Spatial analysis of stated and revealed preference values of farms and parks: a case of Edmonton, Canada

By

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Abstract

Rapid city expansion has meant the conversion of large areas of farmland into developed uses. With increasing social realization of the amenity and non-amenity values of open spaces in urban and peri-urban contexts, this study provides information that policy makers and planners could use as they devise policy tools to guide land use. The provincial Government of Alberta has published several plans for farmland conservation, but none focus on the natural amenity value of farmland nor provide a clear blueprint for the future. This thesis applies two methods for estimating the non-market values of farmland in the regional context of Edmonton, Canada. The first study uses a spatial autocorrelation model (SAC) to estimate the effect of proximity to open space on the price of detached houses in Edmonton during the 2015 to 2017 period. The results show that properties have higher value if they are close to forest land, shrubland, wetland, parks and rivers and lower if near agricultural land. The second study uses the Edmonton data from a discrete choice experiment with spatial distance variables to estimate the effect of respondents' proximity to different types of open space on their non-market values of farmland. Conditional Logit and Random Parameter Logit Models are used to estimate respondents' willingness to pay to conserve farmland. Both studies find positive effects of living close to other forms of open space, but negative effects of living close to developable farmland. This second result supports the hypothesis that most residents support farmland conservation in the region, but those who live closest to the city frontier also appreciate the benefits of urban development in the frontier area. The valuation results could support a variety of policy tools, including property taxes, transferable development credits, and / or conservation easements.

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Chapter 1. Introduction

1.1 Problem

With rapid economic growth and expanding population, the province of Alberta is experiencing a continuous trend of land conversions. This conversion mostly happens when land is converted from agricultural to developed uses in order to fulfill growing needs for housing, light industry and commercial use. There has been rising concerns about conversion of high-quality farmland, particularly in the Highway 2 corridor between Edmonton and Calgary which experienced large-scale land development on land with high agricultural potential (Government of Alberta, 2017a). Farmland not only provides agricultural commodities, jobs, and tax revenue for governments, but also generates environment amenity values such as improved air and water quality, wildlife habitat, recreations, and scenic beauty. The associated market and nonmarket values are transformed when farmlands are converted into developed uses. Losing farmland can also potentially result in losses of food security (Olson and Lyson, 1999). Although not a major concern in Alberta or Canada as a whole, competition for land from other industries might elevate land prices, leading to higher food prices in the future (Government of Alberta, 2017a). Additionally, using high-quality land to accommodate people's living might reflect a policy failure if there are other lands that can be converted at lower opportunity cost[1]. Thus, how to implement an efficient and adequate policy to solve this problem is still a puzzle. In Alberta, despite a lot of focus on land use issues, policies, especially provincial-level planning, is incomplete and the completed ones barely touch on protecting the farmland itself and fail to provide clear guidance for future steps (Powell, 2019).

[1] Here opportunity cost refers to the market and non-market values that could be obtained by converting other areas of land.

Alberta's population grew by 24% between 2006 and 2016, which was the highest rate of increase of any province or state in North America (Government of Alberta, 2017b). The population is projected to increase to 6 billion by 2041 (Government of Alberta, 2016a), which is likely to result in much greater loss of high-quality agricultural land in the Edmonton-Calgary corridor. From 2012 to 2016, approximately 34,700 acres of the highest quality agricultural land was lost due to expansion of non-agricultural uses (Government of Alberta, 2018), and it is expected that another 347,000 acres of high-quality agricultural land will be lost over the next 50 years (Government of Alberta, 2017a).

Agricultural lands in Alberta also make a large contribution to the economy. Alberta has the second largest number of farms in Canada (21%), the second largest farm area (~32% of the total for Canada), and the largest cattle herd (over 41% of the total for Canada) (Statistics Canada, 2016; Statistics Canada, 2017a; Government of Alberta, 2017a). Alberta is also Canada's largest agricultural product exporter, exporting a total of $10 billion of products to over 100 countries worldwide (Government of Alberta, 2016b).

1.2 Policy Context

Concern about lost farmland has led the provincial government to create the Land Use Framework (Government of Alberta, 2008), which points out the need for government actions to address the loss and fragmentation of agricultural land in Alberta. The Land Use Framework suggests that government develop effective mechanisms in terms of agricultural land protection including market-based incentives, transfer of development credits, agricultural and conservation easements and growth planning tools (Government of Alberta, 2008). Procedures for implementing those tools are still involving little to the amount of land that is being converted out of agriculture. For instance, the Edmonton and Area Land Trust has secured 14 natural areas in Edmonton region with a total of 3,343 acres (Edmonton and Area Land Trust, n.d.), compared to the conversion of approximately 118,413 acres of farmland to developed uses between 2000 and 2016 (Luo, 2019). Meanwhile, Alberta Agricultural and Forestry (AF) is mandated to monitor and report the fragmentation and conversion of agricultural lands (Government of Alberta, 2018). The Alberta Land Stewardship Act (Government of Alberta, 2009) seeks to implement the Land Use Framework, supporting the purchase of conservation easements for the purpose of “protection, conservation, and enhancement of agricultural or land for agricultural purposes.” It also mandates the provincial government to develop regional plans for the Lower Athabasca, Upper Athabasca, Lower peace, Upper Peace, North Saskatchewan, South Saskatchewan, and Red Deer. Until now, only Lower Athabasca plan and South Saskatchewan plans have been approved. Both plans have recognized agricultural use as one of the land-use classifications and provided clear intent to protect agricultural land and its ecological benefits. Both plans consider it as municipalities’ responsibilities to address and reduce the loss and fragmentation of farmland.

Complying with the regional plans, the Municipal Government Act (Government of Alberta, 2000) was modified to regulate each municipality regarding its planning and development on agricultural operations. Municipal governments have the power to make final decisions on zoning land for agricultural and other uses. Other provincial and municipal agencies have taken conversion and fragmentation into account. The Alberta Association of Municipal Districts and Counties (AAMDC) has published a document expressing concern about loss and fragmentation of farmland in Alberta, but without any recommendation with regards to mechanisms for protection of agricultural land (Government of Alberta, 2018). Likewise, Alberta Agriculture and Rural Development produced a report with the same concern (Alberta Agriculture, Food and Rural Development, 2002); however, there is still no recommendation of farmland protection. So far, some policies have focused on agricultural business, industries, and operations rather than agricultural land and the policies that have reported the conversion issue fail to provide a conservation tool or guidance (Powell, 2019). The Edmonton Metropolitan Region Board (formerly Capital Region Board) has developed the latest Edmonton Metropolitan Region Growth Plan, with an objective of ensuring wise management of agricultural resources through collaboration of municipal governments in the region (Edmonton Metropolitan Region Board, 2017). A Regional Agricultural Master Plan was then created to provide a framework and support for Region's agricultural policies. Edmonton Metropolitan Region Board will further work with the Government of Alberta, municipalities, and the agricultural sectors to provide better support for the Regional Agricultural Master Plan (Edmonton Metropolitan Region Board, 2017).

As mentioned, the Land Use Framework lists several policy and market-based tools to preserve agricultural land. This list includes conservation easements. Chiasson et al (2012) have reviewed the practice and status of conservation easements in Alberta and concluded that there is currently no focused policy direction for conservation easements for agricultural land. Another instrument mentioned in the Alberta Land Stewardship Act is Transferable Development Credits (TDC). TDCs facilitate market-based transfers in which landowners in a designated conservation area could transfer credits to developers who want to develop and build in a designated development area. While there is a great interest in developing TDC programs and municipalities have the legal ability to do so, implementing agencies still face challenges without explicit provincial direction. Greenaway and Good (2008) have done a feasibility review of the TDC mechanism in Alberta and conclude that the main areas of concern include the inconsistency in program components and the limits in the existing conservation deed restricting tools (2008). Despite some successes, neither conservation easements nor TDCS are widely implemented in Alberta (Driedzic, 2016).

1.3 Research Objectives

The general objective of this study is to determine how people's residential location relative to open spaces affects their willingness to pay for developable and non-developable open space. It could provide more information to the decision makers about the trade-offs people are willing to make between loss of farmland and the development of urban areas; and the non-use values they place on agricultural lands and other types of open spaces (forest lands, wetlands, parks etc.). Certain policies with practical procedures, for example conservation easements and TDC programs, could be proposed and enforced by related policy makers and city developers to make wiser decision on preservation of lands.

The specific objectives of this thesis are to:

1) Develop and estimate a discrete choice experiment model of willingness to pay for preservation of agricultural open space to incorporate the effects of respondents' spatial location in a city-regional context.

2) Develop and estimate a spatial hedonic model of house prices to assess willingness to pay for proximity to developable and non-developable open space in an urban context.
3) Consider how planners and policy makers can use estimates of WTP for developable and non-developable open space to inform land use plans and policies in our study areas.

The next section provides an overview of the methods used in this thesis, while the individual chapters provide more detail on those methods.

1.4 Methods

As farmland is converted, not only are associated market commodities lost, but some of the associated non-tradeable goods and services are diminished. Agricultural land generates a mixture of private goods and public goods, which means that market values may understate value to society. Economists started to use non-market valuation techniques to estimate the amenity value of farmland in the early 1980s. Choice experiment (CE), as one of the stated preference methods (SP), is commonly used to estimate nonmarket value in environmental valuation, transportation choice, and health assessment (Lloyd-Smith et al., 2020). Hedonic price model (HPM) and travel cost method (TCM) are types of revealed preference methods that could be employed to estimate farmland amenity and non-amenity value (Bergstrom and Ready, 2008).

Stated preference valuation techniques rely on the responses collected from surveys to evaluate people's perceptual valuation, while revealed preference valuation techniques use statistical inference to estimate value from people's actual behavior. In this thesis, choice experiment and hedonic price models are used to assess the values of agricultural lands and other types of open space. The thesis uses survey data in which a choice experiment was implemented on alternative land preservation scenarios and WTP estimated on the basis of random utility theory. The thesis also uses property transaction data in a hedonic price analysis to relate the price of land to the attributes of land itself (structural attributes) and several contextual factors (neighbourhood attributes).

An expanding literature has pointed out the relevance of spatial dimensions for stated and revealed preference analysis. Previous studies have demonstrated that ignoring spatial relationships in valuation studies can lead to estimation bias and an inability to capture welfare heterogeneity, which could directly affect policy evaluation and public choices (Bateman et al., 2006, Johnston et al, 2017). However, microeconomic theory does not provide clear guidance with consensus standards as well as insight regarding the best way to incorporate spatial dimensions into environmental goods (Glenk et al., 2019). Despite this, two broad categories can be identified in spatial SP studies. The traditional econometric method is to include spatial variables into the utility function so that they are observable spatial characteristics. This approach raises questions about unobserved spatial heterogeneity or spatial dependence (LeSage and Pace, 2009) that is not readily explainable using observable variables alone (Glenk et al., 2019). In this case, spatial econometric or geo-statistical techniques are required to avoid model specification and results bias. Such models have been applied to analysis of discrete choice data and count data but have been rarely used in SP analysis (Glenk et al., 2019).

Several spatial variables are demonstrated in Glenk et al. (2019)'s study including distance effects, spatial substitutes and compliments, spatial scope and diminishing marginal utility, with some of them appearing together. Estimation of distance effects requires the collection of information from sample respondents' location relative to site or place and related spatial information. Multiple studies have considered the proximity effect on the value of farmland or other types of open space using both stated and revealed preference techniques. Bergstrom and Ready (2008) summarize over 30 studies that used one of the techniques and conclude that HPM tends to reveal use value to private landowners who live close to farmland while CE reveals both use and non-use value that is spatially diverse and applicable to a larger number of households. Moreover, comparison between studies suggest that HPM only captures the amenity effect of properties located relatively close to farmland (e.g. within 2 miles) while stated preference studies capture more geographically dispersed effect in non-use values (Bergstrom and Ready, 2008). A previous study of the same choice experiment data by Luo (2019) has left a certain level of preference heterogeneity unexplained; thus, spatial variables are included in this study in an attempt to capture and explain more of this heterogeneity. In this study, the survey responses and property values are for Edmonton, Alberta, the second largest urban area in Alberta.

1.5 Thesis Structure

This thesis includes two papers with both papers using remote sensing landcover data to categorize land types. Chapter 2 is a hedonic price analysis using a spatial hedonic model that incorporates spatial dependence and generates estimates of the local and spillover effects of agricultural land and other types of open spaces on residential property values in the city of Edmonton. Chapter 3 is an extension based on previous analysis, which uses survey-based data to derive individual's willingness to pay for farmland preservation in the Edmonton Census Metropolitan Area (CMA). Chapter 4 concludes the thesis by summarizing and comparing the results as well as proposing possible policy implications. It also includes some limitations of this study and a discussion of future research areas.

Chapter 2. Measuring the Amenity Value of Urban Open Space Using a Spatial Hedonic Approach

2.1 Introduction

Rapid urban sprawl and economic growth increase the importance of balancing housing needs and limited urban open spaces. In Alberta, the population growth rate was over double than that of Canada from 2012 to 2014 (Government of Alberta, 2020) and projected to have an additional 54% increase between 2012 and 2028 in Edmonton (Wang, 2015). Consequently, city planners and developers increasingly weigh the tradeoff between satisfying housing needs and preserving open space since taxes from higher house prices can be used to strengthen existing green spaces or to counterbalance the effect of urban development (Luttik, 2000). For instance, the tax revenue generated from high property values could be redistributed into the development and implementation of policies associated with land and environment conservation, while environmental problems and land scarcity are major public concerns along with the development. Open space can provide numerous benefits. Urban open space such as parks helps promote mental and physical health by providing psychological relaxation and reducing exposure to pollutants, noise and heat (Braubach et al., 2017). Nielsen et al. (2020) have found that formula-fed babies raised in urban areas benefit from living close to natural green space because the vegetation, soil and water may be beneficial for their early life gut microbiota. Urban green spaces also create opportunities for recreation uses, scenic views and some ecological benefits such as wildlife habitats and improved water or air quality (Irwin, 2002; Anderson and West, 2006).

Several studies illustrate that ecological factors have significant influence on the sales price of houses. Previous spatial studies show that proximity to different types of open space have differing effects on property value (Trojaney et al., 2018; Hicks and Queen, 2016). Specifically, studies by Anderson and West (2006), Geoghegan et al. (1997) and Yoo et al (2017) found that urban residents located in denser neighbourhoods near the central business district (CBD) are willing to pay more for proximity to open space than peri-urban residents. Open space can be distinguished by whether it is preserved or is developable, whether it is publicly or privately owned, and how it is used (Irwin, 2002). Early studies have shown houses proximate to urban parks often have lower prices due to the associated noise and other nuisance factors, while properties proximate to larger natural open spaces and certain types of wildlife habitats have higher prices, with this effect increasing with the size of the open space (King et al., 1991; Shultz and King, 2001, Lutzenhiser and Netusil, 2001). In contrast, Trojanek et al. (2018) found the distance to urban green areas in Warsaw, Poland had a significant nonlinear effect on residential prices such that increasing the direct proximity to park or forest within 100 meters could increase apartment prices by 2.8% to 3.1%. Similarly, Laszkiewicz et al. (2019) found that in Lodz (Poland), the marginal willingness to pay for proximity to selected urban parks rises with apartment prices, perhaps signaling luxury for apartment buyers. Wetlands, as one type of open space, provide ecosystem services such as water purification and filtration, flood control, wildlife habitat, recreation, and aesthetic uses, but sometimes bring negative externalities such as odor and insects and thus lead to a negative value to prices of nearby homes (McConnell and Walls, 2005). In their study in Hangzhou, China, Du and Huang (2018) found that proximity to urban wetlands significantly increases surrounding house prices within 5km, with the most significant impact within 1km. There is also a large and growing number of studies focusing on the effect of lakes on residential property values. Benson et al. (2000) found that, depending on quality, a water view of the house increased house value by 8% to 59% in Bellingham, Washington DC in 1993, while lake frontage increased house price by 126% compared to a non-view / non-frontage house. Asifa and Mats (2018) also found proximity to water have a positive and highly significant impact on apartment prices in Stockholm (Sweden). Crompton and Nicholls (2020) reviewed 33 studies in terms of the impact of proximity to different open spaces on property values and concluded that there is a higher premium for houses located near permanently protected lands than for developable lands.

Previous studies have used hedonic analysis to value the impact of environmental amenities on property values. McConnell and Walls (2005) reviewed 40 open spaces related hedonic studies conducted between 1967 and 2003, most of which were conducted without using spatial econometrics. Regarding our study region, Macdonald and Veeman (1996) used ordinary least squares estimation to derive the characteristics that affected house values in Edmonton, Alberta. Moreover, Islam (2012) incorporates more factors including neighbourhood characteristics such as crime incidences into linear regression models to assess the impact of neighbourhood variables on house prices in the city of Edmonton. With the development of spatial econometrics, more recent hedonic studies have applied spatial econometrics to value environmental amenities. For instance, Cao et al. (2018) used spatial hedonic models to estimate the value of open space in the Alberta town of Okotoks. Yoo et al. (2017) used a spatial lag model and spatial error model to estimate the effect of changes in the urban forest in the city of Corona (California) on amenity value of lake water quality. Moreover, Sohn et al. (2020) have conducted spatial lag and spatial error models to estimate the added value of retention and detention ponds on neighbourhood house values in four sub-divisions in Houston, Florida. Furthermore, a geographically weighted regression (GWR) was employed in Kim et al. (2020)'s study to estimate how the proximity to Jacksonville beach in Florida would affect house prices. A similar approach (GWR) is also adopted in Mittal and Byahut (2017)'s research on the impact of accessibility of scenic lands on single family house prices in Worcester, USA.

Studies that have applied spatial econometrics are mostly using the spatial lag model (SAR) or the spatial error model (SEM) (Osland, 2010). In our analysis, we have examined seven different spatial econometric models and chose the spatial Autocorrelation model (SAC) as our preferred model on the basis of econometric tests including goodness-of-fit and statistical significance of the open space variables. Based on data on transaction records for single-family detached properties between 2015 and 2017 in the City of Edmonton, this paper will develop and estimate a spatial hedonic model of house prices to explore people's valuation on different types of open space, hopefully clarify some of the real trade-offs between development, open space value and environment preservation in this urban context.

2.2 Study Area

The study area of this analysis is the City of Edmonton (Figure 2.1). It is the capital city of the Canadian province of Alberta. It is located on the North Saskatchewan River and is the heart of Edmonton Metropolitan Area. From 2011 to 2016, Edmonton's population grew by 14.8% (812,201 in 2011 and 932,546 in 2016), which made it the second largest city in Alberta and the fifth most populous urban municipality in Canada (Statistics Canada, 2017b). After annexations of parts of five adjacent urban municipalities (Strathcona, North Edmonton, West Edmonton, Beverly, and Jasper Place) that doubled the surface area of Edmonton in the 1980s, Edmonton annexed another 8,260 hectares of land from Leduc County and the City of Beaumont in 2019 (City of Edmonton, 2018). The City of Edmonton maintains 4,600 hectares of grass and contains more than 460 parks. Besides the grassland, the River Valley in the city forms a "Ribbon of Green" that provides great opportunities for walking, jogging, bike riding, picnicking, snowshoeing and cross-country skiing. This includes more than 22 major parks and 150 kilometers of maintained pathways (City of Edmonton, 2017). Using 2016 land coverage data from the Agricultural and Agri-food Canada (AAFC) Annual Crop Inventory website, we estimate that 35% of the City of Edmonton is covered by open space with approximately 12,446 hectares in agricultural uses, 2,861 hectares as woodlands and 9,276 hectares in non-developable lands as mentioned in section 2.1 (Government of Canada, no date). Figure 2.2[2] shows the distribution of different types of open spaces during 2015 and 2017 in Edmonton.

[2] This thesis uses the boundaries that held before the most recent annexations.

Figure 2.1 Map of the Study Area (Edmonton, Alberta, Canada)

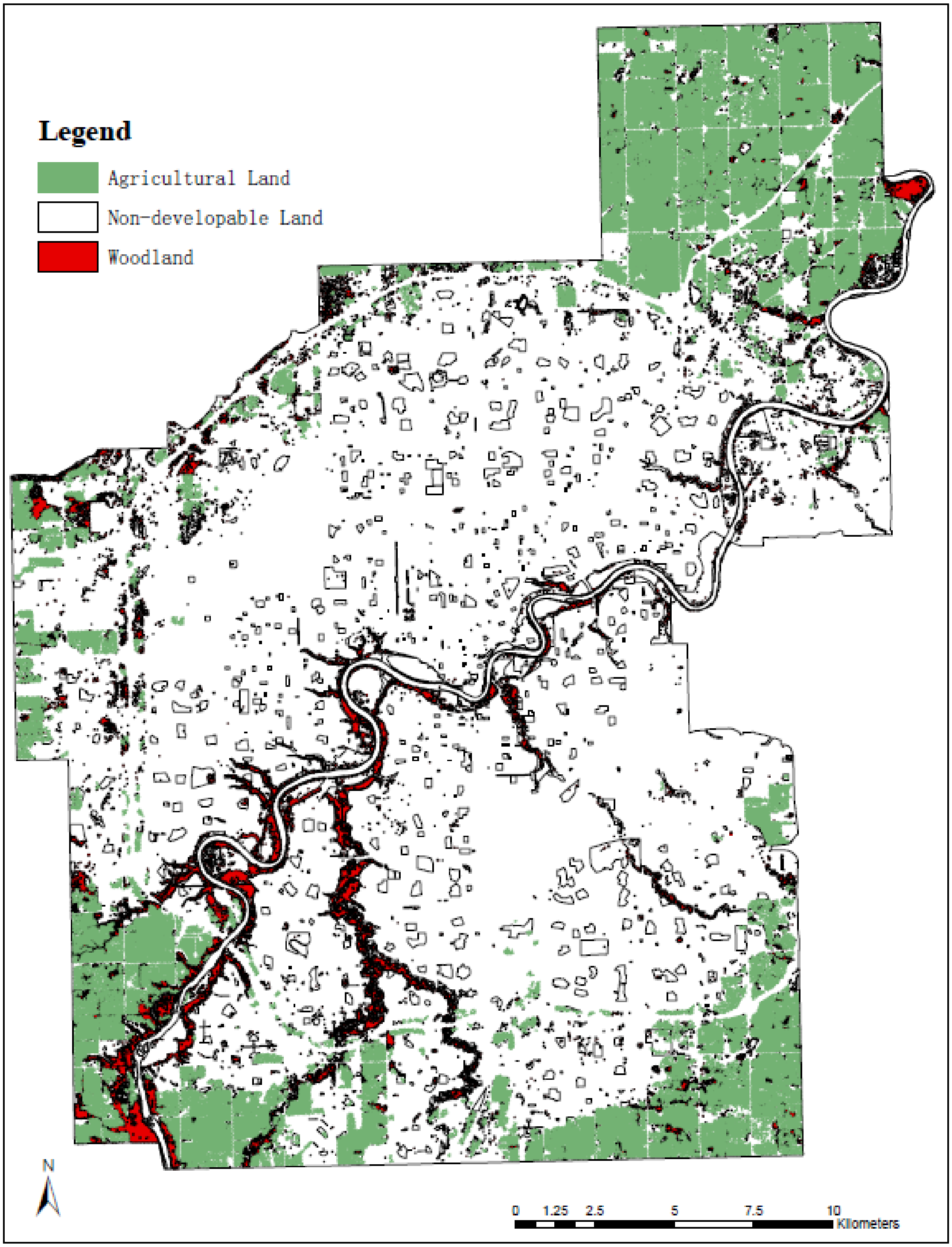

Figure 2.2 Distribution of Open Spaces in Edmonton[3] (Map by the author)

[3] Agricultural land includes cropland, grassland and pastureland. Non-developable land includes water bodies, parks and wetlands. Woodland includes forest land and shrubland. More details are provided in section 2.4. The map boundary is held before the most recent annexations.

2.3 Model

2.3.1 Hedonic Price Model

A hedonic price model is employed as the analytical framework for this study. It assumes that purchasers of a good are purchasing a collection of attributes of that good. Underlying the hedonic framework is a theory of consumer behavior that assumes that goods are valued based on their individual "utility bearing" attributes or characteristics (Rosen 1974). Following this, house prices are a function of their various attributes:

$$P=(S, L, N, E, \varepsilon) \tag{2.1}$$

where P is a vector of housing prices; S, L, N, E are vectors of structural attributes, locational attributes, neighbourhood attributes and environmental attributes respectively; ε is a vector of error terms that capture all unobserved variables. The partial derivative of the price function with respect to an explanatory variable j is the marginal willingness to pay for that attribute, or the implicit price of that attribute. The traditional hedonic model assumes that stringent idealized conditions hold. That includes market equilibrium in the housing market with perfect competition, perfect information for buyers and sellers, and a continuum of products (Singn.et al 2018). However, according to Benkard and Bajari (2005), the hedonic price model is still valid without all these conditions, noting that not all product attributes are observable, which is relevant for the case of house prices. For instance, features of the surrounding environment, such as the crime level in the neighbourhood, could also have impacts on house prices.

Following previous studies of house prices, we have tried different functional forms (log-log, lin-log, lin-lin, log-lin) and decided to conduct log-transformations of the dependent variable and all explanatory variables that are distance or area based. Palmquist (1984) finds that the relationship between interior space and sale price may not be linear. Moreover, Bin and Polasky (2004) state that a log transformation of distance variables will generally perform better than a simple linear functional form because logged variables are better able to capture the declining marginal effect of these distance variables. In addition, the log transformation is a way to reduce heterogeneity among explanatory variables because it reduces variation in the observations.

The logged function of the hedonic price model is as follows:

$$ln(P_i) = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad (2.2)$$

where ln(Pi) is the natural log of the sale price of a house i; *;* x_{ik} are variables of (some of which are logged) structural, neighbourhood, and the natural logs of the k location and environmental characteristics (x include *S, N, L, E*).

2.3.2 Spatial Hedonic Price Model

In a linear regression model under OLS estimation, all observations are assumed to be independent of each other. Spatial models are needed to deal with data that exhibit spatial dependence where the values observed at one location depend on values at nearby locations (Lesage and Pace, 2009). It is commonly observed that housing values are influenced by prices of surrounding properties, which implies potential spatial interactions. Ignoring spatial dependence would lead to biased and inconsistent estimators (Lesage and Pace, 2009; Anselin and Arribas-Bel 2013).

Detecting spatial dependence (or autocorrelation) is a fundamental process of all attributes located in space. Moran's I, Geary's C, General G etc. are common measures for assessing whether a variable exhibits spatial dependence at a given level. In this paper, we adopt the most commonly used Moran's I to measure the spatial autocorrelation. Besides, analysts have developed several spatial models that we briefly review. To select among available models, we conduct a log-likelihood ratio test (LR test) to see which model performs better. This is also called a common factor restriction test. If the LR test is rejected, then the added variables have significant explanatory power for the regression and must be estimated (Elhorst, 2014).

2.3.3 Spatial weights matrix

The weights matrix is at the core of spatial econometric models. In this study, we implement an inverse-distance weights matrix, which is the most frequently used weights matrix. The weights are inversely related to the physical distance between observations (houses sold in our case) and are shown in equation (2.3):

$$w_{ij} = \begin{cases} 1, & 0 \leq d_{ij} \leq d \\ 0, & d_{ij} > d \end{cases} \tag{2.3}$$

where d is the truncated distance (as known as bandwidth). If the distance between observation i and j is no more than d, then there is spatial correlation. W is usually normalized to avoid singularity of the term $(I - \rho W)$ where ρ is a spatial parameter to weight the corresponding spatial lag (Seya et al., 2013; Montero et al., 2017). Among methods for normalization, this paper will follow the most widely used one, row-normalization, so that the elements of the rows sum to unity.

2.3.4 Spatial Autocorrelation Model

The scalar parameters, ρ and λ, are used to measure the magnitude of spatial dependence between units while β and θ are K*1 vectors of response parameters that need to be estimated (Vega and Elhorst, 2013). As shown in Figure 2.3 (Vega and Elhorst, 2013), the model labelled GNS is the general nesting spatial model which includes all types of spatial interaction effect. When there is no spatial lag on the error term (λ=0), the Spatial Durbin model (SDM) is the result. When there is no spatial lag on the independent variables ($WX\theta = 0$), it simplifies to the Spatial Autocorrelation model (SAC). If there is no spatial lag on the dependent variable, it simplifies to the Spatial Durbin Error model (SDEM). Furthermore, there are three types of non-nested spatial models[4], which are Spatial Lag Model (SAR), Spatial Lagged-X model (SLX), and Spatial Error Model (SEM).

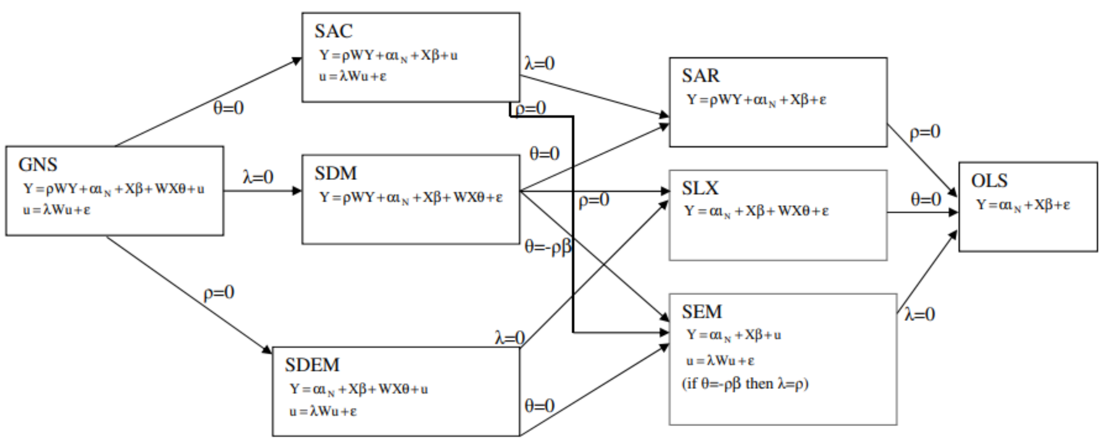

Figure 2.3 Comparison of different Spatial Econometric Model Specifications (Vega and Elhorst, 2013)

Selecting the model that best matches the true data generating process is important for spatial analysis. For instance, if the true data generating process is a SAC model, which includes both

[4] Nested models mean there is interaction effect between any spatial coefficient.

spatial lag and spatial error, the SAR and SDM will produce unbiased coefficient estimates while SEM will produce biased estimates (Lesage and Pace, 2009). However, the SAR model ignores spatial dependence in the error terms while the SEM does not account for spatial dependence in the dependent variable (Lesage and Pace, 2009). Here we report SAC as our preferred spatial model. The SAC is defined by (Anselin, 1988):

$$\begin{aligned} y &= \rho W_y + \mathrm{X}\beta + u \\ u &= \lambda M_\varepsilon + \epsilon \end{aligned} \tag{2.4}$$

where y is an $n \times 1$ vector which consists of one observation on dependent variable for each spatial units; W and M are $n \times n$ spatial weights matrices; X is an $n \times p$ matrix of independent variables; ρ and λ are spatial autoregressive parameters, which could measure the degree of spatial dependence in the dependent variable y and the disturbance term u respectively; β is an $p \times 1$ vector of parameters; ϵ is an $n \times 1$ vector of error terms.

Figure 2.4 shows the decomposed effect of each spatial model. As noticed, SAR and SAC share the same direct and indirect properties. The diagonal elements are the direct effects which are the effects of the change in a particular explanatory variable in a particular unit on the dependent variable of the same unit. The off-diagonal elements contain the indirect effects, also called spillover effects, that are the effects on dependent variable in a location by change in the explanatory variable in another location. One limitation of this model is that the ratio between direct and indirect effects is the same for every explanatory variable, which is unlikely to hold in practice. An alternative is to estimate the spatial Durbin model (SDM) which allows for flexible ratio between variables. However, SAC is our preferred model since SDM generates many counter-intuitive results (see Appendix 1 for SDM decomposed effects).

	Direct effect	Spillover effect
OLS / SEM	β_k	0
SAR / SAC	Diagonal elements of $(I - \rho W)^{-1}\beta_k$	Off-diagonal elements of $(I - \rho W)^{-1}\beta_k$
SLX / SDEM	β_k	θ_k
SDM / GNS	Diagonal elements of $(I - \rho W)^{-1}[\beta_k + W\theta_k]$	Off-diagonal elements of $(I - \rho W)^{-1}[\beta_k + W\theta_k]$

Figure 2.4 Direct and Indirect Effect under Different Spatial Models by Vega and Elhorst (2013)

2.3.5 Estimation Approach

Estimation of most spatial econometric models is carried out by maximum likelihood (ML) approach that the probability of the joint likelihood for all parameters are maximized (Fischer and Wang, 2011). This approach is desirable for its consistency and asymptotic normality (Fischer and Wang, 2011; Lesage and Pace, 2009).

2.4 Data Description and Hypotheses

As stated above, the main objective of this paper is to determine how people's willingness to pay for living near to farmland is reflected in housing prices. Among different types of houses, we choose single-family-detached houses as our observations because they comprise nearly 80% of the houses that are sold in the Edmonton real estate market (Zolo,2020). Housing transaction data are generously provided by Brookfield Real Property Solutions (RPS), which is a leading national resource for housing data. We don't have access to data on all housing transactions in the Edmonton area for our time period. However, for the Calgary area, Yeates et al (2012) found that the Brookfield RPS database represented approximately 70% of all recorded Real Estate Board sales (Yeates et al., 2012). The property selling price is illustrated in Figure 2.5. As shown in Figure 2.6, there is relatively high variation in house prices over time. Thus, we pool data on property transactions from the most recent years that we have data (2015, 2016 and 2017) to provide a more comprehensive picture. If we compare the house price index from these three years to the other years in the last decade (Figure 2.7),we see no major fluctuation in price in the 2015-2017 period, which supports the generalizability of our results (Tenant and National Bank of Canada, 2020). After dropping some missing values and keeping only one transaction for houses that had recorded more than one transaction during the study period, we reach a sample size of 9495 observations from 2015 to 2017. We use the House Price Index (HPI) (The Canadian Real Estate Association) for Edmonton to adjust all property values to constant 2016 Canadian dollars. In order to conduct a hedonic price analysis, we include structural, neighbourhood and environmental variables to estimate the direct effects of these characteristics on the price of a particular home, and the indirect effect on the value of homes in close proximity to that particular home. The variable names, definitions and sources are listed in Table 2.1 and the descriptive statistics are listed in Table 2.2.

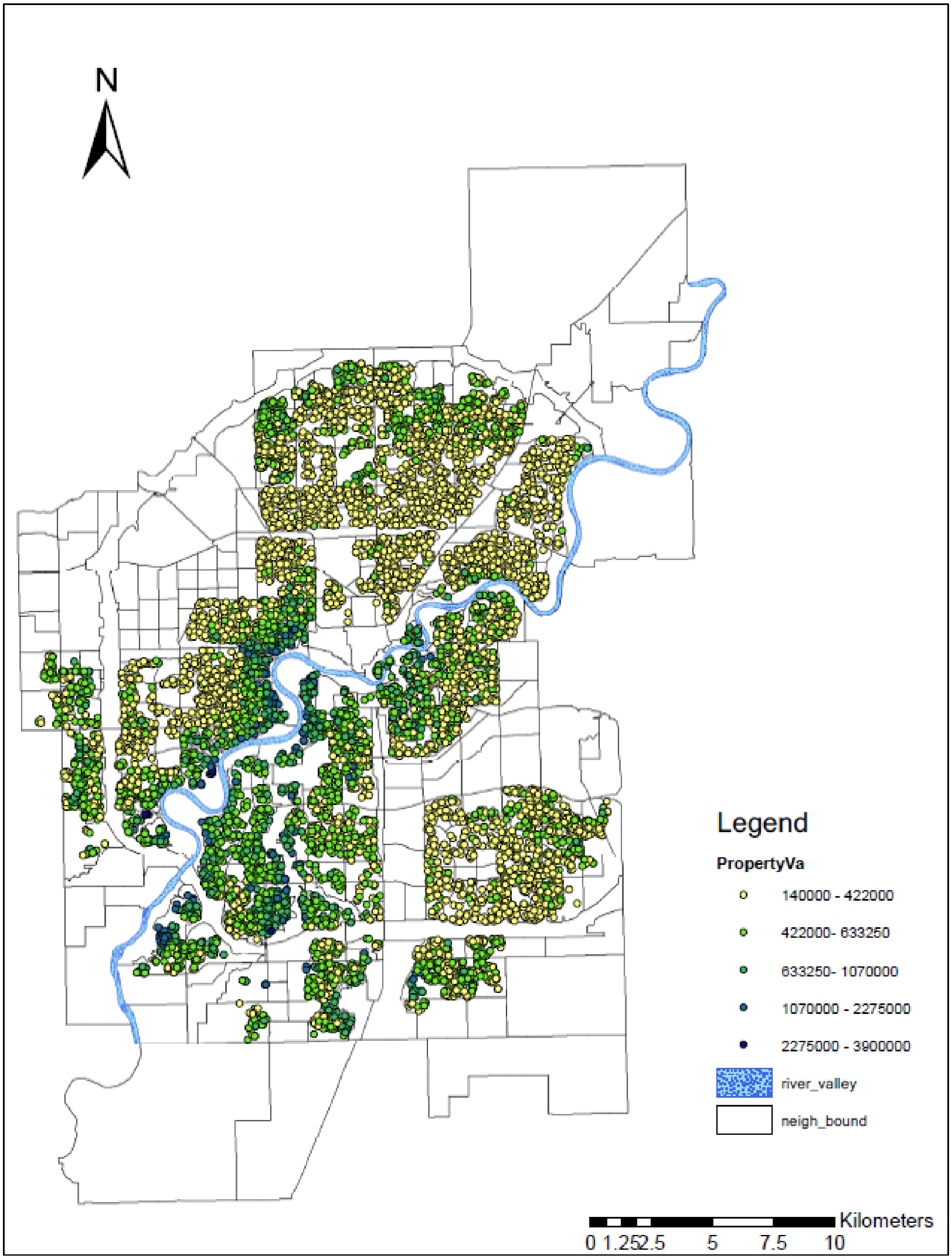

Figure 2.5 Property Sold in the City of Edmonton from 2015 to 2017 (by author)

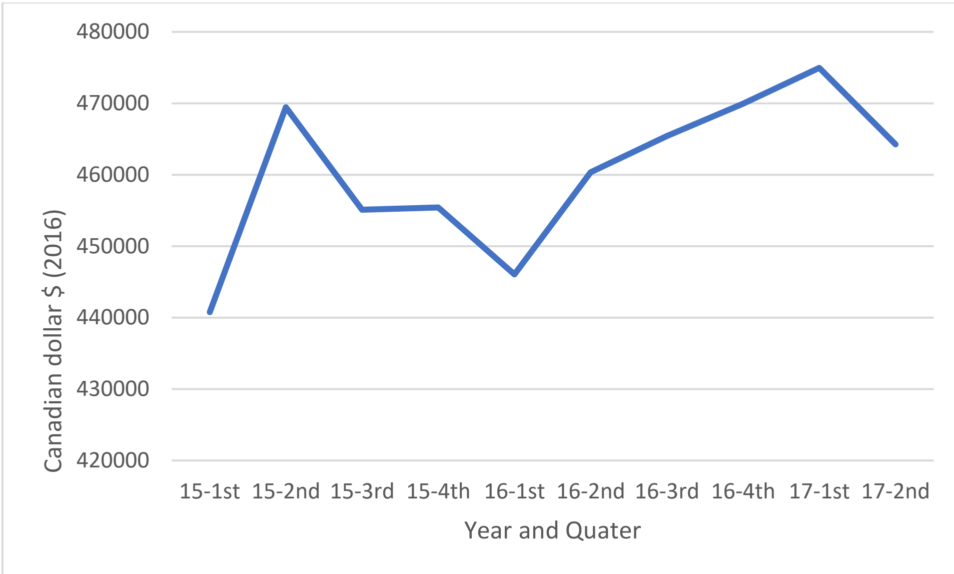

Figure 2.6 Average Price of Single-detached Houses Sold in Edmonton

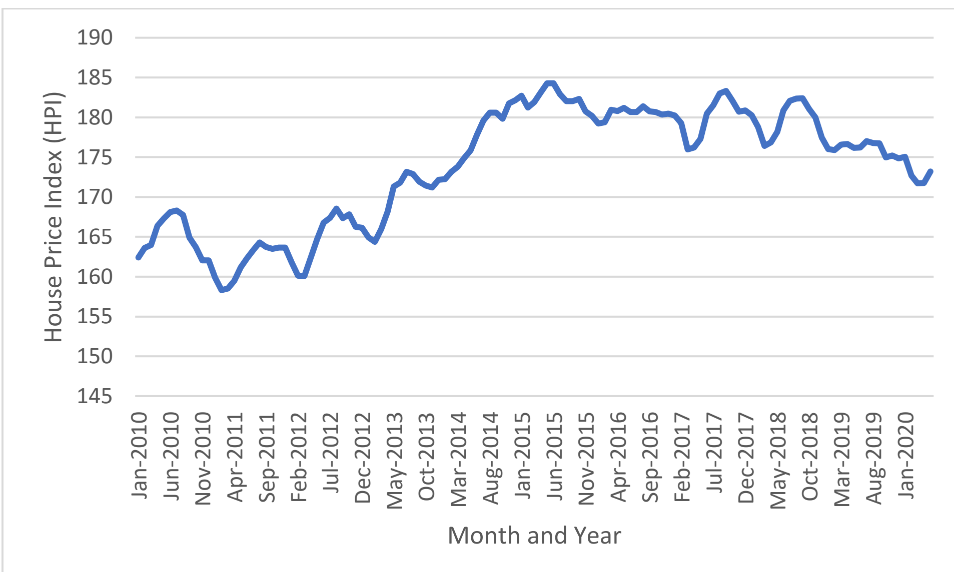

Figure 2.7 House Price Index from 2010 to 2020 for Edmonton

Data on most structural characteristics are available in the dataset provided by Brookfield RPS, including living area, lot size, year sold, number of bathrooms, number of bedrooms, condition of the house, condition of the basement and number of parking spaces. The season when the house is sold is added because the value of the house tends to be higher if it is sold between April and September.

Locational characteristics are generated using the proximity tool in ArcGIS software. Distance to downtown Edmonton is included since the downtown area is the core of employment in the city. The Provincial legislature, City administration, and the financial and engineering service sectors are all centered in the downtown core. Proximity to Light Rain Transit (LRT) stations reduce transit times and have exerted upward pressure on the prices of nearby houses in other studies (Dziauddin et al., 2015; Hui et al., 2007).

House prices are often found to be affected by neighbourhood characteristics. Our study uses 2016 census information for the neighbourhood in which the property is located (Open Alberta; City of Edmonton). In Edmonton, there are 400 neighbourhoods in total with an average size of 1.96 square kilometer. Population density is included, as higher density residential areas may be associated with negative congestion externalities such as high traffic volume and noise. The percentages of youth and elderly people define the dynamics of a neighbourhood and often the maturity of the housing market. Edmonton has experienced rapid growth over the last 50 years, often with younger families moving into newer developments near the edge of the city. We expect lower turnover and lower prices in neighbourhoods with higher percentages of older people, and higher turnover and prices in neighbourhoods with higher percentages of children. Highly-educated households with children may have higher demand for environmental quality, which in turn, may put upward pressure on house prices (Brasington and Hite, 2003; Sedgley et al.,2008). Previous studies indicate that neighbourhoods with more university-educated individuals generally have higher house prices (Borchers and Duke, 2012). One way to define a neighbourhood's education quality is through the quality of its public elementary school. Edmonton's elementary schools have defined catchment areas, mostly related to specific neighbourhoods. In order to examine the quality of schools, we record the 2017 school quality score which is calculated by the Fraser Institute (Fraser Institute). It provides us with a range from 0 to 10. The rationale behind using the 2017 score instead of the 2016 score is because neighbourhood structure plans always state the designated schools 2 years before the school is ready for use. Two of the Elementary Schools, Ivor Dent and Mayfield, do not have their scores posted on the Fraser Institute website due to low attendance and high percentage of special needs students, so we record an average score of 5.8 for each of them. We choose elementary schools rather than junior high schools because many junior high schools in Edmonton are associated with either elementary schools or high schools. We postulate that high school quality has less influence over housing choices because many high school students commute longer distances and many Edmonton high schools attract students through specialty programming in languages, arts or sports. We include crime incidence in each neighbourhood because homeowners are concerned about public safety (Dubin and Goodman, 1982). Moreover, percentage of residents with low income, percentage of people with high income, as well as unemployment rate are included as measures of the relative economic position of a neighbourhood (Downs, 2002). Regional effect is controlled by a regional dummy to see if the property has a higher value when the average property value in that neighbourhood is higher than the average for all neighbourhoods. .

Environmental characteristics of a property could potentially capture the effect of proximity to amenities and dis-amenities that influence property value (Cho et al., 2006). Here, variables related to open space are calculated by several tools available in the ArcGIS software. The raster data layers on actual land use are downloaded from Government of Canada Annual Crop Inventory website (Government of Canada). We aggregate different land-use types from the Crop Inventory data into three categories: developable agricultural land, woodland, and the wetlands in non-developable land. The rest of shapefiles used for non-developable land including water bodies and parks are obtained from the Open Data Edmonton portal. Developable agricultural land is land that is suited for producing agricultural products, which includes cropland, pastureland and grassland. This is a land use designation and does not account for whether or not the municipality has designated the land for a developed use. Woodland includes forest land and shrubland which is also an actual land use rather than permitted land use. This analysis focuses on large-scale land uses, although there is small-scale urban agriculture such as community gardens and urban farms. There is some overlapping between non-developable land and agricultural land in the middle of the city along with river valley, as shown in Figure 2.2. We prioritize non-developable land so that the land polygons of agricultural land are removed if they overlap with non-developable land.

As indicated in the literature review above, the value of living near these non-developable open spaces may be complex. That is, while many people enjoy the amenity values associated with nearby views of rivers or parks (Crompton and Nicholls, 2020; Crompton, 2001), there may also be dis-amenity values due to congestion, noise and loss of privacy brought about by some of those amenities (Benson et al, 2000). Investors and early residents may overestimate the net value of these amenities, with downward pressure on prices over time (Benson et al, 2000). The main area of contiguous agricultural land near the centre of the City of Edmonton is the University of Alberta South Campus, also known as the university farm. It is primarily used for agricultural experiments and could be further developed as the built infrastructure of the university expands. We thus include it as a separate type of open space. We also include acres of land-use change (from agricultural to developed) that has recently occurred within a 1 km buffer of the property. The effects of recent change in land use on housing prices are less well studied (Acharya and Bennett, 2001). We use the data on the 1 km buffer here, after trying buffers with radii of 100m, 200m, 500m, 1km and 2km. The 1km buffer produced the results with the highest statistical significance level. For different years, we use data on land use change in the previous 6 years. For instance, 2009 and 2015 raster layers are used to calculate the acres of land-use change for houses sold in 2015.

The rationale behind our categorization of open spaces is as follows. While open spaces can generate natural amenity values as commonly emphasized, the magnitude of those values may differ for different types of open spaces. Smith et al. (2002) regard open spaces as "fixed," not changing over time. We thus refer to this type of open space as "non-developable land". This is different from lands that are more "adjustable", such as agricultural lands and vacant lands. Also, amenity values may vary across different types of farmland. Thus, we distinguish agricultural land into developable agricultural land if it has intensive agricultural production, and non-developable agricultural land if it is currently covered by forests or shrubs. We expect all open space variables to have significant effects on property values, with non-developable open space having the largest effect because it provides the highest level of scenic beauty and other services. Proximity to the University of Alberta farm should have the second-largest impact because it mixes the recreational use of a park and the natural amenity value of a less active farmland. The third largest effect on price should be non-developable agricultural land, that produces some of the same amenity values as non-developable land. Productive agricultural land will be the least valuable type because it may be associated with noise, dust, odor, and other inconveniences as well as the potential pesticide leakage or water pollution (Johnston et al., 2001).

Table 2.1 Definition of Variables and Sources Included in Hedonic Price Model

Variables	Definition	Sources
Dependent variable	Adjusted House Transaction price from 2015 to 2017 (2016$)	
Structural Variables		
Living area	Square feet of living space	
Lot size	Square feet of lot size	
Age	Age of the house (years)	
Bath	Number of full bathrooms	
Bed	Number of full bedrooms	Brookfield RPS
Condition	1 if condition is "excellent" or "good", 0 otherwise	
Basement	1 if basement is "finished", 0 otherwise	
Parking	Number of parking spaces	
Season	1 if the house is sold between April and September, 0 otherwise	
Locational Variables		
Downtown	Distance to downtown (km)	Open Edmonton Dataset
LRT	Distance to nearest LRT station (km)	
Neighbourhood Variables		
Density	Population/acres of developed land in neighbourhood	
Child	Percentage of population aged 5 to 19 years old	
Elder	Percentage of population aged over 60	Open Alberta Dataset
Unemployment	Unemployment rate in 2016	
Low Income	Percentage of people with income less than $30,000	
High Income	Percentage of people with income more than $150.000	

Bachelor	Percentage of people with at least get bachelor's degree	
Crime Incidence	Number of crime events in each neighbourhood in 2016	Edmonton Open Analytics
Quality	Score of designated public elementary school (0-10)	City of Edmonton, Fraser Institute
Regional Factor	Dummy variable that equals 1 if average house price in the neighbourhood is higher than sample mean, 0 otherwise	Brookfield RPS
Environmental Variables		
Agricultural	Distance to nearest developable agricultural land (km)	
Woodland	Distance to nearest developable woodland (km)	Calculated from Government of Canada Annual Crop Inventory
Non-developable	Distance to nearest non-developable land (km)	
UA farm	Distance to University of Alberta Farm (km)	
Land-use change	Acres of recent six-year land-use change within 1km buffer	

Table 2.2 Descriptive Statistics of Variables Included in Hedonic Price Model

Variables	Mean	Std. Dev.	Min	Max
Dependent variable	454,736	203,264	140,000	3,749,619
Living area	1,569	626	348	10,183
Lot size	5,838	4,325	348	247,570
Age	29	23	0	114
Bath	1.65	0.67	0	6
Bed	2.92	0.66	0	13
Condition	0.52	0.5	0	1
Basement	0.66	0.48	0	1
Parking	1.78	0.57	0	5
Season	0.51	0.5	0	1
Downtown	7.66	3.52	0.18	15.69
LRT	4.57	2.64	0.1	12
Density	3,001	1,052	65.95	11,810
Child	17.4	4.19	5.71	29.46
Elder	19.33	9.4	1.83	54.39
Unemployment	5.14	2.06	1.44	15.30
Low Income	12.14	9.64	0	72.60
High Income	17.25	11.43	1.44	71.88
Bachelor	32.06	14.6	5.56	79.84
Crime Incidence	27.06	20.26	5.38	142.93
Quality	5.97	1.78	0	10.00
Agricultural	2.54	2.04	0	7.86
Woodland	0.33	0.28	0	2.01
Non-developable	0.17	0.11	0	2.01
UA farm	7.93	3.34	0.04	14.18
Land-use change	69.72	137.97	0	770.65

2.5 Results

2.5.1 Test for Spatial Dependence

A Moran I's test for detecting spatial correlation among residuals is conducted in STATA software. The error lag is tested with a spatial weights matrix of 700 meters. Based on the result (Table 2.3), it is confirmed that ($p<0.01$) that there is spatial dependence in the logged property value.

Table 2.3 Moran I's test for Spatial Dependence

H0: error is i. i. d. Errorlags: W700	chi2(1) = 1793.15
	Prob > chi2 = 0.0000

2.5.2 Log-likelihood Ratio Test

Following the log-likelihood ratio test described in section 2.3.2 above, we can see the spatial autocorrelation model (SAC) cannot be simplified into the spatial lag model and that the spatial Durbin model (SDM) cannot be simplified into the spatial error model (Table 2.4).

Table 2.4 LR Test for SDM and SAC

SAR SDM	LR chi2(26) = 729.55	prob >chi2 = 0.0000
SLX SDM	LR chi2(1) = 841.82	prob >chi2 = 0.0000
SAR SAC	LR chi2(1) = 518.88	prob >chi2 = 0.0000
SEM SAC	LR chi2(1) = 119.23	prob >chi2 = 0.0000

Table 2.5 shows the log-likelihood value, AIC and BIC value for each spatial model. These values are commonly used as indicators in model specification for goodness of fit. All else equal, we prefer a higher log-likelihood value and lower AIC and BIC values. While log-likelihood value only considers goodness of fit, a disadvantage is that it will always increase when we add variables to make a more complex model. AIC and BIC measure goodness of fit, as well as the tradeoffs between model complexity and fit. In this case, there is no clear pattern for all three indicators, so we need to consider other criteria for model selection. We think that the SAC has more intuitive appeal because of what we understand about the spatial dependence in property values. SAC controls for the spatial interactions on unobserved term.

Table 2.5 LR Test Results under Different Spatial Models

LR test	SLX	SAR	SEM	SAC	SDM	SDEM	GNS
d.f.	54	29	29	30	52	55	56
ll(model)	5492.98	5549.12	5748.94	5808.56	5913.89	5907.18	5919.74
AIC	-10877.96	-11040.23	-11439.88	-11557.11	-11717.79	-11704.37	-11727.47
BIC	-10491.41	-10832.64	-11232.28	-11342.36	-11324.07	-11310.65	-11326.6

2.5.3 Test on Multicollinearity of Explanatory Variables

We use variance inflation factors (VIF) to check the extent of multicollinearity among independent variables in the SAC model. A VIF value greater than 10 implies a serious multicollinearity issue which could potentially inflate standard errors and bias estimates

(Mansfield and Helms, 1982). Based on the results (Table 2.6), no serious multicollinearity is detected.

Table 2.6 Multicollinearity Test for Variables

Variable	VIF	1/VIF
Downtown	6.79	0.15
Bachelor	5.61	0.18
UA Farm	5.29	0.19
High Income	4.79	0.21
Low Income	4.55	0.22
Crime Incidence	4.17	0.24
Agricultural	3.99	0.25
Child	3.38	0.3
Unemployment Rate	3.08	0.33
Elder	2.85	0.35
Living Area	2.78	0.36
Regional Factor	2.72	0.37
Age	2.5	0.4
LRT	2.25	0.45
Bath	2.17	0.46
Quality	2.06	049
Land-use change	1.87	0.53
Density	1.52	0.66
Woodland	1.49	0.67
Bed	1.45	0.69
Parking	1.23	0.81
Basement	1.16	0.86
Condition	1.10	0.91
Non-developable	1.08	0.93
Season	1.01	0.99
Mean VIF	2.77	

2.5.4 Test of heteroskedasticity

A Breusch-Pagan Lagrange multiplier test is conducted to detect heterogeneity in the error distribution. From Table 2.7, the null hypothesis is rejected, hence, there is still heteroskedasticity in the error term. Therefore, it would be inappropriate to use OLS.

Table 2.7 Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

H0: Constant variance	chi2(1) = 6490.82
Variables: fitted values of lnValue	Prob > chi2 = 0.0000

2.5.5 Truncated Distance Selected for Spatial Weights Matrix

As noted above, the spatial weights matrix plays a critical role in the spatial hedonic model. Selecting the right truncated distance is important for defining the inverse-distance weights matrix. To assist with this selection, we ran the model with weight matrixes with threshold values ranging from 100 meters to 1000 meters. The results show highest significance level is at 700 meters. This distance is consistent with our neighbourhood size, which is provided by the Open Edmonton Dataset. In Edmonton, the median size of residential neighbourhoods is 1.18km^2, thus the radius of 700m from any particular house will cover most of the relevant neighbourhood. Shorter threshold distances also have the advantage of having land-related variables that are more intuitive to interpret.

2.5.6 Empirical Results from Spatial Autocorrelation Model

Based on the LR test result, the null hypotheses that the SAC can be simplified into the spatial lag or spatial error models are rejected. Also, SAC is more intuitive on the variables (Appendix

2). Therefore, a spatial Autocorrelation model (SAC) is preferred for interpretation of the results. Appendix 2 shows the coefficients of all spatial models and OLS. Since the significance of each variable estimation coefficient is different between the non-spatial model and spatial models, the result from OLS model in Appendix 2 cannot be used to compare with the SAC results. Based on LeSage and Pace (2009)'s suggestion, direct effect and indirect effect is further decomposed to illustrate true spillovers. The results are shown in Table 2.8.

Table 2.8 Decomposed Effects from Spatial Autocorrelation Model

Variables	Direct Effect	Indirect Effect	Total Effect
Living area	.000262***	.000079***	.00034***
	(3.78e-06)	(8.58e-06)	(9.43e-06)
Lot size	7.41e-06***	2.22e-06***	9.63e-06***
	(3.3e-07)	(2.63e-07)	(4.94e-07)
Age	-.00213***	-.00064***	-.00278***
	(.000095)	(.000075)	(.00014)
Bath	.0317***	.00951***	.0412***
	(.003)	(.00135)	(.00399)
Bed	-.0132***	-.00395***	-.0171***
	(.00247)	(.00083)	(.00321)
Condition	.0494***	.0148***	.0643***
	(.00281)	(.00187)	(.00607)
Basement	.0846***	.0254***	.11***
	(.00306)	(.00297)	(.00496)
Parking	.0601***	.018***	.0781***
	(.00264)	(.00212)	(.0039)
Season	.0168***	.00504**	.0218***
	(.00264)	(.00097)	(.0035)
Downtown	-.0398***	-.0119***	-.0517***
	(.0114)	(.0237)	(.015)
LRT	.00638	.00191	.0083
	(.00581)	(.00174)	(.00754)
Density	-6.16e-06**	-1.85e-06**	-8e-06**
	(2.45e-06)	(7.63e-07)	(3.19e-06)
Child	.000613	.000184	.0008

	(.000923)	(.000277)	(.001199)
Elder	.00125***	.000375***	.00163***
	(.00037)	(.000117)	(.00048)
Unemployment	-.0071	-.000213	-.00093
	(.00168)	(.00051)	(.00219)
Low Income	.000045	.0000136	.000059
	(.00041)	(.000123)	(.00063)
High Income	.00163***	.000489***	.00212***
	(.0004)	(.000118)	(.00051)
Bachelor	.00202***	.000607***	.00263***
	(.000363)	(.00011)	(.000456)
Crime Incidence	-.00059***	-.000178***	-.00077***
	(.00021)	(.00006)	(.00027)
Quality	.00235	.00071	.00306
	(.00164)	(.00049)	(.00213)
Agricultural	.0152***	.00455***	.0197****
	(.00383)	(.00128)	(.00503)
Woodland	-.0232***	-.00696***	-.0302***
	(.00227)	(.00096)	(.00296)
Non-developable	-.0064***	-.00193***	-.00838***
	(.00175)	(.00057)	(.00229)
UA Farm	-.088***	-.0264***	-.1143***
	(.0101)	(.00364)	(.01302)
Land-use Change	.000012	3.7e-06	.000016
	(.000016)	(4.81e-06)	(.000021)

The direct and indirect effects of all structural variables are statistically significant. The results indicate that people have higher willingness to pay for larger living area, larger lot size, more bathrooms, and more parking spaces. Specifically, increasing one square foot of living space would generate 0.026% ($118)[5] higher property value for the house and increase neighbour's house prices by 0.0079%. The number of parking spaces is highly significant that increasing one more parking space could raise the house's property value by 6.01% ($27,330) and increase the

[5]Dollar value of the variable impact (MWTP for semi-log function) is the $y * \beta$.For instance, $118=454736*0.00026

value of neighbours' houses by 1.8% ($8,185). Compared with the number of bathrooms, increasing the number of bedrooms significantly decreases property value. The reason may be that a house with more bedrooms, but equal in size to a similar house, would have smaller bedrooms, or possibly more bedrooms in the basement that reduce space that would otherwise be available for recreation. The result also indicates that people have higher willingness to pay for a finished basement, which could increase their property value by 8.46% ($38,471). People also prefer a house in better condition. Age is found to have significant negative direct and spillover effects. If the house is built one year earlier, that would decrease the property value by 0.21% ($954) and also decrease surrounding properties' values by 0.064% ($291). The seasonal effect of houses sold matches our hypothesis. Both direct and indirect on seasonal effects show that houses sold between April and September have higher prices. Generally speaking, the indirect effect of all structural variables is shown with smaller magnitude because the characteristics of one person's house have less impact on neighbours' house prices.

Distance to downtown has significant impact on house price. If the house is 1km further away from the downtown area, its property value will decrease by $2,363[6]. Meanwhile, the value of the neighbour's houses will decrease by $706. Despite the negative externalities such as traffic noise and congestion, people are still willing to pay more for houses near the city centre. Surprisingly, proximity to the nearest LRT station is shown to have no significant impact on house value. This might imply the nuisance and congestion effects of the LRT stations.

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[6] Dollar value for logged distance variables (MWTP for log-log function) is $\beta * \frac{y}{x}$. For instance, $2363=0.0398*454736/7.66 while y is the mean value of house price ($454,736) and x is the mean value of explanatory variable shown in Table 2.2.

As expected, a majority of the neighbourhood variables show significant relationships with property value. Population density has negative direct and indirect effects indicating people prefer to live in a less densely populated neighbourhood. In terms of age groups, the proportion of children in a neighbourhood is shown to have no significant impact, while the proportion of older people has positive direct and indirect effects. It is surprising to see that both unemployment rate and proportion of low-income group in a neighbourhood are not affecting house price, while more high-income residents within the neighbourhood could potentially increase the house value in the area. The percentage of university-educated people is also important for determining house price. If there is 1 percent more people having a bachelor's degree in the neighbourhood, the house will have 0.202 percent ($919) greater value. Elementary school quality within a neighbourhood is found to have no significant impact on particular house price and neighbours' house prices. In addition, number of crime incidence within the neighbourhood is significantly affecting property value that house price decreases by 0.059% ($286) with one more crime incidence found.

The results for the environmental variables indicate that people are willing to pay more to live closer to woodlands, non-developable open space (parks) and the University of Alberta South Campus farm, but less to live closer to agricultural open space, as hypothesized. To capture different effects of open spaces, we conduct a t-test showing that these four open space types are significantly different from each other (Table 2.9). The direct and spillover effects of distance to agricultural land are both positive and significant. With 1km further from agricultural land, the property value increases by $2,721 and neighbourhood's property value increases by $815. People may be less likely to consider living near farmland due to the odor, dirt, noise and other negative externalities associated with agricultural production. Although the University of Alberta farm is one type of agricultural open space, it appears that people place different value on it as indicated by the negative sign on its direct and indirect coefficients. With 1km closer to University of Alberta farm, the property value increases by $5,046. People would pay more to live near this farm, possibly due to the scenic views and recreation services it provides. The same result arises from the proximity to woodlands, which includes shrubland and forest land. Locating 1km closer to woodlands and non-developable lands would bring an incredibly $31,969 and $17,119 increase in house price respectively. Closer proximity to forests, shrub land, and non-developable parks and water bodies increases own house prices and prices of neighbouring houses. This is consistent with the findings of McConnell and Walls (2005) and Luttik (2000). That implies that people make their residential location based on the scenic view and recreational uses of these non-developable lands, and the same impact is shown in their neighbours' house prices. The result shown for the land-use change variable is negative, but not significant, indicating the nearby land-use change has no significant impact on people's house purchase decisions.

Table 2.9 T-test of Open Space Variables

Variables	Mean	Std. Err.	$Pr\ (\lvert T\rvert > \lvert t\rvert)$
Developable Agricultural Land	0.184	0.011	0.0000
U of A farm	1.886	0.007	
Developable Agricultural Land	0.184	0.011	0.0000
Woodland	-1.441	0.009	
Developable Agricultural Land	0.184	0.011	0.0000
Non-developable land	-2.096	0.009	
Woodland	-1.441	0.009	0.0000
Non-developable land	-2.096	0.009	
Woodland	-1.441	0.009	0.0000
U of A farm	1.886	0.007	
Woodland	-1.441	0.009	0.0000
U of A farm	1.886	0.007	

2.6 Concluding Remarks

This study uses property transaction data in Edmonton collected from Brookfield RPS to identify the direct and indirect effects of different open spaces on house prices. We have run all spatial models to check the robustness (shown in Appendix 2). After running the LR test, we report results from a spatial Autocorrelation model under a ML estimation to assess the value of open spaces and other contextual variables. In interpreting the results, some limitations of spatial models should be kept in mind. One major weakness of spatial models is the spatial weights matrix, which needs to be specified in advance and cannot be estimated (Leeders, 2002). Several approaches to improve the specification of the spatial weights matrix are summarized in Elhorst (2010). Although a common practice is to test the robustness of the specification of spatial weights matrix, a wide range of it (k-nearest, distance-based, rock/queen/king contiguity, etc.) would complicate the selections and interpretation of the results. Another complicating factor that is often raised in open space studies is the representation of open space. Studies have shown that other factors such as size of open spaces, soil quality, water quality, orientation of the houses, and accessibility of open spaces could also affect property values. This study only uses proximity to the nearest open spaces as a measure of open space benefits or costs. We encourage future studies to include more determinants to increase the robustness of the results. In addition, the data we used for agricultural open space, woodland and the wetland in non-developable open space retrieved from AAFC website may ignore open spaces that are less than 900 square meters (Landsat pixels are 30m x 30m pixels) while some open spaces like community gardens and playgrounds are smaller. Thus, this could also affect our estimates.

As shown above in section 2.5.6, the spatial Autocorrelation model has produced 19 out of 25 significant variables with interesting direct and indirect effects. The signs of these decomposed effects on variables are summarized in Table 2.9. Most of the structural variables (except for number of bedrooms and age of the house) have significant positive direct and indirect effects on house prices meaning that a higher value could generate benefits for the property itself and nearby properties. Locational variables show that houses closer to the downtown area have higher property value, which means the convenience of living in the city core could override some of the negative outcomes that proximity may bring. Neighbourhood variables are consistent with our hypotheses, better crime performance and more educated people in the neighbourhood could raise the price of nearby homes. The surprising results are the insignificance found in the unemployment rate and quality of elementary school.

Somewhat to our surprise, the main focus of this study – four types of open spaces (Agricultural, Woodlands, Non-developable, U of A farm) are highly significant and consistent with our hypotheses. The only positive variable is for agricultural open space, indicating that living close to it would have significant negative effects on property values. The major reason may be the negative externalities such as the related noise and odor. The highest added value is generated by living near woodlands, including forests and shrubland. Woodland open space is mostly located at the edges of the city, where it appears to confer both direct and indirect effects. The magnitude on house price for woodlands is double than that for non-developable land and six times more than that for south campus farm. In contrast to agricultural open space, proximity to the University of Alberta South Campus farm generates larger impact on house price comparing to the negative impact from agricultural land. The South Campus is located relatively near the City

Centre, the main campus of the University of Alberta and the river valley and appears to confer recreation benefits that other agricultural land does not. Initially, we predicted the largest impact should be from non-developable open spaces because they are the most scenic. The result shows it is not the highest, but still provides significant direct and indirect value.

Table 2.10 Summary of Variables' Signs

Significant Positive Effect	Living Area; Lot Size; Condition; Bathroom; Basement; Parking; Season; Elder; High Income; Bachelor; **Agricultural**
Significant Negative Effect	Age; Bed; Downtown; Woodland**; Non-developable; UA Farm**; Population Density; Crime Incidence
Insignificant Effect	LRT; Child; **Land-use Change**; Low Income; School Quality; Unemployment Rate

The study contributes to the spatial econometrics literature about the values of urban open spaces. The Spatial Auto-Correlation model is adopted. Compared to SAR and SEM, SAC could capture the spatial lag in the dependent variable and disturbance term at the same time. The green space in residential area is shown to attract a premium in house prices, which further supports the value of green spaces in urban area with health benefits and other benefits with open spaces nearby. These results support urban planning that conserves urban green spaces. People who benefit most from these spaces do pay for those spaces through the extra property tax that they pay for the extra value that gets built into the assessed value of their homes. Policy makers could also decide to charge higher tax rates to cover more of the costs of open space. Meanwhile, the result on agricultural open space justifies our hypothesis that they are less favored in house-purchasing behavior. Despite a decrease in value, agricultural land still has a variety of benefits, which means there are strategies needed for raising people's interest in protecting these lands.

Taking University of Alberta farm as an example, its recreational and scenic functions attract residents to come and purchase the houses near it. Similarly, agricultural landowners could figure out the alternative use for part of the land such as establishing a park to improve the attractiveness of land. In this way, not only the revenue generated could be redistribute into the conservation of this land, but also the incoming residents could contribute to the local economy. Example of such land uses within the City of Edmonton are the Edmonton Corn Maze (www.edmontoncornmaize.com) and Riverbend gardens (riverbendgardens.ca).

One final note: we need to emphasize that this analysis considers the values of relatively large open spaces. The approach is not appropriate for valuing small open spaces, such as community gardens, that may also confer values. Many of those are located within demarcated parks or church grounds.

Chapter 3. Spatial Analysis of Farmland Preservation Values in Alberta

3.1 Introduction

The effects of rapid economic growth on the distribution of land uses is a concern for governments, academics, and the public throughout the world. In the Canadian province of Alberta, there is a concern that forests, wetlands and agricultural lands have been increasingly converted into residential, commercial, and industrial uses (Haarsma and Qiu, 2015; Qiu et al., 2015). Open space, especially urban open space such as parks, helps promote mental and physical health by providing psychological relaxation and reducing exposure to pollutants, noise and heat (Braubach et al., 2017). Open space also creates opportunities for recreation uses, scenic views and some ecological benefits such as wildlife habitat and improved water or air quality (Irwin, 2002; Anderson and West, 2006). Loss of open space may have significant environmental impact by increasing carbon emissions (Ojima et al., 1994; Fearnside, 2000), causing loss of biodiversity (Reidsma et al., 2006) and degrading water and soil quality (Dale et al., 2005). Among different types of open space (forest land, wetland, park, cropland etc.), the loss of high-quality farmlands and the associated amenities provided has been of high concern to the Alberta public (Wang and Swallow, 2016) and policy makers. Since most Alberta cities are located close to high quality farmland, which is usually in urban-rural frontier areas, farmland is most likely to be converted if a growing urban area expands (Martellozzo et al., 2015).

Hofmann et al. (2005) find that in Canada, approximately 87% of dependable agricultural land (land without constraint for crop production) is located in Alberta, Manitoba, Saskatchewan and Ontario, but there is no provincial level legislation to promote preservation that primarily for agricultural uses in Alberta yet (Martellozzo et al., 2015). In Alberta, the Land Use Framework

(2008) and Alberta Land Stewardship Act (2009) provide planning guidance for land use; however, open space, especially conservation easements with respect to farmland still needs further direction. Generally speaking, agricultural lands provide not only agricultural products, but also other environmental and socio-economic goods and services such as job opportunities, wildlife habitats, tax revenue, and agri-tourism. Loss of agricultural lands could lead to severe outcomes such as soil degradation, food insecurity, reduced biodiversity, and unsustainable growth (Week and Wizor, 2020; Shen et al., 2019; Qiu et al., 2015; Traba and Morales, 2019; Irwin and Bockstael, 2007).

Various environmental and socio-economic factors have been shown to drive farmland conversion. Several studies conclude that population growth is one of the key factors that trigger this type of land-use change (Tong and Qiu, 2020; Martellozzo et al., 2015; Haarsma and Qiu, 2015; Lambin and Meyfroidt, 2011). For the case of Alberta, Tong and Qiu (2020) find population growth and land development are two-way interactions. When suburban lands are converted into developed uses, more immigrants from other regions tend to move there, which could result in further land development (Mulder, 2006). Other factors include the area of farmland (Bergstrom et al., 1985; Ready et al., 1997; Johnston et al., 2001), the scarcity of farmland (Johnston et al., 2001; Bergstrom et al., 1985; Roe et al., 2004; Geoghegan et al., 2003), the productivity of farmland (Nickerson et al., 2012), the types of competing land uses (Beasley et al., 1986; Irwin, 2002) and human uses factors such as accessibility (Johnston and Duke, 2007), socio-demographic characteristics such as individual income and education (Bergstrom et al., 1985) and land ownership (Ready and Abdalla, 2005).

Inconclusive results are found in terms of the effect of distance to farmland from a residential location (Bergstrom and Ready, 2008). Based on over 30 studies analyzed by Bergstrom and Ready (2008), the results regarding the relative amenity and disamenity values associated with distance to farmland is not well-understood. Johnston et al. (2001) find in Peconic Estuary System of Suffolk County, New York, a higher amenity value for farmland than other types of open space in a contingent choice model while in a hedonic price model study, they find property located near farmland has lower price than property located near other resources[7]. Proximity to farmland is found to have discontinuous effects on house prices in many studies. Ready and Abdalla (2005) find in Berks County (southeastern Pennsylvania) that farmland within 400 meters of a house has less effect on house price than forest land, while the reverse results hold for farm and forest land outside of 400 meters. The authors speculate that these mixed results hold because of the disamenities of agriculture such as odor, noise and dust. The activity of farming, the existence of substitutable non-farmland amenities, whether the person lives in urban, suburban and rural settings and the community characteristics make valuation results relatively locational-specific.

Several previous researchers have included spatial dimensions in their studies, although there is no definitive guidance on the most effective way of modelling these spatial effects. As mentioned in section 1.4, Glenk et al. (2019) have reviewed multiple studies that address spatial dependence related to elicitation, estimation, interpretation and aggregation of stated preference welfare measures. Including spatial dimensions in stated preference studies can produce less biased individual or mean willingness to pay estimates. Glenk et al (2019) also summarized the

[7] Resources in Johnston et al. (2001) include farmland, undeveloped land, wetlands, safe shell fishing areas, and eelgrass. These resources are measured in acres remaining in the Peconic Estuary watershed.

challenge of the absence of guidance related to spatial dimensions in microeconomics theory. It would be preferable to base empirical applications of spatial econometrics and geo-statistics on guidance from theory (Glenk et al., 2019).

Luo (2019) designed and implemented a binary choice experiment survey in order to estimate the value of farmland conservation around Alberta's six largest urban areas. Without considering spatial effects, Luo (2019) found high heterogeneity of preferences, with no consistent preference for conserving particular agricultural land uses. In this further spatial analysis of those data, therefore, we do not differentiate agricultural land into types.

As a following step, we include spatial variables such as the distance between respondents' location and the nearest farmland in order to explore spatial variation in willingness to pay. Our modelling work allows us to infer implicit prices for farmland preservation depending on their location relative to farmland and other substitutable open space. The purpose of involving spatial variables is to explore alternative explanation for preference heterogeneity found in the previous study. Our study is motivated by the growing interest in studying the spatial dimension in the stated preference values. Are the benefits of preserving agricultural land highest for people living closest, which might imply a scenic beauty motivation, or for people living further away, which might imply a food production motivation.

3.2 Conceptual Background

Bergstrom and Ready (2008) discussed the theoretical background for willingness to pay (WTP) for farmland preservation. The fundamental reason for farmland conversion is scarcity of land, especially at the urban-rural fringe. Figure 3.1 shows the allocation between competing farmland use and developed use. The horizontal axis measures the proportion of less-developed land such as farmland, which equals to 1 minus the proportion of developed land use. When farmland is protected, its amenity values are preserved such that people can fully enjoy and benefit from these values. Thus, where farmland is scarcer (the left side of figure), people tend to have higher WTP and the marginal WTP ($MWTP_{Farmland}$) decreases as it becomes less scarce. Meanwhile, there is still a need for developed land in terms of the urban amenity values it provides such as job opportunities and higher property taxes. Hence, when the developed land is relatively scarce (the right side of figure), people want to pay more for developed land and the marginal WTP ($MWTP_{Developed}$) for additional units declines as there is more developed land. The negative value in "$MWTP_{Developed}$" curve represents the disamenity values with over-development such as noise and traffic congestion. Q2 shows the socially-optimal point for this land allocation while it is not necessarily socially optimal because of participation of private market. The authors also mention that the farmland value often estimated for instance through a survey is not "$MWTP_{Farmland}$", but instead a difference between "$MWTP_{Farmland}$" and "$MWTP_{Developed}$". It is shown as the "Net_ $MWTP_{Farmland}$". It equals to 0 if "$MWTP_{Farmland}= MWTP_{Developed}$" and equals to "$MWTP_{Farmland}$" if "$MWTP_{Developed}=0$."

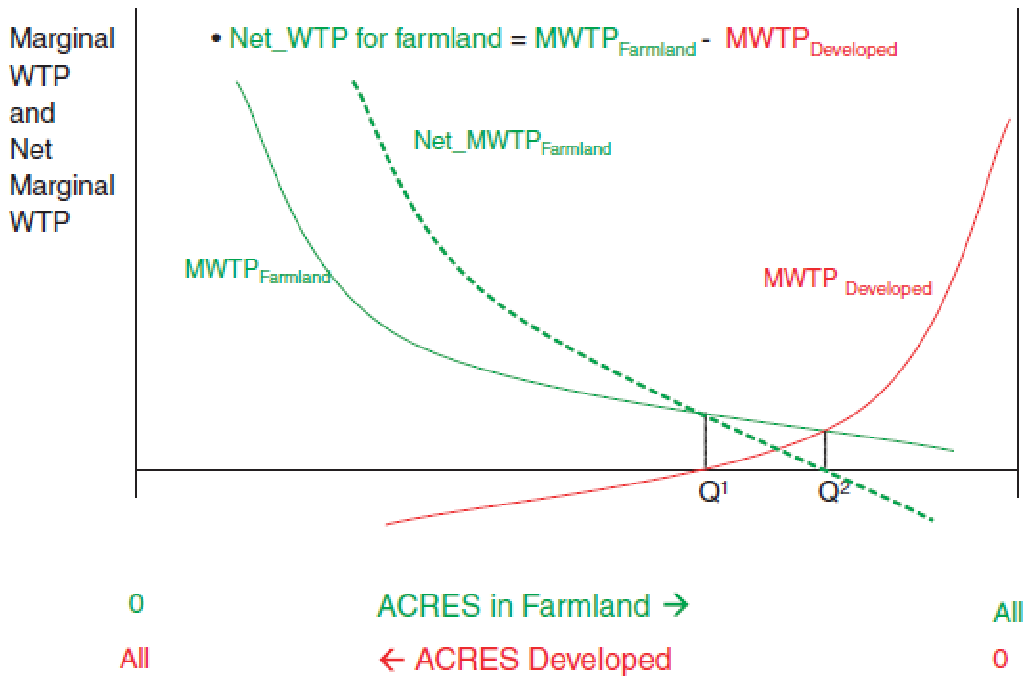

Figure 3.1 Allocation between Compete Land Uses by Bergstrom and Ready (2008)

The hedonic analysis reported in a previous section has revealed a strong negative preference for living near to agricultural land, which may also have an impact on their attitudes towards conservation of agricultural land in the adjacent area. Theoretically, people's willingness to pay for agricultural conservation can be positively or negatively related to distance to agricultural land. Firstly, the law of demand suggests that people are more willing to conserve lands if the lands are scarcer to them, which means the lands located further from them may increase their willing to pay. This is the logic of the Bergstrom and Ready analysis above, which shows a downward sloping MWTP function. Secondly, the travel cost model postulates that the transaction cost or transportation cost for people to access to one place is a measure of their willingness to pay (Bockstael et al., 1987). Therefore, we hypothesize that people who live further and do not have accessibility to these lands would be less willing to pay to protect these farmlands. Thirdly, we consider that people may exhibit NIMBYism (not in my backyard) towards agricultural land. Scholars use the term NIMBY to represent residents who disagree with locating a significant public service facility near their houses, although they recognize the importance of having such facilities in the area. These facilities, including waste facilities, energy facilities etc., provide benefits for the community or wider population, but also may bring some negative externalities to the local residents (Whittemore and BenDor, 2018). Agricultural land could be the object of NIMBYism because of the odor, noise, and any negative impacts brought by intensive farming. This logic thus supports the hypothesis that people who live closer to farmland could be less likely to vote for the conservation strategy. Thus, we have two plausible hypotheses supporting a positive relationship between distance to agriculture and willingness to pay, and one plausible hypothesis supporting a negative relationship.

3.3 Study Area

Farmland in Alberta is continuously being taken by developers (Stan and Sanchez-Azofeifa, 2017; Masuda and Garvin, 2008). Several studies have been undertaken in Edmonton-Calgary Corridor region in Alberta and important drivers of loss of farmland and associated policy implications have been identified (Haarsma and Qiu, 2015; Tong and Qiu, 2020; Stan and Sanchez-Azofeifa, 2017; Ruan et al., 2016). Edmonton, as the second largest urban city in Alberta, has experienced rapid development and also a conversion of farmland into developed lands in the past decades. Our study area is the Edmonton census metropolitan area (CMA), which is the region that is formed by one municipality that centered on a population center (city of Edmonton). To be classified as a CMA in Canada, the metropolitan region must have a total population of at least 100,000, with 50,000 or more people living in the population center. From 2011 to 2016, the Edmonton CMA experienced a 13.9% increase in its population (Calgary, Red Deer CA and Lethbridge have 14.6%, 10.9% and 10.8% population increase respectively) and approximately 128,210 acres increase in urban land development (Luo, 2019), which is the second-fastest population growth municipality in Alberta. Figure 3.2 shows the land that was converted between 2000 and 2016 where the red color suggests that a massive land conversion occurred on the edge of the City of Edmonton. According to data from Agriculture and Agrifood Canada (AAFC), Edmonton CMA had 592,622 hectares of agricultural land in 2012 while 31,416 hectares of land was converted into developed uses between 2012 and 2018. Despite the previous conversion, Edmonton still has great potential for further land development.

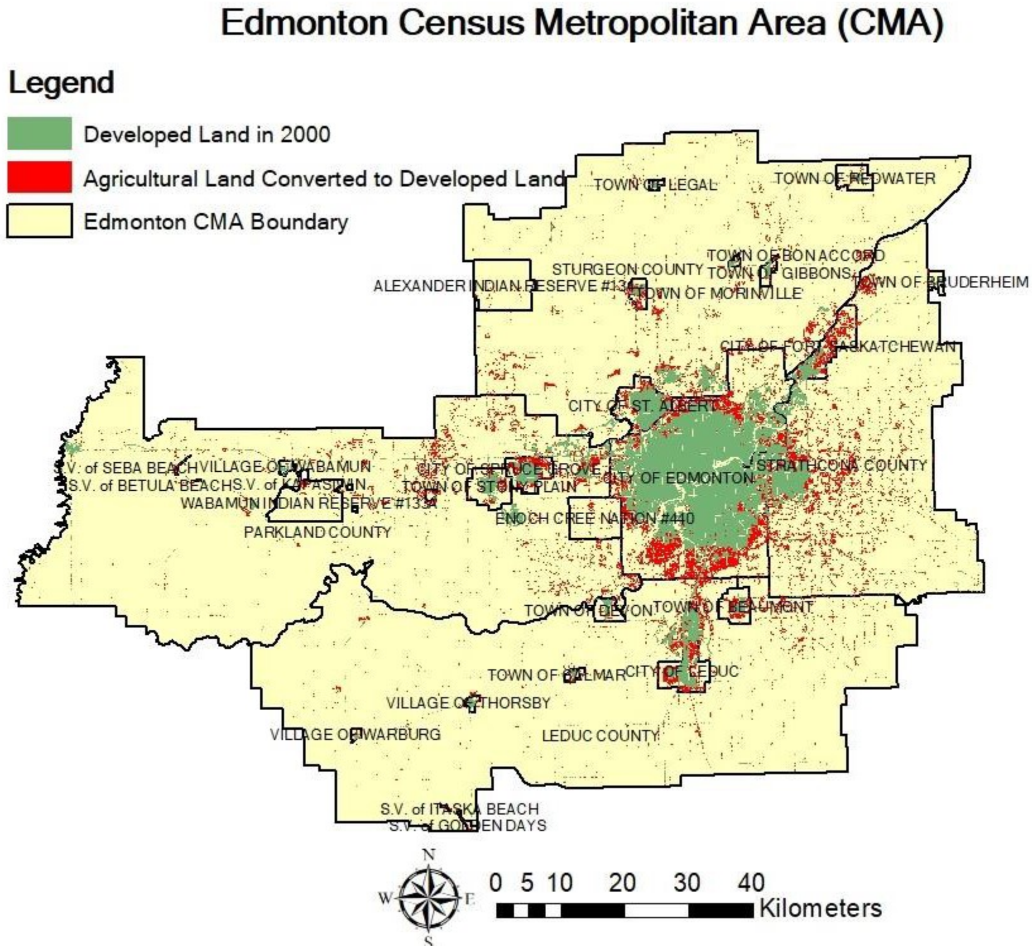

Figure 3.2 Agricultural Land Converted into Developed Uses from 2000 to 2016 in Edmonton CMA, Alberta[8]

[8] These boundaries held prior to the annexation in January, 2019.

3.4 Model

3.4.1 Random Utility Theory

This study applies random utility theory to value agricultural land in the Edmonton CMA from the choice experiment data generated by Luo (2019). McFadden (1974) was the first to apply a random utility theory for welfare analysis of urban travel demand. Random utility theory is based on the hypothesis that each individual is a rational decision-maker who tries to maximize his or her utility by choosing one option from a set of available alternatives. The theory itself is based on some assumptions. 1) Choice sets considered by individual decision-makers may vary across respondents. 2) The utility assigned by each respondent to their selection is a "perceived utility" and respondents choose the alternative that maximizes their perceived utility. 3) The perceived utility assigned to each choice alternative is based on the attributes of that alternative. 4) The perceived utility assigned should be represented by a random variable because it would not be known with certainty by an external researcher wanting to observe it (Cascetta, 2004). Therefore, a researcher does not know with certainty the alternative that will be selected by an individual but can estimate the probability that the individual will make a particular choice.

3.4.2 Conditional Logit Model

Conditional logit model, also called multinomial logit model, can be derived based on the random utility model. Suppose individuals need to choose among N alternatives (i=1, …, N). Selection of one alternative i indicates that the individual could obtain more utility from i than any of the other alternatives. Different discrete choice models are obtained with different assumptions about the distribution of the random error terms (Holmes et al., 2017). Based on random utility, the likelihood of alternative i being chosen by respondent k in the conditional logit model is as follows,

$$P_{ik} = \frac{exp\ (\mu v_{ik})}{\sum_{j=1}^{N} exp\ (\mu v_{jk})} \tag{3.1}$$

where μ is a scale parameter that represents the variance of the unobserved part of utility. It is typically normalized to 1 and assumed to have a type I extreme value error distribution. The model is specified so that the probability of making a selection is a function of attributes of that choice and of the alternative specific constant (ASC), which is equal to 1 when the strategy is chosen, and to 0 if not. The conditional logit model has the limitation that it requires the assumption that respondents have the same preferences or that their preferences depend on observable characteristics (Holmes et al.,2017). Another assumption is the IIA property, which states that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives. If the IIA property is violated, the conditional logit model will be biased (Holmes et al., 2017).

Thus, a discrete choice model that does not require the IIA property and homogenous preferences should be used, such as the random parameter logit model (RPL), which is also called the mixed logit model. RPL can enable estimation for unbiased results and thus enhance the accuracy and reliability of estimates of demand, participation, and total welfare. More importantly, accounting for preference heterogeneity allows policy makers to understand who will be affected by the policy change in addition to understanding the aggregate economic value (Boxall and Adamowicz, 2002).

3.4.3 Interaction terms

There are some variables such as age and gender that would not change across alternatives. Thus, their effect cannot be captured in the conditional logit model. According to Adamowicz et al. (1997), analysts can interact these variables with monetary variables or the alternative specific constant. For instance, we could generate a new variable, male*price so that the estimation of the marginal utility of money can be shown as a function of gender.

3.4.4 Random Parameter Logit Model

In order to obtain more accurate and realistic estimates of preference, participation, and welfare measures, a random parameter logit model is estimated to account for unobserved and unconditional heterogeneity (Kontoleon, 2003). Recent studies also show that the random parameter logit model presents a better overall fit and welfare estimates than the conditional logit model (Birol et al., 2006). It extends the standard conditional logit model by allowing one or more of the parameters in the model to be randomly distributed. Theoretically, random parameter logit probabilities are the integrals of standard logit probabilities over a density of parameters. The random parameter logit choice probability of respondent k choosing alternative i is given as:

$$v_{ik} = \beta Z_i + \varepsilon_{ik} = \overline{\beta} Z_i + \widetilde{\beta_k} Z_i + \varepsilon_{ik} \tag{3.2}$$

where Z_i is a vector of attributes including the monetary attribute. In this case, the parameters are random coefficients. β is each individual's coefficient vector, $\overline{\beta}$ is the sum of population mean and $\widetilde{\beta_k}$ is the individual deviation. The right side of the equation is the stochastic part of utility, which is correlated among alternatives and does not exhibit the IIA property (Holmes et al., 2017). We can assume that coefficients vary in the population with a density distribution

$f(\beta|\theta)$, where θ is a vector of underlying parameters of the preference distribution. The unconditional probability of choosing alternative i can then be expressed as the integral of conditional probability over all β:

$$P_{ik|\theta} = \int \frac{exp\ (\beta Z_i)}{\sum_{j=1}^{N} exp\ (\beta Z_k)} f(\beta|\theta)d\beta \qquad (3.3)$$

3.4.5 Welfare Measures

To make choice experiment measuring useful for policy analysis, we usually use quantitative measures to estimate the tradeoffs between attributes and economic welfare. Marginal values are expressed as the amount of money that respondents are willing to pay for a certain change of attributes or whether implementation of a strategy can make people better off, which could provide estimates for compensating variation (Holmes et al., 2017). If we assume a simple linear utility function of alternatives and we wish to estimate the respondents' willingness to pay for a change in the attribute vector from an initial condition to a changed condition, then the compensating variation of this change is

$$CV = \frac{1}{\lambda}\{V^1 - V^0\} \qquad (3.4)$$

where V^1 and V^0 express the utility of new and base conditions. If there are three attributes within the choice experiment including a cost attribute, we estimate this utility function as:

$$v_{ik} = \beta_1 z_{i1} + \beta_2 z_{i2} + \lambda(y_k - p_i) + \varepsilon_{ik} \qquad (3.5)$$

And the willingness to pay for the changes in two non-monetary attributes relative to the base is calculated as:

$$WTP = -\frac{\beta_1 \Delta z_{i1} + \beta_{2\Delta} z_{i2}}{\lambda} \qquad (3.6)$$

To report these welfare estimates for a discrete change in multiple attributes, we often use marginal willingness to pay (MWTP). It is the marginal rate of substitution between the coefficient of an attribute and the marginal utility of money (Holmes et al.,2017):

$$MRS = -\frac{\beta_I}{\lambda} = MWTP \quad (3.7)$$

3.5 Data

The data were collected from a choice-experiment survey conducted in February-March 2019 by Luo (2019) through the international survey company, Qualtrics. The purpose of the Luo (2019) study was to access people's willingness to pay for land preservation in peri-urban areas of Alberta. The choice experiment was implemented with respondents in Alberta's six most populous urban areas and included a split-sample study of willingness to pay and willingness to accept. The study area used in this thesis work is the Edmonton CMA and only includes respondents residing within the City of Edmonton. The WTP survey received 643 responses in total, with 188 responses in the City of Edmonton. Each of the 188 respondents answered 16 choice questions for a choice sample of 3008. The survey required respondents to be taxpayers, English-speakers, and either owners or renters of their residence. The WTA survey data were not analyzed for this paper.

The survey followed the best practice in identifying the attributes, levels of attributes and the payment vehicle. In the WTP survey, respondents were asked to choose between continuation of the current development trend and an incremental change of protecting 1,000 acres of nearby farmland. Before posing the choice questions, the online survey provided information about recent trends in farmland conversion and development, with information about the Edmonton CMA provided to the Edmonton residents. The WTP survey asked respondents to consider the incremental preservation of an additional 1000 acres of farmland within 10km of the urban frontier that would be otherwise developed. The attributes used are types of current agricultural use, type of replacement urban development and a one-time increase in property tax or rent in the next year (Cdn$). Consistent with existing land use practices in the area, Luo (2019) used grain or oilseed farming, livestock grazing and vegetable farming as the current agricultural land types, while residential, light industrial and retail were identified as the urban land types converted into. Luo (2019) also provides a comprehensive explanation of the reasons for choosing each different land type and the related payment levels. With regards to some of the common issues that might occur with survey responses, Luo (2019) uses the following methods to increase the validity of the results. 1) Because the full factorial design would provide a small number of observations for each combination of attributes, they instead use an efficient design (d-optimal). 2) To reduce information bias, respondents were provided with background information to read before they started the survey. 3) Luo (2019) also reduced the complexity of the choice problems by using a dichotomous choice format, incorporating certainty and uncertainty follow-up questions, and re-coding uncertain responses to reduce the effect of social desirability bias. After each choice scenario question, respondents were asked, “how certain are you with your decision if you are actually going to make a vote.” People needed to answer with five possible answers: “very certain”, “somewhat certain”, “neither certain nor uncertain”, “somewhat uncertain”, and “very uncertain”. Respondents who answered yes and either very certain or somewhat certain were coded as yes. Respondents that answered no, or yes, but uncertain were coded as “no”. 4) To increase consequentiality, respondents are informed that their responses will be shared with relevant government agencies and used in policy making. 5) To address the independence of the responses to different scenarios, respondents were instructed to choose independently and not compare the options from different choice sets. Also, respondents were not allowed to go back to previous questions. 6) To reduce hypothetical bias and avoid respondent fatigue, respondents were only given information for their specific regions. Besides, a trap question is designed and respondents who failed the trap question are screened out.

The model results from Luo (2019) show high preference heterogeneity among respondents, with little systematic sources of variation. Based on this work, we generate similar socio-demographic variables and include their interactions with the alternative specific constant (ASC) in the model. These variables include gender (a dummy variable equals to one if the respondent is male), age (continuous variable), employment (a dummy variable equals to one if the respondent has a full-time job), income (continuous variable). Besides these variables, our focus is how people's spatial location relative to open spaces would affect their willingness to pay for farmland conservation. Hence, the postal codes of each respondent's home address were inserted into ArcGIS to generate location, and that location information was then combined with land use maps to calculate proximity to nearest open space.

In order to test the hypotheses, the open space variables are categorized and calculated the same way as in the hedonic analysis (see previous chapter). We aggregate open spaces retrieved from Government of Canada Annual Crop Inventory (Government of Canada) into three categories: developable agricultural land, woodland, and non-developable land. Developable agricultural land includes cropland, pastureland and grassland that mainly produce agricultural products. This is a designated land use and does not account for how a municipality would designate land for developed use. Woodland, which includes forest land and shrubland, is an observed land use based on the land-use classification from AAFC and designated for possible development by a responsible municipality. Non-developable land includes parks, river bodies and wetlands. We also include proximity to the University of Alberta farm as a separate land type since it is primarily used for agricultural experiments and is located near to the heart of the city. We also include a 1km buffer of land-use change in the past six years for each respondent to determine how nearby land-use change could affect people's willingness to pay for preserving agricultural land from future development.

Attribute	Level	Explanation
Type of Current Agricultural Use	• Grain or Oilseed Farming • Livestock grazing on native pasture • Commercial Vegetable Farm	Major types of agriculture in your area.
Type of development without conservation	• Residential • Light Industrial • Retail	Major types of urban development without conservation in your area
One-time additional cost to each taxpayer ($)	• 50 • 100 • 300 • 600 • 1000	One-time additional increase in property tax or rent to each taxpayer in your area

Figure 3.3 Attributes and attributes level used in the survey by Luo (2019)

3.6 Results

3.6.1 Results from Conditional Logit Model

Multinomial logit model (MNL) is conducted through maximum likelihood estimation. Table 3.1 provides the coefficient estimates for each attribute and interaction term with socio-demographic characteristics and open space variables under MNL estimation. Table 3.2 shows adding socio-demographic variables and land-use variables increases the goodness of fit. In the basic MNL model, price is negative and statistically significant as expected, which means that people have a positive marginal utility of money towards the strategy and their utility will decrease with the increase in one-time payment. ASC (alternative specific constant) is the utility of choosing the baseline conservation strategy, which in this case, is avoiding vegetable farm converting into retail. A positive and significant ASC coefficient indicates the utility of choosing the baseline conservation strategy increases indirect utility compared with continuation of the status quo level of development. Coefficients on the dummy variables for all land conversions (from livestock grazing and grain as current agricultural uses and light industry and residential as development uses) are all statistically insignificant. These results show respondents have no common preferences on the type of land they would like to preserve or the type of alternative land they prefer to be developed into.

Table 3.1 Coefficient Estimates for MNL including Interaction Terms

Attributes	Basic Model (a)	Model with Socio-demographic Variables (b)	Model with Land-use Variables (c)	Model with All Variables (d)
Price	-.001383*** (.000159)	-.001389*** (.0001594)	-.00141*** (.00016)	-.001414*** (.0001612)
ASC	1.0759*** (.1428)	.8056*** (.2442)	.6391*** (.2373)	.1999 (.3277)
Grain	-.1863 (.1338)	-.1866 (.1340)	-.1905 (.1351)	-.1911 (.1353)
Livestock	-.0625 (.1421)	-.0519 (.1424)	-.0748 (.1434)	-.06228 (.1438)
Light Industry	-.1315 (.1379)	-.1530 (.1385)	-.0748 (.1434)	-.0623 (.1438)
Residential	-.0554 (.1342)	-.0595 (.1344)	.0522 (.1354)	.00573 (.1357)
ASC*gender		-.2068* (.1159)		-.2004* (.1184)
ASC*age		.0071* (.0036)		.0065* (.0037)
ASC*employment		-.0001 (.1160)		-.0802 (.1199)
ASC*income		.0127 (.0358)		.0620 (.0379)
ASC*land-use change			-.00545 (.00391)	-.0055 (.00396)
ASC*nondevelopable			-.2194 (.5219)	-.2158 (.5268)
ASC*non-ag developable			-.3883* (.2267)	-.4320* (.2305)
ASC*ag developable			.3049*** (.0703)	.3303*** (.0721)
ASC*UofA farm			.03182** (.01578)	.0398** (.01622)
Log Likelihood	-974.06	-971.02	-.961.73	-957.65
AIC	1960.13	1962.03	1945.45	1945.30
BIC	1996.18	2022.12	2011.56	2035.43
Number of Observations		3008		

Table 3.2 Likelihood Ratio Test for Adding Socio-demographic Variables and Land-use Variables to Conditional Logit Model

	Chi (2)	P value
Basic model / Model with socio-demographic variables	8.3727	0.0152
Basic model / Model with land-use variables	24.6678	4.400e-06
Basic model / Model with all variables	34.0888	3.960e-08

Adding the demographic variables in model variant (b) generates the results shown in the second column. The coefficient estimates with ASC interaction terms included have slightly changed while the significance levels and the signs of coefficients are unchanged. The socio-demographic characteristics' results show some significant effects of gender and age. Gender is negative and significant at the 10 percent level, which indicates that males are less willing than females to pay for the preservation strategy. The coefficient on age is positive and significant, indicating that elderly people would be willing to pay more for this preservation strategy. The rest of the socio-demographic variables are not significant (employment, income), which means they do not have consistent effects on respondents' willingness to pay on farmland preservation. These results are similar to the results obtained by Luo (2019), using a larger sample for the 6 most populous urban areas in Alberta.

Comparing model variant (c) and (d), land-use variables in both models show similar results. Model (d) builds on the Luo (2019) analysis, which has similar AIC and BIC and log-likelihood statistics and produces nearly identical parameter estimates to model (c) that excludes the demographic factors. Thus, model (d) is a preferred model for interpretation. We hypothesized that the spatial variables would explain some of the preference heterogeneity in our data. In model variant (d), the income variable becomes significant and positive. People with higher income generally would be more willing to pay for the conservation strategy. The coefficient on proximity to woodland is negative and significant, indicating that people who live closer to forest land and shrubland would be willing to pay more for farmland preservation. By contrast, the coefficient on the proximity to agricultural land is positive and highly significant, indicating that respondents who live further away from those agricultural lands would be more likely to vote for farmland preservation. A similar result is found for distance to the University of Alberta farm: the further they are from the University of Alberta farm, the more they are willing to pay for farmland conservation.

3.6.2 Results from Random Parameter Logit Model

Table 3.3 Coefficients' Estimates in Random Parameter Logit Model (Basic Model and Land-use Change Variable)

Attributes	Basic Model (1)		Land-use Change Nearby (2a_)		No Land-use Change Nearby (2b)	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Price	-.002156*** (.0002376)		-.00296*** (.00045)		-.00177*** (.000279)	
ASC	1.3216*** (.19355)		1.5515*** (.3513)		1.2162*** (.2319)	
Grain	-.0660 (.1978)	1.4902*** (.2767)	-.5079 (.3845)	2.078*** (.5204)	.03859 (.2183)	.8957** (.3719)
Livestock	.4046 (.2883)	2.3448*** (.3748)	-.3726 (.4477)	2.341*** (.6621)	.7295** (.3672)	2.244*** (.5185)
Industry	.004785 (.2259)	1.5916*** (.3123)	-.3214 (.3521)	1.155** (.4652)	.2109 (.2958)	1.665*** (.4247)
Residential	.3081 (.1990)	1.3474*** (.3016)	.3676 (.3624)	1.431*** (.5240)	.3218 (.2541)	1.639*** (.3666)
Log Likelihood	-892.50		-311.73		-569.90	
Observations	3008		1056		1952	

The Random Parameter Model provides an alternative way to understand preference heterogeneity. In this model, all non-monetary attributes are regarded as random variables, which are normally distributed. The model generates estimates of the mean and standard deviation of the non-monetary attributes, in this case the land use attributes of the choice scenario. Table 3.3 reports results for the basic model with all observations, as well as for models estimated for sub-samples that represent two situations regarding land use change near to their residence. The designation into "land use change nearby" and "no land use change nearby" was based on the frequency distribution of nearby land use change. We created a binary variable that equals 1 for respondents who had land use change within 1km of their location, 0 otherwise. We also used frequency distributions (shown in Figure 3.4) to ascertain designations for living "near" and "far" from all types of open space. The cutoff distance is quite different for the different land types. For instance, we regard people who live within 0.2km of non-developable land as near that land since most of respondents tend to live relatively close to this type of land. We consider people who have access to agricultural land within 1km, woodland within 0.4km, and University of Alberta farm within 3km as "near" these lands. The results for the Random Parameter Logit Models estimated for near and far sub-samples are reported in Tables 3.4 and 3.5.

Non-developable

class limit	bin
0-0.1	0.1
0.11-0.2	0.2
0.21-0.3	0.3
0.31-0.4	0.4
0.41-0.5	0.5
0.51-0.6	0.6
0.61-0.7	0.7

bin	*Frequency*
0.1	19
0.2	74
0.3	55
0.4	25
0.5	14
0.6	1
0.7	0
More	0

Woodland

class limit	bin
0-0.2	0.2
0.21-0.4	0.4
0.41-0.6	0.6
0.61-0.8	0.8
0.81-1	1
1.01-1.2	1.2
1.21-1.4	1.4
1.41-1.6	1.6

bin	*Frequency*
0.2	57
0.4	62
0.6	39
0.8	14
1	9
1.2	3
1.4	3
1.6	1
More	0

Agricultural

class limit	bin
0-0.5	0.5
0.51-1.0	1
1.01-1.5	1.5
1.51-2	2
2.01-2.5	2.5
2.51-3	3
3.01-3.5	3.5
3.51-4	4
4.01-4.5	4.5
4.51-5	5

bin	*Frequency*
0.5	53
1	39
1.5	24
2	31
2.5	23
3	7
3.5	7
4	3
4.5	1
5	0
More	0

Uafarm

class limit	bin
0-3	3
3.1-6	6
6.1-9	9
9.1-12	12
12.1-15	15
15.1-18	18
18.1-21	21

bin	*Frequency*
3	26
6	51
9	49
12	37
15	21
18	3
21	1
More	0

Figure 3.4 Frequency Distribution Chart to Distinguish "Near" and "Far" Open Spaces

In the basic RPL model (Table 3.3) all standard deviation coefficients are statistically significant, which means that the model captures unobserved heterogeneity. This is consistent with the province-wide research of Luo (2019). The standard deviation estimates are much larger than the parameter estimates, indicating large preference heterogeneity in the sample. Moreover, all the coefficient estimates are insignificant for these four types of land uses, while their standard deviations are highly significant. This means respondents as a group do not have consistent preferences for the types of agricultural land use they are most concerned about preserving, or the type of developed land use they are most interested in avoiding.

In the same table (Table 3.3), the results for sub-samples of near and far land-use change are reported, with the number of choice observations of each type indicated at the bottom of the table (1056 vs. 1952 choice observations for 66 and 122 respondents). We hypothesized that respondents who have experienced or are experiencing a nearby land-use development within the last 6 years would be more likely to be concerned about future farmland preservation. There is weak support for this hypothesis. The ASC estimate is 1.55 for the nearby land use change group and 1.22 for the no nearby land use change group, indicating higher willingness to pay for the nearby land use change group.

The ASC coefficient estimates for four groups reported on Table 3.4 provide weaker evidence that respondents who live closer to the non-developable land or non-developable agricultural land are more likely to support the baseline conservation strategy. It is worth noting that the coefficient estimate is positive and significant for livestock land for the near non-developable land sub-sample. This indicates that respondents living near non-developable open space have higher value for preserving livestock grazing land than vegetable farms.

Table 3.5 shows the results for sub-samples living near and far from agricultural lands and near and far from the University of Alberta farm. Based on the hedonic analysis reported elsewhere in this thesis, we hypothesize that people living near to agricultural land would have lower willingness to pay for the farm conservation strategy while people living near the University of Alberta farm would have higher utility. The hypothesis was supported. The only statistically significant land-use coefficient indicates that people who live further away from agricultural lands prefer development into residential rather than into retail.

Table 3.4 Coefficients' Estimates in Random Parameter Logit Model (Non-developable Land and Woodland)

Attributes	Near NDVP (3a)		Far NDVP (3b)		Near NAG (4a)		Far NAG (4b)	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Price	-.00285*** (.00038)		-.00161*** (.000308)		-.00259*** (.000318)		-.00152*** (.00036)	
ASC	1.385*** (.2739)		1.291*** (.27703)		1.396*** (.2465)		1.297*** (.3206)	
Grain	.1378 (.2904)	1.594*** (.4248)	-.3095 (.2629)	1.232*** (.3523)	-.00861 (.2363)	1.274*** (.3668)	-.3026 (.3297)	1.4865*** (.4418)
Livestock	.8946** (.4228)	2.651*** (.5972)	-.2181 (.3498)	1.977*** (.4686)	.6188 (.3863)	2.630*** (.5534)	-.01172 (.4374)	2.001*** (.5713)
Industry	-.3573 (.3317)	1.671*** (.4326)	.2939 (.3176)	1.598*** (.3828)	-.3078 (.269)	1.334*** (.3360)	.7229 (.4431)	1.965*** (.5506)
Residential	.3671 (.2954)	1.440*** (.4004)	.2906 (.2875)	1.507*** (.3922)	.3321 (.2753)	1.771*** (.3768)	.2304 (.3135)	1.124*** (.4087)
Log Likelihood	-425.330		-458.129		-554.56		-328.57	
Observations	1488		1520		1904		1104	

Table 3.5 Coefficients' Estimates in Random Parameter Logit Model (Agricultural Developable Land and University of Alberta Farm)

Attributes	Near Ag (5a)		Far Ag (5b)		Near UA Farm (6a)		Far UA Farm (6b)	
	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Price	-.00224*** (.00033)		-.0021*** (.00035)		-.00171** (.00071)		-.00232*** (.000264)	
ASC	1.305*** (.282)		1.311*** (.2675)		1.552** (.6151)		1.341*** (.2071)	
Grain	-.2017 (.2751)	1.465*** (.3804)	.0709 (.2993)	1.671*** (.3994)	-.2854 (.6215)	1.652** (.7165)	-.06116 (.2098)	1.449*** (.2782)
Livestock	.09706 (.3658)	2.243*** (.5428)	.4251 (.3925)	2.530*** (.5717)	-.2418 (.8313)	-2.770** (1.1257)	.3771 (.2958)	-2.26*** (.3883)
Industry	-.2945 (.2908)	1.231*** (.3759)	.3115 (.3554)	1.778*** (.4136)	-.7823 (.8446)	2.779*** (1.0168)	.1749 (.243)	1.492*** (.2944)
Residential	.1385 (.2904)	1.531*** (.4878)	.5158* (.2908)	1.473*** (.4103)	-1.093 (.9409)	3.67*** (1.301)	.4882** (.2226)	1.417*** (.2882)
Log Likelihood	-447.22		-441.78		-115.18		-763.15	
Observations	1472		1536		416		2592	

3.6.3 Welfare Measure Results

Table 3.6 presents estimates of the marginal willingness to pay for farmland preservation generated under the conditional logit and random parameter logit models. Overall, the marginal willingness to pay in both models are positive and significant. The difference of the results between models ranges from 0.7% (grain or oilseed farming to residential) to 15% (commercial vegetable farm to retail). The highest marginal willingness to pay in both the conditional logit and random parameter logit models is preserving vegetable farm from conversion into residential ($754 and $732) and the lowest marginal willingness to pay is to preserve grain or oilseed farm from conversion into light industrial development ($446 and $411). The mean willingness to pay for conditional logit and random parameter models are $656 and $633 respectively. Respondents show most preference for preserving vegetable farm from being converted to residential and least preference for preserving grain or oilseed farms from being converted to light industry. This is consistent with the results generated from Wang and Swallow (2016) and Luo (2019). Based on their survey responses and model results, people were concerned more about vegetable farms and less about grain and hay land, perhaps because vegetable farm is associated with local food production and consumption. Besides, people are more willing to pay to preserve land near highways and outside of the city (Wang and Swallow, 2016).

Following these results, people tend to have lower value for preserving land from conversion into light industrial development rather than the other two types of urban development. However, the difference between willingness to pay for avoiding conversion into different urban uses is not large. This may reflect the tradeoffs that people associate with the urban uses. For instance, a lower willingness to pay for preserving land from being converted into light industrial may indicate that people want some light industrial activities for the jobs and tax revenues that it generates and prefer it to be located within the 10 km buffer zone of the city rather than in the current city area. Accordingly, retail and residential uses are also essential for city development, which should occur mostly within the current city limit.

Furthermore, we estimate marginal willingness to pay for individuals in subgroups living at different proximities to open space. The subgroups are the same as those used in the random parameter logit model. The estimation is taken under both the conditional logit model (Appendix 3) and random parameter model (Appendix 4). The WTP estimates derived from the random parameter model show some inconsistency and less precision, which may be mostly due to the small sample sizes. Thus, in this paper, we will focus on the results from the conditional logit model. With some insignificant estimates for land-use change by variable, the results generally show a higher willingness to pay for respondents who do not experience nearby land-use change in the past six years. Respondents who live further from agricultural land have much higher willingness to pay for farmland preservation, which is consistent with the findings from the conditional logit model.

Table 3.6 MWTP under Conditional Logit and Random Parameter Logit Model

Preservation Strategy	Conditional Logit	Random Parameter Logit Model
	Coefficient	Coefficient
Commercial vegetable farm; Retail	662.00***	575.13***
Commercial vegetable farm; Residential	754.56***	732.00***
Commercial vegetable farm; Light industrial	734.70***	719.25***
Grain or oilseed farming; Retail	626.23***	638.24***
Grain or oilseed farming; Residential	654.82***	649.49***
Grain or oilseed farming; Light Industrial	445.62***	411. 30***
Livestock grazing on native pasture; Retail	698.12***	660.21***
Livestock grazing on native pasture; Residential	714.91***	661.86***
Livestock grazing on native pasture; Light industrial	622.64***	655.95***
Observations	3008	

3.7 Concluding Remarks

This study shows the results of people's willingness to pay for farmland preservation using a stated preference method. Following the theoretical background of random utility theory, conditional logit and random parameter logit models are estimated to evaluate the non-market value of preserving farmland in the City of Edmonton. This paper contributes to the literature on the non-market valuation of farmland preservation, using an up-to-date survey and analytical tool in a spatial context. With limited guidance on the spatial analysis of farmland preservation, we adopt one of the traditional ways to evaluate the effect of the spatial variables through proximity (Glenk et al., 2019). The WTP estimates quantify people's interest in preserving certain types of agricultural lands, which provides policy makers information to implement government programs such as transfer of development credits on farmland preservation.

Some potential limitations should be noted. First, in order to match the target study area with hedonic analysis, we use the data collected from the City of Edmonton, while the study area in this research is the much larger Edmonton CMA. Luckily, we are able to compare the results with the results Luo (2019)'s province-wide study for a robustness check. One other limitation is stated in several studies (Knetsch, 2010; Koszeqi and Rabin, 2006) that the assessment of value of change in losing farmland is a loss and a more appropriate measure of this loss is the use of willingness to accept compensation (WTA). Moreover, the survey design only includes three possible current agricultural land uses and three replacement urban developments, but people might also have some other land conversion in mind when they responded to the revealed preference scenarios. In addition, although the survey design has minimized the effect of the potential consequentiality and uncertainty problems, they are not eliminated. Several determinants other than proximity to farmland are stated in section 3.1 that could have large impact on valuation of farmland preservation. We advocate the inclusion of more factors especially the intensity of agricultural use if data allowed. Lastly, a more precise way of conducting spatial analysis is to use spatial econometrics (Glenk et al., 2019), which allows us to incorporate spatial dependence in the model. We also note that the data on woodland and agricultural developable open space land use data used in this paper is derived from interpretation of remote sensing data by Agriculture and Agri-Food Canada. The data pixels of Landsat TM are 30 meters by 30 meters, meaning that some small urban open spaces may have been missed. Also, dividing the sample data into sub-samples based on distance to open space could lead to selection bias. For instance, it is likely that people who choose to live near certain open spaces have fundamentally different land-use preferences.

The section above (section 3.6) has shown the main results derived from two models and the willingness to pay assessment, with most results consistent with the findings of Luo (2019). Gender and age are two socio-demographic characteristics that affect people's perception on preservation in the conditional logit model. These results show further that proximity to open spaces do affect preferences for agricultural land conservation. Distance to agricultural land has the greatest magnitude of impact, followed by distance to the University of Alberta South Campus farm. Land-use change and proximity to non-developable land, as opposed to the findings from the hedonic analysis, have no significant effect on people's willingness to pay for farmland preservation. In the random parameter model, results from subgroups confirm the results from the conditional logit model. Comparing these results for Edmonton with the Luo (2019) results for the 6 most populous urban areas in Alberta, it appears that people in Edmonton generally have higher willingness to pay for farmland preservation than in other regions. MWTP ranges from CAD$754 and CAD$446 in conditional logit model and CAD$732 and CAD$411 in random parameter model. In both models, people are most willing to pay to preserve vegetable farm from conversion into residential and least interested in preserving grain or oilseed farm from conversion into light industrial development.

Chapter 4 Conclusion

4.1 Discussion

This chapter presents a brief discussion of the results of the hedonic price analysis and choice experiment. Although they use different methods, and estimate different values, both studies examine the value of open space to residents of urban and peri-urban areas of the Edmonton area of Alberta. The same open space characteristics are used in the analysis of the hedonic prices of residential properties and the analysis of farmland protection choice experiments. The hedonic analysis measures the portion of amenity value of different types of large open space within the City of Edmonton that is reflected into property values, while the choice experiment measures more aggregate values of agricultural land within the greater CMA area.

In the hedonic analysis, we find that homeowners are willing to pay more for properties located near non-developable lands, which includes parks, rivers and wetlands. The random parameter model of the choice experiment data shows that people who live near non-developable open spaces lands are more likely to vote for the farmland preservation strategy. These results suggest people who live near to non-developable lands are willing to pay more for their house and also willing to contribute more to the public benefits of farmland preservation in the larger metropolitan area. The reason for this finding is still unclear and may be related to other factors that underlie people's housing location decisions. This is similar to the results for woodland. All else equal, properties located near to woodland such as forests and shrublands are more expensive and the people who can afford these properties tend to have higher willingness to pay for farmland preservation. In other words, people who live near parks pay for nearby parks through higher property taxes and would be willing to pay more to help preserve agricultural land in the wider region. The results of people's willingness to pay on the conservation of University of Alberta farm is not clear because of the insignificance resulting from the small sample size (26).

The results for proximity to agricultural lands are consistent across the two studies. According to hedonic analysis, properties near agricultural lands are priced lower than properties located further away, while the choice experiment results also show that people located near agricultural land are less willing to conserve these lands. Our initial hypotheses (NIMBY, Law of Demand, Travel Cost) were that residents who are willing to pay for living near farmlands, could be more or less willing to pay to conserve the public benefits of agricultural land preservation. Subsequently, our results from hedonic analysis show a lower house value if located near agricultural land and results of the choice experiment analysis indicate that people who choose to live near agricultural lands are less willing to pay to preserve them. To conclude, people do not regard agricultural land as a treasure to have in the living zone. And the result in choice experiment indicates people who already have the tangible and visible benefits of living near agricultural lands do not worry about preserving those benefits for others. They may behavior as NIMBY hypothesized. Due to the negative externalities, even though they would like to preserve it, but they do not want it to happen beside their houses. Or perhaps people living near agricultural land have purchased houses in former frontier areas because they place lower value on the preservation of such agricultural land. In other words, people who live in the frontier of urban sprawl are satisfied to have additional sprawl into the surrounding farmland.

Another possible cause of the difference in the two studies relates to individuals' valuation disparities. We should not expect people to have the same valuation preferences or endowments (Knetsch, 2010). These endowments would affect the reference states that respondents use when they respond to the farmland preservation scenarios. Koszeqi and Rabin (2006) have found that assessment procedures and circumstances among individuals have major influence on the reference state, which is what people's valuation is based on, and leads to a presence or absence of endowment effect. In our study, the groups who live in the city core and at the periphery of the city are likely to have different reference states towards the land development and conversion. For instance, a growth or an expansion of the city edge may be expected by people who live there and certainly a conversion from farmland to developed land is not surprising. Especially for the people who seek for development benefits such as job opportunities (possibly younger families), they may not be as concerned about preservation of farmland. On the contrary, people who live in more densely populated areas near the city center of city may have a reference state that peri-urban development is taking open spaces away, and could thus place a higher value on farmland preservation.

This interpretation can be further supported by the Bergstrom and Ready (2005) model that was reviewed in section 3.2. Conversion of land at the rural-urban margin produces additional urban amenity values while it reduces agricultural and open space amenity values. People who live closest to the frontier may gain most of the new urban amenity values and reductions in agricultural dis-amenities (eg noise, dust, pesticide drift), even while they lose open space amenities associated with farmland. People who live closer to the city centre perceive peri-urban land conversion as a loss of open space values, without any meaningful change in urban amenity or agricultural dis-amenity values. Our results from the choice experiment show that, although people who live nearer to farmland are less likely to support the conservation strategy, this group still holds positive attitudes towards farmland conservation. Combining this result with the theory of valuation disparity, we know that people choose their living location under certain expectations. Thus, there may also be a selection effect: people who live closer to the rural-urban frontier expect new development to occur around them. This interpretation is supported by the result from the hedonic analysis indicating a lower house price around farmland. To conclude, residents from live near the city frontier have chosen a bundle of house attributes that include lower price and ongoing development at the frontier, even though they inherently value living near open space and would still be willing to pay to preserve agricultural land in the larger CMA area.

4.2 Implication

This thesis analyses data from a choice experiment survey that reveals people's willingness to pay for farmland preservation and an analysis of house prices that can reflect people's willingness to pay to live near different types of open spaces. Based on the results from both studies, there are some insights provided for the policy makers.

Firstly, the results provide a clear picture of the local real estate market that can help investors and planners to better understand the values of houses based on their attributes, locations and environmental characteristics regarding proximity to different types of open space. Planners could also use these results in setting property taxes and allocating land for different types of open space. The health research evidence clearly shows health advantages of open space preservation within urban areas. This research shows how those benefits affect the housing market.

Secondly, agricultural open space is the main focus in the choice experiment study, which generates a much different valuation from the other results. Since most farmland amenities provide non-excludable benefits, the value of these "public goods" are not revealed in farm market prices, nor quantified by private market (Irwin et al., 2003). Thus, some type of government intervention would be needed to preserve those lands. However, as stated in section 1.2, none of the Alberta legislation provides clear guidance and step-by-step methods on farmland preservation. Policies used to target the preservation of agricultural lands according to their productivity while the most efficient way proposed by Irwin et al. (2003) is to target the lands with the highest non-market amenity values such as scenic beauty. Wang and Swallow (2016) proposed that expenditures on land preservation should be targeted to generate the greatest benefit for the available budget. This thesis complements that analysis by providing information about the type of open spaces that adds highest premium to the houses and the types of land conversion that people most want to avoid.

More importantly, this study helps policy makers and developers to understand the tradeoffs between WTP for preservation of land in different agricultural uses and creation of non-developable open spaces like parks and recreation facilities. For instance, based on our results, there is strong marginal WTP for properties located adjacent to open space, then an additional levy such as a higher property tax mill rate could be implemented on residents or developers to help maintain the natural amenities they value. This could possibly be done through strict zoning regulations such as nature reserves or the purchase of conservation easements on certain types of agricultural land. Alternatively, development permits could be given on condition that all concerned residents could more directly benefit from the open space benefits. For instance, it could involve features like public access routes and shared bicycle / walk paths along water bodies and through preservation areas. However, a direct property tax could actually lead to double taxation since people already pay taxes on house prices. If these values are capitalized into house prices, then part of tax is a tax on those values. Therefore, the tradeoffs from multiple dimensions should be deeply considered. Another suggestion is to estimate the value for the nearby open space so that a proportion of it can be converted or sold to developers and generate a relatively high tax revenue, which could further be used in preservation of that open space (following the logic if transfer of development credits). This may be occurring in Edmonton where the city is repurposing parts of parks to allow new high-rise development.

To conclude, this thesis provides several insights into people's values for agricultural land and other types of open space that exist in an urban context. Although our study tries to improve the methods and offer more accurate results, much of the preference heterogeneity in the choice experiment is still left unexplained. Besides, identifying and quantifying the dollar amount and arrangement of open space value, especially farmland amenity value, is a complex task because of the potential substitution effect provided by other amenities. We know the amenity values of open spaces and farmland that matter most. How to capture the value most accurately remains an open question and needs future study.

References

Acharya, G., L.L. Bennett. 2001. Valuing Open Space and Land Use Patterns on Urban Watersheds. *Journal of Real Estate Finance and Economics* 22: 221-237.

Adamowicz, W., J. Swait, P. Boxall, J. Louviere and M. Williams. 1997. Perceptions versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Models of Environmental Valuation. *Journal of Environmental Economics and Management* 32 (1): 65-84.

Alberta Agriculture, Food and Rural Development. 2002. Loss and Fragmentation of Farmland. http://www.assembly.ab.ca/lao/library/egovdocs/2002/alard/135192.pdf. (accessed Aug 15, 2020).

Anderson, S.T. and S.E. West. 2006. Open Space, Residential Property Values, and Spatial Context. *Regional Science and Urban Economics* 36 (6): 773-789.

Anselin, L. and D. Arribas-Bel. 2013. Spatial Fixed Effects and Spatial Dependence in a Single Cross-section. *Papers in Regional Science* 92(1): 3-17.

Bateman I.J., B.H. Day, S. Georgiou and I. Lake. 2006. The Aggregation of Environment Benefit Values: Welfare Measures, Distance Decay and Total WTP. *Ecological Economics* 60 (2): 450-460.

Beasley, S., W. Workman and N. Williams. Amenity Values of Urban Fringe Farmland: A Contingent Valuation Approach. *Growth Change 17* (4): 70-78.

Benkard, C.L. and P. Bajari. 2005. Hedonic Price Indexes with Unobserved Product Characteristics, and Application to Personal Computers. *Journal of Business and Economic Statistics* 23 (1): 61-75.

Benson, E.D., J.L. Hansen, A.L. Jr. Schwartz. 2000. Water Views and Residential Property Values. *The Appraisal Journal*, 68(3): 260-271.

Bergstrom, J.C., B.L. Dillman and J.R. Stoll. 1985. Public Environmental Amenity Benefits of Private Land: The Case of Prime Agricultural Land. *Southern Journal of Agricultural Economics* 17 (1): 139-149.

Bergstrom, J.C., and R.C. Ready. 2008. What Have We Learned from Over 20 Years of Farmland Amenity Valuation Research in North America? *Review of Agricultural Economics* 31 (1): 21-49.

Bin, O. and S. Polasky. 2004. Effects of Flood Hazards on Property Values: Evidence Before and After Hurricane Floyd. *Land Economics* 80(4): 490-500.

Birol, E., K. Karousakis and P. Koundouri. 2006. Using a Choice Experiment to Account for Preference Heterogeneity in Wetland Attributes: The Case of Cheimaditida Wetland in Greece. *Ecological Economics* 60 (1): 145-156.

Bockstael, N.E., I.E. Strand and W.M. Hanemann. 1987. Time and the Recreational Demand Model. *American Journal of Agricultural Economics* 69 (2): 293-302.

Borchers, A.M. and J.M. Duke. 2012. Capitalization and Proximity to Agricultural and Natural Lands: Evidence from Delaware. *Journal of Environmental Management* 99: 110-117.

Boxall, P.C. and W.L. Adamowicz. 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. *Environmental and Resource Economics* 23: 421-446.

Brasington, D.M. and D. Hite. 2005. Demand for environmental quality: a spatial hedonic analysis. *Regional Science and Urban Economics* 35 (1): 57-82.

Braubach, M., A. Egorov, P. Mudu and T. Wolf. 2017. Effects of Urban Green Space on Environmental Health, Equity and Resilience. In *Nature-Based Solutions to Climate Change Adaptation in Urban Area* edited by M. Braubach, A. Egorov, P. Mudu, C. W. Thompson, M. Martuzzi and T. Wolf. Read, pp. 187-205.

Cao, Y., B. Swallow and F. Qiu. 2018. Does Municipal Development Policy Affect Property Values: A Quasi-Experimental Hedonic Model Approach in Alberta, Canada. Paper presented at International Association of Agricultural Economists conference, Vancouver, British Columbia, July 28-August 2.

Cascetta, E. 2004. Random Utility Theory. *In Transportation Systems Engineering: Theory and Methods* (95-173). Springer.

Chiasson, C., K. Good, G. Greenaway and J. Unger. 2012. Conservation Easements for Agriculture in Alberta: A Report on a Proposed Policy Direction. https://landuse.alberta.ca/LandUse%20Documents/Conservation%20Easements%20for%20Agriculture%20in%20Alberta%20-%202012-03.pdf. (accessed June 2, 2020).

Cho, S., J.M. Bowker and W.M. Park. 2006. Measuring the Contribution of Water and Green Space Amenities to Housing Values: An Application and Comparison of Spatially Weighted Hedonic Models. *Journal of Agriculture and Resource Economics* 31(3): 485-507.

City of Edmonton. 2017. Ribbon of Green Recreation Assessment. https://www.edmonton.ca/city_government/documents/PDF/RoG_RecreationAssessment.pdf. (accessed on August 25).

City of Edmonton. 2018. City of Edmonton Annexation Application. https://www.edmonton.ca/documents/PDF/Annexation-Application-Summary.pdf. (accessed on August 25).

Crompton, J.L. 2001. The Impact of Parks on Property Values: A Review of the Empirical Evidence. *Journal of Leisure Research* 33 (1): 1-31.

Crompton, J.L. and S. Nicholls. 2020. Impact on Property Values of Distance to Parks and Open Spaces: An Update of U.S. Studies in the New Millennium. *Journal of Leisure Research* 51 (2): 127-146.

Dale, V., S. Archer, M. Chang and D. Ojima. 2005. Ecological Impacts and Mitigation Strategies for Rural Land Management. *Ecological Applications* 15 (6): 1879-1892.

Downs A. 2002. Having Housing Prices Risen Faster in Portland than Elsewhere? *Housing Policy Debate* 13: 7-31.

Driedzic, A. 2016. Buying a better environment? Market-based instruments & the Alberta Land Stewardship Act. Environmental Law Centre, Edmonton. Environmental Law Centre and Miistakis Institute, 2019. http://www.ce-alberta.ca/. (accessed 25 August 2020).

Dubin, R.A. and A.C. Goodman. 1982. Valuation of education and crime neighborhood characteristics through hedonic housing prices. *Population Environment* 5: 166-181.

Dziauddin, M.F., N. Powe and S. Alvanides. 2015. Estimating the Effects of Light Rail Transit (LRT) System on Residential Property Values Using Geographically Weighted Regression (GWR). *Applied Spatial Analysis* 8: 1-25.

Edmonton and Area Land Trust. Conservation Land. https://www.ealt.ca/conservation-lands. (accessed Nov.21, 2020).

Edmonton Metropolitan Region Board. 2017. Edmonton Metropolitan Region Growth Plan. http://emrb.ca/Website/media/Shared/Banners/EMRB-Growth-Plan-(2020).pdf. (accessed June 2, 2020).

Elhorst, J.P. 2010. Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis* 5 (1): 9-28.

Elhorst. J.P. 2014. *Spatial Econometrics from Cross-sectional Data to Spatial Panels.* Springer.

Fearnside, P.M. 2000. Global Warming and Tropical Land-use Change: Greenhouse Gas Emissions from Biomass Burning, Decomposition and Soils in Forest Conversion, Shifting Cultivation and Secondary Vegetation. *Climate Change* 46 (1-2): 115-158.

Fischer, M.M. and J. Wang. 2011. *Spatial Data Analysis: Models, Methods and Techniques.* Springer Briefs.

Fraser Institute. School Rankings, Alberta. https://www.compareschoolrankings.org/. (accessed on May 5, 2020).

Geoghegan, J., L. Lynch and S. Bucholtz. 2003. Capitalization of Open Spaces into Housing Values and the Residential Property Tax Revenue Impacts of Agricultural Easement Programs. *Agriculture and Resource Economics Review* 32 (1): 33-45.

Geoghegan, J., L.A. Wainger and N.E. Bockstael. 1997. Spatial Landscape Indices in a Hedonic Framework: An Ecological Economics Analysis Using GIS. *Ecological Economics* 23 (3): 251-264.

Glenk K., R.J. Johnston, J. Meyerhoff and J. Sagebiel. 2019. Spatial Dimensions of Stated Preference Valuation in Environmental and Resource Economics: Methods, Trends and Challenges. *Environmental and Resource Economics* 75: 215-242.

Government of Alberta. 2000. Municipal Government Act. https://www.qp.alberta.ca/570.cfm?frm_isbn=9780779818785&search_by=link. (accessed Sept 1, 2020).

Government of Alberta. 2008. Land Use Framework. https://open.alberta.ca/dataset/30091176-f980-4f36-8f5a-87bc47890aa8/resource/bc4b3fac-5e59-473b-9a99-1a83970c28e7/download/4321768-2008-land-use-framework-2008-12.pdf. (accessed June 2, 2020).

Government of Alberta. 2009. Alberta Land Stewardship Act. https://www.qp.alberta.ca/1266.cfm?page=A26P8.cfm&leg_type=Acts&isbncln=9780779777259. (accessed June 2, 2020).

Government of Canada. 2013. Agriculture and Agri-Food Canada Annual Crop Inventory. https://open.canada.ca/data/en/dataset/ba2645d5-4458-414d-b196-6303ac06c1c9. (accessed on August 25, 2020).

Government of Alberta. 2016a. Population Projections Alberta and Census Divisions, 2016-2014. https://open.alberta.ca/dataset/90a09f08-c52c-43bd-b48a-fda5187273b9/resource/509cc23c-e135-4004-b4dc-4845a12d273c/download/2016-2041-alberta-population-projections-census.pdf. (accessed June 2, 2020).

Government of Alberta. 2016b. Alberta Agri-food Export, 2007 to 2016. https://open.alberta.ca/dataset/b92e9a1b-2a1b-4e10-9f46-431edb53cf1a/resource/92e43fec-68af-4f15-a0e3-d0718da14a24/download/2007-2016albertaexprpt.pdf. (accessed June 2, 2020).

Government of Alberta. 2017a. Food Security in the Context of Agricultural Land Loss in Alberta. https://open.alberta.ca/dataset/7fefa49b-a668-457a-8996-

7ca567f02685/resource/65b162c7-5b9e-4d61-b9f4-f483f9e0b574/download/food-security-ab-ag-land-loss.pdf. (accessed June 2, 2020).

Government of Alberta. 2017b. Alberta Economic Quick Facts. https://open.alberta.ca/dataset/e61b7101-bcbe-46c6-84a9-377c4e5956e9/resource/bdb7841a-608a-46f8-b631-69863a04bd0b/download/sp-eh-Falbertaeconomicquickfacts.pdf. (accessed June 2, 2020).

Government of Alberta. 2018. Fragmentation and Conversion of Agricultural Land in Alberta. https://www1.agric.gov.ab.ca/$Department/deptdocs.nsf/all/luf16125/$FILE/fragmentation-conversion2018-07-13.pdf. (accessed June 2, 2020).

Government of Alberta. 2020. Annual Report 2019 Land Use Changes in Alberta. https://open.alberta.ca/dataset/cb0d63dc-d080-4c54-914d-603d0510468d/resource/0bf3e90f-69b2-4f36-a4a0-ef71210b623b/download/af-annual-report-2019-land-use-changes-in-alberta.pdf. (accessed on Aug 25, 2020).

Haarsma, D.G. 2014. Spatial Analysis of Agricultural Land Conversion and its Associated Drivers in Alberta. M. Sc. Thesis. Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta.

Hicks, R.L. and B.M. Queen. 2016. Valuing Historical and Open Space Amenities with Hedonic Property Valuation Models. *Agricultural and Resource Economics Review* 45 (1): 44-67.

Hofmann, N., G. Filoso and M. Schofield. 2005. The Loss of Dependable Agricultural Land in Canada. Rural and small town Canada analysis bulletin, Statistics Canada 6 (1).

Holmes, T.P., W.L., Adamowics and F. Carlsson. 2017. Choice Experiments. *In a Primer on Nonmarket Valuation* (133-186). Springer.

Hui, E.C.M., C.K. Chau, L. Pun and M.Y. Law. 2007. Measuring the Neighboring and Environmental Effects on Residential Property Value: Using Spatial Weighting Matrix. *Building and Environment* 42 (6): 2333-2343.

Irwin, E.G. 2002. The Effects of Open Space on Residential Property Values. *Land Economics* 78 (4): 465-480.

Irwin, E.G., C.J. Nickerson and L. Libby. 2003. What are Farmland Amenities Worth? *Agricultural and Applied Economics Association* 18 (3): 21-23.

Irwin, E.G. and N.E. Bockstael. 2007. The Evolution of Urban Sprawl: Evidence of Spatial Heterogeneity and Increasing Land Fragmentation. *Proceedings of the National Academy of Sciences of the United States of America* 104 (52): 20672-20677.

Islam, S. 2012. Impact of Neighbourhood Characteristics on House Prices. *American Society of Business and Behavioral Sciences* 19 (1): 443-451.

Johnston, R.J. and J.M. Duke. 2007. Willingness to Pay for Agricultural Land Preservation and Policy Process Attributes: Does the Method Matter? *American Journal of Agricultural Economics* 89 (4): 1098-1115.

Johnston R.J., E.Y. Besedin and R. Stapler. 2017. Enhanced Geospatial Validity for Meta-analysis and Environment Benefit Transfer: An Application to Water Quality Improvements. *Environmental and Resource Economics* 68: 343-375.

Johnston, R.J., J.J. Opaluch, T.A. Grigalunas and M.J. Mazzotta. 2001. Estimating Amenity Benefits of Coastal Farmland. *Growth and Change* 32: 305-325.

King, D.A., J.L. White and W.W. Shaw. 1991. Influence of Urban Wildlife Habitats on the Value of Residential Properties. In *Wildlife Conservation in Metropolitan Environments: A National*

Symposium on Urban Wildlife edited by L.W. Adams and D.L. Leedy, pp 165-169. Columbia: National Institute for Urban Wildlife.

Kim. J., S. Yoon, E. Yang and B. Thapa. 2020. Valuing Recreational Beaches: A Spatial Hedonic Pricing Approach. *Journal of Coastal Management* 48 (2): 118-141.

Knetsch, J.L. 2010. Values of Gains and Losses: Reference States and Choice of Measure. *Environment Resource Economics* 46: 179-188.

Kontoleon, A. 2003. Essays on Non-market Valuation of Environmental Resources: Policy and Technical Explorations. Thesis, University College London, University of London.

Laszkiewicz, E., P. Czembrowski and J. Kronenberg. 2019. Can Proximity to Urban Green Spaces Be Considered a Luxury? Classifying a Non-tradable Good with the Use of Hedonic Pricing Method. *Ecological Economics* 161: 237-247.

Lambin, E.F. and P. Meyfroidt. 2011. Global Land Use Change, Economic Globalization, and the Looming Land Scarcity. *Proceedings of the National Academy of Sciences of the United States of America* 108 (9): 3465-3472.

Leenders, R.T.A. 2002. Modeling Social Influence through Network Autocorrelation: Constructing the Weight Matrix. *Social Network* 24(1): 21-47.

LeSage, J. and R.K. Pace. 2009. *Introduction to Spatial Econometrics*. CRC Press.

Lloyd-Smith, P., E. Zawojska and W. Adamowicz. 2020. Moving beyond the Contingent Valuation versus Choice Experiment Debate: Presentation Effects in Stated Preference. *Land Economics* 96 (1): 1-24.

Luo, Y. 2019. Comparing Willingness-to-pay and Willingness-to-accept Approaches for Valuing Farmland Protection and Conversion in Alberta. M. Sc. Thesis. Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta.

Luttik, J. 2000. The Value of Trees, Water and Open Space as Reflected by House Prices in the Netherlands. *Landscape and Urban Planning* 48: 161-167.

Lutzenhiser, M. and N.R. Netusil. 2001. The Effect of Open Spaces on a Home's Sale Price. *Contemporary Economic Policy* 19 (3): 291-298.

Macdonald, D.H. and M.M. Veeman. 1996. Valuing Housing Characteristics: A Case Study of Single Family Houses in Edmonton, Alberta. *The Canadian Journal of Economics* 29 (2): 510-514.

Mansfield, E.R. and B.P. Helms. 1982. Detecting Multicollinearity. *The American Statistician* 36 (3a): 158-160.

Martellozzo, F., N. Ramankutty, R.J. Hall, T. David, B. Purdy and M.A. Friedl. 2015. Urbanization and the Loss of Prime Farmland: A Case Study in the Calgary-Edmonton Corridor of Alberta. *Regional Environmental Change* 15: 881-893.

Masuda, J.R. and T. Garvin. 2008. Whose Heartland?: The Politics of Place in a Rural-urban Interface. *Journal of Rural Studies* 24 (1): 112-123.

McConnell, V. and M. Walls. 2005. The Value of Open Space: Evidence from Studies of Nonmarket Benefits. *Lincoln Institute of Land Policy.*

McFadden, D. 1974. The Measurement of Urban Travel Demand. *Journal of Public Economics 3*: (303-328).

Mittal, J. and S. Byahut. 2017. Scenic Landscape, Visual Accessibility and Premium Values in a Single Family Housing Market: A Spatial Hedonic Approach. *Environment and Planning B: Urban Analytics and City Science* 46 (1): 66-83.

Montero, J., R. Mínguez and G. Fernández-Avilés. 2018. Housing Price Prediction: Parametric versus Semi-Parametric Spatial Hedonic Models. *Journal of Geographical Systems* 20: 27-55.

Mulder, C.H. 2006. Population and Housing: A Two-sided Relationship. *Demographic Research* 15 (13): 401-412.

Nickerson, C., M. Morehart, T. Kuethe, J. Beckman, J. Ifft and R. Williams. 2012. Trends in U.S. Farmland Values and Ownership. Economic Information Bulletin-92, Nebraska: University of Nebraska, Department of Agriculture: Agricultural Research Service, Lincoln, February.

Nielsen, C.C., M. Gascon, A.R. Osornio-Vargas, C. Shier, D.S. Guttman, A.B. Becker, M.B. Azad, M.R. Sears, D.L. Lefebvre, T.J. Moraes, S.E. Turvey, P. Subbarao, T.K. Takaro, J.T. Brook, J.A. Scott, P.J. Mandhane, H.M. Tun, A.L. Kozyrskyj. 2020. Natural Environments in the Urban Context and Gut Microbiota in Infants. *Environment International* 142.

Ojima, D.S., K.A. Galvin and B.L. Turner. 1994. The Global Impact of Land-Use Change. *BioScience* 44 (5): 300-304.

Olson, R.H. and T.A. Lyson. 1999. *Under the Blade: The Conversion of Agricultural Landscapes*. Westview Press.

Osland, L. 2010. An Application of Spatial Econometrics in relation to Hedonic Price Modeling. *Journal of Real Estate Research* 32: 280-320.

Palmquist, R.B. 1984. Estimating the Demand for the Characteristics of Housing. *Review of Economics and Statistics* 66(3): 394-404.

Powell, B.H. 2019. Agricultural Lands Law and Policy in Alberta. Alberta: Environment Law Centre.

Qiu, F., L. Laliberté, B. Swallow and S. Jeffery. 2015. Impacts of Fragmentation and Neighbor Influences on Farmland Conversion: A Case Study of the Edmonton-Calgary Corridor, Canada. *Land Use Policy* 48: 482-494.

Ready, R.C. and C.W. Abdalla. 2005. The Amenity and Disamenity Impacts of Agriculture: Estimates from a Hedonic Pricing Model. *American Journal of Agricultural Economics* 87 (2): 314-326.

Ready, R.C., M.C. Berger and G.C. Blomquist. 1997. Measuring Amenity Benefits from Farmland: Hedonic Pricing vs. Contingent Valuation. *Growth and Change* 28: 438-458.

Roe, B., E.G. Irwin and H.A. Morrow-Jones. 2004. The Effects of Farmland, Farmland Preservation, and Other Neighborhood Amenities on Housing Values and Residential Growth. *Land Economics* 80 (1):55-75.

Rosen, S. 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy* 82 (1): 34-55.

Ruan, X., F. Qiu and M. Dyck. 2016. The Effects of Environmental and Socioeconomic Factors on Land-use Changes: A Study of Alberta, Canada. *Environmental Monitoring and Assessment* 188: 446.

Sedgley, N.H., A.W. Nancy and W.D. Frederick. The Effect of Educational Test Scores on House Prices in a Model with Spatial Dependence. *Journal of Housing Economics* 17 (2): 191-200.

Seya, H., Y. Yamagata and M. Tsutsumi. 2012. Automatic Selection of a Spatial Weight Matrix in Spatial Econometrics: Application to a Spatial Hedonic Approach. *Regional Science and Urban Economics* 43: 429-444.

Shen, C., Y. Wang and L. Zhao. 2019. Characteristics of Material Migration During Soil Erosion in Sloped Farmland in the Black Soil Region of Northeast China. *Tropical Conservation Science* 12: 1-11.

Shultz, S.D. and D.A. King. 2001. The Use of Census Data for Hedonic Price Estimates of Open-Space Amenities and Land Use. *Journal of Real Estate Finance and Economics* 22 (2/3): 239-252.

Smith, V.K., C. Poulos and H. Kim. 2002. Treating Open Space as an Urban Amenity. *Resource and Energy Economics* 24: 107-129.

Sohn, W., H.W. Kim, J. Kim and M. Li. 2020. The Capitalized Amenity of Green Infrastructure in Single-Family Housing Values: An Application of the Spatial Hedonic Pricing Method. *Urban Forestry and Urban Greening* 49.

Stan, K.D. and A. Sanchez-Azofeifa. 2017. The Edmonton-Calgary Corridor: Simulating Future Land Cover Change under Potential Government Intervention. *Land Use Policy* 63: 356-368.

Statistics Canada. 2016. 2011 Farm and Farm Operator Data. https://www150.statcan.gc.ca/n1/pub/95-640-x/2011001/p1/prov/prov-48-eng.htm. (accessed Aug 20, 2020).

Statistics Canada. 2017a. Farm and Farm Operator Data. https://www150.statcan.gc.ca/n1/pub/95-640-x/2016001/article/14808-eng.htm. (accessed Aug 20, 2020).

Statistics Canada. 2017b. Population and Dwelling Count Highlight Tables, 2016 Census. https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/hlt-fst/pd-pl/About.cfm. (accessed on Aug 2, 2020).

Tenant and National Bank of Canada. 2020. House Price Index, Edmonton. https://housepriceindex.ca/#maps=ab_edmonton. (accessed on June 2, 2020).

The Canadian Real Estate Association. n.d. MLS Home Price Index. https://www.crea.ca/housing-market-stats/mls-home-price-index/hpi-tool/. (accessed on May 1, 2020).

Tong, Q. and F. Qiu. 2020. Population Growth and Land Development: Investigating the Bidirectional Interactions. *Ecological Economics* 169.

Traba. J. and M.B. Morales. 2019. The Decline of Farmland Birds in Spain is Strongly Associated to the Loss of Fallowland. *Scientific Reports* 9.

Trojanek. R., G. Michal and T. Justyna. 2018. The Effect of Urban Green Spaces on House Prices in Warsaw. *International Journal of Strategic Property Management* 22 (5): 358-371.

Vega, S.H. and J.P. Elhorst. 2013. On Spatial Econometric Models, Spillover Effects, and W. Paper presented at 53rd ERSA conference, Palermo, August 27-31.

Wang, H. 2015. Examination of Agricultural Land Conservation in the Alberta Capital Region, Canada. M. Sc. Thesis. Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, Alberta.

Wang, H. and S. Brent. 2016. Optimizing Expenditures for Agricultural Land Conservation: Spatially-Explicit Estimation of Benefits, Budgets, Costs and Targets. *Land Use Policy* 59: 272-283.

Week, D.A. and C.H. Wizor. 2020. Effects of Flood on Food Security, Livelihood and Socio-economics Characteristics in the Flood-prone Areas of the Core Niger Delta, Nigeria. *Asia Journal of Geographical Research* 3 (1): 1-17.

Whittemore, A.H. and T.K. BenDor. 2018. Reassessing NIMBY: The Demographics, and Geography of Opposition to High-density Residential Infill. *Journal of Urban Affairs* 41 (4): 423-442.

Yeates, M., P. Du and T. Hernandez. 2012. Calgary CMA Residential Property Valuation: Background Paper. Centre for the Study of Commercial Activity, Ryerson University, Toronto, Ontario, Canada.

Yoo, J., J. Browning and K. Minesinger. 2017. Open Space Premium Near Commercial Zones – a Case Study in the City of Corona, California. *International Journal of Urban Sciences* 22 (3): 322-333.

Zolo. 2020. Edmonton Real Estate Trends. https://www.zolo.ca/edmonton-real-estate/trends. (accessed on August 25, 2020).

Appendix

Appendix 1. Decomposed Direct and Indirect Effects under Spatial Durbin Model

Variables	Direct Effect	Indirect Effect	Total Effect
Living area	.0002646***	.0002359***	.0005005***
	(3.78e-06)	(.0000344)	(.0000349)
Lot size	8.05e-06***	.0000473***	.0000553***
	(3.44e-07)	(6.25e-06)	(6.36e-06)
Age	-.0022422***	-.0003137	-.0025559***
	(.0000954)	(.000762)	(.0007767)
Bath	.0317019***	-.0630623**	-.0313604
	(.0030242)	(.0275825)	(.0283556)
Bed	-.0185662***	-.1629592***	-.1815254***
	(.0025372)	(.0261139)	(.02689)
Condition	.0495443***	.0666251**	.1161694***
	(.0028867)	(.02707)	(.0280076)
Basement	.0849252***	.1402238***	.225149***
	(.0031222)	(.0289208)	(.0298682)
Parking	.0600378***	.0552259**	.1152636***
	(.0026752)	(.025149)	(.0258446)
Season	.0166299***	-.0054796	.0111503
	(.0027857)	(.027678)	(.028785)
Downtown	.0317036*	-.2192675***	-.1575639***
	(.0366352)	(.0496338)	(.0229153)
LRT	.0183757	-.0245515	-.0061758
	(.0149765)	(.0199134)	(.0098157)
Density	3.07e-06	-9.03e-06	-5.96e-06
	(3.66e-06)	(9.56e-06)	(7.52e-06)
Child	.005099***	.0048221	.0039987
	(.001903)	(.0033042)	(.0026066)
Elder	.0010732**	-.002236	-.0011629
	(.000531)	(.001457)	(.0012181)
Unemployment	.0039126*	-.0190585***	-.0151458***
	(.0022885)	(.006841)	(.0057087)
Low Income	.0008723*	-.0046562**	-.0037839**
	(.000523)	(.0018364)	(.0015789)
High Income	.0034389***	-.0077379***	-.004299***
	(.0005257)	(.0014925)	(.0012427)
Bachelor	.0036453***	-.0035978***	.0000475
	(.0005055)	(.0011941)	(.0009565)

Crime Incidence	-.00001898 (.00002757)	-.001544** (.000769)	-.0017338*** (.0006373)
Quality	-.0012353 (.0022861)	.0172485*** (.0062183)	.0160133*** (.0050039)
Regional factor	.029318 (.009826)	-.0194748 (.0255546)	.0098431 (.0203345)
Agricultural	.0077031 (.007346)	-.0085633 (.0140554)	-.0008602 (.0105578)
Woodland	-.0260541*** (.0026306)	.308287*** (.0119429)	.0047746 (.0108785)
Non-developable	-.0049834*** (.001867)	-.0291004** (.0130083)	-.0340838*** (.0124561)
UA Farm	.0471643* (.0286235)	-.0792119** (.0366096)	-.1263762*** (.0190186)
Land-use Change	.0000247 (.0000166)	.0002852*** (.0000695)	.0003099*** (.0000695)

Appendix 2. Results from all spatial models

Variables	OLS	SAR	SEM	SAC	SLX	SDM	SDEM	GNS
Living area	.00028***	.00025***	.000266***	.00026***	.000027***	.00026***	.000262***	.00026***
	(3.87e-06)	(3.81e-06)	(3.79e-06)	(3.79e-06)	(4.04e-06)	(3.81e-06)	(3.8e-06)	(3.8e-06)
Lot size	8.32e-06***	7.75e-06***	7.41e-06***	7.4e-06***	7.1e-06***	7.07e-06	7.2e-06***	7.1e-06***
	(3.55e-07)	(3.36e-07)	(3.29e-07)	(3.29e-07)	(3.49e-07)	(3.28e-07)	(3.29e-07)	(3.3e-07)
Age	-.00205***	-.0019***	-.00215***	-.0021***	-.00226***	-.00224***	-.00222***	-.0022***
	(.000098)	(.00009)	(.0000954)	(.000095)	(.000101)	(.000095)	(.000095)	(.000095)
Bath	.0266***	.00254***	.0332***	.0316***	.032***	.033***	.032***	.0322***
	(.00321)	(.00304)	(.00298)	(.00299)	(.00314)	(.00296)	(.00302)	(.00297)
Bed	-.0215***	-.0136***	-.0148***	-.0131***	-.0183***	-.0152***	-.0164***	-.0157***
	(.00267)	(.00254)	(.00245)	(.00246)	(.0026)	(.00245)	(.00251)	(.00247)
Condition	.0525***	.0516***	.048***	.0492***	.0489***	.0482***	.049***	.0486***
	(.00305)	(.00289)	(.00279)	(.0028)	(.00296)	(.00278)	(.0029)	(.0028)
Basement	.0935***	.0889***	.0828***	.0843***	.0846***	.082***	.0842***	.0827***
	(.0033)	(.00312)	(.00303)	(.00304)	(.00321)	(.00303)	(.0031)	(.00305)
Parking	.0661***	.0592***	.0603***	.0598***	.0603***	.0589***	.0603***	.059***
	(.00284)	(.0027)	(.00263)	(.00263)	(.0028)	(.00262)	(.0027)	(.0026)
Season	.01581***	.0159***	.0166***	.0167***	.0164***	.0167***	.0168***	.0167***
	(.00292)	(.00276)	(.0026)	(.00263)	(.0028)	(.00264)	(.0027)	(.00266)
Downtown	-.0592***	-.0454***	-.0218	-.0396***	.1489***	.0663*	.0857*	.079*
	(.00632)	(.006)	(.0147)	(.0113)	(.0398)	(.0376)	(.049)	(.0414)
LRT	.00679**	.00102	.0122	.00635	.0382**	.019	.0175	.0194
	(.00303)	(.00287)	(.0076)	(.00579)	(.0163)	(.0153)	(.0195)	(.0167)
Density	-.00001***	-8.43e-06***	-5.47e-06**	-6.1e-06**	8.53e-06**	3.3e-06	3.46e-06	3.59e-06
	(1.7e-06)	(1.62e-06)	(2.75e-06)	(2.44e-06)	(4.03e-06)	(3.8e-06)	(4.55e-06)	(4.05e-06)
Child	.00082	.00061	.00069	.00061	-.0007	-.00092	-.00168	-.0011
	(.00064)	(.000604)	(.00103)	(.00092)	(.00146)	(.00138)	(.0016)	(.00146)
Elder	.00089***	.00096***	.00132***	.00013***	.00158***	.0011**	.00088	.00107*
	(.00026)	(.00025)	(.000413)	(.000365)	(.00058)	(.00054)	(.00064)	(.00058)
Unemployment	-.0031**	-.0036***	.00175	-.00071	.00905***	.0043*	.00354	.0043*
	(.00123)	(.0012)	(.00184)	(.00167)	(.00252)	(.0024)	(.00278)	(.0025)
Low Income	-.00054*	-.00062**	.000304	.000045	.00118**	.00097*	.00098	.00099*
	(.00032)	(.000304)	(.00044)	(.00041)	(.00058)	(.00055)	(.00063)	(.00057)
High Income	.00167***	-.00019	.00279***	.00163***	.00466***	.0036***	.0028***	.00347***
	(.000278)	(.00027)	(.000425)	(.0004)	(.00058)	(.00055)	(.00064)	(.00058)
Bachelor	.0024***	.00059**	.0033**	.00202***	.00441***	.00372***	.0035***	.00367***
	(.00024)	(.00023)	(.00039)	(.000167)	(.00055)	(.000522)	(.00061)	(.00055)
Crime Incidence	-.00147***	-.00055***	-.00071***	-.00059***	.00014	-.00016	-.00021	-.00016
	(.00015)	(.00014)	(.00023)	(.000204)	(.000303)	(.00029)	(.00033)	(.0003)
Quality	.00838***	.00354***	.0027	.00234	-.00467*	-.0016	-.0036	-.0024
	(.00117)	(.0011)	(.00182)	(.00163)	(.00252)	(.00237)	(.0027)	(.0025)
Agricultural	.0151***	.0167***	.0126***	.0151***	.0018	.00788	.0113	.0087
	(.00258)	(.00245)	(.00437)	(.00382)	(.0067)	(.0063)	(.0076)	(.00674)
Woodlands	-.0246***	-.0193***	-.0264***	-.0231***	-.0265***	-.0267***	-.0269***	-.0268***

	(.00194)	(.00185)	(.00236)	(.002267)	(.00293)	(.00276)	(.00304)	(.0029)
Non-developable	-.00859***	-.0078***	-.00643***	-.0064***	-.00265	-.00438**	-.0045**	-.0043**
	(.00167)	(.00158)	(.00179)	(.0017)	(.0021)	(.00198)	(.0021)	(.00202)
UA farm	-.11***	-.0808***	-.1115***	-.0876***	-.0661**	-.0455	-.0028	-.0361
	(.00541)	(.0052)	(.01313)	(.0101)	(.0311)	(.0293)	(.034)	(.0314)
Land-use change	.000059***	.000034**	.000014	.000012	.000026	.000019	.000027*	.000023
	(.000014)	(.000014)	(.000016)	(.000016)	(.000018)	(.000017)	(.0000163)	(.000017)
Regional factor	.0237***	-.00052	.0308**	.0163**	.0328***	.0297***	.0303**	.03***
	(.0049)	(.0047)	(.0078)	(.00709)	(.0108)	(.01012)	(.0117)	(.0107)
Constant	12.49***	7.13***	12.35***	9.41***	12.68***	4.62***	12.44***	6.49***
	(.0252)	(.174)	(.0435)	(.253)	(.0471)	(.253)	(.085)	(.798)
W*Living area					.000115***	-.00008***	.00012***	-.000031
					(.000014)	(.000014)	(.000017)	(.000024)
W*Lot size					.000032***	.000013***	.000023***	.000017***
					(2.43e-06)	(2.36e-06)	(3.21e-06)	(2.92e-06)
W*Age					-.00057*	.0013***	.00018	.001***
					(.00031)	(.0003)	(.00039)	(.00035)
W*Bath					-.0569***	-.044***	-.014	-.0381***
					(.0111)	(.0104)	(.0127)	(.0115)
W*Bed					-.0849***	-.051***	-.056***	-.054***
					(.01001)	(.0095)	(.011)	(.0101)
W*Condition					.0372***	-.0058	.0253**	.0035
					(.0107)	(.01012)	(.0118)	(.0113)
W*Basement					.0832***	-.00011	.0574***	.0177
					(.0113)	(.011)	(.0126)	(.0133)
W*Parking					.0201**	-.0168*	.041***	-.0029
					(.01)	(.0095)	(.0112)	(.0119)
W*Season					-.0051	-.0127	.0015	-.0089
					(.0108)	(.0102)	(.0111)	(.0107)
W*Downtown					-.2779***	-.124***	-.195***	-.152***
					(.0439)	(.0416)	(.058)	(.0471)
W*LRT					-.04**	-.0211	-.0184	-.0217
					(.0177)	(.0167)	(.0236)	(.0184)
W*Density					-.000018***	-5.43e-06	-.000012	-7.4e-06
					(5.89e-06)	(5.56e-06)	(8.63e-06)	(6.3e-06)
W*Child					.00279	.0024	.0043	.0027
					(.0021)	(.0019)	(.0031)	(.0022)
W*Elder					-.00244***	-.0015*	-.00092	-.0015*
					(.00086)	(.00081)	(.00125)	(.00091)
W*Unemploymen					-.0232***	-.0098***	-.011*	-.0109**
					(.00395)	(.0037)	(.00596)	(.00423)
W*Low Income					-.00343***	-.0023**	-.0031**	-.00263**
					(.001)	(.00095)	(.00153)	(.00108)
W*High Income					-.00689***	-.0052***	-.00258*	-.0049***
					(.00087)	(.00082)	(.00133)	(.00094)

W*Bachelor					-.00307***	-.0037***	-.00258**	-.0035***
					(.00075)	(.00071)	(.0011)	(.0008)
W*Crime Inciden					-.000205***	-.00047	-.001	-.0067
					(.00045)	(.00043)	(.00068)	(.00049)
W*Quality					.0191***	.0074**	.0183***	.0107**
					(.00375)	(.0035)	(.0055)	(.0042)
W*Agricultural					.00695	-.0082	-.0066	-.0074
					(.00915)	(.0086)	(.0133)	(.00965)
W*Woodland					.0174***	.0284***	.0203**	.0264***
					(.00595)	(.0056)	(.009)	(.0065)
W*Non-developable					-.0261***	-.0081	-.0135	-.0108*
					(.0059)	(.0056)	(.0086)	(.0064)
W*UA farm					-.0385	-.00058	-.118***	-.0264
					(.033)	(.0311)	(.0403)	(.0352)
W*Land-use change					.0002***	.00009***	.000129***	.00011***
					(.000032)	(.00003)	(.000047)	(.000034)
W*Regional Facto					-.0173	-.0261*	-.0198	-.0243
					(.0157)	(.0148)	(.0226)	(.0165)
ρ		.419***		.2336***		.635***		.485***
		(.0135)		(.0199)		(.0197)		(.0642)
λ			.745***	.608***			.668***	.232***
			(.0171)	(.235)			(.0203)	(.0791)
Wald test		970.47***	1903.36***	1456.4***	817.93***	1961.98***	1713.4***	1551.37***
R-squared	.8258	.8191	.8216	.8227	.8396	.8384	.836	.8385
Number of Observations	9495							

Appendix 3. MWTP for Sub-groups (Land-use Change, Proximity to Different Types of Open Spaces) under Conditional Logit Model

Preservation Strategy	Land-use change nearby	No Land-use change nearby	Near NDVP	Far NDVP	Near NAG	Far NAG	Near AG	Far AG	Near UofA Farm	Far UofA Farm
Commercial vegetable farm; Retail	675.99***	648.81***	548.48***	829.41***	646.35***	694.32**	712.68***	619.91***	956.73	625.31***
Commercial vegetable farm; Residential	539.32***	908.24***	600.58***	963.31***	589.46***	1147.15***	584.22***	922.04***	677.54*	760.62***
Commercial vegetable farm; Light industrial	493.17***	926.72***	439.80***	1137.98***	552.17***	1200.45***	590.34***	913.39***	746.05*	729.58***
Grain or oilseed farming; Retail	295.87*	853.96***	547.04***	727.33***	545.38***	819.21***	518.83***	729.98***	1137.71***	565.61***
Grain or oilseed farming; Residential	441.91***	779.16***	627.46***	693.55***	688.24***	580.63***	563.64***	735.62***	257.79	699.43***
Grain or oilseed farming; Light Industrial	195.20	651.80***	375.27**	535.80*	399.09**	704.71**	269.32	667.90***	656.91	414.92**
Livestock grazing on native pasture; Retail	403.15***	889.99***	767.55***	600.54***	705.03***	678.05***	589.44***	800.68***	452.68	724.21***
Livestock grazing on native pasture; Residential	425.99*	876.16***	718.26***	667.04**	803.85***	547.75*	777.43***	662.24***	1090.89	663.95***
Livestock grazing on native pasture; Light industrial	207.17	909.62***	568.34***	704.68***	496.62***	920.31***	485.90***	754.27***	330.55	654.81***
Observations	1056	1952	1488	1520	1904	1104	1472	1536	416	2592

Appendix 4. MWTP for Sub-groups (Land-use Change, Proximity to Different Types of Open Spaces) under Random Parameter Model

Preservation Strategy	Land-use change nearby	No Land-use change nearby	Near NDVP	Far NDVP	Near NAG	Far NAG	Near AG	Far AG	Near UofA Farm	Far UofA Farm
Commercial vegetable farm; Retail	573.31***	561.45***	438.69***	730.96***	545.49***	529.38***	587.11***	487.26***	547.55***	549.33***
Commercial vegetable farm; Residential	557.54***	886.99***	609.85***	927.55***	601.23***	1148.17***	611.71***	2010.43	1163.01***	770.46***
Commercial vegetable farm; Light industrial	444.60***	1068.78***	420.78***	1165.64***	518.69***	1145.18***	522.92***	815.09***	723.86***	657.29***
Grain or oilseed farming; Retail	244.90	968.80***	479.58**	891.02	538.51***	33686.55	548.40***	859.45*	1456.09***	553.60***
Grain or oilseed farming; Residential	499.38***	759.76***	638.57***	692.16***	742.03***	500.41***	557.89**	616.09***	646.11***	711.40***
Grain or oilseed farming; Light Industrial	269.28	6149.29	568.92**	668.79	310.27	453.84**	-371.5***	873.26	25885.55***	411.27*
Livestock grazing on native pasture; Retail	376.41***	803.76***	705.28***	571.67***	669.80***	558.72***	524.28***	828.78***	346.04***	650.62***
Livestock grazing on native pasture; Residential	595.07	674.34***	881.96	811.22	801.04**	341.28*	1423.47	461.39**	15242.69	848.57
Livestock grazing on native pasture; Light industrial	146.73	828.26***	670.22**	744.75**	590.09**	1189.92*	1635.77***	628.46***	420.08***	725.50*
Observations	1056	1952	1488	1520	1904	1104	1472	1536	416	2592