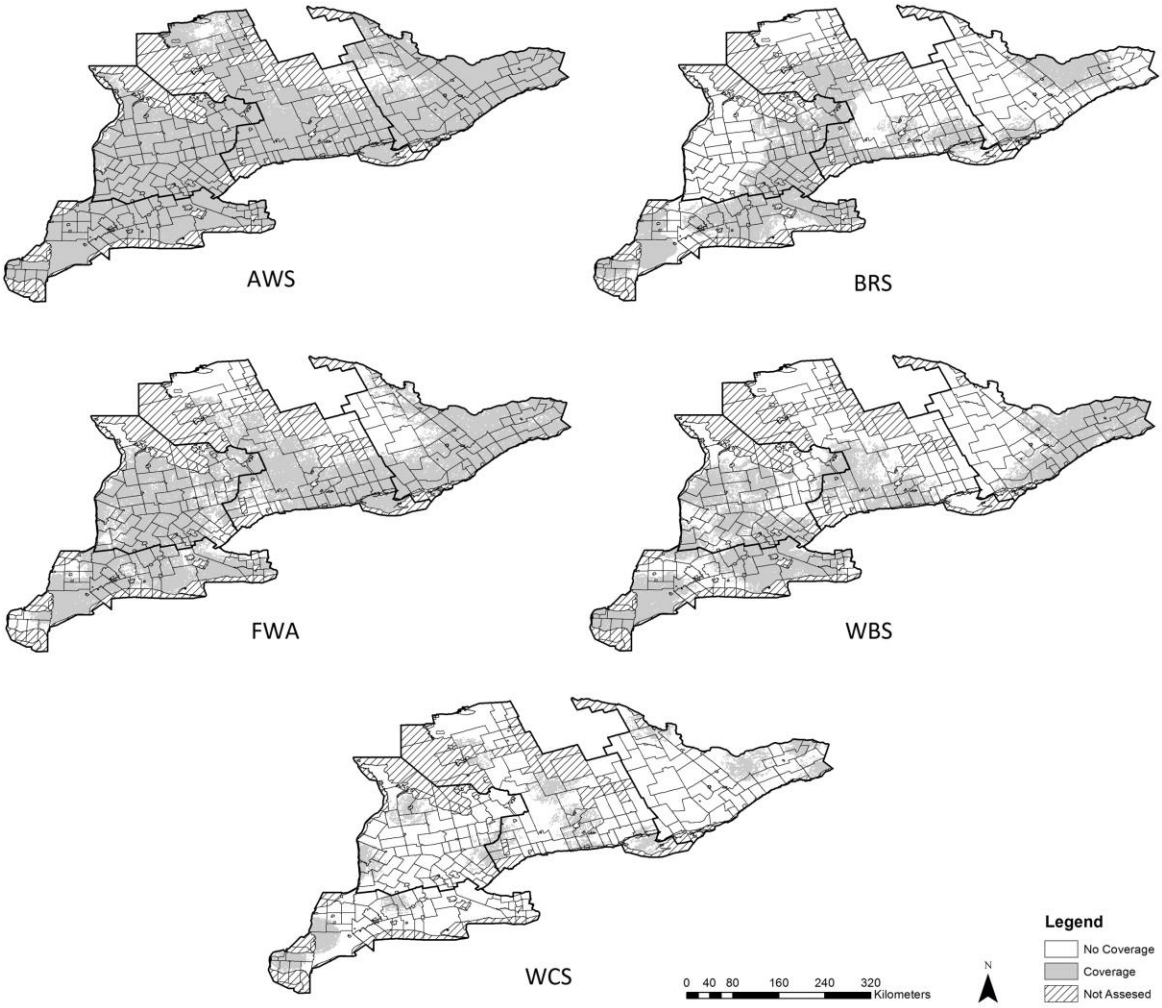

Figure 11: Spatial coverage of wireless ICT by band

Rogers, Bell, Xplornet, Inukshuk, and Freedom had the largest coverage of CSDs (respective of order), each serving over half of the study area's CSDs. Comparatively, Silo, Telus, Videotron, and Terrago each reported relatively lower overall coverage across the study area, present in less than 40 CSDs across the study area.

Table 12: Summary table of wireless ICT carriers by presence in CSDs and total area (km^2)

Carrier	**CSDs**	**Area (km^2)**
Bell	249	62,213
Inukshuk	175	26,862
Rogers	285	101,209
Silo	34	6,987
Telus	18	3,082
Terrago	13	1,690
Videotron	19	5,890
Freedom	141	24,501
Xplornet	252	75,258

The binary presence of different technology bands demonstrated a much lower variance and less distinct division amongst different technologies compared to wireless carriers. AWS and FWA bands were the predominant technologies, each representing a very high coverage of nearly all CSDs in the study area. BRS and WBS bands both equated to coverage of two-thirds of the study area. Finally, the WCS band represented the lowest representation of wireless technology, only present in 116 CSDs across the study area, representing around 40% total coverage.

Table 13: Summary table of wireless ICT bands by presence in CSDs and total area (km^2)

Band	**CSD**	**Area (km^2)**
Advanced Wireless Access	285	101,712
Broadband Radio Services	206	44,889
Fixed Wireless Access	257	77,198
Wireless Broadband Services	207	16,920
Wireless Communication Services	116	49,753

3.2 Market Competition and Technology Prevalence

The total number of carriers (Figure 13) and bands in each region (Figure 14) were used to assess the level of market competition and technology prevalence. Market competition, representing the number of carrier service providers, allowed for the assessment of service availability and product differentiation amongst different settlements. CSDs surrounding large metropolitan areas along the Macdonald-Cartier Freeway possessed a high level of competition (3 to 7 carriers). Further, CSDs north of the Toronto metropolitan in the Central agricultural region also had a high-level of competition. Market competition along the Macdonald-Cartier Freeway, however, exhibited some regional drops from high to low competition in Chatham-Kent, Durham, Northhumberland, Leeds & Grenville, and Stormony, Dundas & Glengarry, spanning from west to east.

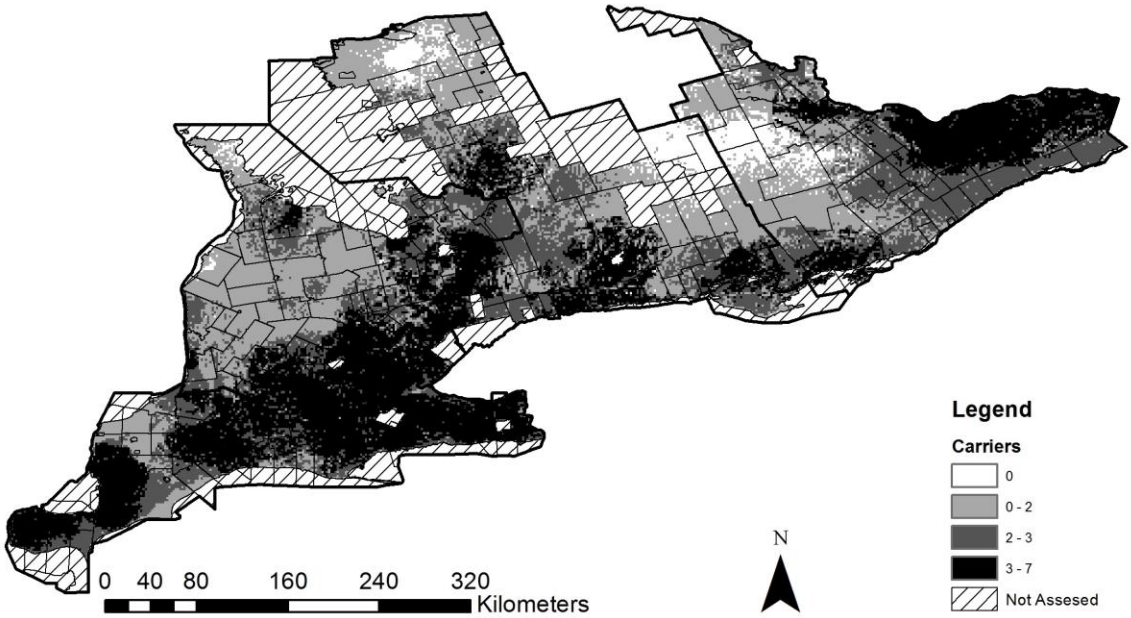

Figure 12: Market competition representing the number of carriers

Band prevalence had a similar spatial pattern to market competition, however, exhibiting a greater amount of variability among the agricultural regions. CSDs surrounding the metropolitan areas of Sarnia, Windsor, Toronto, and Ottawa made greater use of the frequency spectrum, possessing 4 or more bands. Band utilisation exhibited high variability in areas surrounding the fringe of the metropolitan areas, utilising 1 to 3 bands, with generally lower band utilisation as the distance from metropolitan areas increase. Contiguous areas spanning a large portion of the Eastern agricultural region from Hastings to Frontenac had smaller band prevalence, only utilising one to two bands over the frequency spectrum. Paralleling market competition, regions extending towards the north had little to no wireless ICT coverage, using 2 or fewer bands.

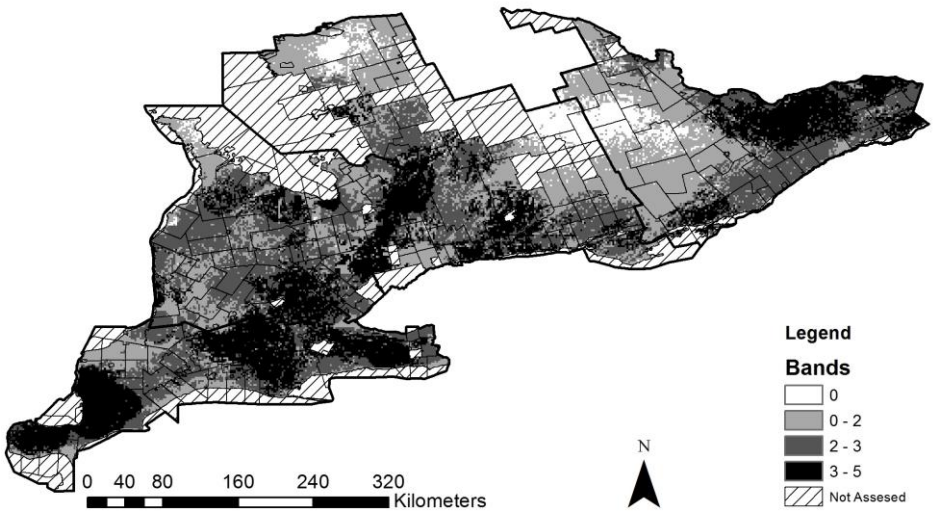

Figure 13: Technology prevalence representing the number of bands

3.3 Distribution and Classification of Rural Settlements

The results of the grouping analysis (Table 14) identified six distinct classes of rural settlements based upon the density of natural-centric land-cover types (land and water) and then human-centric land-cover types. The rural settlement classifications were mapped (Figure 14) to situate within the larger contextual landscape of the study area. The Low-Density Small Town and Fringe class was identified to be large areas of population that ran along the heavily densified strip spanning the Macdonald-Cartier Freeway These regions had a large abundance of natural features alongside large population centres such as Peterborough, Belleville, and Kingston running from the West to the East.

Table 14: Grouping analysis standardised values and rural settlement classification

Group	**1**	**2**	**3**	**4**	**5**	**6**
Urban	-0.25	0	0	0	0.5	2
Agriculture	-1	-1	0	0.75	0	-0.5
Natural Land	1.5	0	0.25	-0.5	0	-1
Natural Water	0.25	4	0.25	-0.25	0	0.5
Natural	1.75	4	0.5	-0.75	0	-0.5
Human	-1.25	-1	0	0.75	0.5	1.5
Density	Low	Low	Low	High	High	High
Classification	Dispersed	Village	Small town and fringe	Dispersed	Village	Small town and fringe
Area (km^2)	37823.88	3052.62	49221.04	49221.04	9873.35	2855.92
CSDs	75	9	22	141	26	13

The Low-Density Village class encompassed CSDs with a large presence of water features, mostly falling adjacent to Hudson's Bay and Lake Simcoe; large population centres fall within these areas, with groupings mostly describing dense populations situated on the fringe of these natural water features. The Low Density Dispersed class described population centers that are surrounded by large areas of natural-centric land-cover types, surrounded by both natural water features (i.e. populations falling between Lake Huron and Hudson's Bay, and surrounding Lake Nippising to the north) and natural land features (i.e. populations falling in areas surrounding national parks, and other natural land features).

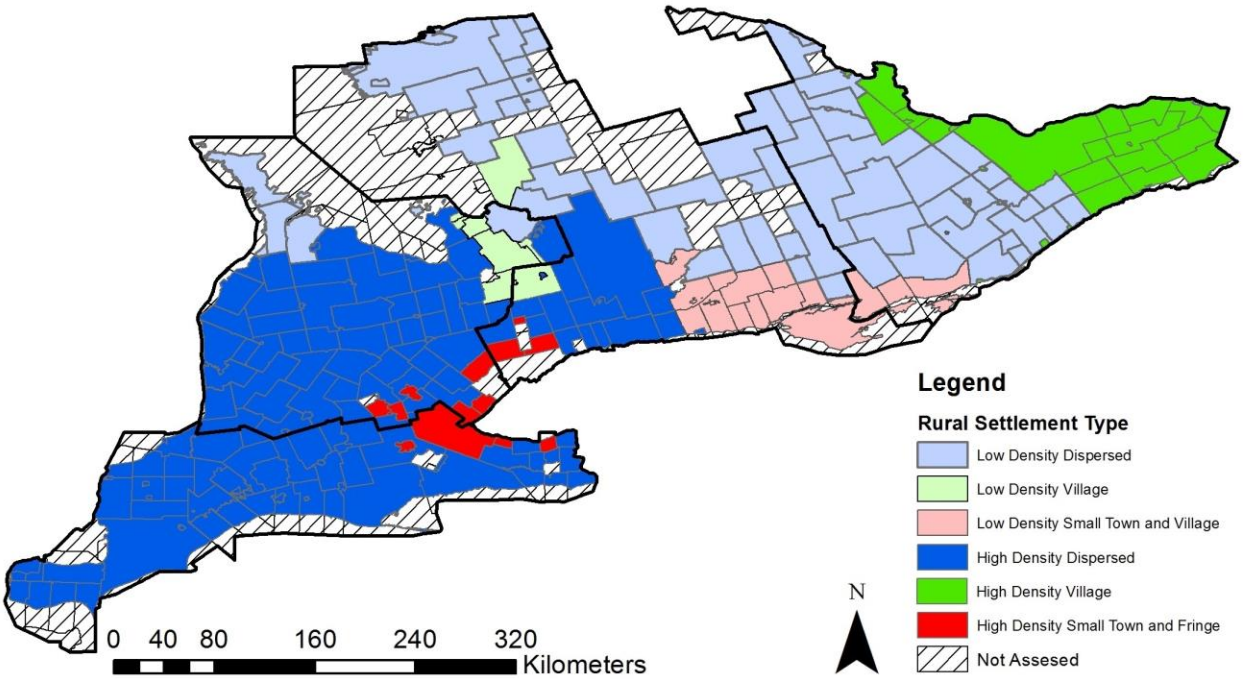

Figure 14: Rural settlement classifications

The High Density Small Town and Fringe class encompassed highly densified, metropolitan fringe CSDs, mostly contained within the Golden Horseshoe metropolitan area running between Toronto and Hamilton (Greater Toronto and Hamilton Area; GTHA), and the Kitchener-Waterloo metropolitan area. CSDs within this class had an abundance of human-centric land-cover types surrounding urban populations.

The High Density Village class surrounding the greater Ottawa metropolitan area possessed a dense population and high presence of agricultural activities, each contributing to the high presence of human-centric land-cover in the area. Lastly, the High-Density Dispersed class encompassed the largest set of CSDs spanning the agriculturally-significant population of southwestern Ontario. This region is well dominated by agricultural land but also includes major urban population centres such as Windsor, Sarnia and London[23].

[23] http://www.omafra.gov.on.ca/english/stats/county/southern_ontario.htm (Accessed 2017-01-10)

3.4 ICT Characteristics of Rural Settlements

Statistics of the carrier and band ICT characteristics were summarised to evaluate the relative presence within each of the rural settlement classes (Table 15 & Table 16). Rogers, Bell, and Xplornet each had a relatively high presence in each of the rural settlement classes. Rogers had a consistent representation of wireless coverage of over 95% in all settlements except for the low-density dispersed settlement, having a lower but relatively high coverage of 81%. Bell's coverage in high-density small town and low-density village settlements was pronounced, with a stark drop in coverage for low-density dispersed settlements. Xplornet had a high coverage in high-density settlements; however, coverage in the small town and fringe settlements had a stark drop. Further, low-density settlements had a high representation of coverage ranging from high coverage in low-density small towns and fringe regions (96%), but dropping significantly for villages and dispersed settlements (66% and 44% coverage, respectively).

Freedom and Inukshuk each had a low representation of coverage of one-third across all settlements, except Freedom that exhibited a high coverage of 93% in the high-density small town and fringe settlement. Terrago and Silo had coverage in only high-density small town and fringe, and dispersed settlements, covering one-third and one-tenth of the area, respectively. Silo, however, had a consistently higher representation of coverage in comparison to Terrago of approximately 10% of the area. Videotron had a significant presence in only the high-density village settlement, dominant in the regions surround the Ottawa metropolitan area, and adjacent to the Quebec provincial border. Telus possessed the smallest coverage representation, with only 6% coverage in the high-density dispersed settlement and less than .01% coverage in the low-density village settlement.

Table 15: Summary of band coverage area and percentage of rural settlement

Density	Low	Low	Low	High	High	High
Settlement	**Dispersed**	**Village**	**Small town and fringe**	**Dispersed**	**Village**	**Small town and fringe**
Bell	12,689.25 **(33.55%)**	2,810.63 **(92.07%)**	4,526.15 **(70.47%)**	31,564.34 **(64.13%)**	7,803.08 **(79.03%)**	2,820.17 **(98.75%)**
Inukshuk	5,766.94 **(15.25%)**	1,012.54 **(33.17%)**	2,826.09 **(44.00%)**	14,252.67 **(28.96%)**	2,018.57 **(20.44%)**	985.26 **(34.50%)**
Rogers	30,918.44 **(81.74%)**	3,042.44 **(99.67%)**	6,219.3 **(96.83%)**	48,482.79 **(98.50%)**	9,702.94 **(98.27%)**	2,843.79 **(99.58%)**
Silo	0 **(0.00%)**	0 **(0.00%)**	0 **(0.00%)**	5,752.47 **(11.69%)**	0 **(0.00%)**	1,235.01 **(43.24%)**
Telus	0 **(0.00%)**	2.55 **(0.08%)**	0 **(0.00%)**	3,079.59 **(6.26%)**	0 **(0.00%)**	0 **(0.00%)**
Terrago	0 **(0.00%)**	0 **(0.00%)**	0 **(0.00%)**	872.13 **(1.77%)**	0 **(0.00%)**	818.69 **(28.67%)**
Videotron	146.53 **(-0.39%)**	0 **(0.00%)**	0 **(0.00%)**	0 **(0.00%)**	5,743.71 **(58.17%)**	0 **(0.00%)**
Freedom	682.75 **(-1.81%)**	1,143.29 **(37.45%)**	1,301.42 **(20.26%)**	15,743.18 **(31.98%)**	2,973.23 **(30.11%)**	2,657.80 **(93.06%)**
Xplornet	16,626.94 **(43.96%)**	2,014.81 **(66.00%)**	6,194.72 **(96.45%)**	40,039.59 **(81.35%)**	9,323.25 **(94.43%)**	1,058.95 **(37.08%)**

Note: Absolute area coverage is expressed in square kilometres (km^2; top) and percentage of rural settlement coverage (bottom)

Band ICT characteristics varied significantly across the rural settlement classes, with relatively high and low band presence based on density and settlement types. AWS had the most dominant band presence across nearly all rural settlement classes with nearly 100% coverage, except in the low-density dispersed settlement. Each of the other bands had dominance in one or two other rural settlements groups and a vastly smaller representation for other groupings. FWA was the second most dominant band, however, exhibiting much larger variation across different settlement types. High-density villages and dispersed settlements and low-density small towns and fringe and village settlements were well covered by FWA bands ranging from 75% coverage to nearly 100% coverage. Coverage in high-density small towns and fringe and low-density dispersed settlements had a much smaller representative coverage of only half the area.

BRS had a large presence in high-density small towns and fringe CSDs, as well as within low-density villages of (97 and 82%, respectively). Other groupings had coverage of around 50% of the area, with a much smaller representation in low-density dispersed settlements. WBS had a high variability of coverage across rural settlements, ranging from 14% in low-density dispersed settlements to 73% coverage in high-density villages. The distinct difference in percentages can largely be attributed to the density of the settlement, with lower density CSDs ranging in coverage from 14% to 35%, and high-density regions ranging from 64% to 73%. Finally, the WCS had relatively low utilisation in all regions, with the highest representation in low-density small town and fringe settlements with only 25% coverage.

Table 16: Summary of carrier coverage area and percentage of rural settlement

Density	Low	Low	Low	High	High	High
Settlement	**Dispersed**	**Village**	**Small town and fringe**	**Dispersed**	**Village**	**Small town and fringe**
WBS	5,661.9 **(14.97%)**	1,042.16 **(34.13%)**	2,302.77 **(35.85%)**	31,588.26 **(64.18%)**	7,265.27 **(73.58%)**	1,892.92 **(66.28%)**
WCS	3,584.85 **(9.48%)**	277.52 **(9.09%)**	1,636.69 **(25.48%)**	7,813.39 **(15.87%)**	3,159.22 **(32.00%)**	448.86 **(15.72%)**
FWA	18,046.94 **(47.71%)**	2,272.37 **(74.44%)**	6,236.72 **(97.10%)**	40,105.28 **(81.48%)**	9,053.85 **(91.70%)**	1,483.53 **(51.95%)**
BRS	5,771.5 **(15.26%)**	2,529.95 **(82.88%)**	3,391.68 **(52.81%)**	26,057 **(52.94%)**	4,356.46 **(44.12%)**	2,782.94 **(97.44%)**
AWS	31,056.95 **(82.11%)**	3,047.38 **(99.83%)**	6,291.36 **(97.95%)**	48,685.71 **(98.91%)**	9,776.48 **(99.02%)**	2,854.77 **(99.96%)**

Note: Absolute area coverage is expressed in square kilometres (km^2; top) and percentage of rural settlement coverage (bottom)

A two-way analysis of variance (ANOVA) was used to assess the relative impact of the factors of carrier and band, and rural settlement types. Wireless ICT carrier and rural settlement factors assessed using ANOVA each reported statistically significant p-values evaluated at the 0.05 alpha levels (Table 17). Each factor had a difference in p-value of one order of magnitude, indicating relatively similar statistically significance between the two factors being assessed. Comparing the F-statistic to the F-Critical value indicated that both factors contribute to

variability in the total area of coverage of the study area. Although each of the factors contributes to the variability of the total coverage area, settlement class had a relatively higher F-statistic value in comparison to the F-critical value, indicating a high degree of influence in describing total coverage.

Table 17: Two-way analysis of variance (carrier and settlement)

Source of Variation	SS	df	MS	F	P-value	F crit
Carrier	1,779,312,814	8	222,414,101.8	4.51	5.74E-4	2.18
Settlement	1,814,270,412	5	362,854,082.4	7.36	5.66E-05	2.45
Error	1,970,712,182	40	49,267,804.55			
Total	5,564,295,408	53				

The factors of wireless ICT band and rural settlement (Table 18) each had statistically significant p-value at the 0.05 alpha levels. However, although each factor was identified as statistically significant, the settlement factor had a p-value several orders of magnitude smaller than the band factor, indicating a greater confidence in the variability of coverage is described by the settlement factor. Assessing the associated F-statistic values to the F-critical value for each factor, settlement class had a higher relative impact in influencing spatial coverage in comparison to the wireless band.

Table 18: Two-way analysis of variance (band and settlement)

Source of Variation	SS	df	MS	F	P-value	F-crit
Band	701,126,012.2	4	175,281,503.1	4.05	1.44E-02	2.87
Settlement	310,794,8673	5	621,589,734.6	14.38	4.86E-06	2.71
Error	864,570,418.1	20	43,228,520.9			
Total	4,673,645,103	29				

4 Discussion

4.1 Deconstructing Coverage of ICT

The first research question was interested in assessing spatial coverage of wireless carriers (Table 12 and Figure 10) and bands (Table 13 and Figure 11) across Southern Ontario. Rogers, Bell, and Xplornet each exhibited a large spatial coverage of wireless ICT, representing major provincial carriers of wireless technology. Freedom and Inukshuk each had widespread coverage over the province, however, with a lower density, and a tendency towards concentrating around metropolitan areas. Silo, Terrago, Telus, and Videotron generally represented highly-localised coverage patterns, typically focusing coverage in a specific region (i.e. Hamilton, Sarnia/Winsor, and Ottawa).

4.1.1 Market Competition

Market competition, describing the number of carriers present in each area, exhibited variation among the rural settlement classes. The high and low-density small town and fringe and village settlement classifications each had at least three carriers supporting the region. Dispersed rural settlements with both high and low density each had a large variation in market competition, ranging from extremely high in portions of the settlement close to the dense metropolitan area, and low competition in remote regions surrounding natural features such as Algonquin National Park and the water bodies of Hudson's Bay and Lake Michigan.

Silo[24] and Terrago[25] each provide service to residential and commercial users of wireless Internet in the Hamilton metropolitan area, a highly-saturated carrier market. Videotron is a Quebec-native carrier with a small representation of coverage in the Province of Ontario.

[24] http://www.silowireless.com (Accessed 2017-01-10)
[25] http://www.terago.ca (Accessed 2017-01-10)

Wireless coverage of Videotron[26] is present at the provincial border of the metropolitan area of Ottawa, an area with a large human-centric landscape, with a high amount of market competition. Telus is a Vancouver-based company with only a small wireless coverage footprint near the border of the United States surrounding the metropolitan areas of Windsor and Sarnia.

Although Telus is a major carrier of wireless broadband coverage in Canada, a partnership agreement with Bell[27] has enabled wireless transmission towers to be shared among the carriers, enabling a more effective use of resources. The partnership between Bell and Telus is apparent through the spatial coverage of their shared towers. Bell has a wide coverage over the Province of Ontario, with a small representation in coverage near the Sarnia/Windsor border where there is a heavy presence of Telus coverage.

4.1.2 Who is on the Bandwagon?

Wireless coverage across the across frequency bands exhibited a large amount of variability, with some regional clustering in large metropolitan areas that made heavy use of the full frequency spectrum. AWS was the most ubiquitous technology over the study area, having a cumulative coverage of 96%, and being present in nearly all CSDs. AWS represents an implementation of the LTE standard, representing a major component of the mobile smartphone revolution. The observed patterns allude to a high level of adoption and general acceptance of the newer technology across the study area and the dominance of the AWS band over the other broadband technologies. All rural settlement classes possessed a wide spectrum of broadband mobile and cellular technologies, with most areas having coverage represented by more than two bands. The low-density dispersed settlements had the lowest use of the spectrum for broadband

[26] http://www.videotron.com (Accessed 2017-01-10)

[27] http://www.bce.ca/news-and-media/releases/show/bell-signs-wireless-agreement-with-telus-which-will-significantly-expand-access-to-digital-voice-and-data-services-across-canada (Accessed 2017-01-10)

mobile and cellular technology, with some remote regions surrounding national parks having no coverage in any wireless band.

4.2 Rural Settlements of Southern Ontario

The second research question looked to assess land-cover compositions of CSDs. The numerical results of the Grouping Analysis **(**Table 14**)** identified rural settlement classes based on land-cover. The groupings identified rural settlement compositions that largely parallel well-known metropolitan, agricultural, and low-density natural regions that span much of the province (Figure 14). The major metropolitan regions spanning the MacDonald-Cartier Freeway identified the Toronto and Ottawa metropolitan areas as high-density settlements, representing the small town and fringe, and village settlement classifications, respectively. CSDs within each of these high-density settlement groups are transitional zones that lie between large urban centres with relatively high and low-density human-centric landscapes represented as a vast agricultural landscape. The high-density dispersed settlements identified a large region representing 141 CSDs spanning from the Western and Central agricultural regions. This vastly-spanning high-density area corresponds well with the region defined as southwestern Ontario, a human-centric region supporting a large agricultural presence known to have long growing seasons, enabling a higher level of productivity due to the relative latitude compared to the rest of the province[28].

Low-density rural settlement groups were identified through the association with vast areas of natural-centric land cover types. The small town and fringe settlement identified the population centres of Kingston, Belleville and Peterborough spanning along the MacDonald-Cartier Freeway. Each of these cities represents large population centres with adjacent natural features. National parks and water bodies such as Lake Ontario lie adjacent to these areas, generally exhibiting a lower population density. Similarly, the village settlement grouping largely

[28] http://www.omafra.gov.on.ca/english/crops/facts/climzoneveg.htm (Accessed 2017-01-10)

fell in areas with vast water bodies nearby such Barrie, Orillia and Georgina located adjacent to Lake Simcoe, and natural land features that surround Huntsville, in proximity to Algonquin National Park. Low-density dispersed settlements encompassed large regions falling in CSDs in the Eastern agricultural region, north of the MacDonald-Cartier Freeway.

The low-density dispersed rural settlements fall in the geological region defined as the Canadian Shield. The Canadian Shield[29] presents a natural-centric landscape consisting of vast bedrock formations and thin soil composition that makes this settlement sparsely inhabited by humans. The class identified through the grouping analysis largely parallels geographic regions describing the various human and natural-centric characteristics; this descriptive background information adds confidence when interpreting the settlement classifications.

4.3 Variation of Wireless ICT among Rural Settlements

The final research question looked to assess the influence of wireless factors (carriers and bands) and rural settlement classes on wireless coverage area. Statistical summaries among carriers (Table 15) and bands (Table 16) illustrate distinctive variations that exist among each rural settlement class.

Rogers, Bell, and Xplornet had a presence in all rural settlement types, however, the intensity of coverage was varied. Rogers had predominant coverage in all settlement types, with only a minor decrease in low-density dispersed regions. Comparatively, Bell and Xplornet each have wide coverage, but each carrier exhibits a specialisation based on rural settlement type. Bell has a pronounced presence of coverage in high-density small towns and fringe and low-density villages compared to Xplornet that has a low comparative coverage in these regions. In the high-density village and dispersed settlements, and low-density small town and fringes, the converse relationship is true; Bell has a weak spatial coverage. Finally, in low-density dispersed regions,

[29] https://www.ontario.ca/page/about-ontario (Accessed 2017-01-10)

both Bell and Xplornet each exhibited coverage of less than 50% of the class compared to Rogers that has the highest coverage in these areas. Rogers was the dominant carrier, and has the most extensive network in all rural settlements; Bell and Xplornet, however, take a more targeted approach to providing coverage, focusing on the density and settlement characteristics in their decision to compete in different markets.

Freedom and Inukshuk each had a presence in all rural settlements. Inukshuk had a modest but consistent coverage representation in all rural settlements, ranging from 15% to 45%. Comparatively, Freedom had a similar range to Inukshuk in most settlements except high-density small town and fringe, and low-density dispersed settlements. Freedom exhibited an extremely high coverage within the high-density, small town and fringe rural settlements, representing a more targeted approach to locating wireless ICT infrastructure than Inukshuk. Freedom also had an extremely low representation of coverage in low-density dispersed settlements, further alluding to a more targeted market orientation than Inukshuk.

Telus, Terrago, Silo, and Videotron each had distinctive coverage among the rural settlement groups, representing the only carriers that did not have a presence in all rural settlement types. Both Terrago and Silo were only present within the high-density small town and village and dispersed settlements, centralised around the Hamilton metropolitan area and surrounding regions. Each carrier had high coverage within the small town and village settlements, and low coverage in dispersed settlements. Silo exhibited a 10% difference in overall coverage, implying a strong presence of infrastructure within this shared region. Although each carrier has only a modest coverage in these settlements, the similarity among the carriers describes a focused and targeted market strategy, focusing on supporting density of users within a small metropolitan area.

Videotron had a high presence in only the high-density village settlement, centred on the Ottawa metropolitan area, extending eastward from the provincial border of Quebec. The concentration of Videotron within this settlement class represents a targeted market approach that

allows for the support of Quebec-based users that might see usage patterns that extend outside of Videotron's strongest market, Quebec. However, this pattern might also indicate a growing interest in expanding operational capability into the province of Ontario to compete more directly with competitors in this market. Telus had the smallest representation of wireless ICT over the study area, with only a 6% coverage representation in high-density dispersed settlements, mainly encompassing the areas surrounding Winsor and Sarnia, in proximity to the United States border. This regional coverage of Telus aligns with a partnership made with Bell, allowing the sharing of infrastructure among carriers[30]. This partnership explains the small presence of the Vancouver-based carrier, allowing them to take a more strategic approach to offering coverage in Ontario without the necessity of building vast amounts of infrastructure.

ICT coverage of bands in rural settlements exhibited similar regional variation to wireless carriers. AWS was the predominant band used across all rural settlements, with nearly 100% representation except low-density dispersed settlements. FWA and BRS bands exhibited regional usage patterns, with increased levels of utilisation in different settlements. FWA had a strong prevalence in the high-density village and dispersed, and low-density small-town and fringe settlements, with over 80% coverage. Conversely, BRS exhibited prevalence in high-density small town and fringe and low-density village settlements. WBS and WCS bands had a low utilisation in most settlements, with the exception of WBS possessing a high utilisation in higher density regions.

ANOVA statistical testing methodology was used to assess for statistically significant variability in spatial coverage influenced by settlement groupings, and wireless factors (carrier and band). The results assessed the variability of wireless ICT coverage (Table 17 and Table 18); each factor was determined to be statistically significant, with an F-statistic significantly greater than the F-critical value, indicating that each factor played a role in describing variation in

[30] http://business.financialpost.com/fp-tech-desk/telus-and-bells-wireless-partnership-still-a-sore-spot-for-competitors (Accessed 2017-01-10)

coverage. For the factors of band and settlement, the settlement grouping had a significantly greater influence on the variation of ICT coverage. Each of the ANOVA results indicates that rural settlement class was the most dominant factor in explaining the variation in wireless coverage. Wireless carriers had a modest impact in describing variation in coverage, with band coverage having a relatively small impact on variation in comparison to carrier and settlement class.

4.4 From Coverage to Accessibility

The research presented in this paper has assessed wireless coverage independent of socioeconomic and demographic variables. However, linkages between wireless coverage and accessibility of coverage can add breadth to the scope of the research presented in this chapter (Sawada et al., 2006). Coupling the idea of accessibility to coverage, with the topics of market competition and technology prevalence explored in this chapter, a framework for accessing physical, socioeconomic and demographic barriers can be established. Barriers to entry serve as a platform to identify areas where accessibility issues might be present; mechanisms facilitated through telecommunications policy can be used to minimise the barriers to entry that prevent the equal access to wireless ICT infrastructure, and more broadly ICT in general.

Telecommunications policy encompasses a complex and ever-changing topic of research that can be investigated through many different lenses (Fulle, Ronald, 2010; Tey & Brindal, 2012). The Canadian government has long been a proponent in promoting the equal accessibility of wireless ICT through a number of key strategies spanning many of these different telecom lenses, striving to create “smart communities”, promoting the development of ubiquitous accessibility for all Canadians, independent of differences that exist among urban and rural settlements. Initiatives such as wireless spectrum auctioning, regulatory enforcement, and economic assistance proposed through the Digital Canada 150 Plan and realised through

telecommunications policy can all be used to lower the barrier to entry and fuel the digital economy in Canada[31].

4.5 Limitations

The research presented in this paper strived to describe the coverage area of wireless broadband across Ontario. To make the task of assessing wireless coverage over such a vast area more achievable, a number of assumptions were made within the rural context (e.g. no human-made obstacles, negligible atmospheric impedance, tree canopy). Although these factors were considered when choosing the LOS scenario that provided a conservative estimate of the maximum transmission distance of a wave, care should be taken when interpreting absolute coverage extent, especially when evaluating coverage at boundaries between two wireless antennas.

A comparison between carrier-provided maps and the coverage maps presented within this study was facilitated by selecting a region, generating an image, then manually geocoding to assess the similarities and differences between the datasets qualitatively. The qualitative assessment was taken for four carriers with a common region surrounding Hamilton that had an abundance of carrier competition (Appendix E: ICT Coverage Comparison with Carrier Data); the assessment revealed that each dataset contained a similar orientation and shape across space. The carrier data tended to have a smaller area coverage than the derived coverage maps; however, the derived dataset tended to better account for dips in coverage within large homogeneous areas of coverage. Taken together, the qualitative assessment revealed that the derived dataset generally has a larger coverage area that should be considered when interpreting the results of this study.

The classification of rural settlements was based on the underlying land-cover composition of CSDs in the study area, minimising variability that exists between each grouping

[31] http://www.ic.gc.ca/eic/site/028.nsf/eng/home (Accessed 2017-01-10)

of CSDs, and maximising variability among the groupings themselves. Although this method satisfied the requirements of this research, providing a macro-level land-cover compositional classification over the study area, micro-level human-centric factors that exist within each CSD were not included. Micro-level socioeconomic and demographic factors that compose CSDs at a finer spatial extent can enable classification within rural settlements, allowing for investigation of spatial coverage at a finer scale within a CSD. Due to the consideration of only macro-level human-centric factors in this study, care should be taken in drawing conclusions about the micro-level compositions of a CSD based upon the macro-level classification applied in this study (i.e. ecological fallacy; O'Sullivan & Unwin, 2010a).

The dynamic nature of ICT in Southern Ontario presented a number of changes that require mentioning. As of September 2016, beyond the completion of the analysis performed within this chapter, Inukshuk[32] seized operations of its network. Further, the dynamic nature of the ICT market further saw a rebrand of Freedom in December 2016 from the former Wind; the carrier is owned by VimpleCom Ltd., an Amsterdam-based company, that licenced the name to the Canadian company owned by Shaw Media. The rebrand came due to increasing licensing fees were being paid as the company became more successful, as reported by the Company's CEO Alek Krstajic[33]. The changes in the market since the start of the analysis presented in this chapter emphasise the highly-dynamic nature of wireless ICT.

4.6 Future Direction

The findings of this paper identified regional characteristics that exist amongst different rural settlement types. The regional disparities that were identified through the investigation of market competition can aid in the initiatives set forth by Industry Canada, driving more equitable

[32] http://www.inukshuk.ca/ Accessed 2017-01-10)

[33] http://www.theglobeandmail.com/report-on-business/wind-mobile-to-become-freedom-mobile-launch-faster-network-in-toronto-vancouver/article32954738/ (Accessed 2017-01-10)

distribution of the wireless spectrum, promoting entry into markets that have a monopoly, and allowing diversification amongst services and products. Key priorities set forth through the telecommunications act serve to promote competitive, innovative, and affordable services for ICT users independent of settlement type. Policy regulations could utilise a number of tools alongside the findings of this paper to target policy decisions in the telecommunications industry such as the promotion of carrier entry through regional subsidies that promote competition, patent protection for the invention of novel techniques for expanding the infrastructure network, increasing effectiveness of existing infrastructure, and minimising the digital divide amongst Internet users (Audirac, 2005).

The findings of this paper can further be used to augment existing regional initiatives such as the SouthWestern Ontario Integrated Fibre Technology (SWIFT) project[34]. Regional patterns of ICT coverage, classified by rural settlement types, can aid in the planning and rollout of infrastructure that might have disparities in connectivity in 'last-mile' situations, allowing for an integrated wired-wireless solution to enable connectivity for the largest number of users (Popov, 2010; Riaz et al., 2010). This hybrid approach to infrastructure development can allow a greater outlook on issues concerning the role of information and communications infrastructure, allowing for the targeting of issues of the utmost importance in the digital world.

The analysis of broadband wireless access utilised the line-of-sight approach to identify the geographic coverage of a range of bands of wireless signals over a set of service providers. The approach allows for a geographic simplification of wave propagation that assumes that any barrier or impedance will not allow a wave to be received. Although this analysis technique allows for an approximation of wireless coverage, the impedance that serves to attenuate the signal might extend the coverage under the LOS scenario, resulting in a wider coverage area than the analysis presented. To extend the analysis to model situations where NLOS waves extend the

[34] http://swiftnetwork.ca (Accessed 2017-01-10)

overall coverage of a wireless signal, two approaches might be considered as an extension of this analysis. The first technique might incorporate additional factors into the analysis that can serve to add impedance distance of a wave at a global extent. Secondly, applications that require a more granular investigation of the geographic context might additionally incorporate radio propagation analysis (RPA; Sawada et al., 2006) to analyse local interactions that occur between landscape features and the wireless signals. Each modelling technique can allow for additional factors to be incorporated into the model such as atmospheric scattering, foliage density, small-scale obstacles and path characteristics not incorporated into this analysis. The trade-off in incorporating additional precision in modelling coverage is the complexity that comes with computing the interaction of each additional factor on the propagation of a wave.

5 Conclusion

The research presented in this paper looked to assess the spatial coverage of wireless information and communications technology (ICT) over rural settlements. Key findings found that the study area possessed a wide-spread coverage over the study area. However, there exists heavy variation in the availability of service for regions that contain dispersed human populations, specifically in regions heavily dominated by agricultural land as well as an abundance of natural features. Regions that contain these dispersed human populations and associated low market competition allude to a number of physical barriers to entry that might exist and thus indicate regions of interest to target future initiatives promoting equitable access to wireless ICT. Further, the findings of this research identified that although both carrier and band factors influence coverage, rural settlement class plays a much larger role in describing the extent of wireless coverage.

Recommendations from the findings of this research were to continue with existing programs focused on reducing the digital divide, but facilitate a more targeted approach to ensure

that rural settlements are given equal opportunity for investment by offering a greater incentive to carriers to participate in markets. The continued promotion of wireless policy initiatives set out by Industry Canada alongside the promotion of regional initiatives such as the SouthWestern Ontario Integrated Fibre Technology (SWIFT) Project, with the continued backing of both government and industry organisations, will promote a more prosperous Ontario, with equitable access to ICT, regardless of the underlying urban or rural characteristics of the landscape.

Chapter 4: Conclusion

1 Overview and Summary

The chapters presented in this thesis set out to contextualise and facilitate a better understanding of the role that information and communications technology (ICT) plays within agricultural systems in Southern Ontario. A review of literature situated the study of ICT in light of two dimensions of technology innovation: factors of adoption and spatial accessibility.

The second chapter explored the factors of adoption and spatial patterns of ICT in agricultural systems. A literature review was first performed to establish factors of adoption that contribute to the adoption of innovation in agricultural systems. Based on classical diffusion theory, as laid out by Rogers (1995), two emerging factor categories within literature were used to propose a framework for assessing technology adoption in agriculture: site factors, describing the characteristics of farm and farm operators; and situational factors, describing the geographical context in which a farm is situated. The framework was then used to assess ICT adoption within the context of Southern Ontario agriculture: first, spatial and statistical summary techniques were used to identify patterns of ICT adoption; second, site and situational factors were used to construct a global model of ICT adoption; third site and situational factors were used to construct a localised model that allows factors to vary over space. Notable findings of the analysis identified eight factors as having an association with ICT adoption: six site factors and two situational factors. Site factors related to a farm's operating arrangements, labour, and land inputs were identified as influencing the adoption of technology. Situational factors relating the proximity of a farm to educational institutions were further identified; proximity to universities had a negative association with adoption and proximity to technical and vocational schools had a positive association with adoption. The conclusions of the research emphasised the importance of

the context in situating factors of adoption in the broader context to avoid drawing generalised conclusions towards global adoption factors.

The third chapter addressed the topic of spatial accessibility of ICT in the context of rural settlements in Southern Ontario. Wired and wireless ICT was discussed in light of rural-urban digital divide; wireless ICT was identified as being a more cost-effective solution to facilitate equitable access in rural settlements due to its lower implementation cost. Wireless ICT was analysed through a viewshed analysis incorporating transmitter, environmental and human-related factors. A classification methodology for rural settlements was then established incorporating morphological characteristics of the underlying land-cover; six rural settlement classes were derived based on the presence of human-centric and natural-centric land-cover features. Wireless ICT coverage was then summarised by rural settlement type to assess spatial variation of coverage among carrier and band ICT factors. Notable findings found that carrier, band, and settlement class factors each significantly contribute to variation in ICT coverage, however, rural settlement was the dominant factor. Further, settlement regions that encompassed dispersed human-centric land-cover features were identified as having low levels of competition with only 1 or 2 carriers present. Findings from this research suggest that the problem of urban-rural divide is still a pressing issue in the equitable access to wireless ICT in Southern Ontario, and that a targeted approach to infrastructure investment, facilitated through existing initiatives and government programs, should be used close the urban-rural divide and promote equitable access to ICT in Southern Ontario.

2 Modelling Diffusion over Space and Time

The research presented in this thesis applied a static analysis of the factors of adoption and accessibility of ICT. Kelly et al. (2013) have outlined five purposes of a model in facilitating a better understanding of system processes: prediction, forecasting, management and decision-making under uncertainty, social learning, and developing system understanding/experimentation. The approach taken in this study can be classified for the purposes of prediction and the development of system understanding, whereby a value is estimated in a time period given knowledge of other variables within the same time period (Kelly et al., 2013).

Contemporary schools of thought focused on the process of diffusion, however, have proposed that time is inextricably linked with spatial processes (May & Thrift, 2003). Although a number of approaches to modelling have been proposed to integrate time-related factors into the modelling of diffusion process (Kelly et al., 2013), one modelling methodology that has gained significant traction in the realm of land-use science and the diffusion of technology is agent-based modelling (ABM; Berger, 2001; Le, Park, Vlek, & Cremers, 2008; Matthews et al., 2007; Murray-Rust, Robinson, Guillem, Karali, & Rounsevell, 2014).

ABMs represent an emerging approach used to model a variety of social, economic, and physical phenomenon that are typical in land-use science scenarios (Salamon, 2011). The methodology employs a ground-up approach to describing a system, whereby the actions and interactions of individual constituent parts within an environment are modelled and assessed in aggregate to allow the emergence of complex macro-level behaviours (Matthews et al., 2007). In constructing a system with complexity, the words of John Gall, a systems theorist, should be echoed: “a complex system that works is invariably found to have evolved from a simple system that works” (Gall, 1975); a corollary to his findings describes that trying to model a complex system is doomed never to work as a fundamental understanding is a key to building complexity.

In approaching the modelling of a complex system, a fundamental understanding of the relationships of between components in a system should be understood.

An extension of the findings presented in this thesis can be used to facilitate a better understanding of the relevant factors that contribute to the behavioural decisions of a farmer impacting the adoption of ICT. Factors such as site, situational, and accessibility of ICT contextualise the construction of an empirically-informed ABM, incorporating classical components of the process of diffusion including an innovation (ICT), adopters (farm or farm operators), communication channels (network of adopters and spatial proximity factors), and the contemporary component of time. Further, integration of the census data, GIS, and remotely-sensed data utilised and derived throughout this study can further serve as an initial condition and introduce heterogeneity among agents in an ABM modelling ICT diffusion in agriculture (Robinson et al., 2007).

3 Extending the Census of Agriculture

The work presented in this thesis largely depended on the availability of public and private dataset, allowing for the interrogation of ICT through the dimensions of factors of adoption and accessibility. Some potential factors that could contribute to the adoption of ICT include applications such as marketing, checking the weather, pricing of commodities (as provided as an example in the Census of Agriculture Survey; Statistics Canada, 2012), or more advanced applications such as precision agriculture. Further, the self-reported nature of high-speed Internet in the COA leaves a potential for uncertainty in the number of standard and broadband users that report.

Incorporation of factors such as technology application and ambiguity in the interpretation of ‘high-speed’ in the COA questionnaire offers an opportunity to add breadth to the study of ICT in the agricultural sector. One improvement that could be made to mitigate

misrepresentation of the results of the COA in the future is the incorporation of additional questions to aid in the distinction of standard and high-speed Internet. One question might involve a multiple-select question that asks the respondent to check all applications that are used in conjunction with ICT. The incorporation of a question that integrates application for farm business can act as a gauge for the level and quality of service that is required for on-farm work. A similar approach has been taken in a 2015 Internet and Telecommunications Survey conducted by the Ontario Federation of Agriculture (Sykanda, 2015); the question allowed the selection of multiple applications such as email, social media, research and information gathering and a number of e-services. Further, a second question might serve to rate the quality of service for the application to gauge network performance requirements. Used in conjunction, each of these questions can allow for a greater level of granularity in dissecting the application of ICT on the farm, and correlate factors of adoption to the demand for high-performance network applications.

The limitations and the potential for improvement through the augmented survey questions and the incorporation of additional variables related to the application ICT offer an opportunity beyond the scope of the research presented. The integration of factors related to on-farm products and the commodity market can offer a new dimension beyond those found strictly through the site and situational factors investigated through this study. Through the integration of commodities, additional dimensions of ICT adoption can be investigated related to the variation of ICT with respect to the demand of a specific type of on-farm product or commodity. With a greater scope in future questionnaires, the intensity of demand on ICT for each product class can gauge how adoption can vary among commodities classes.

4 Implications for Canadian Policy

The adoption of ICT presents a rapidly-changing landscape by which the technology utilisation and policy are rarely static but change to keep up with the ever-growing demand to be

relevant in the digital domain through applications such as management information, e-commerce, and weather forecasting (Taragola & Van Lierde, 2010). Canada has largely embraced the potential that the digital revolution has brought to all citizens spanning from densely-populated metropolitan areas to rural and remote regions. The central idea of digital divide comes at the forefront of the discussion of regional differences in not only adoption but accessibility to ICT infrastructure. One such challenge that presents itself in promoting the equitable access to digital resources is the communication of the potential advantageous of ICT technologies not only on a national scale but extending further to the international community of users. The concept of network externalities comes at the forefront of the important advantageous that can be gained through ICT, as discussed by Katz & Shapiro (1986), however, the added benefits that come with the dependence of users also increases the barrier to entry for the promotion, setup, and adoption of such a technology.

The incredible potential of this technology brings with it a need to promote and educate the public as to the benefits that can be obtained through community access. As mentioned and explored in this thesis, accessibility plays an important role alongside education in lowering the barrier to entry to adopting technology. Barriers to entry, however, can extend far past the knowledge barriers and can also include physical and economic barriers to adoption (Spielman & Birner, 2008).

Initiatives that promote the reduction of these barriers to entry present some important and pertinent opportunities that can be harnessed to reduce the overall digital divide that exists between urban and rural regions. Since the initiation of this research project, the release of a new Telecom Regulatory Policy issued by the Canadian Radio-television and Telecommunications commission (CRTC; Canadian Radio-television and Telecommunications Commission, 2016) on December 21, 2016, established the next step in Canada's path to modernise telecommunications. The report establishes several initiatives moving forward including a new baseline of 50 Mbps download and 10 Mbps upload with unlimited bandwidth capacity; this acts in contrast to the 10

Mbps download and 1 Mbps upload as proposed in the 2011 Telecom Regulatory Policy (Telecom Regulatory Authority of Canada, 2011)**.** The updated policy, beyond the 10-fold increase in target broadband Internet speeds and unlimited bandwidth capacity, further serves to emphasises the importance of bridging the digital divide between urban and rural settlements moving forward.

In the promotion of the equitable access to ICT in rural and remote regions, the findings in this study can serve to guide the targeted promotion of regions that exhibit the most disparities in the Southern Ontario. The analysis of utilisation metrics for standard and high-speed Internet in the agricultural sector can offer a gauge as to where the population of individual CSDs lie along the innovation diffusion curve; regions with low utilisation of high-speed Internet, can serve to highlight where promotion through education and training in technology can be most effective reducing the barrier to entry and identifying the benefits that can be gained through the adoption of innovation. The analysis of wireless broadband accessibility and market barriers to entry can further aid in creating a dialog between public and private stakeholders to enhance the marketing and promotional capabilities, as was set forth through the Digital Canada Plan and the forthcoming Innovation Agenda, to allow a greater number of service providers to participate in settlements that have relatively little levels of competition.

The topic of diffusion in agriculture presents a unique challenge that requires expertise in many disciplines and the integration of public and private datasets to understand socioeconomic, demographic, and accessibility factors that influence the adoption of technology. The research presented within this thesis contextualised ICT in Southern Ontario through the discussion of factors of adoption and accessibility. Moving forward, the framework for assessing the site and situational factors of a farm can be used to facilitate research upon the 2016 Census of Agriculture; the exploration of the forthcoming census can be used to assess changes in agricultural ICT adoption since 2011, and the role of policy in bridging the digital divide.

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Appendices

Appendix A: Census of Agriculture 2011 Farm and Farm Operator Data

Note: Bold indicates selection of tables used for study

Table	Table Number
Farms classified by the North American Industry Classification System (NAICS)	004-0200
Farms classified by total farm area	**004-0201**
Farms classified by area in crops and summerfallow (excluding Christmas tree area)	004-0202
Land use	**004-0203**
Tenure of land owned, leased, rented, crop-shared, used through other arrangements or used by others	**004-0204**
Tillage practices used to prepare land for seeding	**004-0205**
Land inputs in the year prior to the census	**004-0206**
Manure and manure application methods in the year prior to the census	**004-0207**
Land practices and land features	**004-0208**
Forms of weed control on summerfallow land	**004-0209**
Irrigation in the year prior to the census	**004-0210**
Organic products for sale	004-0211
Crop residue baled in the year prior to the census	004-0212
Hay and field crops	004-0213
Fruits, berries and nuts	004-0214
Vegetables (excluding greenhouse vegetables)	004-0215
Nursery and sod	004-0216
Greenhouse products and mushrooms	004-0217
Christmas trees	004-0218
Forest products in the year prior to the census	004-0219
Maple taps	004-0220
Cattle and calves on census day	004-0221
Sheep and lambs on census day	004-0222
Pigs on census day	004-0223
Other livestock on census day	004-0224
Poultry inventory on census day	004-0225
Poultry production in the year prior to the census	004-0226

Egg production in the year prior to the census	004-0227
Commercial poultry hatcheries in the year prior to the census	004-0228
Bees on census day	004-0229
Farms classified by operating arrangements	**004-0230**
Computers used for farm business	**004-0231**
Farms classified by total farm capital	**004-0232**
Farms classified by total gross farm receipts in the year prior to the census	**004-0233**
Farm capital (farm machinery and equipment, livestock and poultry, land and buildings)	**004-0234**
Farm business operating expenses in the year prior to the census	**004-0235**
Paid agricultural work in the year prior to the census	**004-0236**
Total number of farms and farm operators	**004-0237**
Number of farm operators per farm by sex	**004-0238**
Number of farm operators per farm by age	**004-0239**
Number of farm operators who lived on the farm at any time during the 12 months prior to the census	**004-0240**
Number of farm operators by average number of hours per week worked for the agricultural operation in the calendar year prior to the census	**004-0241**
Number of farm operators by paid non-farm work in the calendar year prior to the census	**004-0242**

Appendix B: Summary of Viewshed 2 Tool Analysis Parameters

Parameter	Attribute
Input Raster	Digital Elevation Model
Input Point	Antenna Towers
Output Raster	{carrier/band_specific_raster)
Output Above Ground (Optional)	--
Analysis Method (Optional)	ALL_SIGHTLINES
Analysis Type (Optional)	FREQUENCY
Vertical Error (Optional)	--
Surface Offset	1 meter
Observer Elevation	Antenna Elevation (DEM + Height)
Observer Offset	0
Inner Radius	0
Outer Radius	32 Kilometers
Horizontal Start Angle	0 Degrees
Horizontal End Angle	360 Degrees
Vertical Upper Angle	90 Degrees
Vertical Lower Angle	-90 Degrees

Appendix C: Crop Inventory Coded Land-Type Values

Class	Value	Code
Agriculture (1)	Crop and pasture	120-190
	Greenhouse	35
Natural (2)	Shrubland	50
	Wetland	80
	Grassland	110
	Exposed/Barren	30
	Forest	200
	Coniferous	210
	Broadleaf	220
	Mixedwood	230
Water (3)	Water	20
Urban (4)	Urban/Developed	34
Unclassified	Cloud	10
Total		66

(Agriculture and Agri-Food Canada (AAFC), 2016)

Appendix D: Viewshed Analysis Processing Parameters

The computation of a viewshed for 1938 wireless antennas was a computationally expensive task. The Viewshed 2 Tool (ESRI), supports the use of a general-purpose graphics processing unit (GPGPU) to parallelise the computation. A Nvidia GTX 970 was used for the viewshed analysis, with the following select specifications:

Graphics Card	GTX 970
Graphics Memory	4 GB
Computer Memory	12 GB
CUDA cores	1664

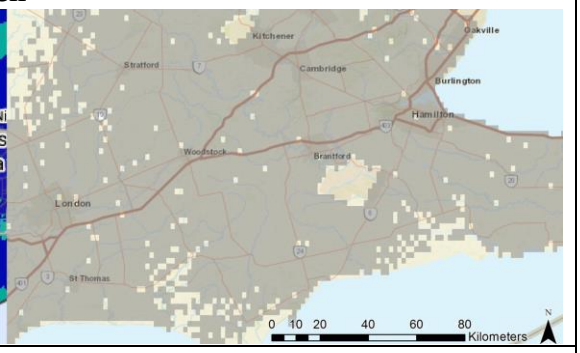
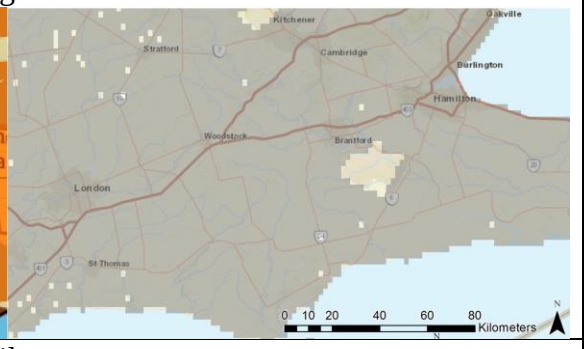
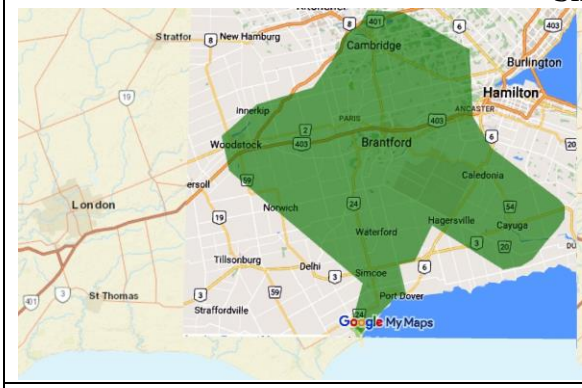
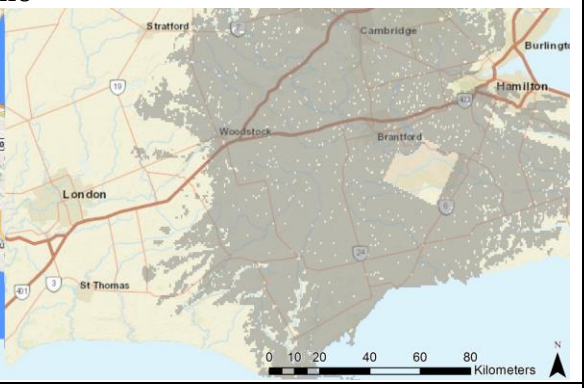
Source: http://www.geforce.com/hardware/desktop-gpus/geforce-gtx-970/specifications

Each carrier-band pair were run individually to break up the processing time and make data and errors in execution easier to manage. The computation results for each pair, indicating the total and average time in hours:

Viewshed	Antenna count	Total (hours)	Average (hours)
FWA_Xplornet	308	1.35	0.00
FWA_Bell	3	0.06	0.02
FWA_Inukshuk	26	0.16	0.01
WBS_Silo	43	0.24	0.01
WBS_Terago	1	0.05	0.05
WBS_Xplornet	115	0.49	0.00
WCS_Bell	1	0.03	0.03
WCS_Inukshuk	9	0.09	0.01
WCS_Xplornet	8	0.09	0.01
BRS_Bell	9	0.07	0.01
BRS_Rogers	218	1.82	0.01
BRS_Xplornet	2	0.04	0.02
AWS_Rogers	705	7.08	0.01
AWS_Bell	333	1.71	0.01
AWS_Telus	32	0.25	0.01
AWS_Videotron	22	0.14	0.01
AWS_Freedom	103	0.77	0.01
Total	**1938**	**14.45**	**0.01**

Note: 0.01 hours is approximately 30 seconds (36 exact)

Appendix E: ICT Coverage Comparison with Carrier Data

Carrier Coverage	Derived Coverage
Bell	
	
Rogers	
	
Silo	
	
Freedom